ABSTRACT

Title of Dissertation: THE IMPACT OF MULTIPLE SPATIAL LEVELS OF THE BUILT ENVIRONMENT ON NONMOTORIZED TRAVEL BEHAVIOR AND HEALTH

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Over the past several decades, the primacy of the automobile in American travel culture has led to rising congestion and energy consumption levels, rampant air pollution, sprawled urban designs, pervasiveness of sedentary behaviors and lifestyles, and prevalence of many health problems. Nonmotorized modes of travel such as walking and bicycling are sustainable alternatives to the automobile and suitable remedies to the adverse environmental, economic, and health effects of automobile dependency.

As research continues to reveal the many benefits of nonmotorized travel modes, identification of the factors that influence people's levels of walking and bicycling has become essential in developing transportation planning policies and urban designs that nurture these activities, and thereby promote public health. Among such factors are the built environment characteristics of the place of residence.

To date, research on the impact of the built environment on nonmotorized travel behavior has been focused on neighborhood-level factors. Nonetheless, people do not

stay within their neighborhoods; they live and work at a regional scale and travel to different places and distances each day to access various destinations. Little is known, however, about the impact of built environment factors at larger scales including those representing the overall built environment of metropolitan areas on nonmotorized travel behavior and health status of residents.

Guided by the principles of the ecological model of behavior, this dissertation systematically tests the impact of the built environment at hierarchical spatial scales on nonmotorized travel behavior and health outcomes. Advanced statistical techniques have been employed to develop integrated models allowing comprehensive examination of the complex interrelationships between the built environment, nonmotorized travel, and health.

Through inclusion of built environment factors from larger spatial scales, this research sheds light on the overlooked impact of the macro-level built environment on nonmotorized travel and health.

The findings indicate that built environment factors at various spatial scales—including the metropolitan area—can influence nonmotorized travel behavior and health outcomes of residents. Thus, to promote walking and bicycling and public health, more effective policies are those that include multilevel built environment and land use interventions and consider the overall physical form of urban areas.

THE IMPACT OF MULTIPLE SPATIAL LEVELS OF THE BUILT ENVIRONMENT ON NONMOTORIZED TRAVEL BEHAVIOR AND HEALTH

by

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Dedication

To the faculty of BIHE whose great sacrifices made higher education possible for me.

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"Knowledge is as wings to man's life, and a ladder for his ascent. Its acquisition is incumbent upon everyone."

—Bahá'u'lláh, Tablet of Tajallíyát (Effulgences)

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Chapter 1: Introduction

1.1 Background and Research Motivations

Statistics and research findings pertaining to the state of travel within the U.S. reveal that automobile remains the dominant mode of transportation in the U.S., whereas walking and bicycling remain the modes less traveled. These trends have adverse economic, environmental, and health consequences. For instance, in 2011, traffic congestion caused Americans to purchase an additional 2.9 billion gallons of fuel, while at the same time, approximately 65% of the U.S. population was either overweight or obese and 32% lived with high blood pressure (Milne and Melin 2014). Other statistics show that transportation activities accounted for 27% of total U.S. greenhouse gas emissions in 2015 (EPA 2017). On the other hand, research continues to reveal health, social, and economic benefits of nonmotorized travel—both for individuals and the communities. Walking and bicycling are deemed sustainable and cost-effective modes of travel and have been suggested to lower risks of many health problems including obesity as well as chronic diseases, mental disorders, and mortality (Andersen et al. 2000; Lindström 2008; Buehler et al. 2011; Nehme et al. 2016; Liao et al. 2016; Tajalli and Hajbabaie 2017).

Considering the numerous benefits of walking and bicycling, promoting these modes of travel has become the focus of many transportation and planning professionals and agencies in recent years. As a result, land use policies that encourage moving away from a sedentary lifestyle (in which automobile is the dominant mode of travel) and moving toward more sustainable travel patterns and a more viable lifestyle (in which nonmotorized travel modes are utilized more often) are gaining increased importance.

Identification and gaining a deeper understanding of the factors that influence the extent of walking and bicycling activities are key elements in planning sustainable and livable communities, particularly within urban areas. Due to their denser form of development, urbanized areas (e.g., metropolitan areas) have been suggested to be the most promising areas in the U.S. to promote nonmotorized travel modes (Delmelle et al. 2012). Similar arguments regarding the role of urban development form on walking and bicycling activities highlight one of the factors that can potentially influence nonmotorized travel behavior—the built environment.

Empirical evidence within the travel behavior literature shows that built environment attributes of the place of residence may influence walking and bicycling of individuals. However, previous research on the determinants of nonmotorized travel can be faulted on a number of grounds.

The chief point that can be raised against prior work is the inattention to the potential role of the built environment at larger spatial scales (e.g., the metropolitan area) on nonmotorized travel behavior. It has been assertively argued by past studies that walking and bicycling trips stay within the neighborhood due to the shorter trip lengths compared with the length of trips made by other travel modes. Consequently, research on nonmotorized travel behavior and its link with the built environment has heavily concentrated on the micro-level (i.e., residence or destination neighborhood) built environment factors thus far, while the potential impact of the built environment at larger spatial scales on nonmotorized trips has been largely overlooked. Nonetheless, the complex interrelation between built environment factors and travel choices gives rise to untested hypotheses regarding the potential impact of the built environment at larger spatial scales (i.e., macro-level built environment) on nonmotorized travel behavior.

Theoretically, the macro-level built environment (i.e., built environment characteristics of the region or the metropolitan area) can be influential in nonmotorized travel behavior. For instance, built environment characteristics that reduce reliance on regional automobile trips and support regional transit trips may lead to generation of more transit-related nonmotorized trips by residents. The ecological model of behavior provides further theoretical support for the argument that in probing the relationship between the built environment and nonmotorized travel behavior, a more comprehensive framework is one that considers multiple levels of the built environment influence including that of the macro level (e.g., metropolitan area level).

Additionally, literature hints on the potential role of the built environment at larger spatial scales in nonmotorized travel behavior. For example, it has been postulated that the built environment—at many geographic scales including the region—can affect the propensity of being physically active (e.g., engage in walking or bicycling activities) (National Research Council 2005). Also, macro-level built environment features such as low-density, sprawling suburban developments have been suggested to discourage nonmotorized travel choices such as walking (Leslie et al. 2007; Cao et al. 2009). A more recent study argued that because people spend most of their daily hours away from their home, the implicit assumption that walking distance from place of residence is the operative scale at which the built environment influences physical activity (e.g., nonmotorized travel) is just that: “an assumption” (Ewing et al. 2014).

On the other hand, literature also suggests that macro-level built environment attributes as well as two related concepts—mobility and regional accessibility—play important roles in shaping individuals’ motorized travel behavior. Thus, it can be hypothesized that as the overall physical form of the metropolitan area[1] impacts household’s mode choice and travel outcomes, it can also be influential in nonmotorized travel behavior of residents.

[1] The overall physical form of the metropolitan area can be represented by factors such as population and employment densities, regional accessibility, extent of decentralization and urban sprawl, transportation network design characteristics, and the extent of mixed-use development within the metropolitan area.

These effects can be exerted either directly through providing access to additional pedestrian- and bicyclist-friendly destinations, or indirectly through affecting the motorized travel behavior. For instance, less driving by household members (i.e., fewer VMT) can mean more walking or bicycling by them, and vice versa. Both the direct and indirect effects of the physical form of the metropolitan area on nonmotorized travel behavior can be a result of increased accessibility and mobility throughout the entire metropolitan area as well as the effects of other macro-level built environment characteristics that may or may not support nonmotorized travel.

The bottom line is that as Guo and Bhat (2007) suggested: the attractiveness of a location (e.g., travel destination) depends not only on its immediate neighborhood but also on how it spatially relates to the urban area it locates in. Thus, it becomes evident from the preceding arguments that in investigation of the link between the built environment and nonmotorized travel behavior, a more comprehensive analysis is one that considers the macro-level (e.g., metropolitan area) built environment in addition to the micro-level (i.e., neighborhood) built environment. Such analysis could give a more complete picture of nonmotorized travel behavior of individuals and its link with the built environment attributes of their place of residence. Therefore, to systematically test the mechanisms behind the built environment and nonmotorized travel connection, it is important to sketch out a comprehensive framework that includes built environment characteristics at both the micro and macro spatial levels.

By consideration of factors representing the built environment at multiple spatial levels—including attributes of the macro-level (i.e., metropolitan area-level) built environment—in the analysis of nonmotorized travel behavior, this dissertation research makes a significant step toward that goal and fills the gap in the body of knowledge on the role of the macro-level built environment in nonmotorized travel behavior.

Moreover, a snapshot of the state of physical activity levels and state of health within the U.S. indicates that physical inactivity has become a trend in the U.S. and as a result, health problem such as obesity are increasing in prevalence. Regular physical activity is a major contributing factor to human health as it leads to reduced risk of many health problems and diseases including obesity, diabetes, hypertension (i.e., high blood pressure), coronary heart disease, stroke and premature death (DHHS 2018). Despite the many health benefits of physical activity, statistics show that between 1998 and 2015, on average, nearly half of U.S. adults did not meet the recommended physical activity requirements[2]. This is while the average percentage of the U.S. population that was overweight or obese increased from 56% to approximately 70% between 1988 and 2014[3]. A recent report estimated the annual healthcare cost of lack of physical activity in the U.S. and its related adverse health outcomes be around $117 billion (DHHS 2018).

Thus, identification of the factors that influence peoples' physical activity levels and their health status is an essential step in promoting public health and lowering healthcare costs within the U.S. Literature suggests that the built environment is among the factors that affect health and physical activity—both in its general form and its transportation-related form (e.g., walking and bicycling). To examine the link between the built environment, physical activity and health outcomes, a three-level built environment hierarchy has been proposed, which includes: the micro level (e.g., immediate local area/neighborhood), the meso level (e.g., neighborhood/community) and the macro level (e.g., metropolitan or county) (King et al. 2002; Ewing et al. 2003b).

[2] See "Table 057. Participation in leisure-time aerobic and muscle-strengthening activities that meet the federal 2008 Physical Activity Guidelines for Americans among adults aged 18 and over, by selected characteristics: United States, selected years 1998–2015": https://www.cdc.gov/nchs/hus/contents2016.htm

[3] See "Table 058. Normal weight, overweight, and obesity among adults aged 20 and over, by selected characteristics: United States, selected years 1988–1994 through 2011–2014": https://www.cdc.gov/nchs/hus/contents2016.htm

Many past studies on the role of the built environment in health behavior such as physical activity and health outcomes considered built environment attributes of the neighborhood or county. Other studies suggested that macro-level built environment attributes including the extent of urban sprawl have a potential to influence individuals' health through affecting physical activity levels and access to healthy food (see e.g., Ewing et al. 2014). Nonetheless, due to the limited number of the latter studies, the role of built environment characteristics of the metropolitan area of residence in physical activity levels and health status of individuals remains under-examined.

The ecological model of behavior supports the argument that in examination of the link between the built environment, health behavior and health status of individuals, a more comprehensive framework is one that considers the macro-level (e.g., metropolitan area-level) built environment in addition to the micro-level (e.g., neighborhood-level) and meso-level (e.g., county-level) built environment. This is because various spatial levels of the built environment may interact to influence health behavior and health outcomes.

Thus, it can be hypothesized that the overall physical form of the urban area (i.e., the built environment of the metropolitan area) can be influential in residents' health behavior such as physical activity levels and their health outcomes. Therefore, to systematically test the mechanisms that influence physical activity and health, it is important to employ a comprehensive framework that includes variables representing various spatial levels of the built environment including the micro, the meso and the macro levels. This theoretical perspective conforms to the principles of the ecological model and is consistent with arguments by previous research (King et al. 2002).

The present dissertation aims toward that goal by inclusion of factors representing various spatial levels of the built environment—including the macro-level built environment—in the analysis of physical activity and health outcomes.

Additionally, the health impacts of travel-related activities such as telecommuting and teleshopping remain unclear.

With respect to psychological health, telecommuting has been suggested by some researchers to positively affect psychological health status (see e.g, Baruch 2001; Steward 2001; Ganendran and Harrison 2007). Others argued that telecommuting has a potential to adversely affect psychological health of individuals (see e.g., Robertson et al. 2003; Henke et al. 2015). However, little empirical research exists to provide evidence of the effects of telecommuting on psychological health. Previous research also suggested that sufficient evidence has not been provided by existing studies to conclude about psychological health benefits of telecommuting and further research is needed in this area as telecommuting grows in popularity (De Croon et al. 2010).

With respect to physical health, there have been few hints in the literature that telecommuting can impact physical health outcomes such as various illnesses, particularly stress-related illnesses (Steward 2001; Lister and Harnish 2011). Nonetheless, the limited number of empirical studies that investigated the role of telecommuting in physical health outcomes and the inconsistent findings do not yield adequate evidence to conclude about the effects of telecommuting on physical health (see Henke et al. 2015; Tajalli and Hajbabaie 2017).

Further, the role of teleshopping in health is currently an open field of research as there seems to be no empirical studies on the health impacts of teleshopping.

The present study fills the gaps in research regarding the health impacts of telecommuting and teleshopping by exploring the role of these travel-related behaviors on both mental and physical health outcomes.

Appendix A provides a more detailed discussion on the background information, problem statements, and research motivations for this dissertation.

1.2 Research Objectives

The present dissertation consists of two parts that are linked to one another by their conceptual and empirical findings. This section gives a synopsis of the research undertaken and the main research questions to be examined in each part of the dissertation.

The first part of the study investigates the link between nonmotorized travel behavior and the environment (in terms of both built and social environments). The main research questions to be explored in this part include:

- How is nonmotorized travel behavior associated with built environment characteristics such as land use patterns, street network patterns, and accessibility at various spatial levels including the micro level (i.e., neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area)?
- How is nonmotorized travel behavior associated with social environment characteristics such as socioeconomic, sociodemographic, and sociocultural factors at various levels of influence including the micro level (e.g., household or neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area)?
- Does residential self-selection play a role in nonmotorized travel behavior?
- Is the link between nonmotorized travel behavior and built environment factors—as measured in the samples analyzed—a causal one?

To investigate the links between built and social environments and nonmotorized travel behavior, the research examines the connections between measures of nonmotorized travel and measures representing the environment at three spatial levels: the neighborhood (i.e., TAZ or census block group), the county, and the metropolitan area. Two analysis levels are considered: the household and the individual.

At the household level, the research tests the hypothesis that built and social environment attributes beyond those of the neighborhood are associated with the number of nonmotorized trips generated from households. Measures of regional accessibility are also included in the analysis as important large-scale built environment factors, which can potentially impact nonmotorized trips.

At the individual level, the analysis examines how multiple levels of built and social environments influence nonmotorized mode share. By inclusion of county-level and metropolitan area-level environmental factors, the study aims to test the role of the built and social environments at larger geographical scales on walking and bicycling of residents. The effect of residential self-selection is controlled for in the individual-level analysis and causality of the links between environmental factors and individual-level nonmotorized mode share is examined.

The second part of the study explores the interrelationships between the environment, human health and health behavior such as nonmotorized (i.e., active) travel and other forms of physical activity. The main research questions to be examined in this part of the research are:

- How are built environment characteristics such as land use patterns, street network patterns, and accessibility at various spatial levels including the meso level (i.e., county), and the macro level (i.e., metropolitan area) related to health behavior such as physical activity levels and health outcomes for individuals and communities?
- How are social environment characteristics such as socioeconomic, sociodemographic, and sociocultural factors at various levels of influence including the micro level (e.g., household or neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area) related to health behavior such as physical activity levels and health outcomes for individuals and communities?

- How are the telecommuting and teleshopping behaviors of residents of a community related to health behavior such as physical activity levels and health outcomes for individuals and communities?
- Does reverse causality exist between health outcomes and health behavior such as nonmotorized travel behavior and other forms of physical activity?

To probe the link between built and social environments, health outcomes, and physical activity (including active travel), the interrelationships between health outcomes, factors representing the environment (i.e., in terms of built and social environment), active travel and other forms of physical activity are examined at two analysis levels: the individual and the community (i.e., county). As indicated previously, two spatial levels are considered in the analyses: the county and the metropolitan area.

At the individual level, the present research investigates how multiple levels of built and social environments influence levels of physical activity performed by individuals and their health status. By inclusion of county-level and metropolitan area-level environmental characteristics in the statistical models developed, the study seeks to test the role of built as well as social environment at larger geographical scales on physical activity levels and health status of residents. The existence of reverse causality and endogeneity bias are also controlled for in the individual-level health outcome analysis.

At the community level, the analysis tests the hypothesis that indicators of community health status are linked with built and social environment attributes at both county and metropolitan levels. The issue of reverse causality between active travel and health is addressed by examination of the reciprocal effects between the extent of active travel within the community and the health outcomes measured for the community.

1.3 Research Contributions

Compared to the existing literature, this research is unique in several ways. Each part of the present dissertation offers its own contributions. These contributions lie in the following aspects:

1.3.1 Research Contributions in Analysis of Nonmotorized Travel Behavior

The first part of this dissertation contributes to the body of knowledge on the link between environmental factors and nonmotorized travel behavior in terms of theoretical framework, methodology, empirical findings, and policy debates.

In terms of theoretical contribution, this study derives a theoretical framework of the link between built environment and nonmotorized travel behavior from the ecological model of behavior. This theoretical framework allows empirical testing of mechanisms by which environmental factors at multiple levels of influence impact nonmotorized travel behavior. Over the last two decades, a considerable body of research on the link between nonmotorized travel behavior and built environment has focused on micro-level (neighborhood-level) built environment characteristics. Studies that tested the impact of built environment characteristics at larger spatial scales—such as that of meso-level (i.e., county-level) and macro-level (metropolitan area) built environment attributes—on nonmotorized travel are relatively scant.

The theoretical framework proposed in this study provides a comprehensive framework for simultaneous examination of the role of environmental attributes (in terms of built and social environments) at various hierarchical levels of influence including the micro level, the meso level, and the macro level on nonmotorized travel behavior. This research is one of the first studies to examine the role of built environment factors in walking and bicycling trips within an integrated theoretical framework, which incorporates measures of macro-level (i.e., metropolitan area-level) built and social environments in addition to those of the meso level (i.e., county level) and the micro level (i.e., neighborhood level).

The comprehensive research framework proposed in this study advances the body of knowledge on nonmotorized travel behavior by providing insights into the role of the overall structure of metropolitan areas in walking and bicycling trips of residents. Macro-level built environment has rarely been tested for its link with walking and bicycling trips. Accordingly, the role of macro-level built environment in nonmotorized trips is of focal interest in this study. Therefore, the main contribution of the first part of the dissertation with regards to theoretical framework is taking into account the position of the neighborhood with respect to the county and the metropolitan area it lies within when analyzing nonmotorized travel behavior.

Further, the theoretical framework of the nonmotorized travel behavior models at the individual level developed in this study accounts for residential self-selection bias (i.e., endogeneity bias). Literature suggests that the link between the built environment and activities such as walking and bicycling should be tested using more comprehensive conceptual models, which account for endogeneity bias (Handy 2005). Therefore, this study contributes to the body of knowledge on the role of self-selection in nonmotorized travel behavior by using a comprehensive framework that allows for addressing the self-selection bias, while incorporating various hierarchical levels (i.e., micro, meso, macro) of built as well as social environment influence.

In terms of the methodology, this study contributes by examining the causality of the link between nonmotorized travel behavior and the built environment as well as by addressing spatial autocorrelation using solid methodologies. As it will be discussed in Chapter 2, evidence supporting the causality of the link between the built environment and nonmotorized travel is currently sparse due to only few studies controlling for self-selection bias or using reliable methodologies when testing for causality. Further, the clustered structure of the data in many past studies subjected the analysis to spatial autocorrelation issues, which remained unaddressed.

To simultaneously examine the effects of the built environment—at multiple spatial levels—on nonmotorized travel behavior within an ecological model framework and while addressing self-selection and spatial autocorrelation issues, this study employs multilevel Structural Equation Modeling (multilevel SEM) techniques. Employment of the multilevel SEM techniques in this research provides several methodological advantages. First, the advanced multilevel modeling capabilities offered by these techniques conform to the multilevel framework of ecological models. Second, the multilevel techniques allow for controlling for any potential spatial autocorrelation issue in the analysis, which may exist due to the clustered and hierarchical nature of the data. Further, the structural equation modeling techniques embedded in multilevel SEMs allow for addressing residential self-selection bias and examining the causal links between nonmotorized travel behavior and the built environment.

Multilevel SEM techniques have rarely been applied in a transportation context despite their many capabilities for being used in travel behavior research. The employment of multilevel SEM techniques in travel behavior research has been proposed in the past (Van Acker et al. 2010). Aside from only two empirical studies (Chung et al. 2004; Kim et al. 2004), however, no other studies were found by the author that used multilevel SEMs in analysis of travel behavior. By employment of such techniques and testing for causality and spatial autocorrelation, this research contributes to a more accurate modeling of the complex link between the built environment and nonmotorized travel behavior and obtaining more methodologically sound results.

With regards to empirical contributions, this study systematically examines the link between nonmotorized travel behavior and built as well as social environment, at three geographical levels—the census block group (i.e., neighborhood), the county, and the metropolitan area—and at two levels of analysis: the individual and the household level. Also, given the lack of empirical research on the association between nonmotorized travel behavior and built environment factors at larger spatial scales, this study contributes to the body of empirical knowledge on the link between the two by including measures of metropolitan area-level (macro-level) and county-level (i.e., meso-level) built environment in the analysis, in addition to those of the micro-level (neighborhood-level) built environment.

To the best of the author's knowledge, this is one of the first studies attempting to advance the body of knowledge on the topic of nonmotorized travel behavior by including measures of built environment from multiple spatial scales (i.e., micro, meso, macro levels) to capture the effects of built environment at multiple hierarchical levels on nonmotorized travel, simultaneously.

By offering analyses that incorporate multiple levels of influence, this dissertation gives more meaningful attention to built environment contingencies and provides more comprehensive insights into the role of the built environment in nonmotorized travel behavior. The knowledge developed from this research can be integrated with past research that examined the impact of micro-level (i.e., neighborhood-level) built environment on walking and bicycling to provide a deeper and more comprehensive understanding of how the built environment influences people's nonmotorized travel patterns.

Moreover, the treatment of built and social environments in this research is extensive, integrating variables representing various dimensions of the built environment (the *five D*s of the built environment) as well as those representing the social environment at multiple levels of geography. This is to accommodate past arguments, which suggest that using rigorous measures of the built environment is an essential step in understanding how the built environment shapes behavior (Ryan and Frank 2009). Using objectively measured, individually observable measures (vs. subjective measures or composite indices) has been suggested to facilitate the interpretation of results for policy and interventions (Moudon et al. 2005; Lee and Moudon 2006).

By including objective and independent measures of the built and social environments, this study contributes to facilitated interpretation of empirical findings and drawing more effective policy strategies that can promote nonmotorized travel. Findings add to the existing empirical knowledge by providing insights into the effects of the overall structure and context of the urban areas (i.e., macro-level built and social environment) in residents' nonmotorized travel behavior.

In addition, as modeling of bicycling travel behavior remains an under-studied area of research, the present study contributes to the body of knowledge on the role of built and social environments in bicycling by developing bicycling-specific models to analyze bicycling behavior.

In terms of contributions to policy and practice, the study findings contribute to policy debates concerning the role of the built environment in nonmotorized travel behavior. The focus of this research is on the influence of the macro-level environment; therefore, findings provide insights into policy interventions that can promote walking and bicycling through modifications to the built (and social environment) within metropolitan areas.

The implications of these findings can assist transportation/urban planners and policy decision-makers to identify the most promising interventions and develop more effective policies through which more sustainable and more environmentally friendly modes of travel are promoted. In practice, more effective operational models can be developed by incorporating the approach proposed in this study to capture walking and bicycling patterns and demand.

1.3.2 Research Contributions in Analysis of Health Outcomes

The second part of this dissertation contributes to the body of knowledge on the complex interrelationships between the built environment, health outcomes, and health behavior such as walking and bicycling as well as other forms of physical activity. The contributions are in terms of theoretical framework, methodology, empirical findings and policy implications.

With respect to theoretical contributions, this research derives a theoretical framework from the principles of the ecological model of behavior as well as past research that emphasizes the role of multiple levels of the environment in health outcomes (see e.g., Joshu et al. 2008) to disentangle the links between physical activity (e.g., active travel), built and social environments and health. Research to date, which examined the role of built environment factors in physical activity and health, has been concentrated on the micro-level (i.e., neighborhood) and meso-level (i.e., county-level) built environment factors. Nonetheless, literature suggests that the structural characteristics of an urban area can potentially influence health outcomes. For instance, sprawling metropolitan areas have been postulated to impact health of residents through restricting access to healthy food as well as producing long commutes, which can cut physical activity times short (Ewing et al. 2014).

The role of macro-level (i.e., urban area and metropolitan-level) built environment factors in health, however, has not been fully examined in previous research. This study contributes to the body of knowledge on the link between built environment and health by considering the role of macro-level built environment in human health. Using an ecological framework as the theoretical foundation, this research examines the health impacts of various dimensions of the built environment at hierarchical spatial levels. More specifically, the analysis explores the hypothesis that built (and social) environment at various levels affect individual and community health outcomes as well as individuals' physical activity levels.

With respect to methodological contributions, this analysis employs sophisticated statistical techniques, which have rarely been applied in a transportation context, to test the causality of the links between physical activity (e.g., active travel), health outcomes and the built environment. The complex interrelationships between physical activity, health, and the built environment can produce interdependencies due to reverse causality as well as the nested nature of the data. Reverse causality may subject the analysis to the endogeneity bias but is often neglected in studies that probe the links between physical activity, health, and the built environment. Endogeneity bias can be accounted for by using advanced statistical methods such as structural equation modeling and instrumental variable techniques. A nested data structure can subject the analysis to spatial autocorrelation issues and can be accounted for by using multilevel (i.e., hierarchical) modeling.

To concurrently control for endogeneity bias and spatial autocorrelation, multilevel modeling can be combined with structural equation modeling in the form of multilevel Structural Equation Modeling (multilevel SEM) techniques, which allow for a more thorough examination of the links between physical activity, built environment factors, and health outcomes. Studies employing multilevel SEM techniques in a transportation context remain rarely found. To the author's knowledge, multilevel SEM techniques have not been previously applied to empirical data in probing the health impacts of physical activity and built environment factors. The present dissertation contributes to this research field by using multilevel SEMs to control for endogeneity bias and to test the causality of the links between physical activity and health.

In terms of empirical contributions, this research systematically examines the link between measures of travel behavior (including active travel), objectively measured built environment factors, and health outcomes. The analyses are conducted within an ecological model framework using two levels as the unit of analysis: the individual level and the community (i.e., county) level. This analysis framework offers a comprehensive approach that has never been applied to empirical data before and is one of the contributions of this study. The findings provide a more comprehensive picture of the interrelationships between travel behavior, physical activity, the built environment, and health outcomes and add to the existing empirical knowledge on these topics.

Moreover, the study contributes to the body of knowledge on the link between travel behavior and health by including measures of travel-related behaviors such as telecommuting and teleshopping in the analysis. Research in the past postulated that telecommuting influences psychological health indicators such as level of job satisfaction and social isolation. However, there have been only a handful of empirical studies to investigate the link between telecommuting and psychological health with little consistency in the findings.

In addition, the effect of telecommuting on physical health has not been thoroughly investigated in the past and studies on that topic are scarce. Further, to the best of author's knowledge, no empirical studies exist regarding the health impacts of teleshopping. Considering these gaps in research, this study incorporates measures of travel-related behavior including telecommuting behavior and teleshopping behavior in addition to other travel behavior measures (e.g., nonmotorized travel) in the analysis framework to capture the effects of these travel behavior patterns on physical and psychological health of individuals and communities.

With regards to policy and practice, the study findings contribute to the current policy debates on the role of the built environment in physical activity and health. Findings provide insights into the most promising policy interventions that can promote public health through changing the built and/or social environments within urban areas. The findings can be used by transportation/urban planning and public health decision-makers to develop more effective policies that maximize health benefits for individuals and communities.

1.4 Organization of the Rest of the Document

In the following chapter (Chapter 2), a comprehensive literature review relative to nonmotorized travel behavior research and health research is presented in terms of both theoretical foundations and empirical research findings. Chapter 3 discusses the research design of this dissertation with respect to the conceptual framework, hypotheses to be tested, datasets utilized, and analytical techniques employed. Chapters 4 and 5 comprise the analytical chapters. In Chapter 4, nonmotorized travel behavior is analyzed providing model specifications, model results and discussion of the findings. Chapter 5 provides the analysis of health outcomes including model specifications, model results, and discussion of the findings. Conclusions, policy implications, and future research directions are discussed at the end of each analytical chapter (Chapters 4 and 5). Lastly, Chapter 6 provides the closing remarks. Additionally, ten appendices are provided:

Appendix A complements Chapter 1. It provides a more detailed discussion on background and research motivations for this dissertation. Appendix B complements Chapter 2 and provides a more comprehensive literature review on nonmotorized travel behavior, the built environment, and health and the connections between them. Appendix C complements Chapter 4 and presents a Baltimore-Washington D.C. case study of the link between nonmotorized travel and the built environment. Appendices D through H supplement analyses presented in Chapter 4. Appendix I complements work in Chapter 5 and presents an analysis of the county-level health outcomes. Finally, Appendix J provides a summary of the findings of this dissertation.

Chapter 2: Literature Review

This dissertation aims at developing an integrated travel behavior—built environment—health framework to model nonmotorized trips and health outcomes. Thus, an extensive literature review was conducted to synthesize the findings of previous research and to identify gaps in the existing knowledge on the relationships between nonmotorized travel behavior, the built environment, and human health. In the interest of brevity, this chapter only discusses the takeaways revealed from the literature review along with gaps in existing research. A comprehensive review of the literature, which provides the basis for the discussion presented in this chapter, can be found in Appendix B.

Studies on nonmotorized travel behavior and its relationship with the built environment and health outcomes are abundant. An important note confirmed by the review of this literature is the multidisciplinary nature of the research concerning walking and bicycling activities. Any research on these modes of travel inevitably involves perspectives of professionals from many scientific disciplines. Consequently, factors influencing walking and bicycling travel, and the impact of these activities on health outcomes are prolific areas of research in several fields such as transportation planning, urban design, preventive medicine, psychology and public health.

The transportation/urban planning fields of research view walking and bicycling as alternatives to automobile travel and potential remedies to the problems associated with automobile-oriented modern urban societies. In the past two decades, the transportation/urban planning literature has been trending on concepts such as smart growth, new urbanism, transit-oriented development, complete streets, livable communities, and sustainable transportation—all of which advocate for urban planning and designs that promote walking and bicycling as competing modes to the automobile. Walking and bicycling are often referred to as *nonmotorized travel* in the transportation planning and urban design literature.

On the other hand, the health benefits of walking and bicycling—to both the individual and the society—are what prompts health professionals to be interested in these modes of travel. In the health fields, health outcomes are considered to depend, in part, on health behavior such as physical activity, while walking and bicycling are considered important forms of physical activity. Thus, the health literature often refers to walking and bicycling as *physical activity* or *active travel*. Health benefits of active travel are well established in the health-related literature. For instance, research has provided ample evidence that active travel—particularly in the form of walking—is an essential element in maintaining a healthy weight while providing many other health benefits (see e.g., Ewing et al. 2003b; Frank et al. 2004; and Schauder and Foley 2015).

Further, literature provides evidence that several factors influence nonmotorized travel behavior. These factors can be categorized into three major groups:

1) socioeconomic and sociodemographic factors (e.g., age, race, gender, car ownership);
2) built environment factors (e.g., the *five D*s of the built environment—namely, density, diversity, destination accessibility, design, and distance to transit—as suggested by past research such as Cervero and Kockelman (1997) and Ewing and Cervero (2010); and
3) psychological factors (e.g., attitudes, self-selection, social and cultural norms).

Also, various factors that play an important role in health outcomes of individuals emerge from the literature. These include:

1) physical activity (e.g., active travel such as walking or bicycling);
2) built environment factors (e.g., the *five D*s);
3) social environment factors (e.g., crime levels); and
4) travel and travel-related behavior such as telecommuting.

Particularly, components of the environment are revealed to have a potential to impact nonmotorized travel behavior and human health. Professionals in the public health, transportation engineering, and urban planning communities are increasingly learning about the mechanisms by which attributes of the built, natural, and social environments influence physical and mental health (Frank et al. 2016). Among these components, the built environment is shown to play a key role in walking and bicycling as well as in health outcomes.

The literature review also shows that researchers in each of the afore-mentioned disciplines have utilized various theories and methodologies to explain various travel behavior outcomes. Through these efforts, the body of knowledge on walking and bicycling activities and their relationship with built environment characteristics and health outcomes has advanced substantially.

However, due to different theoretical and methodological perspectives from each discipline, ambiguity in empirical evidence still exists and many aspects of the complex interrelationships between walking and bicycling travel behavior, the built environment, and human health remain to be explored.

This chapter summarizes the key takeaway notes from the comprehensive review of the literature on the factors affecting walking and bicycling and health as well as the role that built and social environments play in walking and bicycling travel and health outcomes (see Appendix B). In addition, the main gaps in existing research are identified and opportunities for further research, which guided the present study in its endeavor to fill some of the gaps in research, are discussed.

Walking and bicycling are interchangeably referred to as nonmotorized travel, active travel, and physical activity in the following sections—depending on the context within which they are being discussed (i.e., the travel behavior context or the health context).

2.1 Nonmotorized Travel Behavior: The Role of Sociodemographic and Socioeconomic Factors

Empirical studies on nonmotorized travel behavior provide evidence that socioeconomic and sociodemographic characteristics including age, gender, race, and income influence walking and bicycling. Past findings are summarized below to provide a synopsis of the current state of empirical knowledge on the role of socioeconomic/demographic factors in nonmotorized travel.

Age: Many studies on nonmotorized travel provide evidence for the impact of age on walking and bicycling. Overall, it seems that those who make nonmotorized trips tend to be younger (Hess et al. 1999; Pucher et al. 1999; Ross 2000; Handy and Clifton 2001; Troped et al. 2001; Zhang 2004; Targa and Clifton 2005; Zacharias 2005; Clifton and Dill 2005; Handy et al. 2006; Dill and Voros 2007; Boarnet et al. 2008; Merom et al. 2010; Siu et al. 2012; Ma and Dill 2015). Therefore, age appears to have a negative correlation with nonmotorized travel based on current findings. This means that being older is often associated with fewer nonmotorized trips.

Gender: Past findings suggest that gender influences nonmotorized travel behavior. Specifically, those who are male seem to engage in walking and bicycling at higher rates (Pucher et al. 1999; Ross 2000; Troped et al. 2001; Cervero and Duncan 2003; Rodríguez and Joo 2004; Stinson and Bhat 2004; Targa and Clifton 2005; Plaut 2005; Moudon et al. 2005; Dill and Voros 2007; Gatersleben and Appleton 2007; Merom et al. 2010; McDonald et al. 2011; Mitra and Buliung 2012; Ma and Dill 2015). Thus, based on the existing literature, higher levels of nonmotorized trip-making are generally associated with being male.

Education: Existing findings indicate that higher education is associated with increased nonmotorized travel as many studies found higher education to be positively correlated with walking and bicycling (Ross 2000; Troped et al. 2001; Ewing et al. 2003b; Targa and Clifton 2005; Plaut 2005; Agrawal and Schimek 2007; Siu et al. 2012; Nehme et al. 2016; Wasfi et al. 2016).

Income: The effect of higher income levels on nonmotorized travel has been generally found to be negative in past studies, suggesting that higher income correlates with lower levels of nonmotorized travel (Cervero and Radisch 1996; Cervero and Kockelman 1997; Handy and Clifton 2001; Ewing et al. 2004; Schwanen and Mokhtarian 2005; Plaut 2005; Bento et al. 2005; Agrawal and Schimek 2007; Boarnet et al. 2008; Schneider 2015). However, the findings on income are not universal and vary based on the context or trip purpose (Cervero and Duncan 2003; Moudon et al. 2005; Clifton and Dill 2005; Zacharias 2005; Agrawal and Schimek 2007; Merom et al. 2010). Some suggest that higher income levels are associated with more recreational nonmotorized travel but fewer nonmotorized utilitarian trips (Dill and Voros 2007; Marcus 2008). Also, safety concerns have been presumed to be related to lower levels of nonmotorized travel in low-income neighborhoods (Cervero and Duncan 2003). Considering the inconsistent findings, further research may be needed into the role of income in nonmotorized travel behavior.

Race: Race seems to have a significant association with walking and bicycling with more studies suggesting that non-Whites are more likely to make nonmotorized trips (Hess et al. 1999; Cervero and Duncan 2003; Scuderi 2005; Yarlagadda and Srinivasan 2008; Pucher et al. 2011).

Car Ownership and Possessing a Driver's License: Having a car and/or a driver's license is almost always negatively associated with walking and bicycling in the past studies (Cervero 1996; Cervero and Radisch 1996; Kockelman 1997; Kitamura et al. 1997; Cervero and Kockelman 1997; Dieleman et al. 2002; Bagely and Mokhtarian 2002; Cervero and Duncan 2003; Dill and Carr 2003; Zhang 2004; Ewing et al. 2004; Rodríguez and Joo 2004; Stinson and Bhat 2004; Targa and Clifton 2005; Plaut 2005; Næss 2005; Cao et al. 2010; McDonald et al. 2011; Mitra and Buliung 2012). This implies that owning a car and the ability to drive it may adversely impact walking and bicycling activities.

2.2 Nonmotorized Travel Behavior: The Role of Environmental Factors

2.2.1 Theories Applied

The theoretical foundations for nonmotorized (i.e., active) travel behavior come from a variety of disciplines that explain human behavior such as the economics and the psychology fields. The chief theories that have been used in travel behavior research as well as health behavior (i.e., physical activity and active travel) research are: the utility-maximization demand theory (McFadden 1974), which originated in the field of economics and behavioral theories including the theory of planned behavior (Ajzen 1991); the social cognitive theory (Bandura 1986); and the ecological model of behavior, which come from the field of psychology.

A comprehensive review of literature (see Appendix B) reveals that the ecological model of behavior provides the most integrated framework for modeling human behavior such as active travel. This is because an ecological model framework incorporates all the components of the theory of planned behavior (i.e., attitudes, subjective norms, and perceived behavioral controls), and those of the social cognitive theory (i.e., social environment factors) and adds to them the influence of *built environment* factors on behavior.

In terms of the built environment, the ecological model can include factors representing hierarchical spatial levels such as the micro level (e.g., neighborhood), the meso level (e.g., county), and the macro levels (e.g., metropolitan area or city).

2.2.2 Methodologies

The literature review shows that various methodologies have been used by researchers in examination of the link between nonmotorized travel behavior and the built environment and this research often faces challenges in term of confounding factors. A few of the methodological issues generic to this research include: *i*) complex and interrelated factors that may be spatially clustered

(Lee and Moudon 2004); *ii*) limited data availability on nonmotorized travel, especially for bicycling; *iii*) inconsistencies in built environment and land use data; *iv*) inconsistencies in defining the *neighborhood* as the most common spatial unit of analysis; *v*) inattention to spatial autocorrelation; *vi*) difficulties in controlling for self-selection bias and establishing causal links.

In terms of methodological perspectives, this literature review unveils new promising avenues for research on the connection between nonmotorized travel behavior and the environment in terms of the built and social environments. The advanced theoretical perspectives on human behavior offered by the field of psychology can be combined with the sophisticated methodological perspectives offered by the fields of public health and econometrics to develop comprehensive conceptual frameworks that can guide further empirical examination of the link between nonmotorized travel behavior and the environment.

Because it includes all the components of the other psychological theories and models, the ecological model of behavior provides a good vehicle for an integrated framework. <u>The multilevel framework of the ecological model of behavior, which allows integration of variables representing multiple influence levels on behavior as well as various spatial levels (e.g., micro, meso, and macro levels), can be analyzed using hierarchical modeling techniques to statistically deal with multilevel effects and spatial clustering dependencies (i.e., spatial autocorrelation).</u> Employment of hierarchical models has been suggested in past research to help in statistical treatment of spatial autocorrelation (Moudon et al. 2005).

Further, <u>in dealing with residential self-selection issues, statistical methods such as Structural Equations Modeling (SEM) techniques can be utilized in testing the link between nonmotorized travel and the built environment.</u> SEM techniques have been suggested to offer a conceptual improvement over the single-equation regression methodology (Cao et al. 2009).

2.2.3 Empirical Findings

2.2.3.1 Nonmotorized Travel Behavior and the Built Environment

This literature review reveals that many studies that examined factors influencing health behavior such as active travel included built environment factors in their conceptual frameworks. The focus has been on empirically testing the effects of micro-level (neighborhood-level) built environment attributes. However, several shortcomings in this research including lack of comprehensive analysis, methodological weaknesses, data limitations, widely dissimilar approaches to measuring neighborhood-level built environment attributes, using land-use and travel data at different levels of aggregation, and testing different travel outcomes have resulted in mixed, and in many cases, insignificant evidence (Badoe and Miller 2000; Targa and Clifton 2005).

Nonetheless, five key built environment dimensions that have a potential to influence active travel behavior can be derived from the evidence provided by past research. These include neighborhood-level (i.e., micro-level): density, diversity, distance to destinations, design, and distance to transit. Literature refers to these dimensions as the *five Ds* of the built environment (see e.g., Cervero and Kockelman 1997; Ewing and Cervero 2010). Previous findings on the role of these factors in active travel can be summarized as follows:

Density: Density has been operationalized in various studies using various methods yielding the use of different measures of density such as population density, employment density, residential density, housing density, and activity density (see e.g., Frank and Pivo 1994; Kitamura et al. 1997; Badoe and Miller 2000; Rodríguez and Joo 2004; Boer et al. 2007; Weinberger and Sweet 2012). Regardless of the density measure used, existing literature suggests that the effects of neighborhood-level density on nonmotorized travel behavior remain unclear. This statement is consistent with previous literature arguing that compared to other *Ds* of the built environment, density is of less importance and its effects sometimes are captured by the other *Ds* (Ewing and Cervero 2010).

Diversity (Land Use Mix): It is evident from the literature review that previous findings on the association between the level of neighborhood diversity and walking/bicycling behavior are inconsistent. Many studies found that presence of or proximity to mixed-use and/or commercial establishments positively affected nonmotorized travel (see e.g., Frank and Pivo 1994; Cervero 1996; Kitamura et al. 1997; Shriver 1997; Cervero and Kockelman 1997; Handy and Clifton 2001; Giles-Corti and Donovan 2002; Cervero and Duncan 2003; Limanond and Niemeier 2004; Scuderi 2005; Plaut 2005; Moudon et al. 2005; Cao et al. 2006 ; Pikora et al. 2006; Kerr et al. 2007; Lin and Chang 2010). However, others reported mixed, negative or non-existent correlations between local mixed land use or commercial establishments and nonmotorized travel (see e.g., Kitamura et al. 1997; Hess et al. 1999; Zhang 2004; Ewing et al. 2003a; Moudon et al. 2005; Forsyth et al. 2008; Rodríguez et al. 2009; Mitra and Buliung 2012; Wang 2013; Ma and Dill 2015).

The overall ambiguity in the empirical evidence and the inconsistency in findings seems to be due to: *i*) differences in methods of quantifying mixed land use and usage of different factors (e.g., ratio of employment to population, ratio of public and commercial areas to residential areas, presence of retail and mixed-use developments including parks, size or number of retail establishments, and distance to the nearest store or park); *ii*) differences in trip purpose (e.g., shopping vs. entertainment, work vs. non-work); and *iii*) differences in the travel behavior outcome being examined (e.g., trip frequency vs. mode choice). The inconclusive findings suggest that the effects of mixed-use development on walking and bicycling may merit further investigation.

Destination Accessibility: Empirical findings are more consistent in terms of the role of destination accessibility in walking and bicycling. Past research findings suggest that local destination accessibility influences nonmotorized travel behavior. More specifically, limited access to local destinations in terms of distance (i.e., greater distances to destinations) has been reported in many studies to negatively impact nonmotorized travel (see e.g., Handy 1996a, 1996b; Kitamura et al. 1997; Handy and Clifton 2001; Greenwald and Boarnet 2001; Giles-Corti and Donovan 2002; Cervero and Duncan 2003; Limanond and Niemeier 2004; Stinson and Bhat 2004; National Research Council 2005; Handy 2005; Hoehner et al. 2005; Shay et al. 2006; Lee and Moudon 2006; Cao et al. 2006; Goddard et al. 2006; Handy and Xing 2011).

Thus, with respect to nonmotorized travel behavior, local destination accessibility—typically represented by distance to destinations—is a key attribute of the neighborhood built environment. This is in line with Ewing and Cervero (2010) who concluded in their meta-analysis of past studies that destination accessibility had a strong connection with nonmotorized travel (i.e., walking in that study).

Design: The impact of various variables representing characteristics of neighborhood design as well as transportation infrastructure on nonmotorized travel has been investigated in the past.

To measure grid-like street patterns, past studies often measured block size and/or intersection density. Findings of these studies suggest that the impact of block size on nonmotorized travel behavior is somewhat ambiguous with researchers finding either no significant correlation between nonmotorized travel and block size or a significantly negative one (Cervero and Duncan 2003; Ewing et al. 2003a; Moudon et al. 2005; Boer et al. 2007; Forsyth et al. 2008; and Lin and Chang 2010). The inconsistent findings have been suggested to result from the potentially mixed effects of block sizes and street connectivity. On the one hand, smaller block sizes may increase access to destinations, and thereby encourage nonmotorized trips. On the other hand, smaller block sizes may also create more conflict points between vehicles and pedestrians (or bicyclists), which can discourage walking or bicycling (van Loon and Frank 2011).

More consistency can be seen in empirical findings on the effect of street connectivity on nonmotorized travel behavior as studies consistently found that higher extents of street connectivity were correlated with higher levels of nonmotorized travel (Zhang 2004; Targa and Clifton 2005; Dill and Voros 2007). Previous research also suggests that presence and/or higher density of intersections (a proxy for street connectivity) seems to positively affect nonmotorized travel (Cervero and Kockelman 1996; Boer et al. 2007; Kerr et al. 2007; Wang 2013).

Based on previous studies, density of major roads does not appear to have an impact on the walking/bicycling travel (Mitra and Buliung 2012; Wang 2013).

Research findings have also shown that vehicular traffic as well as vehicular network and facilities influence nonmotorized travel behavior. Traffic volumes and speeds have been found to adversely affect walking (Appleyard 1981; Gehl 1987; Cao et al. 2006; Nehme et al. 2016). However, no significant association has been found between traffic volumes and bicycling (Moudon et al. 2005). Further, higher parking costs seem to be associated with increased nonmotorized travel rates (Cervero and Kockelman 1997; Handy and Xing 2011).

In addition, presence and extent of pedestrian and bicyclist infrastructure and amenities play a key role in nonmotorized travel behavior. Presence of sidewalks and extent of their completeness and connectivity have been shown to be positively associated with nonmotorized trips (Kitamura et al. 1997; Hess et al.1999; De Bourdeaudhuij et al. 2003; Rodríguez and Joo 2004; Fan 2007; Forsyth et al. 2008; Lin and Chang 2010). Presence of walking and bicycling paths has not suggested consistent correlations with nonmotorized mode choice (Rodríguez and

Joo 2004). Further, presence and/or density of bicycle lanes has been found to be an insignificant factor in predicting the likelihood of bicycling (Moudon et al. 2005; Dill and Voros 2007).

Considering these findings, the reviewed material has proved inconclusive with respect to the effects of neighborhood design and transportation infrastructure on nonmotorized travel behavior. While there appears to be a correlation between some design and infrastructure attributes and nonmotorized travel, the significance and direction of such correlation varies considerably among empirical studies. This conclusion is somewhat similar to that of Rodríguez and Joo (2004) and Handy (2005). The former study stated "relationships between nonmotorized travel and street and road network attributes other than connectivity are less clear. These attributes include sidewalk continuity, sidewalk width, presence of cycling and walking paths, and the local topography, among others." (Rodríguez and Joo 2004). The latter study performed a comprehensive review of literature and concluded that due to various approaches and inconsistencies in measuring design, design-related variables were largely insignificant in studies reviewed, and that the design dimension of the built environment requires further attention in future studies (Handy 2005).

Distance to Transit: Literature suggests that distance to transit is the most important measure of access to transit services influencing nonmotorized travel. Findings of the studies that examined the effects of access and distance to transit facilities on walking and bicycling behavior suggest that shorter distances to local transit is correlated with higher rates of nonmotorized travel. However, further research is needed to investigate these findings as it seems that the effects of access to transit (in terms of distance) on walking and bicycling have not been fully explored in the past. Overall, it is concluded that although empirical research provides strong evidence that the *five Ds* of the built environment at the neighborhood level are correlated with walking and bicycling, for some of these dimensions, the direction and magnitudes of correlations are less clear than the others. More specifically, the effects of density and diversity (i.e., mixed land use) are less consistent than the effects of distance to destinations and distance to transit services, which seem to negatively impact walking and bicycling. Findings of existing studies also indicate that the effects of some attributes of neighborhood design such as street and sidewalk connectivity on walking and bicycling trips are more consistent than the other micro-level design attributes.

2.2.3.2 Nonmotorized Travel Behavior and the Social Environment

Literature suggests that the social environment can influence nonmotorized travel behavior through concepts such as social and cultural norms as well as perceptions of crime.

Social and Cultural Norms: Social norms are values that a group or the society holds, which influence behavior by individual members of that group or society. In other words, social norms are the perceived pressure that the individual feels in performing or not performing a certain behavior; thus, social norms have the power to regulate an individual's behavior (Heinen et al. 2010; Van Acker et al. 2010).

With respect to nonmotorized travel behavior, social and cultural norms can influence walking and bicycling activities through concepts such as observational learning and social stigma. The former encourages individuals to perform an activity that they frequently observe others perform. The latter may discourage them to engage in an activity due to the feeling of shame.

Many studies found a link between walking or bicycling and observing others perform the same activities (see e.g., Dill and Voros 2007; Ma and Dill 2015; Nehme et al. 2016). On the other hand, concerns about public prestige in societies with cultural norms that associate utilitarian walking/bicycling with social stigma may discourage these activities. Thus, the social norms within a society can create a culture for travel behavior including for walking and bicycling travel. For individuals, this travel culture may also be influenced by the structural characteristics of the geographical area of current or prior residence. Past research found that living in areas with a high population of immigrants was linked with higher levels of walking to school among children (McDonald 2005), whereas having a parent who was born in the U.S. was associated with a lower likelihood of walking/bicycling to school by children (McMillan 2003). These findings imply that the geographical context (i.e., metropolitan area, country) of residence can influence cultural norms, and thereby can play a role in nonmotorized travel behavior of individuals. The importance of geographical context (e.g., region, metropolitan area, country) in walking and bicycling activities has been highlighted in literature, with many researchers suggesting that nonmotorized travel behavior may vary depending on the geographical context (see e.g., De Bourdeaudhuij et al. 2003; Targa and Clifton 2005; Heinen et al. 2010; Pucher et al. 2010; Buehler et al. 2011). Also, several studies investigated nonmotorized travel behavior among citizens of different countries (see e.g., Buehler et al. 2011) and discussed cross-cultural differences in levels of these activities. Thus, the social norms and travel culture held by a community as well as the geographical context which contains the community can play key roles in nonmotorized travel behavior of residents.

Crime: Perceptions of crime as well as actual crime rates have been found by some to be negatively associated with nonmotorized travel (see e.g., Ross 2000; Joh et al. 2009; Nehme et al. 2016). However, others did not find any relation between nonmotorized travel such as walking and perceived safety from crime (De Bourdeaudhuij et al. 2003). In addition, perceptions of crime have been found to have a stronger influence on behavior than objective crime measures (Nehme et al. 2016). Overall, the empirical evidence seems to be inconclusive with regards to the relationship between levels of nonmotorized travel and crime rates within the area of residence as well as perceptions of crime held by residents. Thus, further research may be needed to clarify the role of crime-related factors in nonmotorized travel behavior.

2.2.4 Nonmotorized Travel Behavior and Environmental Factors: Gaps and Limitations in Research

This literature review unveils a few gaps and limitation in the existing research on the link between nonmotorized travel behavior and the environment—particularly the built environment. These include limitations in methodologies used as well as a few empirical research gaps.

Methodologies Used: As previously mentioned, the framework of the ecological model of behavior, which allows integration of variables representing multiple levels of influences on behavior as well as various spatial levels, is a suitable framework for analysis of nonmotorized travel behavior. This multilevel framework can be analyzed using hierarchical modeling techniques to statistically deal with any potential spatial autocorrelation issues. Although few studies reviewed (for this literature review) employed hierarchical modeling methods (see e.g., Hovell et al. 1992; Craig et al. 2002; Ewing et al. 2003b, 2008; Ewing et al. 2014), spatial autocorrelation remains largely overlooked in examination of nonmotorized travel behavior. As environmental factors are known to covary spatially, the nature of spatial autocorrelation and the utility of hierarchical modeling techniques need to be further examined (Lee and Moudon 2004). Further, in dealing with confounding factors such as the residential self-selection, methodologies such as Structural Equations Modeling (SEM) techniques, which literature deems as a conceptual improvement over the single-equation methodologies (Cao et al. 2009), can be used.

Hence, advanced statistical tools such as the SEM techniques that allow controlling for self-selection bias can be applied to a comprehensive research framework that includes objective built environment factors from multiple spatial levels in examining the causal links between nonmotorized travel behavior and the built environment. Specifically, the employment of multilevel SEM techniques seems to provide methodological improvements

in nonmotorized travel behavior research. Despite capabilities in dealing with endogeneity bias (i.e., self-selection bias in this context) as well as spatial autocorrelation issues, multilevel SEM techniques are surprisingly underutilized in travel research behavior.

Multiple Spatial Levels of the Built Environment: The ecological model of behavior assumes the possibility that multiple levels of the built environment influence behavior. These levels can include the micro level (i.e., the neighborhood), as well as the meso level and the macro level (i.e., geographical scales that are larger than the neighborhood). <u>However, a notable knowledge gap revealed from the literature review is the inattention of research efforts to the effects of various levels of geography on nonmotorized travel behavior</u>. To date, almost all the studies that examined the association between nonmotorized travel behavior and the built environment focused on the micro-level (i.e., neighborhood-level) built environment factors, and did not include built environment attributes from the other levels of geographical aggregation.

Past literature draws attention to the issue of geographical scales in examining the impact of land use and the built environment in travel behavior and suggests that future studies should compare land use and built environment factors at various levels of geography (Boarnet and Srmiento 1998). Moreover, some uncertainties exist within the literature about the appropriateness of the geographical scale of current studies of nonmotorized travel behavior. For instance, Mitra and Buliung (2012) suggested that future research into the built environment's role in nonmotorized travel should be conducted at different levels of geographical aggregation. Also, National Research Council (2005) suggested that stratification of the effects of the built environment on physical activity such as walking and bicycling should be considered in future studies as differences in contextual factors (such as subpopulation and urban settings) may cause variations in the relationship between these activities and the built environment. Another study recommended examination of the role of regional-level attributes on physical activity (Handy 2005) such as walking and bicycling, which has been ignored so far in research.

Considering all the above, it can be inferred that nonmotorized travel behavior can vary based on factors representing various levels of geography (i.e., neighborhood vs. metropolitan area). The influence of the built environment beyond the neighborhood level on nonmotorized travel behavior is yet to be determined. In particular, macro-level built environment factors have not previously been tested for that purpose. However, as discussed previously, there are many reasons based on the literature as to why testing meso-level and macro-level (i.e., regional and metropolitan area level) built environment factors for their potential role in nonmotorized travel seems a plausible argument. The simultaneous inclusion of various spatial levels of the built environment may shed light on the influence exerted by factors at each level.

Therefore, investigating the effects of the built environment at different spatial levels including the neighborhood (micro level), the county/region (meso level), and the metropolitan area (macro level) on nonmotorized travel behavior is a research idea that fits the ecological model framework but has not been previously explored.

Micro-level Built Environment: Several attributes of the neighborhood (i.e., micro-level) built environment have been tested in previous research. The relationship between these attributes and nonmotorized travel behavior varies according to the context and type of travel behavior being examined such as trip frequency, mode choice, and trip purpose (Rodríguez and Joo 2004). From the literature, it appears that better street connectivity within the neighborhood as well as shorter distances to local destinations and transit facilities are correlated with increased nonmotorized travel. <u>However, evidence on the effects of other neighborhood-level built environment factors</u> (e.g., density, mixed land use, density of roads, traffic volumes and bicycle lanes) <u>on nonmotorized</u>

travel is either inconsistent or slim. In addition, micro-level built environment factors have rarely been considered in a model that also includes meso and/or macro-level built environment factors.

Thus, additional research is required to clarify the role of micro-level density, diversity, and design dimensions of the built environment in nonmotorized travel behavior. Moreover, additional analysis of the relationship between the micro-level built environment and nonmotorized travel behavior—especially within a framework that includes built environment factors from other spatial levels (i.e., meso and macro)—can strengthen the existing knowledge by further clarifying the effects of each spatial level of the built environment on walking and bicycling activities.

Macro-level Built Environment: It is noteworthy that a disproportionate number of the studies reviewed were conducted within a neighborhood context and included only micro-level built environment variables in their analysis of nonmotorized travel behavior. The existing literature almost entirely disregards any potential effects of macro-level built environment on walking and bicycling. For instance, variables describing the overall structure of the metropolitan area (i.e., the regional structure dimension) have not been considered in the analysis of nonmotorized trips. Perhaps the reason for this is that in the past, researchers considered the regional structure dimension one that closely related to VMT with a much less sensitivity to walking and bicycling (Fan 2007). Only few researchers suggested that macro-level built environment characteristics such as regional accessibility and urban sprawl have a potential to affect walking and bicycling travel by promoting sedentary behavior and increasing automobile use (see e.g., King et al. 2002; National Research Council 2005; Plantinga and Bernell 2007).

Nonetheless, empirical studies that considered the role of macro-level built environment in nonmotorized travel behavior are scarce. Findings of these studies indicated that: *i)* regional (zipcode level) densities did not impact walking (Greenwald and Boarnet 2001); *ii)* metropolitan area-level compactness promoted walking (Ewing et al. 2003b, 2008); and *iii)* regional-level walkability influenced walking mode share (Weinberger and Sweet 2012). With regards to bicycling, past empirical findings showed that city-level bicycle infrastructure was associated with higher rates of bicycle commuting (Dill and Carr 2003). However, the following limitations exist in the case of each of these studies, which can be addressed by further research:

Greenwald and Boarnet (2001) examined the impact of regional-level land use on walking behavior. The authors defined regional level land use factors as zipcode-level population density and retail employment density. They concluded that regional densities did not have any effects on walking behavior[4]. However, their analysis of the regional effects had two limitations: 1) besides population and retail employment, no other measure of the built environment was included in the regional model; and 2) regional-level density variables were included in a separate model and not in combination with neighborhood-level built environment variables. Nonetheless, the authors suggested that the effects of regional density attributes and other regional-level built environment measures should be examined in future analyses to allow inferences about the influence of the built environment beyond the neighborhood level.

To examine minutes of walking among other outcomes, Ewing et al. (2003b, 2008) developed county-level and metropolitan area-level sprawl indices by combining several built environment variables capturing the levels of residential density, land use diversity, centralization, and street accessibility. The two studies found that the extent of county-level and metropolitan area-level sprawl impacted walking. Based on these findings, the studies suggested that county-

[4] The authors of this study did not consider the effects of the regional-level density variables as statistically significant because the coefficients of these variables were insignificant at the 5% level of significance. However, the effects of the zipcode-level population density were significant at the 10% significance level in the models (Z scores 1.945 and 1.934 in Table 5, page 38 of Greenwald and Boarnet 2001).

level as well as metropolitan area-level compactness promoted walking. Because both studies also examined the effects of county-level and metropolitan area-level sprawl indices on many health outcomes, the limitations of these studies will be discussed under Section 2.5[5].

Dill and Carr (2003) analyzed city-level data from 42 U.S. cities to examine the relationship between a city's extent of bicycle infrastructure and the percentage of workers in the city that commuted by bicycle. The study found that having a higher level of bicycle infrastructure within the city was positively correlated with higher percentages of commuting by bicycle. However, except for a bicycle infrastructure variable and one potential transit availability variable (which according to the paper was excluded from models due to being insignificant), this study did not include any other built environment variables in the analysis.

Leslie et al. (2007) divided a mega-metro region in Australia into five various sub-regions to examine walking behavior of residents of each sub-region. The study found significant sub-regional differences in walking. However, one limitation of the study was the coarse-categorization of sub-regions into five broad areas, which probably masked walking behavior due to substantial variability in the built environment attributes of different sub-regions. The authors concluded that "variations within sub-regions and the mix of local area characteristics are likely to be more useful than categorizing sub-regional areas more broadly". Thus, a more consistent spatial categorization of the study area will help in analysis of the influence of macro-level built environment on nonmotorized travel behavior.

Weinberger and Sweet (2012) examined the effects of walkability at micro (TAZ) level as well as macro (regional) level on walking mode share. The study concluded that walkability at both levels influenced walking mode share. However, the only built environment factor considered

[5] See Subsection "2.5.3 Health and Environmental Factors: Gaps and Limitations in Research".

in this study was walkability measured by Walk Score, which is a composite measure of the built environment inclusive of many *D*s of the built environment. Although, Walk Score is a valid measure of the built environment (see Subsection 3.2.10), the authors of the study stated that "it is not comprehensive and still lacks information" (Weinberger and Sweet 2012). Therefore, Walk Score by itself cannot be assumed to represent all of the built environment attributes of the study area. To more comprehensively investigate the connection between nonmotorized travel behavior and the built environment, various built environment variables representing various dimensions of the micro- as well as macro-level built environment should be considered in the analysis.

Considering the limited empirical research regarding the potential effects of macro-level built environment factors on nonmotorized travel behavior, it is fair to say that empirical knowledge contains a gap in this area as the role of macro-level built environment in nonmotorized travel has not been thoroughly examined in the past.

Thus, it is time to move beyond the micro-level spatial scope and also consider the macro-level built environment in the analysis framework of walking and bicycling research. Such integrated framework can help researchers and policymakers determine the role of the overall structure of metropolitan areas in nonmotorized travel behavior of residents.

Multiple Spatial Levels of the Social Environment: Theories of human behavior such as the social cognitive theory and the ecological model of behavior consider the role of the social environment in human behavior. The social environment factors in this context represent the sociocultural norms of the social circles that the individual is a member of. The ecological model further recognizes the influence of multiple levels of the social environment on behavior. These levels can include the micro-level (e.g., the household or the neighborhood), the meso-level (e.g., county) and the macro-level (e.g., city) social environment.

It should be noted, however, that the effect of the social environment may not be mutually exclusive from that of the built environment. Literature suggests that structural (i.e., built environment) effects and contagion effects (i.e., adopting a behavior due to seeing others perform it) can mutually reinforce each other; for example, if the built environment encourages some individuals to walk, others who see these walkers may also start walking (Ross 2000).

Other researchers also argue that social norms can influence travel behavior by creating a travel culture, which in turn, may be influenced by the structural attributes of the urban area (Næss 2005). The current literature posits that nonmotorized travel behavior can vary among various levels of geography (i.e., neighborhood vs. metropolitan area) as well as among different geographical contexts that may have the potential to exert "cultural" (i.e., social environmental) effects on travel behavior (e.g., the cultural effects of one metropolitan area vs. those of another).

Considering the existing empirical studies, the role of social environment factors such as social and cultural differences—at various levels of influence—on nonmotorized travel seem to be under-investigated. Additionally, it is important to consider the effects of the social environment on nonmotorized travel behavior within a framework that also includes built environment factors. The ecological model of behavior provides such comprehensive framework.

The effects of the social environment in an integrated ecological framework—which includes social and built environment factors at various spatial levels (e.g., the neighborhood, the region, and the metropolitan area)—on nonmotorized travel behavior has not been previously explored. Macro-level social environment (sociodemographic and socioeconomic) attributes as well as macro-level built environment factors can be included within an integrated framework as proxies for cultural and contextual effects. This will shed light on the differences in nonmotorized travel between various contexts and geographical levels.

Bicycling, the Built and the Social Environments: Literature suggests that bicycling and walking are distinct activities (see e.g., Porter et al. 1999; Pikora et al. 2003; Schlossberg et al. 2006); thus, factors that affect bicycling trips may not necessarily be the same factors that affect walking trips. However, most empirical studies that examined nonmotorized travel behavior focused on walking trips only (see e.g., Hess et al.1999; McMillan 2003; Boer et al. 2007; Agrawal and Schimek 2007; Rodríguez et al. 2009 among many others) or conducted their analysis and reached their conclusions based on a general "nonmotorized" or "non-auto" dataset—which combined walking and bicycling, and occasionally, even transit data as one category (see e.g., Cervero and Radisch 1996; Cervero and Kockelman 1997; Schwanen and Mokhtarian 2005). This has been mainly due to data limitations on bicycling travel (Merom et al. 2010).

Therefore, compared with walking, bicycling travel behavior seems to be under-examined. Although few studies exist that focused on bicycle travel only (see e.g., Moudon et al. 2005; Dill and Voros 2007), there have been calls in literature for further research into the correlations between the built and social environments and bicycling, especially with regards to bicycling frequency (Heinen et al. 2010). In other words, understanding the link between bicycling travel behavior and the built and/or social environment can benefit from further research. **Thus, a comprehensive study that focuses on the impact of built and social environments on bicycling-specific travel behavior merits undertaking.**

2.3 Nonmotorized Travel Behavior: The Role of Psychological Factors and the Issue of Causality

Literature provides evidence that psychological factors such as attitudes, perceptions, and preferences play key roles in nonmotorized travel behavior. Past findings with this respect can be summarized as follows:

Attitudes, Perceptions, and Preferences: It appears from the literature that attitudes, perceptions, and preferences toward daily travel as well as toward physical activity, personal health, and the environment have an important influence on nonmotorized travel behavior. In a few cases, literature suggests that the effects of these attitudinal predispositions may supersede the effects that built environment and land use factors exert on nonmotorized mode choices (Kitamura et al. 1997; Lund 2003; Cao et al. 2006). This statement is supported by the past reviews of the literature on the role of attitudes in physical activity (e.g., nonmotorized travel), which also concluded that compared with land use characteristics, attitudes may exert a stronger effect on nonmotorized travel (National Research Council 2005).

Self-selection and Causality: Attitudes and preferences also influence residential location choices—leading to self-selection bias. That is, individuals with a preference toward nonmotorized modes of travel may self-select themselves into pedestrian- and bicyclist-friendly residential areas. Self-selection results in spuriousness, and thereby confounds the relationship between nonmotorized travel behavior and the built environment.

Some researchers argue that in examining the link between the built environment and travel behavior or transportation-related physical activity (e.g., nonmotorized travel), residential self-selection should be controlled for because otherwise, the analysis may produce biased results (see e.g., National Research Council 2005; Chen et al. 2008; Cao 2010; and van Wee and Ettema 2016).

Further, drawing causal links between the built environment and nonmotorized travel behavior will not be appropriate in presence of spurious relationships due to self-selection bias. Therefore, if a correlation is observed between built environment attributes and nonmotorized travel behavior, one must ensure that the possibility of self-selection was addressed in the analysis prior to inferring that causal mechanisms were involved.

Three prominent approaches to account for self-selection bias in examining the relationship between travel behavior and built environment characteristics emerge from the existing literature. These include:

1) structural equation modeling (SEM) techniques;

2) instrumental variables analysis; and

3) longitudinal research designs.

A preference for the SEM techniques emerges from the literature due to the conceptual improvements that these methodologies offer over the single-equation methodology (i.e., OLS techniques). For instance, to investigate self-selection and causality, Cao et al. (2009) recommended the usage of longitudinal structural equations modeling with control groups.

From a review of empirical self-selection studies, the above-referenced paper also suggested that while self-selection plays an important role in explaining the link between the built environment and nonmotorized travel behavior, the attributes of the built environment are still significantly influential in making the choice to walk or bicycle (Cao et al. 2009).

Consistent with what Cao et al. (2009) suggested, many of the empirical studies reviewed for this literature review found a statistically significant influence of built environment attributes (either subjective or objective) on nonmotorized travel behavior, even after accounting for residential self-selection (see e.g., Greenwald and Boarnet 2001; Cao et al. 2006; Handy et al. 2006; Fan 2007; Chatman 2009; Cao 2010; Aditjandra et al. 2016).

Appendix B lists all the self-selection papers reviewed for this literature review along with a summary of their findings (see Table B in Appendix B).

2.3.1 Nonmotorized Travel and Psychological Factors: Gaps and Limitations in Research

While the existing empirical evidence indicates that a correlation exists between the built environment and nonmotorized travel behavior, evidence supporting a causal link is currently sparse as few studies controlled for self-selection issues and/or demonstrated a causal link using reliable methodologies.

Further, notably absent from the literature reviewed are studies that consider the causal links and self-selection issues in an analysis framework that includes macro-level (e.g., metropolitan area level) built environment characteristics to examine nonmotorized travel behavior. The closest to this comes a study by Greenwald and Boarnet who included zipcode-level density variables in their analysis of walking trips and controlled for self-selection by using instrumental variables (Greenwald and Boarnet 2001).

The noninclusion of macro-level built environment characteristics in the analysis is an important missing piece from research examining causal links between nonmotorized travel behavior and the built environment. He and Zhang (2012) provides support for this argument by suggesting that the analysis of causal effects between the built environment and travel behavior can be improved by including metropolitan area-level built environment measures in the analysis.

Also, in a context of self-selection literature review, Cao et al. (2009) stated that many past studies focused on micro-level (i.e., neighborhood-level) built environment characteristics and did not consider the regional location of the neighborhood. The authors suggested that as opposed to neighborhood-level built environment attributes, the regional location within which the neighborhood lies also has a potential to influence travel behavior—in their words "perhaps even more substantially, in some ways, than the former" (Cao et al. 2009).

Although, a subsequent study did address self-selection within a framework that included macro-level built environment variables, it analyzed motorized (and not nonmotorized) travel behavior (Nasri and Zhang 2014). Thus, questions remain regarding the complex interactions between micro- and macro-level built environment characteristics and residential self-selection as well as their relations with nonmotorized travel behavior and the causality of such relations.

This means that research into the role of self-selection in nonmotorized travel behavior and the causal links involved remain tentative and can benefit from more comprehensive frameworks, which include built environment characteristics from micro and macro spatial levels.

Thus, the body of empirical knowledge can be furthered on the issues of self-selection and causality in nonmotorized travel behavior research by using a comprehensive framework that controls for self-selection bias and includes various spatial levels (e.g., micro, meso, macro levels).

2.4 Health: The Role of Nonmotorized Travel (i.e., Physical Activity)

This literature review shows that the impact of walking and bicycling on health has been studied by many researchers in the past. Walking and bicycling are considered types of physical activity; thus, the phrases *walking and bicycling*, *active travel*, and *physical activity* are used interchangeably in health literature.

The health benefits of active travel are well established in the literature. Prior research has provided ample evidence that physical activities such as walking and bicycling are positively associated with a lower risk of mortality (Andersen et al. 2000) and improved health indicators including BMI and obesity (see e.g., Ewing et al. 2003b; Frank et al. 2004; Smith et al. 2008; Schauder and Foley 2015; and Tajalli and Hajbabaie 2017).

2.5 Health: The Role of Environmental Factors

2.5.1 Theories Applied and Methodologies

Health literature suggests that much of the influence of the built environment on health is exerted by facilitating or constraining physical activity, especially in the form of active travel (i.e., walking and bicycling). Thus, the discussion regarding theories and methodologies applied in examination of the link between nonmotorized travel behavior and the built environment holds true here as well (see Section 2.2).

With regards to theoretical foundations, the multilevel framework of the ecological model of behavior can be employed to model health behavior such as physical activity (e.g., active travel) as well as health outcomes.

In terms of methodologies, it is noteworthy that often in health studies, the outcome variable of interest is dichotomous. For example, the researcher is interested in knowing whether (or not) the sufficient level of physical activity for health purposes was achieved, or if the subjects of the study have a certain health problem such as asthma. In both situations, a no/yes survey response can be coded as a dichotomous 0/1 variable for statistical modeling purposes.

Employment of binary logistic regression and binary probit regression in modeling health behavior and health outcomes is a common choice in the case of a dichotomized dependent variable (see e.g., Smith et al. 2008 and Liao et al. 2016 for binary logistic models, and Samimi and Mohammadian 2009; Samimi et al. 2009 as well as Langerudi et al. 2015 for binary probit models).

In addition, hierarchical models can be used to model health behavior and health outcomes and statistically account for any potential spatial autocorrelation issues (Moudon et al. 2005; Marshall et al. 2014).

2.5.2 Empirical Findings

2.5.2.1 Health and the Built Environment

Many of studies reviewed here that examined factors influencing health behavior such as active travel (i.e., walking and bicycling) and health outcomes included characteristics of the built environment in their conceptual frameworks. Literature suggests that built environment attributes can influence human health through three key domains: 1) physical activity; 2) social interaction; and 3) access to healthy food (Kent and Thompson 2012). For instance, by encouraging or discouraging health behavior such as physical activity, the design of communities can influence health outcomes such as weight (see e.g., McCann and Ewing 2003).

Empirical research shows that certain built environment characteristics such as mixed land use and pedestrian friendliness of streets favorably influence both physical and mental health outcomes, especially weight-related health outcomes such as BMI and obesity (see e.g., Lund 2002; Leyden 2003; Frank et al. 2004; Smith et al. 2008; Timperio et al. 2010). However, research findings are mixed when it comes to the effects of other measures of the built environment such as density measures (e.g., residential density, population density) and street connectivity measures (e.g., block size, intersection density) on health outcomes. This is because some of these measures showed insignificant effects or opposite direction of effects in health models in different past studies (see e.g., Frank et al. 2004; Smith et al. 2008; Samimi et al. 2009; Samimi and Mohammadian 2009).

Compactness (defined as a combined measure of density, land use mix, centering of jobs and population and street network design in this context) has also been related to lower BMIs and a lower probability of having health problems such as obesity, diabetes, high blood pressure and heart disease (Ewing et al. 2003b; Ewing et al. 2014). Increased access to open recreational spaces and parks has been found to be associated with lower BMIs (Timperio et al. 2010) and more social interaction (Lund 2003). The latter effect can positively influence mental health.

2.5.2.2 Health and the Social Environment

The literature review reveals that by influencing health behavior such as active travel and physical activity, the social environment can impact health outcomes. Social environment factors such as social norms, culture, and crime rates have been found to influence levels of active travel as well as those of other types of physical activity.

Evidence of the influence of factors representing social and cultural environments on active travel is provided by studies such as McMillan (2003), McDonald (2005), Dill and Voros (2007), Ma and Dill (2015), and Nehme et al. (2016); <u>however, empirical findings on the effects of such factors on active travel and physical activity are not consistent, particularly with respect to crime</u>.

Findings reported in the Morbidity and Mortality Weekly Report (CDC 1999) documented a higher prevalence of physical inactivity among individuals who perceived their neighborhoods unsafe from crime. However, based on a review of empirical studies, Foster and Giles-Corti (2008) concluded that evidence on the link between crime-related safety and physical activity (inclusive of active travel) was inadequate and required further research.

Nonetheless, due to the relations between physical activity and health, any effect exerted by sociocultural norms and crime on active travel can impact health outcomes downstream.

2.5.3 Health and Environmental Factors: Gaps and Limitations in Research

This literature review shows that gaps and limitations exist in research on the link between health, health behavior and the environment (in terms of built and social environment). These include limitations in methodologies used as well as a few empirical research gaps.

Methodologies Used: Although a few studies reviewed for this literature review employed hierarchical modeling techniques in modeling health outcomes (see e.g., Ewing et al. 2003b; Kelly-Schwartz et al. 2004; Joshu et al. 2008; Marshall et al. 2014), spatial autocorrelation in this research remains under-studied. As environmental factors are assumed to spatially covary; the nature of spatial autocorrelation and the utility of hierarchical modeling techniques need further examination (Lee and Moudon 2004).

Moreover, a notable methodological limitation in the existing research concerns the issue of endogeneity bias in the analysis of the interrelationships between health behavior, health outcomes and the built environment. Endogeneity occurs in a model when a few variables are interdependent and need to be jointly determined as dependent variables (Mahmoudi and Zhang 2018b), or when an observed independent (i.e., explanatory) variable is a random function of other independent variables or is correlated with the error term (i.e., unobserved factors) (Train 2009).

Interdependency between variables representing health behavior, health outcomes and the built environment can exist. For instance, the built environment has a potential to influence health behavior (e.g., active travel) as well as health status of individuals. Also, health behavior such as active travel can affect individuals' health status. On the other hand, however, health status can also influence health behavior. For example, due to a better health status, healthier individuals' may be more likely to engage in physical activity. Studies in the past suggested that poor health may act as a personal barrier to physical activity and active travel (see e.g., Lee and Moudon 2004; National Research Council 2005) and that reciprocal causation (i.e., reverse causality) between health status and health behavior such as active travel may exist (Schauder and Foley 2015).

In addition, health status also has a potential to affect the residential choice location (and thereby the built environment characteristics of the place of residence). Health indicators such as

BMI have been found to influence the choice of residential location (Plantinga and Bernell 2007; Zick et al. 2013), which suggests that built environment factors may not be exogenous determinants of BMI. Since BMI and obesity play a role in other health outcomes, it can generally be assumed that bidirectional causality can run between health outcomes and the built environment—a possibility that further confounds the relationships between health behavior, health outcomes, and the built environment and the causality of the pathways between them.

Moreover, existing literature suggests that attitudes and self-selection bias (i.e., endogeneity bias) play a role in health behavior such as physical activity and its travel-related form, active travel (see Section 2.3 and Appendix B). Thus, attitudes and self-selection can potentially influence health outcomes. There is consensus within the health literature that physical activity leads to health benefits (see e.g., Andersen et al. 2000; Frank et al. 2004; Smith et al. 2008; DHHS 2008, 2018; Schauder and Foley 2015). However, the influential role of the built environment in physical activity (e.g., active travel) is a matter of ongoing debate. In other words, while the causal link between adequate levels of physical activity (e.g., walking and bicycling) and health is well established, the other half of the equation—the causal link between the built environment and walking/bicycling activities (as forms of physical activity)—is not quite yet confirmed (National Research Council 2005).

Thus, the complex nature of the links between health behavior, health outcomes and the built environment as well as the possibility of existence of other underlying unmeasurable factors (e.g., persistence to engage in active travel) subject the analysis to endogeneity bias. <u>However, this literature review confirms that endogeneity bias is often neglected in the studies modeling the relationship between health behavior such as active travel and health outcomes</u>, which may result in biased estimates—a point also raised by Schauder and Foley (2015).

The above-referenced study used instrumental variables analysis to address endogeneity in examination of the relations between health behavior (e.g., active travel) and health outcomes. Although, the study did not control for objective built environment factors, a few of the variables used might have potentially represented built environment characteristics. For instance, the authors argued that their usage of a variable indicating whether the individuals rent or own their home represented the density characteristic of the area of residence (Schauder and Foley 2015). Despite not using more rigorously measured built environment variables, this study highlighted the importance of addressing endogeneity bias in testing causal links between health behavior and health outcomes. Zick et al. (2013) also used instrumental variable analysis to adjust for the possible endogeneity in the analysis of residential location selection and BMI of residents.

Another way of addressing endogeneity bias and bidirectional influences is using the SEM techniques. As indicated previously, SEM accounts for multiple directions of causality (National Research Council 2005) and can deal with multiple endogenous variables (Scheiner and Holz-Rau 2007). Thus, the SEM techniques can be utilized to estimate bidirectional relationships between health outcomes and health behavior endogenous variables. The use of advanced statistical techniques such as SEM has been recommended in previous research to disentangle the complex causalities between travel behavior and health (van Wee and Ettema 2016). Further, the SEM techniques have been used in past studies to address endogeneity issues, although not always in a health context (e.g., Bagely and Mokhtarian 2002; Cao et al. 2007; Cervero and Murakami 2010).

Almost all of the studies reviewed for this literature review are cross-sectional studies, and therefore, causality assumption of the statistical analyses may not hold for them. <u>However, there seems to be a need to identify and examine more fully the array of causal links implied in health behavior and health outcome models</u>.

Sophisticated statistical techniques such as instrumental variable analysis and SEM techniques, which allow controlling for endogeneity bias, can be applied to a comprehensive research framework, which includes objective built environment factors, in testing the causal links between built environment, health behavior such as active travel, and health outcomes.

Multiple Spatial Levels of the Built Environment: The other note emerging from the literature is the multilevel nature of the influence of the built environment on health behavior and potentially, on health outcomes. Considering the ecological model of behavior, literature argues that the influence of built environment attributes on health behavior such as physical activity (e.g., active travel) and the related health outcomes should be considered at various spatial levels ranging from micro (e.g., neighborhood) to meso (e.g., county) to macro levels (e.g., metropolitan area and city levels). The principles of the ecological model can provide a basis for identifying high-leverage attributes of micro, meso, and macro environments—each of which can potentially influence individuals' level of physical activity (King et al. 2002), and thereby their health status.

However, most of the health-related studies reviewed were conducted at the neighborhood level (i.e., micro level) or county level (i.e., meso level). Neighborhood-level built environment was only utilized in studies where home addresses of the individuals were available to researchers (see e.g., Frank et al. 2004). Nonetheless, many health studies had to stay within the county-level boundaries due to privacy issues concerning health data.

While it is evident from the literature that the neighborhood (i.e., micro-level) and county-level (i.e., meso-level) built environment play a role in individuals' health, the role of metropolitan area-level (i.e., macro-level) built environment in public health has not been fully examined in the past and merits further research. This brings the discussion to the very related topic of the gaps in knowledge regarding the effects of macro-level environmental factors on human health.

Health and the Macro-level Built Environment: This literature review shows that there have been some calls in the past for future studies to examine the link between the macro-level built environment and health outcomes. For instance, Smith et al. (2008) suggested that macro-level measures of walkability (e.g., land-use mix, density, and street network connectivity) should be studied for their association with weight-related outcomes. The study further suggested that pedestrian-friendly designs were likely related to macro-level as well as micro-level measures of walkability and future work should develop an understanding of how macro- and micro-level factors of walkability were interrelated (Smith et al. 2008) in influencing health outcomes.

Further, health literature argues that macro-level built environment factors such as those of the metropolitan area can influence health by affecting health behavior such as active travel behavior as well as access to healthy food; therefore, measures of the macro-level built environment are needed to represent the broad settings that shape individuals' health-related behavior (Ewing et al. 2014). Specifically, existing literature suggests that urban structural characteristics such as urban sprawl have a potential to affect physical and mental health of residents either directly, or indirectly by constraining physical activity (e.g., active travel), promoting sedentary behavior, and increasing social exclusion (Cervero and Duncan 2003; Khattak and Rodriguez 2005; Næss 2005; Leslie et al. 2007; Plantinga and Bernell 2007).

To date, however, only few empirical studies included measures of macro-level built environment in their analysis of health outcomes. The sprawl index (i.e., a combined measure of residential density, land use mix and street network) at the metropolitan area level was found to be not associated with health indicators in two studies (Ewing et al. 2003b; Kelly-Schwartz et al. 2004). In contrast, city-level built environment measures such as increased levels of major streets with bicycle lanes, number of fast food restaurants and convenience stores, and intersection density were found to be associated with health outcomes in another study (Marshall et al. 2014). City-level street connectivity was not associated with health outcomes in the latter study.

Nonetheless, there remain a few limitations and gaps in the case of each of these studies, which can be addressed by further research. These gaps and limitations are discussed below.

Ewing et al. (2003b, 2008) included macro-level built environment factors in their analysis of health outcomes. However, the following limitations exist in their analysis:

1) even though these studies investigated the effects of county and metropolitan area built environment on health and active travel, they estimated two separate models; one for a county-level analysis, and one for a metropolitan area-level analysis. The studies did not include built environment variables from each spatial area in one integrated model to capture the concurrent effect of the county and metropolitan area on health and active travel behavior. Literature agrees that the effect of each variable in explaining travel behavior is best determined if all variables are considered simultaneously in the framework of the same model (Badoe and Miller 2000);

2) the composite nature of the sprawl index developed in these studies may have masked the individual effects of each built environment factor. This is evidenced by findings of a subsequent study (Kelly-Schwartz et al. 2004) that used the sprawl indices developed by Ewing et al. (2002) and Ewing et al. (2003b) as well as health data at the Primary Metropolitan Statistical Areas level to examine the effect of metropolitan sprawl on health outcomes. The study found that various dimensions of sprawl affected health in different and contradictory ways. The influence of sprawl on health was both positive and negative meaning some aspects of sprawl such as street connectivity showed positive association with better health, but other aspects such as density showed negative association with overall health ratings. The study concluded that the composite measure of sprawl confounded the analysis by combining the positive effect of street connectivity

with the negative effect of density into one index—leading to a failure in finding a significant relationship between the sprawl measure and measures of health (Kelly-Schwartz et al. 2004).

Other studies also suggest that composite factors may not adequately capture the effects of each independent built environment attribute on the outcome variable. Humpel et al. (2002) argued that composite measures may obscure correlations that might have been evidenced if individual components were used independently. Rodríguez and Joo (2004) suggested that it is unclear if the attributes that really influence health behavior such as walking are measured by using composite factors. Further, Foster and Giles-Corti (2008) stated that "composite variable lack specificity".

In addition, having composite factors poses the question of weighing the component variables. As Ewing et al. (2014) asked "should the factors be weighted equally, or should one or another be given more weight than the others?" That study gave all the component factors of the composite sprawl index equal weights in the overall index; however, any analysis conducted using composite indices may produce inaccurate results if differential weights should have been used instead of equal weights. Several other studies have also discussed the generality and challenges of practical policy interpretations of composite factors (e.g., Lee and Moudon 2006; Fan 2007).

Therefore, inferring conclusions and making policy decisions regarding a specific built environment attribute is difficult if a composite index, which combines all dimensions of the built environment, is used. To gain a better understanding of the effects of various metropolitan-level built environment factors on health, they should be included in the analysis as independent factors;

3) the sprawl index did not include many factors that may potentially influence active travel and health outcomes (such as existence of parks and fast food restaurants); and

4) the effects of metropolitan area built environment characteristics on asthma and psychological health indicators was not examined in these studies.

Joshu et al. (2008) assessed the environmental correlates of obesity at both the micro and macro spatial levels—using a sample of adults in the U.S. Important limitations of this study are:

1) usage of perceived as opposed to objective neighborhood built environment measures;

2) inclusion of only one city-level measure (level of urbanization);

3) noninclusion of food-related built environment factors; and

4) consideration of only one health outcome (obesity).

Marshall et al. (2014) also conducted their analysis at both neighborhood and city levels. Study limitations in that research include:

1) it focused on street design-related built environment variables in the model and did not control for other important dimensions of city-level built environment such as population and employment densities, transit accessibility and destination accessibility;

2) except for the household income, no other city-level socioeconomic factor was included in the models; and

3) travel mode choice-related (e.g., neighborhood- or city-level nonmotorized travel mode share) variables were not included in the model.

Braun and Malizia (2015) developed a composite downtown vibrancy index for 48 U.S. cities to examine the association of this index with health outcomes. That study has limitations:

1) a composite index was used, which as previously mentioned, does not allow the effects of individual built environment factors to be assessed separately; and

2) the geographic scales for the vibrancy and health outcome variables were inconsistent. As the authors indicated, vibrancy was measured in this study for downtown areas, whereas the health outcome variables were measured for the county that contained the downtown area; this inconsistency might have weakened the correlations.

Thus, the health impacts (in terms of both physical and psychological health) of various macro-level (i.e., metropolitan area level) built environment characteristics have not been thoroughly investigated in the past and additional research can be conducted in this area.

Health and the Macro-level Social Environment: The literature review reveals that consideration of how the social environment influences health outcomes—particularly with respect to the macro-level measures—has been very limited in past research. The few studies that included macro-level (e.g., metropolitan area-level) measures in their framework to examine health outcomes did not take into account the fact that metropolitan areas differ in their cultural context. Studies that did consider some cultural measures in their analysis did so in a neighborhood (i.e., micro-level) context, and did not take into account the metropolitan area (macro-level) cultural factors.

An example of the former studies is Marshall et al. (2014) who included built environment variables and an income variable at the city-level in their models but did not include variables representing the sociocultural characteristics (e.g., percentage of immigrants) of the different cities under study. For the latter studies, Mitra and builing (2012) can serve as an example whose "walking density" measure was defined at the micro level and their study did not include a macro-level sociocultural measure in the analysis of active travel (which is a type of physical activity, and thereby can influence health outcomes).

Further, as the influence of the social and built environments on health behavior—and consequently, on health outcomes—are considered interwoven (see e.g., Joshu et al. 2008), literature calls for additional research on the effects of both micro- and macro-level built environment factors and their interrelationship with social environment features to influence health outcomes such as BMI (Smith et al. 2008).

Moreover, macro-level crime-related factors have not been considered in the analysis of health outcomes in the past as many studies examining the effects of crime on health were conducted at the neighborhood level (see e.g., CDC 1999). Also, literature suggests that additional research is needed regarding the influence of crime on health behavior such as physical activity as empirical findings in this area are inconsistent (see e.g., Foster and Giles-Corti 2008). Since physical activity can influence health outcomes, it can be concluded that the effects of crime on health outcomes are under-studied and remain unclear.

Therefore, probing the effects of the social environment in an integrated research framework that includes both social and built environment factors at various levels of geography on health outcomes and physical activity require further examination.

Macro-level attributes (e.g., sociocultural, socioeconomic, and crime factors) can be included in the analysis as proxies for cultural and contextual effects to shed light on the role of the macro-level social environment in health status of residents.

2.6 Health: The Role of Telecommuting

Research in the past suggests that telecommuting provides a number of benefits such as improving productivity, conserving energy, protecting the environment from harmful emissions, and enhancing family values by allowing employees work from their homes (see e.g., Balaker 2005; Lister and Harnish 2011; Khan 2015). These effects can have health implications.

Nonetheless, this review of the existing literature on the effect of telecommuting on health reveals that studies examining this topic are limited in number. In addition, they are mostly focused on the health effects of telecommuting in the context of psychological and mental health.

2.6.1 Research Theories and Empirical Findings

2.6.1.1 Psychological Health and Telecommuting

Past research suggests that telecommuting may have various psychological health benefits including lower levels of occupational stress, better job performance, improved job satisfaction, and community improvements (see e.g., Baruch 2001; Steward 2001; Robertson et al. 2003; Ganendran and Harrison 2007). However, literature also highlights the potential negative aspects of telecommuting, which can also have psychological implications, including longer work hours, social isolation and increased work-related stress (see e.g., Baruch 2001; Robertson et al. 2003; Henke et al. 2015).

This literature review reveals that empirical research findings on the link between telecommuting and psychological health are inconsistent. Other studies also suggest that sufficient evidence has not been provided by existing studies to conclude about psychological health benefits of telecommuting such as job satisfaction (De Croon et al. 2010).

2.6.1.2 Physical Health and Telecommuting

The psychological health of an individual is not separate from her/his physical health. Therefore, it is logical to hypothesize that the factors that affect a person's psychological health can also affect her/his physical health.

For instance, commute-related stress (a psychological health factor) may lead to increased levels of stress hormones (adrenaline and cortisol) (see e.g., Evans et al. 2002; Evans and Wener 2006). If commuting occurs chronically, the elevated levels of these hormones may cause physical health problems over time.

Nonetheless, the role of telecommuting in physical health has not been thoroughly examined in the past. Only two studies investigated the role of telecommuting on physical health outcomes, and they yielded different findings. Telecommuting was found to potentially increase the risk for obesity in one study (Henke et al. 2015). However, the other study found that telecommuting was not associated with indicators of physical health such as obesity, blood pressure and diabetes (Tajalli and Hajbabaie 2017).

2.6.2 Health and Telecommuting: Gaps and Limitations in Research

Many research gaps and limitations exist in terms of the link between telecommuting and health. Little is known about the role of telecommuting in psychological health and empirical findings on this topic are inconclusive. Further, very little empirical knowledge exists regarding the role of telecommuting in physical health.

The only two studies that examined the effects of telecommuting on physical health outcomes produced inconsistent results. More specifically, one of these studies concluded that telecommuting may increase the risk of obesity (Henke et al. 2015), whereas the other found that telecommuting was not associated with indicators of physical health including obesity, blood pressure and diabetes (Tajalli and Hajbabaie 2017).

Moreover, the two referenced studies have several limitations. For instance, neither study considered the effects of built environment factors in their analysis framework; Henke et al. (2015) included only a dummy variable for the region of work location, whereas Tajalli and Hajbabaie (2017) did not include any built environment variables.

Past research calls for further examination of the role of telecommuting in health (see e.g., Baruch 2001; De Croon et al. 2010; Henke et al. 2015), which seems a good idea considering the inconsistencies in findings and gaps in empirical knowledge on this topic.

A related topic is the role of teleshopping in health. The present review of literature reveals that to date, there are no empirical studies on health impacts of teleshopping and research in this area is almost silent.

This leaves the question of "how does telecommuting affect health?"—to some degree—unanswered, and the question of "how does teleshopping affect health?" just unanswered! Answering these questions require further research, the findings of which, can shed light on the role of telecommuting and teleshopping in health status.

2.7 Chapter Conclusions

This review of literature on nonmotorized travel behavior (i.e., walking and bicycling behavior), the health impact of walking and bicycling, and the role of the built environment in these activities as well as in health yielded interesting information and provided insights into the theoretical bases as well as empirical research findings on these topics.

By identifying several gaps in existing research, the literature review also unveiled new promising avenues for research in probing the links between nonmotorized travel behavior, the built environment and human health. The identified gaps in existing knowledge are addressed in the present dissertation as discussed in the preceding sections within this chapter.

A comprehensive review of the literature on the topics of nonmotorized travel behavior, the built environment, and health and the interrelationships between these three can be found in Appendix B. The elaborated literature review presented in Appendix B provides the foundation for the discussions in this chapter.

Chapter 3: Research Design

As discussed in previous chapters, interest in nonmotorized travel behavior stems from the health benefits of walking and bicycling activities for both the individual who is engaging in these activities, and the community as a whole. The main goals of conducting research on nonmotorized travel are: *i*) to identify the factors that affect people's decision to walk or ride a bicycle; and *ii*) to determine the extent of the effects of such factors. Transportation and urban planning agencies, engineers, and policymakers can use the knowledge gained from such research in designing more sustainable communities and infrastructure as well as developing and implementing more effective policies to promote the health of individuals and the livability of communities.

Based on these ideas, the goal of this study is to understand how and to what degree the overall physical form of the metropolitan area (in addition to that of the neighborhood of residence) influences residents' nonmotorized travel behavior, their health status and the overall health of the community. A research framework for investigating the relationships between nonmotorized travel behavior, the built and social environments, and health is developed—which takes into account the potential role of environmental factors (in terms of built and social environments) representing the region and the metropolitan area of residence. This chapter discusses the design of this research, the proposed conceptual framework, the datasets used for the empirical analyses as well as the analytical techniques utilized to conduct the research.

3.1 Conceptual Framework

The complexity of human activity and behavior—particularly active travel behavior—calls for a multidisciplinary approach that combines theoretical and methodological perspectives from all related fields including transportation, public health, and psychology. It is evident from the discussion in Subsection 2.2.1 that the ecological model of behavior—a framework borrowed from the field of psychology—provides the most integrated and comprehensive framework to conceptualize health behavior such as nonmotorized (i.e., active) travel behavior. The framework of the ecological model of behavior allows for conceptualization of multiple interacting levels of influence on nonmotorized travel behavior. These levels can include: intrapersonal (e.g., genetic factors and attitudes), interpersonal (e.g., social environment factors and sociocultural norms), organizational, community (e.g., built environment factors), and policy levels. Any influence exerted by any of these levels on nonmotorized travel behavior can be assumed to interact across the other levels of influence. In addition, a few concepts such as the social environment (e.g., sociocultural factors) as well as the built environment (i.e., the *D* factors) cut across these multiple levels of influence and may be applied to more than one level (Sallis et al. 2008).

Research frameworks that are developed based on the ecological model, therefore, demand incorporation of multilevel-approach analysis methodologies and efforts including data collection from multiple levels of influence, development of measures representing these multiple levels, integration of data from various fields of research, and employment of more sophisticated statistical techniques that can handle the complexity of such synthesized analysis.

Past research provides some suggestions regarding the application of the ecological model of behavior with regards to health behavior and travel behavior research. In particular, public health research has been increasingly adopting the framework of the ecological model in determining the factors that influence health-related behavior such as nonmotorized (i.e., active) travel behavior and levels of physical activity as well as other health-related outcomes.

The adoption of the ecological model framework can be emulated in transportation planning and engineering fields as it provides a rich theoretical framework to understand multilevel influences on behavior, which can serve to enhance transportation-related research (Lee and Moudon 2004). In addition, multiple spatial and cultural settings can be considered to achieve adequate variation in environmental characteristics to examine their relationship with behavior (Trost et al. 2002) such as nonmotorized travel behavior. Further, a conceptual model of travel behavior proposed by Van Acker et al. (2010) considers travel behavior as the outcome of a decision hierarchy based on three levels of “opportunities and constraints” including: 1) the individual level; 2) the social level; and 3) the spatial level.

Based on the arguments above, multiple levels of influence should include environmental influence levels—in terms of social and built environments—in the analysis of behavior. Therefore, drawing from previous research and behavioral theories, the present research adopts an ecological model framework to propose a conceptual framework for understanding how various built and social environment factors from multiple levels of influence may influence nonmotorized travel behavior and health outcomes. The factors included in the conceptual framework are derived from the existing body of literature on nonmotorized travel behavior and public health. As a result, this study consists of two parts, which are linked to one another by their conceptual framework and empirical findings. Figure 1 illustrates the conceptual framework that links the two parts.

The first part (Tier 1) of the study examines the role of built and social environment factors at multiple hierarchical levels of influence including the micro level, the meso level, and the macro level in nonmotorized travel behavior. Several environmental attributes are tested for their association with nonmotorized travel behavior at both the household and individual levels. Additionally, the role of self-selection and the causality of the correlations observed are tested. The analyses presented in Tier 1 use data from the metropolitan areas in two different parts of the U.S.: 1) the state of Florida; and 2) the state of Maryland plus District of Columbia.

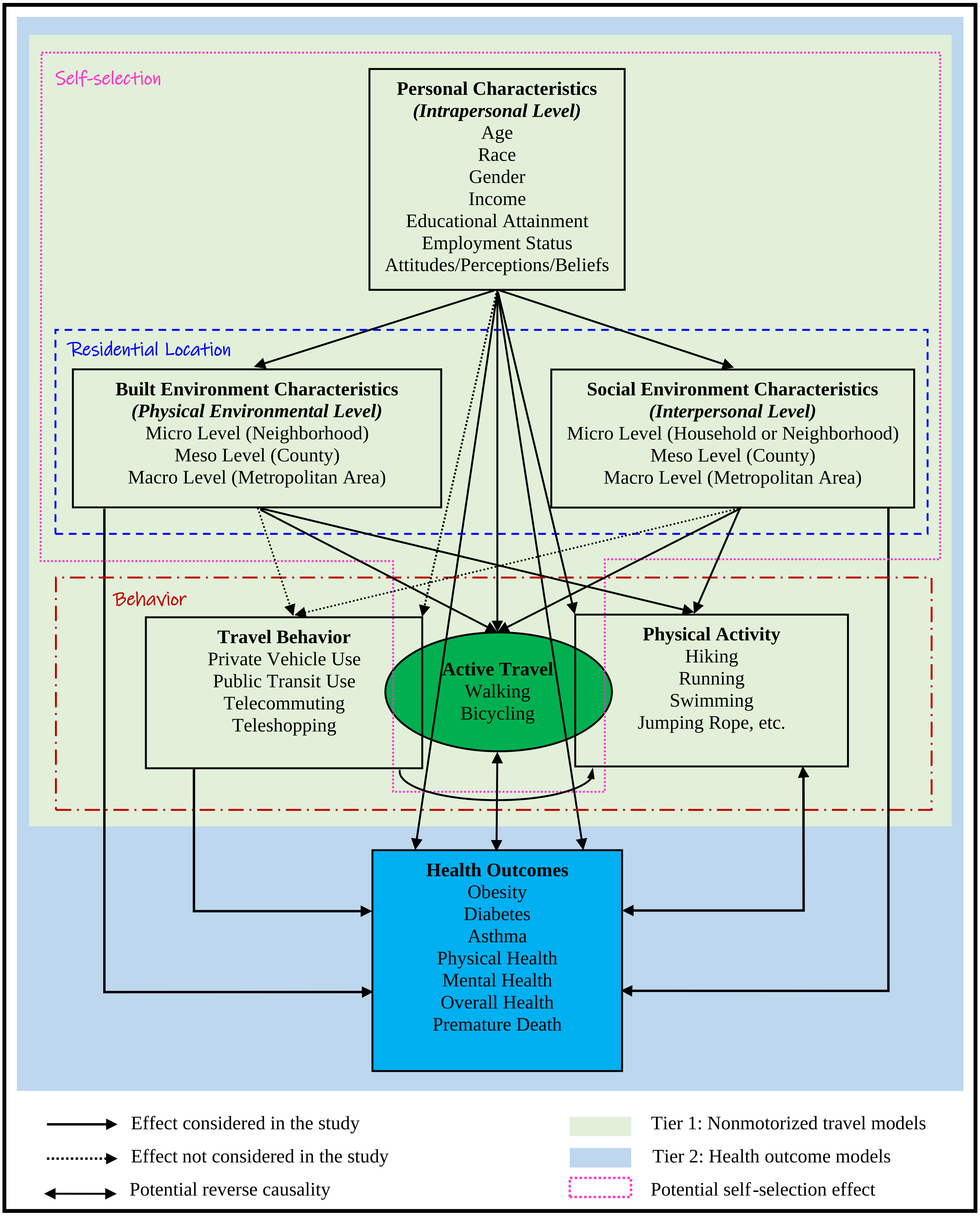

Figure 1. Proposed Conceptual Framework

The second part (Tier 2) of the study explores the health effects of travel behavior including nonmotorized travel behavior and telecommuting behavior as well as the relationship between health and built as well as social environment factors at multiple levels of influence. Particularly, factors representing the built and the social environments of the household's location have been tested for their association with health outcomes at both the community and individual levels.

Consistent with the principles of the ecological model of behavior, the conceptual framework indicates that behavior including health-related behavior (i.e., walking and bicycling travel and other physical activity) is affected by multiple levels of influence including the intrapersonal (i.e., individual), the interpersonal (i.e., social environment), and the physical environment (i.e., built environment) levels. The ecological model framework also shows that factors representing the residential location's built and social environments at various levels of influence affect behavior including travel behavior (e.g., walking and bicycling) and health behavior (e.g., physical activity). The built environment's influence on behavior may be more direct as features of the built environment facilitate or restrict specific behaviors. The influence of the social environment may be more indirect; by providing or limiting opportunities for social interactions, the social environment can help in shaping attitudes, social norms and culture, and thereby affect behavior. The ecological model framework also portrays that built and social environment can influence health outcomes, both directly and indirectly through mediating health-related behavioral factors (e.g., nonmotorized travel behavior and other physical activity behavior).

The main hypotheses to be tested based on this conceptual framework are presented in Table 1. The first set of hypotheses concern the role of larger-scale spatial areas on nonmotorized travel behavior and health outcomes. The other hypotheses concern self-selection bias in nonmotorized travel and endogeneity bias and the role of telecommuting/teleshopping in health.

Hypotheses 1a and 1b: On the Role of Macro-level Built and Social Environments in Nonmotorized Travel Behavior and Health

The discussion in the Literature Review Chapter (Chapter 2) revealed that nonmotorized travel behavior has disproportionately been examined within the environmental context of the immediate neighborhood. That is, built and social environments beyond the neighborhood level (i.e., micro level) have rarely been considered in nonmotorized travel behavior studies except for few cases (see e.g., Greenwald and Boarnet 2001; Ewing et al. 2003b; Dill and Carr 2003; Weinberger and Sweet 2012). Many of the referenced studies did not include a comprehensive set of environmental factors (in terms of the built and social environments) from larger geographical scales in their analysis. Nevertheless, empirical results from these studies showed that there may be a potential for larger-scale environmental factors—particularly factors related to the built environment beyond the neighborhood—to influence nonmotorized travel behavior.

Also, most of health-related studies examined health impacts of environmental factors either at the neighborhood level (i.e., micro level) or county level (i.e., meso level). However, the very few studies that examined the effects of city-level (i.e., macro-level) environmental factors on health outcomes suggest that macro-level environmental factors may play a role in the health status of residents (Joshu et al. 2008; Marshall et al. 2014; Braun and Malizia 2015). Macro-level built environment such as that of the metropolitan area has been postulated to impact residents' health by affecting commute times and distances, access to healthy food, and health behavior such as physical activity and nonmotorized travel behavior (Ewing et al. 2014). Moreover, the ecological model of behavior provides the theoretical foundation for the impact of the built and social environments at larger spatial scales on human behavior including health behavior such as nonmotorized travel behavior (i.e., walking and bicycling) and other physical activities.

Therefore, it is hypothesized in this dissertation that built and social environments beyond the neighborhood boundaries such as those of the county (i.e., the meso level) and the metropolitan area (i.e., the macro level) impact nonmotorized travel behavior and health outcomes. These hypotheses are tested in Chapters 4 and 5 using the individual and the household as the units of analyses in the nonmotorized travel behavior models, and the individual and the county as the units of analyses in the health outcomes models. The conceptual frameworks of these models are based on the ecological framework and include built environment and social environment characteristics at hierarchical levels. The analyses are conducted through employment of advanced statistical methods including the multilevel SEM techniques.

Hypotheses 2 and 3: On the Role of Self-selection in Nonmotorized Travel Behavior and Existence of Causal Links between Built Environment and Nonmotorized Travel Behavior

The literature review in Chapter 2 made it clear that when examining the role of built environment in nonmotorized travel behavior, the importance of self-selection bias is not to be overlooked and underestimated. Theoretically, the potential spurious relation between travel choices and the residential location choice introduces the self-selection bias into the analysis. Existence of self-selection bias makes it difficult to determine whether a causal relationship exists between the built environment and nonmotorized travel or if the correlation observed is the effect of the spuriousness between the two (as shown in Figure B, Appendix B and conceptualized in Figure 1). Therefore, self-selection bias confounds the analysis of the link between nonmotorized travel and the built environment and makes causal inferences difficult as elaborated in many studies in the past (see e.g., Handy 2005; Cao et al. 2009 among other studies as discussed in Chapter 2 and Appendix B).

Empirical findings provide evidence of the effects of self-selection in nonmotorized travel behavior (see Section 2.3 and Appendix B). However, few studies controlled for self-selection issues using sophisticated methodologies (e.g., instrumental variable analysis, structural equation modeling). Thus, evidence supporting a causal link between the built environment and nonmotorized travel behavior is relatively scant.

Considering the above arguments, it is hypothesized in this dissertation that self-selection plays a key role in nonmotorized travel behavior. Also, causal links are hypothesized between built environment factors and nonmotorized travel behavior. These hypotheses are tested in Chapter 4 using the individual as the unit of analysis within an integrated framework, which includes built and social environment attributes at hierarchical (micro-meso-macro) levels, and by employing more reliable methodologies to address self-selection bias (i.e., multilevel SEM techniques).

Hypothesis 4: On the Role of Reverse Causality between Physical Activity and Health, and the Potential Resulting Endogeneity Bias

Health literature has established the benefits of health behavior such as physical activity for human health (see DHHS 2018 and other studies as discussed in Chapter 2). However, the opposite could also be true; health status can affect the ability or willingness to perform physical activity. This introduces reverse causality (i.e., reciprocal causation) into the analysis of the link between physical activity and health. Literature suggests that reverse causality may exist between health status and health behavior such as active travel (Schauder and Foley 2015), which may play a role in physical activity levels; poor health may become a personal barrier to physical activity including active travel (Lee and Moudon 2004; National Research Council 2005; Joshu et al. 2008).

Further, other underlying unmeasurable or omitted factors may exist, which may subject the analysis of the link between physical activity and health outcomes to endogeneity bias, and thereby to biased estimates. However, as Schauder and Foley (2015) argue, endogeneity bias is often neglected in the studies modeling the relationship between health behavior such as active travel and health outcomes. The referenced study highlighted the importance of addressing endogeneity bias in testing the causality of the links between health behavior and health outcomes and used instrumental variables techniques to address endogeneity in examination of the relations between active travel and health outcomes.

The present dissertation hypothesizes that reverse causality may exist between physical activity (both in its general form and its travel-specific form, walking and bicycling) and health outcomes. Accordingly, it tests for endogeneity bias in the analysis, which may be present as a consequence of the potential reverse causality as well as the existence of omitted factors. This hypothesis is tested in Chapter 5 using the individual as well as the county as the units of analyses within a comprehensive ecological framework, which includes built environment and social environment characteristics at hierarchical levels. The analyses are conducted through employment of advanced statistical tools such as instrumental variable analysis and multilevel SEM techniques to address endogeneity bias as well as the issue of reverse causality between physical activity (e.g., nonmotorized travel) and health outcomes.

Hypothesis 5: On the Role of Telecommuting in Health

Telecommuting has a potential to impact psychological health of employees. For instance, through lowering the level of commute-related stress, telecommuting can potentially improve job performance and offer a higher level of job satisfaction. On the other hand, the potential encroachment of work time into personal time, the increased work-related stress, and the social isolation associated with working from home can adversely affect psychological health of telecommuters. As discussed in Chapter 2, the role of telecommuting in psychological health of employees has been examined in prior research but has produced some inconsistent findings (see e.g., Baruch 2001; Ganendran and Harrison 2007; Henke et al. 2015; Tajalli and Hajbabaie 2017).

The impact of telecommuting on physical health remains largely underexamined and ambiguous. This is because the only two studies that probed the effects of telecommuting on physical health of individuals (Henke et al. 2015; Tajalli and Hajbabaie 2017) resulted in inconsistent findings.

Moreover, telecommuting may allow increased levels of physical activity by making available some time that would otherwise be spent on commuting, whereas longer commutes can affect physical activity by cutting leisure times short (Ewing et al. 2014). On the other hand, physical activity levels may decrease for an individual due to the sedentary nature of telecommuting or the blurriness between work and personal time boundaries. This may also affect the telecommuter's health status, especially if telecommuting is performed on a regular basis over a long period of time.

In consideration of these arguments, the role of telecommuting in both psychological and physical health as well as in health behavior such as physical activity is examined in Chapter 5 of this dissertation using the individual as the unit of analysis. It is expected that telecommuting affects physical health outcomes, psychological health outcomes, and physical activity levels; however, the direction of these effects is not hypothesized in advance due to inconsistencies in the findings of past studies.

Hypothesis 6: On the Role of Teleshopping in Health

The appealing features of teleshopping for customers are numerous. For instance, teleshopping adds various purchasing options to buyers' existing ones and relieves them from having to spend time and energy for visiting different stores to find desired goods at desired prices (Mahmoudi and Clifton 2019). This highlights the potential of teleshopping to eliminate actual trips to various destinations (i.e., stores in this case). That is, teleshopping may have a substitution effect with regards to customer trips. On the other hand, teleshopping can also lead to generation of additional short-distance business trips due to deliveries or pick-ups of online orders. That is, teleshopping may have a complementarity effect with regards to business trips.

Activities related to substitution and complementarity effects of teleshopping can impact health differently. The former (i.e., substitution effect) can promote sedentary behaviors and lifestyles as customers barely need to leave their homes to purchase needed or desired goods. A sedentary lifestyle can have health implications for regular online shoppers. The latter (i.e., complementarity effect) may lead to additional vehicular and/or nonvehicular trips by business associates (e.g., deliverer); both of these types of trips have health implications for these associates.

For instance, regular deliveries by automobile may lead to lower levels of physical activity as well as adverse health outcomes for the deliverer due to an increased level of driving and time spent in a car (i.e., sedentary behaviors). On the other hand, one can expect that delivery trips may lead to higher levels of physical activity, and thereby to health benefits if deliveries are made by bicycle or if the deliverer parks his/her car and then walks to several destinations within a certain delivery area to distribute items. The unfavorable health effects of excessive automobile usage as well as the health benefit of using nonmotorized travel modes have been discussed in Chapter 2. For example, each additional hour spent in a car per day was found by Frank et al. (2004) to be associated with a 6% increase in the likelihood of obesity, whereas each additional kilometer walked per day was found to be associated with a 4.8% decrease in likelihood of obesity.

Research on the role of teleshopping in health is almost nonexistent. Therefore, hypothesizing the direction of effects of teleshopping on health outcomes is a difficult task. To elucidate these effects, measures of teleshopping behavior have been tested for their association with health outcomes in Chapter 5 of this dissertation using the individual as the unit of analysis. The existence of such association and the direction and significance of effects remain to be seen.

Table 1. Main Research Hypotheses

Nonmotorized Travel Behavior Analysis	
Hypothesis 1a	In addition to those of the neighborhood (i.e., micro level), built and social environment factors from larger spatial scales such as those representing the county (i.e., the meso level) and the metropolitan area (i.e., the macro level) play a role in nonmotorized travel behavior.
Hypothesis 2 and Hypothesis 3	Self-selection plays a role in nonmotorized travel behavior; and The link between built environment characteristics and nonmotorized travel behavior is a causal one.
Health Outcome Analysis	
Hypothesis 1b	The overall structure and context of the metropolitan area (i.e., the macro-level built and social environments) play a role in health outcomes of residents.
Hypothesis 4	Reverse causality exists between physical activity and health outcomes resulting in endogeneity bias in the model (which needs to be addressed in analysis of the link between health behavior such as physical activity and health outcomes).
Hypothesis 5	Telecommuting is an influential factor in psychological and physical health status as well as in physical activity levels performed by individuals.
Hypothesis 6	Teleshopping impacts health outcomes and physical activity levels performed by individuals.

3.2 Datasets

This study utilizes several databases from various sources. These datasets are listed below in alphabetical order and each are described in detail.

3.2.1 American Community Survey (ACS)

The American Community Survey (ACS) is an annual survey program conducted by the United States Census Bureau. Data collected through this survey provide information about the population (e.g., socioeconomic and sociodemographic characteristics, means of commuting to work, disability characteristics, veteran status) as well as housing (e.g., financial and physical characteristics for housing units) at many geographical scales.

Data from several multiyear estimates of ACS have been used in this research to develop nonmotorized travel behavior models as well as health outcome models.

3.2.2 Behavioral Risk Factor Surveillance System (BRFSS)

The Behavioral Risk Factor Surveillance System (BRFSS) is a health-related survey system, which collects data from the adult residents of the U.S. and its territories on their health behaviors, chronic health conditions, and preventive health-related practices that can influence health status. Initiated by the Centers for Disease Control and Prevention (CDC) in 1984, the BRFSS is conducted monthly by state health departments as a cross-sectional telephone-based survey. The database is managed by the CDC and is the world's largest health survey system. More specifically, the BRFSS data provide self-reported information on respondents' socioeconomic and sociodemographic characteristics, household characteristics, health behavior, access to health care, health status, preventive health practices, and much more.

The BRFSS data are collected from over 400,000 adults each year. The comprehensive survey design and the large number of respondents makes the BRFSS the leading scientific database within the U.S.—providing data on behavioral health risk factors and health outcomes. Due to privacy concerns, however, the smallest geographical unit available for the BRFSS respondents' addresses is the county of residence.

This dissertation uses the 2009 BRFSS data from Florida residents in the analysis of person-level health outcomes[6].

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[6] The usage of the first-person singular pronoun, "I", has been avoided throughout this dissertation. However, the mention of a personal experience related to BRFSS is a very tempting idea and makes using the pronoun "I" inevitable:

The day I started researching the BRFSS and writing this subsection on it, I received a call in the middle of my work. The gentleman on the other side of the line mentioned that he was calling from the Maryland Department of Health to interview me for a health survey. I was very excited and agreed to participate in the survey as I thought it was related to the research I was conducting. The phone interview took approximately 40 minutes.

At the end of the interview, the gentleman thanked me for my participation, and then proceeded to tell me that the survey I had just participated in was called the Behavioral Risk Factor Surveillance System survey! I was so pleasantly surprised! I am certain that my squeaky voice captured my excitement as I was telling the interviewer that I had just been writing about the BRFSS in my dissertation draft.

That was such an interestingly odd coincidence that I could not resist writing about here. While I gained much perspective from participation in the actual survey, I would leave it up to statisticians to calculate the probability of me receiving a call for participation in the BRFSS survey on the very same day and at the very same moments I was writing about the BRFSS!

3.2.3 Community Health Status Indicators (CHSI)

The Community Health Status Indicators (CHSI) dataset provides health status profiles for all of the 3,143 counties in the U.S. as well as the District of Columbia. CHSI data are available through the U.S. Department of Health and Human Services (DHHS), Centers for Disease Control and Prevention (CDC). The dataset provides information on: *i*) county-level population health behavior (e.g., smoking); *ii*) county-level factors that potentially affect population health status (e.g., health access, social and built environment characteristics); and *iii*) county-level health outcomes (i.e., measures of mortality and morbidity). The CHSI fuses data from several data sources to produce county-level health profiles. The data sources used in production of CHSI include the Behavioral Risk Factor Surveillance System data, Medicare Chronic Conditions Report data, and the Area Health Resources Files data. These data are periodically and regularly reported; therefore, the health status profiles for each county have been produced based on multiyear estimates.

The CHSI data are utilized in this study to investigate the health impacts of nonmotorized travel, telecommuting, and the built environment of communities (i.e., counties) within several U.S. metropolitan areas.

3.2.4 County Health Rankings & Roadmaps (CHR & R)

The Robert Wood Johnson Foundation in collaboration with the University of Wisconsin Population Health Institute created the County Health Rankings and Roadmaps (CHR & R) program. The CHR & R dataset provides information on county-level health profile and rankings for each county within a specific state in the U.S.

Ranking measures rank each county based on two categories of health-related indicators: 1) health outcomes (i.e., how healthy the population of a county is); and 2) health factors (i.e., factors that influence the health status of the population in a county).

Health outcomes in this dataset are based on measures of mortality (i.e., length of life) and morbidity (i.e., quality of life). Health factors are represented in this dataset by health behavior measures (e.g., adult obesity), clinical care measures (e.g., uninsured adults), socioeconomic measures (e.g., unemployment, crime), and physical environment measures (e.g., access to healthy food). The CHR & R dataset uses several health data sources to extract information about population health and factors affecting it for each of the U.S. counties. A few of these data sources are: the Behavioral Risk Factor Surveillance System data, National Center for Health Statistics, Small Area Health Insurance Estimates, and the Safe Drinking Water Information System.

The 2010 CHR & R data have been used in this study to examine the health impacts of nonmotorized travel behavior and telecommuting behavior as well as the association between community-level (i.e., county-level) health outcomes and built environment factors within several U.S. counties and metropolitan areas.

3.2.5 National Household Travel Survey (NHTS)

The National Household Travel Survey (NHTS) dataset is the only comprehensive travel dataset at the national level in the U.S. The survey is periodically conducted by the Federal Highway Administration (FHWA) to collect data on both short- and long-term travel behavior of U.S. household members. Sample households throughout the U.S. are surveyed to gather information on their travel behavior. The most recent dataset is the 2017 NHTS[7], which contains data of approximately 130,000 sampled households and updates information in the previous datasets (2009 NHTS and prior years).

The NHTS dataset contains comprehensive information on household geographic area (e.g., census tract, county, and metropolitan area), household socioeconomic and

[7] The 2017 NHTS data were released in March 2018.

sociodemographic characteristics (e.g., household income, size, number of vehicles, and number of workers), as well as detailed information on household members' daily trips made within a designated 24-hour period of time (e.g., trip mode, travel time, trip purpose, and distance traveled). Moreover, the NHTS data provide information on other travel-related behavior of household members such as their telecommuting and teleshopping behavior.

Traditionally, additional random samples of households have also been surveyed in states that are considered within the NHTS Add-on Program area. The Add-on database provides geocoded location of the households located within the Add-on regions. Due to this level of resolution with respect to the geographical location of the surveyed households, the 2009 NHTS Add-on database has been utilized in this study for analyzing the nonmotorized travel behavior of Florida residents and the related health impacts for them. Usage of the NHTS data adds a layer of confidence to the study results and makes this research's findings generalizable.

3.2.6 Smart Location Database (SLD)

The Smart Location Database (SLD), which was first released in 2011, is a nationwide spatial dataset for the U.S. The SLD is a product of the U.S. Environmental Protection Agency (EPA)'s Smart Growth Program and is available to users for free on the EPA web site. The latest version of this dataset is the SLD Version 2.0, which was released in 2013.

This rich dataset provides information on land use and built environment characteristics such as population and employment density, mixed-use development, neighborhood design attributes, destination and transit accessibility, transit service frequency, and demographic characteristics at the census block group level.

In essence, the SLD provides a wealth of information on the *D* indicators of the built environment at a fine spatial resolution (census block group). These characteristics of SLD make it a very appropriate dataset to be utilized in examining the association between the built environment and nonmotorized travel demand and behavior.

The present study uses the SLD in the analysis of nonmotorized travel behavior of Florida residents as well as in the analysis of health outcomes for residents of various counties in the U.S.

3.2.7 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line Shapefiles

An open source data, the U.S. Census Bureau's TIGER/Line Shapefiles are a comprehensive dataset that provide valuable spatial information for use with Geographic Information Systems (GIS) applications. Information such as legal and political geographic boundaries, statistical geographic areas, address information, roads and railroads can be obtained from this dataset.

In this study, TIGER/Line Shapefiles have been used to obtain census block-level and county-level data within all study areas.

3.2.8 Uniform Crime Reporting Program—Federal Bureau of Investigation (FBI)

Created in 1929, the FBI's Uniform Crime Reporting (UCR) program is intended to serve the need for reliable crime statistics for the U.S. through collecting, publishing, and archiving data on crime. As of the present, data have been received from more than 18,000 agencies within the U.S. and are available to the public free of charge.

This dissertation uses multiyear FBI's UCR data on violent crime rates within Florida metropolitan areas in analysis of health outcomes for residents.

3.2.9 Urban Mobility Information—Texas A&M Transportation Institute (TTI)

The TTI Urban Mobility Information data are accessible to the public, and provide multiyear data on the level of mobility (e.g., roadway congestion levels, annual hours of delay, travel times) for nearly 500 urban areas across the U.S. The 2015 Urban Mobility Scorecard is the latest edition of this report, which is published jointly by the Texas A&M Transportation Institute and INRIX. The 2015 Urban Mobility Scorecard provides a comprehensive analysis of traffic and mobility conditions within the U.S. urban areas.

In this dissertation, Urban Mobility data from years 2008 through 2010 have been used to develop health outcome models for residents of Florida metropolitan areas.

3.2.10 Walk Score and Bike Score

Walk Score® (www.walkscore.com) is a publicly available dataset, which provides information on walkability of locations. A *Walk Score* is an objectively measured number that assesses the walkability and pedestrian friendliness of a particular address based on a destination accessibility-oriented approach. Distance to nearby desired walkable amenities (e.g., educational, retail, services, food, and recreational destinations) is used in an algorithm, which calculates the Walk Score of a specific point. Each type of destination is weighted equally in the calculations of the Walk Score of a location. The Walk Score methodology also considers other factors in calculation of the Walk Score. These factors include population density and street network attributes (e.g., block length and intersection density).

Research suggests that Walk Score correlates well with objective and subjective measures of walkability and is a reliable and valid metric for estimating neighborhood destination accessibility (Carr et al. 2010a, 2010b). Research has further validated Walk Score as a measure of neighborhood walkability at multiple spatial scales and for various geographic locations (Duncan et al. 2011). Additionally, Walk Score has been shown to outperform other walkability measures in predicting actual amounts of walking (Manaugh and El-Geneidy 2011). Consequently, the Walk Score has become a widely known measure of walkability in recent years and has been utilized by researchers in the fields of transportation engineering, urban design, real estate, and public health (see e.g., Pivo and Fisher 2011; Weinberger and Sweet 2012; Li et al. 2014; Hirsch et al. 2014; Renne et al. 2015; Wasfi et al. 2015; Braun and Malizia 2015; Barnes et al. 2016).

Similarly, a *Bike Score* is a number designated to a certain location that assesses how bikeable that location is. The calculation algorithm for Bike Score takes into account bicycle infrastructure (e.g., bicycle lanes and bicycle trails), topography (e.g., hilliness) as well as destination and road network connectivity measures.

Walk Score and Bike Score range from 0 for a car-dependent (i.e., non-walkable for Walk Score or non-bikeable for Bike Score) location to 100 for the most pedestrian-friendly (or bicycle-friendly for Bike Score) location. Appendix D lists the Walk and Bike Score categories.

In this dissertation, the Walk and Bike Score data have been used in the analysis of nonmotorized travel behavior in the Florida case study (and the Baltimore-D.C. case study, which is presented in Appendix C). Walk Score data have also been used in this study to analyze health outcomes for residents of different metropolitan areas within the state of Florida.

3.2.11 Woods & Poole Complete Economic and Demographic Data Source (CEDDS)

Produced by Woods and Poole Economics, Inc., the CEDDS data source provides historical (from 1970) economic and demographic data for all U.S. counties, metropolitan areas, and states. These data include information such as population (total as well as by age, sex, race), employment (total as well as by industry), income, retail sales by type of business and more [8,9].

This study utilizes the 2008 and 2009 CEDDS data to develop health outcome models.

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[8] See "Summary Technical Description of the Woods & Poole Economics, Inc. 2018 Regional Projections and Database": https://www.woodsandpoole.com/wp-content/uploads/2018/04/TECH18-summary.pdf

[9] See "CEDDS-The Complete Economic and Demographic Data Source": https://www.woodsandpoole.com/wp-content/uploads/2018/05/CED18.pdf

<u>3.3 Analytical Techniques</u>

The main analytical techniques utilized in this research are:

i) linear mixed-effects (i.e., multilevel or hierarchical) modeling techniques;

ii) ordered probit modeling techniques;

iii) structural equation modeling (SEM) techniques;

iv) instrumental variable analysis (for binary probit modeling); and

v) binary probit modeling techniques.

An overview of each of these techniques is given in the following subsections, which summarize the formulation and assumptions of the technique.

3.3.1 Linear Mixed-effects (Multilevel) Modeling Techniques

Linear mixed-effects modeling is a versatile technique that encompasses various types of modeling tools and is used to analyze grouped (i.e., clustered) data. Linear mixed-effects models are also known as linear multilevel models, linear hierarchical model, random effects models, or random coefficient models (Heck 2001; Chung et al. 2004; Garison 2013).

According to Demidenko (2004), classical statistics assumes that individual observations are drawn from the same general population and are independently and identically distributed (iid). These assumptions may not hold when observations come from various groups within the general population.

If the general population comprises of different groups (i.e., clusters), observations between different groups are independent of each other; however, the same cannot be said about observations within each group. Observations that come from the same group belong to the same subpopulation and may share the characteristics of the particular subpopulation they belong to. In this case, these observations are correlated and are not independent.

Further, in grouped data with a multilevel (i.e., hierarchical) structure, nested data exist at multiple levels and observations in the same level (i.e., group) are likely to be correlated because they share similar characteristics.

Clustering of observations within groups leads to correlated error terms, biased estimations of coefficients, biased estimations of standard errors, and substantive mistakes in interpretation of the effects of explanatory variables (see e.g., Heck 2001; Garison 2013). Therefore, classical regression modeling techniques are not appropriate for modeling grouped observations because the independently and identically distributed (iid) assumption of classical regression modeling techniques is violated for observations that come from the same group (referred to as clusters hereinafter).

According to Heck (2001) and Demidenko (2004), there are two types of observations in a clustered dataset:

1) observations from different clusters, which have independent characteristics from each other; and

2) observations within a specific cluster, which are likely to have similar characteristics.

Consequently, two sources of variation are assumed in a mixed-effects (i.e., multilevel) model using clustered data:

1) variations within clusters (i.e., the intraclass variance); and
2) variations between clusters (i.e., the interclass variance).

The multilevel structure of the mixed-effects model allows for capturing these two sources of variation among clustered data.

Thus, as Demidenko (2004) explains, two types of coefficients are estimated by the mixed-effects model:

1) population-averaged coefficients; and

2) cluster-specific coefficients.

The former coefficients (i.e., population-averaged coefficients) are called *fixed effects* and have the same meaning as in ordinary regression models. The latter coefficients (i.e., cluster-specific coefficients) are called *random effects* and contain the effects of clustering of the observations under different levels.

For multilevel data structures, the model introduces random effects for each level (i.e., cluster) of the data. In other words, and as explained by Hamilton (2013), mixed-effects modeling is regression analysis that allows two types of effects:

1) *fixed effects*, which are intercepts and slopes that describe the population as a whole (similar to the case of classical regression modeling); and
2) *random effects*, which are intercepts and slopes that can vary across clusters within the sample.

Having a small number of clusters with a large number of observations per cluster constitutes the treatment of the cluster-specific coefficients as fixed effects, whereas having a large number of clusters with a small number of observations per cluster necessitates the treatment of the cluster-specific coefficients as random effects (Demidenko 2004).

Therefore, by providing a combination of analysis of variance, variance component, and regression models (Demidenko 2004; Snijders and Bosker 2012), the mixed-effects model treats clustered data, where due to correlation of error terms, the classical assumption of observations being independent and identically distributed (iid) may lead to inaccurate results, and thereby to erroneous interpretations of the effects of explanatory variables.

Based on Verbeke and Molenberghs (1997) and Demidenko (2004), the linear mixed model can be formulated in a general matrix notation as:

$$\text{Y} = \mathbf{X}\beta + \mathbf{Z}u + \varepsilon \qquad \text{Equation 1}$$

where,

Y $=$ $n \times 1$ vector of observations with a mean of $\mathbf{X}\beta$;

$\mathbf{X} =$ $n \times p$ matrix of covariates (i.e., explanatory variables) with fixed effects;

$\beta =$ vector containing the overall mean (population average) and the fixed effects coefficients;

$\mathbf{Z} = n \times q$ matrix of covariates (i.e., explanatory variables) with random effects;

$u =$ vector of the iid random effects;

$\varepsilon =$ vector of random error term such that:

$$\begin{pmatrix} u \\ \varepsilon \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \ \begin{pmatrix} D & 0 \\ 0 & \Sigma \end{pmatrix}\right)$$

D $=$ variance-covariance matrix of random effects (variance components) of u and ε; and

$\sum = \sigma_{\varepsilon}^{2} I_n$ with n being the number of observations.

The mixed-effect model assumes that:

i) variance parameters for each cluster are random;

ii) the distributions of random effects (u) and the random error term (ε) are normal; and

iii) the random vectors (u and ε) are mutually independent.

Also, it should be noted that even though the mixed-effects model is formulated as a linear model, the fact that variance-covariance matrix of random effects (D) is unknown makes it a nonlinear model with a complex estimation methodology.

If the parameters of matrix D are known, the model can be estimated by ordinary least square (OLS) regression modeling techniques (Demidenko 2004).

In multilevel mixed-effects models, the matrix of observed covariates (**X**) can include variables from various levels, which vary at the respective levels[10]. The model formulation for a two-level mixed-effects model can be written as Equation 2 in a matrix notation or as Equation 3 based on the general formulation presented in Snijders and Bosker (2012):

$$y_{ij} = \beta_0 + \mathbf{X}\beta + u_{0j} + \mathbf{Z}_j u_j + \varepsilon_{ij} \qquad \text{Equation 2}$$

$$y_{ij} = \beta_0 + \sum_{h=1}^{p} \beta_h x_{hij} + u_{0j} + \sum_{h=1}^{q} u_{hj} z_{hij} + \varepsilon_{ij} \qquad \text{Equation 3}$$

where,

y_{ij} = observation for subject *i* (level one) within the *j*th cluster (level two);

β_0 = model intercept (the value of y_{ij} when all explanatory variables are equal to zero);

β and u are vectors as defined for Equation 1;

$\mathbf{Z}_j$ = matrix of cluster *j*th (level two) covariates with random effects;

β_h and u_{hj} are model parameters for fixed and random parts of the model, respectively;

p = number of explanatory variables with fixed effects only;

q = number of explanatory variables with random effects;

x_{hij} = the explanatory variables (including level-one and level-two variables) with fixed effects only;

z_{hij} = the explanatory variables (including level-one and level-two variables) with random effects;

u_j and u_{0j} = cluster-specific (level two) random effects and random intercept, respectively, with mean zero and a variance of σ_u^2;

ε_{ij} = random error term (level one) with mean zero and a variance of σ_e^2 .

[10] Therefore, the matrix of observed covariates is just denoted as **X** without any subscripts to assign a particular level (i.e., *i*, *j* or *k*) in Equations 2, 4 and 6.

For a two-level random intercept model, Equations 2 and 3 can be simplified to Equation 4 and Equation 5, respectively:

$$y_{ij} = \beta_0 + \mathbf{X}\beta + u_{0j} + \varepsilon_{ij} \qquad \text{Equation 4}$$

$$y_{ij} = \beta_0 + \sum_{h=1}^{p} \beta_h x_{hij} + u_{0j} + \varepsilon_{ij} \qquad \text{Equation 5}$$

The random intercept model assumes that there is a random effect (i.e., u_{0j}) that applies to all observations from cluster *j*. However, the regression slopes for various explanatory variables in the model are not assumed to be randomly varying from cluster to cluster (i.e., the regression lines for each explanatory variable all have a common slope), and thereby the model is simplified to a random intercept model. Also, in the two-level model, the observation y_{ij} is the observation for subject *i* within cluster *j*, meaning that subject *i*s comprise the first level and cluster *j*s comprise the second level of the model. Here, β_0 is the fixed part of the model, whereas ε_{ij} and u_{0j} comprise the random part. Also, ε_{ij} and u_{0j} are assumed to be uncorrelated. Further, u_{0j} are assumed to be uncorrelated across cluster *j*s and ε_{ij} are assumed to be uncorrelated across subject *i*s (Healy 2001; Rabe-Hesketh and Skrondal 2012).

A three-level model for first-level observations (*i*s) nested within second-level clusters (*j*s) that are themselves nested within third-level clusters (*k*s) is a straightforward extension of the two-level model. The three-level model can be formulated as Equation 6 in a matrix notation or as Equation 7, which is developed based on the general formulas in Snijders and Bosker (2012).

$$y_{ijk} = \beta_0 + \mathbf{X}\beta + u_{0jk}^{(2)} + u_{0k}^{(3)} + \mathbf{Z}_{jk}^{(2)} u_{jk}^{(2)} + \mathbf{Z}_{jk}^{(3)} u_{k}^{(3)} + \varepsilon_{ijk} \qquad \text{Equation 6}$$

$$y_{ijk} = \beta_0 + \sum_{h=1}^{p} \beta_h x_{hijk} + u_{0jk}^{(2)} + u_{0k}^{(3)} + \sum_{h=1}^{q} u_{hjk} z_{hijk} + \varepsilon_{ijk} \qquad \text{Equation 7}$$

where,

y_{ijk} = observation for subject *i* (level one) within the *j*th cluster (level two) within the *k*th supercluster (level three);

β_0 = model intercept (the value of y_{ij} when all covariates are equal to zero);

β and u are vectors as defined for Equation 1;

$\mathbf{Z}_{jk}^{(2)}$ and $\mathbf{Z}_{jk}^{(3)}$ = matrices of cluster *j*th (level two) and supercluster *k*th (level three) covariates with random effects, respectively;

β_h and u_{hjk} are model parameters for fixed and random parts of the model, respectively;

p = number of explanatory variables with fixed effects only;

q = number of explanatory variables with random effects;

x_{hijk} = the explanatory variables (including level-one, level-two, and level-three variables) with fixed effects only;

z_{hijk} = the explanatory variables (including level-one, level-two, and level-three variables) with random effects;

$u_k^{(3)}$ = random effects for supercluster *k* (level three);

$u_{jk}^{(2)}$ = random effects for cluster *j* (level two);

$u_{0k}^{(3)}$ = random intercept for supercluster *k* (level three) with mean zero and a variance of σ_{u0k}^2;

$u_{0jk}^{(2)}$ = random intercept for cluster *j* (level two), which is in supercluster *k* and has a mean of zero and a variance of σ_{u0jk}^2;

ε_{ijk} = random error term (level one) with mean zero and a variance of σ_e^2 .

Random effects ($u_k^{(3)}$, $u_{jk}^{(2)}$, $u_{0k}^{(3)}$, $u_{0jk}^{(2)}$) and error term (ε_{ijk}) are assumed to be mutually uncorrelated, and the total variance is equal to $\sigma_{u0k}^2 + \sigma_{u0jk}^2 + \sigma_e^2$.

Equations 6 and 7 can be simplified to Equations 8 and 9 to formulate a three-level random intercept model as follows:

$$y_{ijk} = \beta_0 + \mathbf{X}\beta + u_{0jk}^{(2)} + u_{0k}^{(3)} + \varepsilon_{ijk} \qquad \text{Equation 8}$$

$$y_{ijk} = \beta_0 + \sum_{h=1}^{p} \beta_h x_{hijk} + u_{0jk}^{(2)} + u_{0k}^{(3)} + \varepsilon_{ijk} \qquad \text{Equation 9}$$

In the present study, two-level and three-level mixed-effects models have been employed to examine the association between nonmotorized travel behavior and built as well as social environment characteristics at various geographical levels including the micro level (i.e., neighborhood), the meso level (i.e., county) and macro level (i.e., region or metropolitan area).

In choosing a fixed- versus a random-effects approach to estimate the cluster-specific intercepts, Rabe-Hesketh and Skrondal (2012) suggests that a random-effects model is suitable if: a) the target of inference concerns the population of clusters (vs. the particular clusters in the dataset); and b) if there is an adequate number (> 10 or 20) of clusters in the sample. Since the present research is concerned with making inferences about the infinite population (i.e., generalizing beyond the specific clusters in the samples at hand) and there is a large number of clusters in the sample for each case study (>1,000), a random-effects (i.e., random intercept) modeling approach is selected—making the models developed mixed-effects models.

Further, some researchers argue that if the larger-scale units (e.g., meso- or macro-level spatial units) have any potential association with the phenomenon under study, analyzing only the aggregated data or only the disaggregated data may lead to erroneous results (Chung et al. 2004; Snijders and Bosker 2012). These authors suggest that a multilevel approach, which accounts for within-cluster as well as between-cluster variations is a more suitable methodology for analyzing such clustered, multilevel data. In multilevel analysis, some authors have referred to level one and level two as micro level and macro level, respectively (see e.g., Heck 2001 and Snijders and Bosker

2012). Others suggest that the multilevel structure of the mixed-effects models allows the analyst to simultaneously focus on both micro-level (i.e., level one) and macro-level (i.e., level two) associations as well as the interaction between the two levels (Healy 2001).

Another advantage of the mixed-effects modeling is that it can account for any potential spatial autocorrelation that may exist due to use of nested data from multilevel geographical areas (Marshall et al. 2014). Due to the nested nature of data used in the present study (e.g., individuals nested in households, households nested in neighborhoods), the mixed-effects models developed in this research are considered multilevel mixed-effects models.

3.3.2 Ordered Probit Modeling Techniques

Ordered probit models are a special case of the statistical models that deal with ordinal dependent variables. Ordinal variables result from cases where the discrete quantity of something is considered or where a nominal factor is measured using a graded scale. Attitudinal surveys using the *Likert Scale*[11] are a good example of such cases where due to lack of a natural unit of measurement for attitudes, survey responses generate data in the form of ordinal responses (Daykin and Moffatt 2002). Due to the ordinal nature of responses, the dependent variable to be modeled becomes an ordinal variable (i.e., categorical variable)—providing information on ordering of different categories of the measured factor (Grilli and Rampichini 2012).

Ordinal dependent variables violate the assumptions of linear regression models, which can lead to inaccurate model estimations. If the observed dependent variable y is a nominal

[11] Satisfaction with a service or agreement with a view are examples of factors measured using the Likert's graded scale. In the former case (i.e., satisfaction), the scale can include responses such as 'very dissatisfied', 'dissatisfied', 'satisfied' and 'very satisfied'. In the latter case (i.e., agreement), the responses can include categories such as 'strongly disagree', 'disagree', 'agree' and 'strongly agree' (Daykin and Moffatt 2002; Grilli and Rampichini 2012). In both cases, the response categories are ordered—generating ordinal data, which in turn, translates into an ordinal dependent variable in the model.

variable, which has ordered categories, sometimes a score can be associated with each category of the observed variable. Due to the statistical methods for quantitative variables being more powerful and easier to interpret, the use of scoring systems to convert ordinal categories into numbers is a common practice in research; however, since the distances between the categories are unknown, the scoring system is just an arbitrary assumption (Grilli and Rampichini 2012). Nonetheless, if categories of the observed dependent variable are ordered and can be coded as consecutive integers, the ordered probit model can be applied.

In research dealing with psychological factors such as attitudes, latent variables are often preferred over observed variables for more effectively capturing factors such as attitudes and perceptions (Moudon et al. 2005). Latent-variable models often serve as a suitable statistical method to analyze attitudinal survey responses. Ordered probit models can be considered a latent-variable model (see Long and Freese 2006). As a latent-variable model, the ordered probit model relates the discrete ordinal observed response y to an unobserved latent variable y^*. This latent variable (y^*) is the exact response, which cannot be observed. Instead, what is observed is the categories of the response (y). The ordered probit model can be presented as Equation 10 based on theoretical aspects discussed by many researchers (see e.g., Daykin and Moffatt 2002; Long and Freese 2006; Gelman and Hill 2007; Wooldridge 2010).

$$y_i^* = x_i'\beta + \varepsilon_i \qquad \text{Equation 10}$$

It is assumed in this formulation that the ordinal dependent variable y has J distinct categories where J is an integer representing each specific category ($J = 0, 1, \ldots, n$). The ordinal dependent variable is represented as y_i where i represents each distinct observation. It is further assumed that the ordinal dependent variable y_i is generated by the latent continuous variable y_i^* with a set of $n - 1$ thresholds α_n such that: $y_i = y_n$ only and only if $\alpha_{n-1} < y_i^* \leq \alpha_n$.

In addition,

y_i^* $=$ a continuous but unobserved (i.e., latent) variable such that $-\infty < y_i^* < +\infty$.

The model estimations only indicate when y_i^* crosses a threshold; and

x_i' = vector of independent (i.e., explanatory) variables;

β = vector of model parameters (not containing an intercept[12]);

ε_i = an iid error term, which follows a normal distribution ($\varepsilon_i \sim N\ (0, 1)$).

The latent variable y_i^* captures the underlined probability of occurrence of a certain category in the ordinal dependent variable. That probability is given by:

Probability $(y_i = y_n) = \Phi\ (\alpha_n - x_i\beta) - \Phi\ (\alpha_{n-1} - x_i\beta)$

where,

n = the number of categories of the ordinal dependent variable *y*;

y_n $=$ a certain category of the ordinal dependent variable *y*;

Φ = the standard cumulative normal distribution function;

α_n $=$ the upper threshold for the range of y^*, which corresponds to *n*;

α_{n-1} $=$ the lower threshold for the range of y^*, which corresponds to *n*;

Therefore, the relationship between y_i and y_i^* can be formulated as below in ordered probit models:

$$y_i = \begin{cases} 0 & if & -\infty \leq y_i^* < \alpha_1 \\ 1 & if & \alpha_1 \leq y_i^* < \alpha_2 \\ 2 & if & \alpha_2 \leq y_i^* < \alpha_3 \\ & & . \\ & & . \\ & & . \\ y_n & if & \alpha_{n-1} \leq y_i^* < \alpha_n\ (= +\infty) \end{cases}$$

12 See page 655 in Wooldridge (2010).

The association between the ordinal dependent (i.e., response) variable (y_i) and the independent (i.e., explanatory) variables is obtained through model estimations. The ordered probit model estimates the model parameters (βs) as well as the thresholds (cut points) as y_i^* crosses them. Also, when i = 1, the ordered probit model becomes the binary probit model.

In this study, ordered probit models have been used to examine the association between nonmotorized travel behavior and built as well as social environment factors at various geographical scales. More specifically, the total number of household's nonmotorized (walking or bicycling) trips is considered as the observed ordinal dependent variable (y_i), which is assumed to take on a series of values ranging from zero to the maximum number of trips in the dataset—depending on the value of the unobserved latent variable y_i^*. The probability of a certain number of walking (or bicycling) trips having been generated from a household is estimated by the ordered probit models developed.

In addition, binary probit models have been developed and estimated in this dissertation to analyze the link between individuals' health status, travel behavior, and built as well as social environment characteristics at various levels of influence.

3.3.3 Instrumental Variable Techniques

In the linear model represented by Equation 11, if one (or more) of the independent (i.e., explanatory) variables contained in vector x' is correlated with the error term (ε), that independent variable becomes endogenous in the equation (Baum et al. 2003; Wooldridge 2010).

$$\mathrm{y} = \beta_0 + x'\beta + \varepsilon \qquad \text{Equation 11}$$

Endogeneity can occur due to many reasons including the existence of omitted variables in the model. In models susceptible to endogeneity, estimations can be biased due to the non-zero correlation between the endogenous independent variable(s) and the error term. Instrumental variable (IV) analysis is an appropriate method, which provides a general solution to the problem of endogenous independent variables (see Train 2009 and Wooldridge 2010); thus, it can be used to address any potential endogeneity bias in the model. To apply the IV method, a column vector of observable variables, which are not included in Equation 11, can be used as instruments (z').

Based on Wooldridge (2010), a reduced-form equation can then be written for the endogenous independent variable—denoted by x_e —as:

$$x_e = \delta_0 + x_1'\delta + z'\theta + \tau \qquad \text{Equation 12}$$

where,

x_e = the endogenous independent variable in Equation 11;

x_1' = vector of independent variables contained in x' except for x_e;

z' = vector of instrumental variables;

β , δ , θ = model parameters; and

τ = error terms of the reduced-form equation, which should be uncorrelated with variables contained in x_1' and z'.

The instrumental variables (i.e., instruments) contained in column vector z' must satisfy two conditions: 1) exogeneity, meaning that the instrumental variable(s) must be uncorrelated with the error term (ε); and 2) correlation, meaning that the instrumental variable(s) must be partially correlated with the endogenous independent variable (x_e) once the other exogenous variables in x_1' have been controlled for (Wooldridge 2010).

All variables contained in x_1' can serve as their own instruments in Equation 11 as they are already uncorrelated with ε. That means that although the instrument for the endogenous independent variable is often referred to as the "instrument", all exogenous independent variables are considered instrumental variables in the model.

By plugging Equation 12 into Equation 11 (i.e., substituting for x_e in vector $x^{'}$), a reduced form for *y* is obtained:

$$y = \alpha_0 + x_1^{'}\alpha + z^{'}\sigma + \vartheta$$

Here, ϑ *is* the reduced-form error term, which is by assumption, uncorrelated with all independent variables in $x_1^{'}$ and $z^{'}$. Thus, the endogeneity problem in Equation 11 has been addressed through employment of instrumental variable analysis.

A simplified instrumental variable formulation for binary probit models with endogenous independent variables can be written based on formulas presented by Newey (1987) for models with limited dependent variables and endogenous independent variables as well as formulas by Rivers and Vuong (1988) for simultaneous probit models (with endogenous independent variables)[13].

If i = (1, …, *N*), the instrumental variable binary probit model can be presented as:

$$y_{1i}^{*} = y_{2i}\beta + x_{1i}\gamma = z_i\delta + \mu_i \quad \text{Equation 13}$$

$$y_{2i} = x_{1i}\mathbf{\Pi}_1 + x_{2i}\mathbf{\Pi}_2 + \vartheta_i \quad \text{Equation 14}$$

Substituting Equation 14 in Equation 13, the final reduced-form equation for y_{1i}^{*} is:

$$y_{1i}^{*} = x_i\alpha + \omega_i \quad \text{Equation 15}$$

where,

y_{1i}^{*} = an unobserved latent variable based on which the observed value of the endogenous variable y_{1i} changes as follows:

$$y_{1i} = \begin{cases} 0 & y_{1i}^{*} < 0 \\ 1 & y_{1i}^{*} \geq 0 \end{cases}$$

[13] For additional information and detailed model formulation, refer to Newey (1987), Rivers and Vuong (1988), Baum et al. (2012) as well as Stata's documentation on instrumental variable binary probit modeling "ivprobit — Probit model with continuous endogenous regressors": https://www.stata.com/manuals13/rivprobit.pdf

y_{2i} $= 1\times p$ vector of observed endogenous variables;

x_{1i} $=$ $1\times k_1$ vector of observed exogenous variables;

x_{2i} $= 1\times k_2$ vector of additional instrumental variables;

$\mathbf{\Pi_1}$ $=$ matrix of coefficients for instrumental variables that are included in Equation 13;

$\mathbf{\Pi_2}$ $=$ matrix of coefficients for instrumental variables that are excluded from Equation 13;

β and γ $=$ vectors of structural parameters.

In addition,

$\delta = (\beta', \gamma')'$; $x_i = (x_{1i}, x_{2i})$; $z_i = (y_{2i}, x_{1i})$; $\mathbf{\Pi} = (\mathbf{\Pi}_1', \ \mathbf{\Pi}_2')'$;

μ_i and ϑ_i $=$ model error terms which are jointly normal; and

$\omega_i = \vartheta_i\beta + \ \mu_i$ $=$ the reduced-form model error term which is normal.

Instrumental variable (IV) analysis has been employed in this dissertation to develop IV binary probit models for person-level health outcomes. The IV analysis in these models accounts for the potential endogeneity bias, which may exist due to reciprocal causation (i.e., reverse causality) effects between physical activity levels and health outcomes.

3.3.4 Structural Equation Modeling (SEM) Techniques

Structural equation modeling techniques provide a methodological framework to examine theory-driven causal relations (Hancock and Mueller 2006). These techniques were first developed in the 1970s and are primarily used in social and behavioral sciences such as sociology, psychology, and marketing (Kelloway 1998; Chung et al. 2004; Kline 2011). According to Chung et al. (2004), the first application of SEM in travel behavior research was in 1980s.

The SEM techniques encompass a series of related statistical procedures that have the capability of incorporating both measurement (i.e., factor analysis) and structural (i.e., path analysis) approaches. Thus, the SEM techniques can be considered a combination of measurement models and path analysis (Chung et al. 2004). In models with both components, the SEM process validates the measurement model through factor analysis and estimates the structural model through path analysis. By providing simultaneous measurement and prediction analyses, SEM techniques allow for specification and examination of elaborate path models and causal links that shape the phenomenon of interest (Kelloway 1998).

For models with both measurement and structural components, the measurement model, which relates the latent (i.e., unobserved) variable(s) with its observed indicators can be formulated as follows—according to Heck (2001) as well as Rabe-Hesketh, Skrondal and Zheng (2007):

$$y_i = \nu + \mathbf{\Lambda}\eta_i + \mathbf{K}x_i + \epsilon_i \qquad \text{Equation 16}$$

$y_i =$ vector of observed dependent (i.e., endogenous) variables for observation i ;

$\nu =$ vector of measurement intercepts;

$\mathbf{\Lambda} =$ matrix of measurement coefficients (i.e., pattern coefficients or factor loadings);

$\eta_i =$ set of latent variables (i.e., factors);

$x_i =$ vector of observed independent (i.e., exogenous) variables;

$\mathbf{K} =$ matrix of regression coefficients; and

$\epsilon_i =$ vector of measurement error terms assumed to be unrelated with other variables.

The structural model, which specifies the causal links between the latent variable(s) (i.e., endogenous variables) and exogenous variables or other endogenous variables, can be formulated as follows:

$$\eta_i = \alpha + \mathbf{B}\eta_i + \mathbf{\Gamma}x_i + \zeta_i \qquad \text{Equation 17}$$

where,

$\eta_i =$ vector of endogenous variables for observation i ;

$\alpha =$ vector of intercepts;

$\mathbf{B} =$ matrix of latent endogenous coefficients representing the direct effect of endogenous variables (η_i) on other endogenous variables;

$\mathbf{\Gamma} =$ matrix of latent exogenous coefficients representing the direct effect of exogenous variables (x_i) on endogenous variables (η_i); and

$\zeta_i =$ vector of structural equation residuals (i.e., error terms).

For models with all observed variables (i.e., with no latent variables), the structural equation reduces to an equation representing a path model:

$$y_i = \alpha + \mathbf{B}y_i + \mathbf{\Gamma}x_i + \zeta_i \qquad \text{Equation 18}$$

A measurement model in which the latent variable(s) is measured by multiple indicators and is also considered to have been caused by additional observed variables is called a multiple indicators and multiple independent causes (MIMIC) model. This means that in measurement models with a MIMIC factor (i.e., latent variable), some observed indicators are specified as effects of the latent variable, whereas other indicators are specified as causes of the latent variable (Kline 2006).

In a MIMIC model, there are no links among the latent variables (Rabe-Hesketh et al. 2004), so Equation 18 becomes:

$$\eta_i = \alpha + \mathbf{\Gamma}x_i + \zeta_i \qquad \text{Equation 19}$$

The specification of the presumed causal effects (i.e., effect priority) is a key part of structural equation modeling (Kline 2011). Causal relations can be hypothesized and accordingly specified in the model for both types of variables, observed and latent. The SEM analysis for a specified model produces parameter estimates in such way to minimize the discrepancy between the covariance matrix of the sample (i.e., observed variables), ($\mathbf{S}$), and the covariance matrix of these variables calculated from the estimated parameters of the model ($\hat{\mathbf{\Sigma}}$) (Hershberger 2006).

3.3.4.1 Multilevel Structural Equation Modeling (multilevel SEM) Techniques

A major recent development with regards to SEM techniques has been the convergence of SEM and multilevel analyses, which accounts for interdependencies resulting from clustering of observations within a lower-level unit in higher-level units (Kline 2011).

In multilevel SEM techniques, the SEM analysis component allows for examination of complex links among various exogenous and endogenous variables while the multilevel analysis component allows for examination of interdependency among data due to nesting of units within hierarchical levels. These tasks occur simultaneously during the multilevel SEM estimation process. These synthetized capabilities make the multilevel SEM a sophisticated and advanced technique to be applied to empirical data in various research fields.

The structural model for a two-level multilevel SEM where first-level observations *i*s are clustered in second-level cluster *j*s can be formulated as:

$$y_{ij} = \alpha + \mathbf{B}y_{ij} + \mathbf{\Gamma}x_{ij} + \mathbf{Z}z_j + \zeta_{ij} \qquad \text{Equation 20}$$

where, α , $\mathbf{B}$, $\mathbf{\Gamma}$, and other parameters are as previously defined;

$z_j =$ vector of observed independent (i.e., exogenous) variables at the cluster level; and

$\mathbf{Z} =$ matrix of regression coefficients for cluster-level variables.

Modeling cases with a nested data structure (such as the one above) by multilevel SEM techniques makes the analysis more powerful than analyzing the data at only the observation level. This is because the multilevel SEM allows for examination of within-cluster (i.e., observation or first level) relations as well as the between-cluster (i.e., cluster or second level) relations. This means that the between-cluster covariance matrix provides additional information about the within-cluster relations (Stapleton 2006). The random effects of clusters are estimated by the multilevel SEM along with coefficients of the structural model (as well as those for the measurement model in multilevel SEMs with both structural and measurement components).

In research based on ecological model frameworks, Smith et al. (2008) suggested using multilevel analytic approaches such as multilevel statistical models. Therefore, this study uses multilevel SEM techniques to examine the link between nonmotorized travel behavior and the built and social environments, while controlling for residential self-selection (i.e., endogeneity) bias as well as interdependency among data from multiple hierarchical levels of influence.

Studies using a multilevel SEM model are rarely found in the transportation field (Chung et al. 2004). The present study aims to the reintroduce these sophisticated techniques to travel behavior research by employment of multilevel SEMs in the analysis of nonmotorized travel behavior. Moreover, multilevel SEM techniques have been used in the current study to test the causality of the links between physical activity, the built environment, and health—highlighting the potential of such techniques for being applied in public health research.

3.4 Chapter Conclusions

Guided by the principles of the ecological model of behavior and the existing literature, a comprehensive conceptual framework is proposed in this chapter for examination of the links between nonmotorized travel behavior, the built and social environments and health outcomes.

Several publicly available datasets are utilized in the analysis including—but not limited to—the NHTS, the ACS, the SLD, the Walk Score, the BRFSS, and the CHR&R datasets.

Advanced statistical techniques are employed to develop integrated models, which allow comprehensive analysis of the complex interrelationships between the environment, nonmotorized travel and health. These include linear mixed-effects (i.e., multilevel) modeling, ordered as well as binary probit modeling, structural equation modeling, and instrumental variable techniques.

Chapter 4: Analysis of Nonmotorized Travel Behavior

"Walking is the best possible exercise. Habituate yourself to walk very far."

—Thomas Jefferson [14]

Identification of factors that influence nonmotorized travel behavior and understanding the extent and direction of the effects of these factors are essential to development of travel demand models with a comprehensive, multimodal framework. The built environment characteristics of the residential location are among the many factors that can influence the choice and the extent of nonmotorized travel by people.

While it is evident that micro-level (i.e., neighborhood-level) built environment factors play a role in generating nonmotorized trips (see e.g., Cervero and Kockelman 1997; Handy and Clifton 2001; Greenwald and Boarnet 2001; Rodríguez et al. 2009; Mitra and Buliung 2012 among other studies), it is not clear how the built environment characteristics of higher-level spatial areas (i.e., meso- and macro-level built environment factors) affect these trips. This gap in knowledge highlights the need for research into the role of regional (i.e., meso-level) and metropolitan area (i.e., macro-level) built environment factors in promotion or prevention of nonmotorized trips.

This chapter contributes to the existing empirical knowledge on nonmotorized travel behavior by using an ecological framework for developing advanced statistical models to analyze nonmotorized travel. First, household-level nonmotorized travel behavior models are developed to examine the association between the number of nonmotorized trips generated from households and objectively measured neighborhood-level (i.e., micro-level) as well as regional- and metropolitan-level (i.e., meso- and macro-level) built and social environment attributes of the place of residence. Second, person-level nonmotorized travel behavior models are developed to examine

[14] Letter to Peter Carr, 19 August 1785 in *The Papers of Thomas Jefferson*.

the link between individuals' daily nonmotorized trip mode share and objectively measured built and social environment attributes of their place of residence at multiple levels of influence.

Nonmotorized travel behavior is defined as walking and bicycling in this study and separate models are developed for each of these activities. It should be borne in mind that modeling bicycling travel behavior remains an under-investigated area of research. Therefore, this chapter also contributes to the body of empirical knowledge on bicycling travel behavior by developing and estimating separate models for bicycling trips. The estimated models provide insights for evaluation of the effects of various factors on walking and bicycling travel.

Nonmotorized travel behavior models have been developed based on data from two different study areas:

1) several metropolitan areas within the state of Florida; and

2) the Baltimore (in state of Maryland) and Washington, D.C. metropolitan areas[15].

Due to data availability time frames, the analyses of the two different study areas utilize different databases. However, both analyses have been designed in such way to include the elements of the same conceptual framework (Figure 1), which follows the principles of the ecological model of behavior.

A central focus of the ecological model is the role of the built environment (in addition to that of the social environment) at multiple levels of influence in human behavior. Accordingly, the proposed frameworks for the nonmotorized travel behavior models developed in this chapter have been conceptualized in such way to examine the effects of built as well as social environment factors at multiple levels of influence on walking and bicycling travel behavior (see Figure 1).

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[15] Due to similarities in the analysis of the two case studies, only the Florida case study nonmotorized travel models are included in the main body of this dissertation. The Baltimore-D.C. case study analysis and models are presented in Appendix C. However, results from the Baltimore-D.C. case study are used in the main body of the dissertation for comparison purposes and are referred to as corroborating evidence for the findings of the Florida case study.

4.1 Nonmotorized Travel Behavior: A Florida Case Study

Based on the principles of the ecological model of behavior, this section presents the analysis of the link between nonmotorized travel and built as well as social environment attributes at various levels of influence using data from several metropolitan areas within the state of Florida. To systematically test the link between walking and bicycling trips and environmental factors[16], two different units of analysis are considered for developing statistical models. First, household-level models are estimated to examine the role of various environmental factors in the number of walking/bicycling trips generated from households. Then, person-level models are estimated to investigate the impact of environmental factors in the level of nonmotorized travel by individuals.

According to the ecological model, the influence of built and social environments on behavior can be considered at multiple spatial levels. As mentioned in Chapter 2, a few studies discussed a three-level hierarchy for the influence of environmental factors on physical activity such as nonmotorized travel including the micro level (e.g., neighborhood), the meso level (e.g., county), and the macro level (e.g., metropolitan area) (see e.g., King et al. 2002 and Ewing et al. 2003b). Specifically, King et al. (2002) suggested that the influence of built environment attributes on physical activity (e.g., nonmotorized travel) should be considered at micro, meso, and macro levels. Thus, this hierarchical structure has been adopted in the Florida case study to develop models that link walking and bicycling travel behavior to household characteristics as well as environmental factors (i.e., built and social environment characteristics).

This means that the role of built environment factors in nonmotorized travel has been examined at the micro-level (i.e., neighborhood), the meso-level (i.e., county), and the macro-level

[16] For the purpose of analyses presented in this dissertation, "the environment" refers to the "built and social environment" (as opposed to the natural environment). Therefore, anywhere the phrase "environmental factors" is used within this analysis, it should be considered in terms of built and social environment factors.

(i.e., metropolitan area). Social environment factors have also been included in the Florida models at the micro, meso, and macro levels (i.e., household, neighborhood, metropolitan area)[17].

Detailed descriptions of the data utilized in the Florida nonmotorized travel behavior case study along with the statistical modeling techniques employed and model estimation results are provided in the following subsections.

4.1.1 Florida Data

The database for the Florida nonmotorized travel behavior models consists of the following individual datasets:

- National Household Travel Survey (NHTS)—2009 Florida Add-on data;
- Smart Location Database (SLD);
- Community Health Status Indicators (CHSI);
- County Health Rankings & Roadmaps (CHR&R);
- American Community Survey (ACS);
- Walk Score data;
- Urban Mobility Information data—Texas A&M Transportation Institute (TTI);
- Uniform Crime Reporting (UCR) Program data—Federal Bureau of Investigation (FBI); and
- Census Bureau's TIGER/Line Shapefiles.

[17] It is noteworthy that compared with the Baltimore-DC case study (Appendix C), which examines the role of the built environment in nonmotorized travel at the micro-level (i.e., neighborhood) and meso-level (i.e., county), the Florida case study adds a macro-level (i.e., metropolitan area) built environment influence to the models. Further, social environment factors have also been included in Florida models at the micro (i.e., household), meso (i.e., neighborhood) and macro (i.e., metropolitan area) levels, whereas the only level of influence for the social environment included in the Baltimore-DC case study (Appendix C) is the household.

As a nationwide travel survey, the NHTS greatly challenges the ability to measure the micro-level built environment near respondents' residences. Instead, the Florida 2009 NHTS Add-on survey identified the census block group of each household as the smallest geographic unit in the survey. This facilitated the operationalization of the micro-level (i.e., neighborhood level) built environment. The Add-on data also provided geocoded information on Florida survey respondents' household location, household socioeconomic, and sociodemographic characteristics as well as detailed information on trips made by individuals within each surveyed household.

Figure 2 shows the mode share for Florida trips based on the 2009 NHTS Add-on travel survey data. Figure 3 shows the percentage of trips by destination based on the data recorded in the Florida 2009 NHTS Add-on sample.

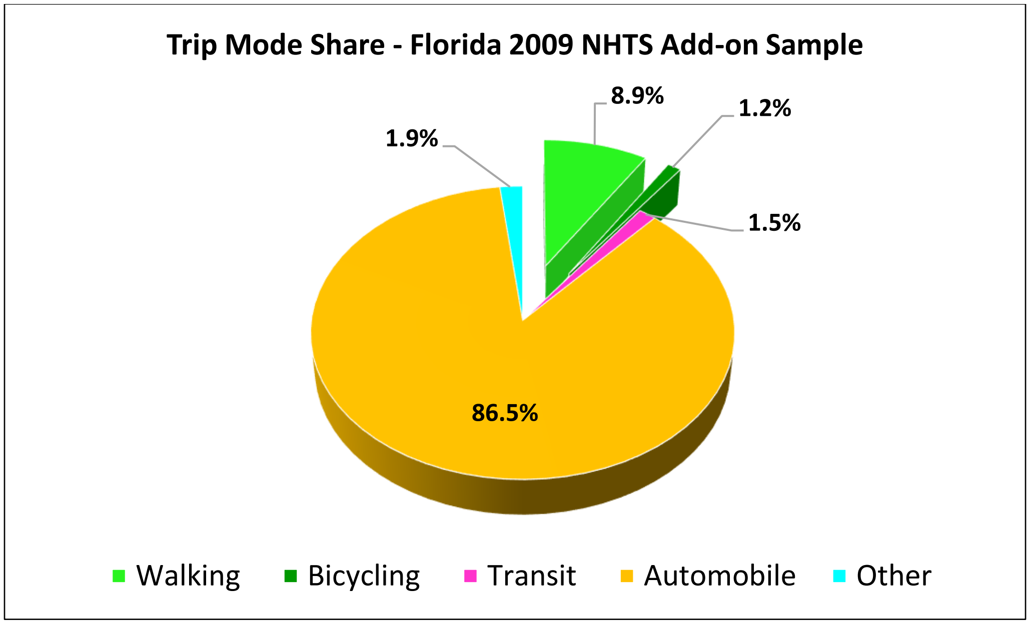

Figure 2. Trip Mode Share Based on the Florida 2009 NHTS Add-on Data

As it can be seen from Figure 3, "Home" was the destination for over 40% of the walking trips and nearly 45% of bicycling trips. Considering walking and bicycling trips as one general "nonmotorized" mode, the Florida 2009 NHTS Add-on data also indicate that of the 11,614 nonmotorized trips (i.e., pedestrian trips plus bicycle trips) that were reported in Florida:

- 4,708 trips (i.e., approximately 41%) listed "Home" as trip destination;
- 1,635 trips (i.e., over 14%) went beyond 1.5 miles in trip distance;
- 1,567 trips (i.e., approximately 13.5%) lasted longer than 30 minutes in trip duration.

These statistics show that a considerable proportion of Florida walking and bicycling trips did not originate at the residence location and may not have stayed within the neighborhood boundaries.

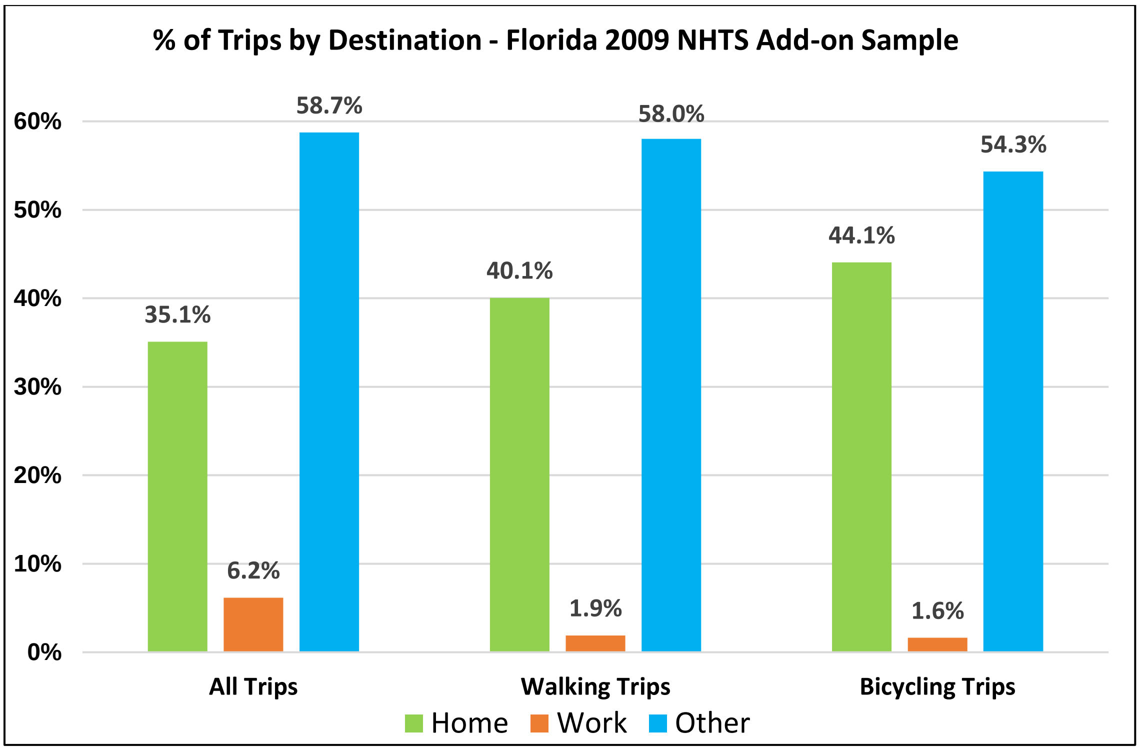

Figure 3. Percentage of Trips by Destination — Florida 2009 NHTS Add-on Data

The SLD provided information on land use and built environment characteristics (i.e., *Ds* of the built environment), in addition to socioeconomic and sociodemographic characteristics at the census block group level. These data include population and employment densities, extent of mix land use development, network and neighborhood design factors, destination and transit accessibility, and transit service frequency. The CHSI, CHR&R, ACS, TTI, and FBI datasets provided additional data on built and social environment factors.

Walk Score data were obtained for counties as well as metropolitan areas in the Florida case study. Also, block-level and county-level shapefiles were obtained from the U.S. Census Bureau's TIGER/Line database. GIS tools were used to spatially link land use and built environment data for each household to nonmotorized travel behavior of the household and individuals and obtain the final integrated Florida database for statistical modeling. Detailed information on the datasets used in this analysis can be found in Chapter 3.

4.1.2 Florida Metropolitan Areas

The National Research Council (2005) reported that by year 2000, 80% of the U.S. population lived in metropolitan areas (i.e., central cities, suburbs of metropolitan areas). For that reason, the present case study focuses on metropolitan areas as study areas and does not include data from non-metropolitan areas (e.g., micropolitan areas, rural areas) in the analysis.

According to the U.S. Census Bureau web site, a Core-Based Statistical Area (CBSA) designated as a *metropolitan area* has "at least one urbanized area of 50,000 or more population, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties."[18]

For the purpose of this case study, a metropolitan area is considered the CBSA where the surveyed household was located. Data from 23 metropolitan areas (CBSAs) in the state of Florida are utilized in the analysis. Figure 4 shows a few of these metropolitan areas on a map of Florida along with the location of households for which walking and bicycling activities were recorded in the Florida 2009 NHTS Add-on data.

[18] "Core Based Statistical Areas": https://www.census.gov/topics/housing/housing-patterns/about/core-based-statistical-areas.html

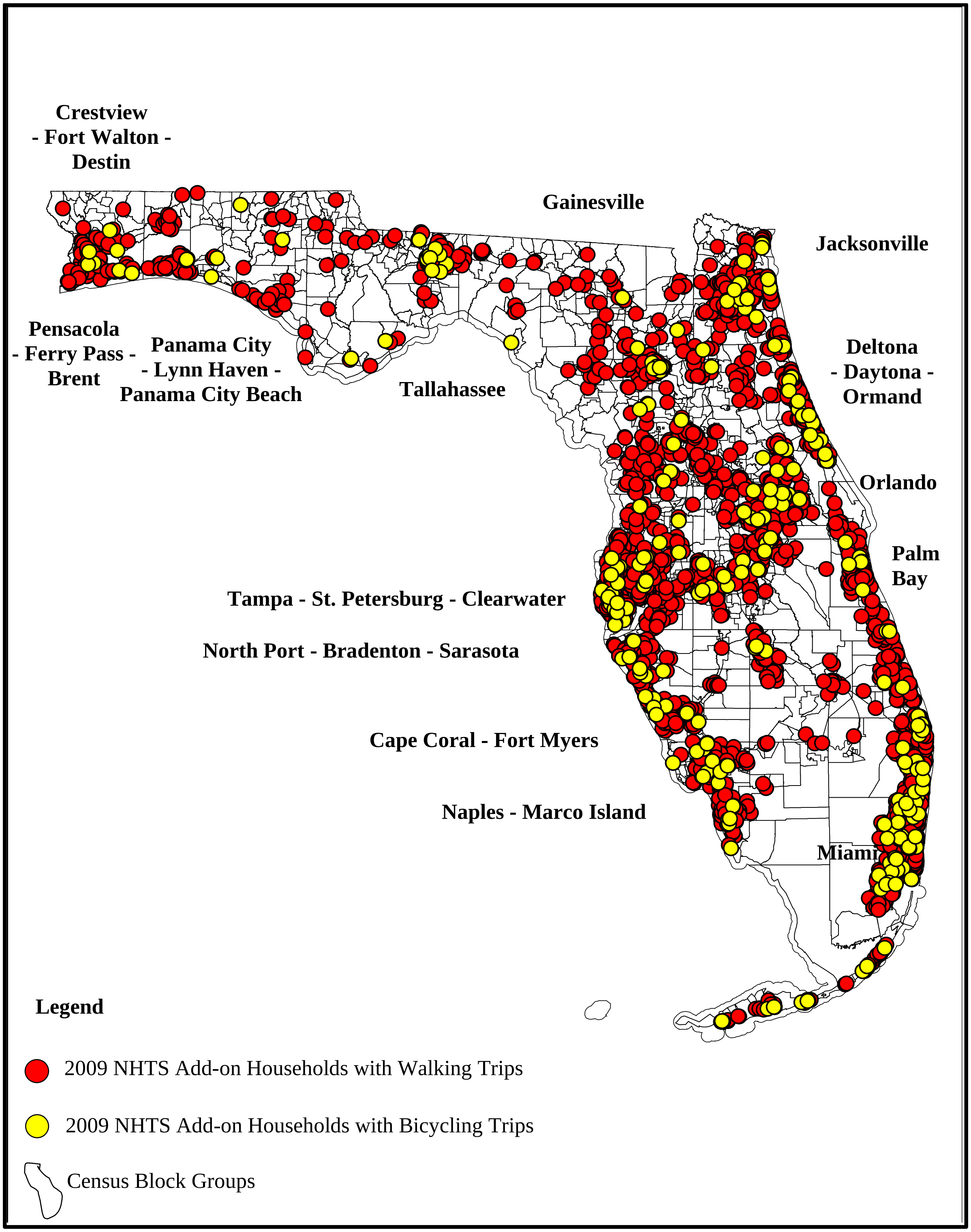

Figure 4. Florida Case Study Map

Table 2 lists the Florida metropolitan areas with their corresponding sample size and total population (according to U.S. Census Bureau 2010[19]). Population and employment densities have been computed for each metropolitan area based on information available in the SLD.

Table 2. Florida Case Study Metropolitan Areas

Metropolitan Area (CBSA)	Sample Size	Population (2010)	Mean Residential Density[a]	Mean Employment Density[b]
Cape Coral-Fort Myers	478	618,754	3.62	0.92
Crestview-Fort Walton Beach-Destin	325	180,822	3.29	1.14
Deltona-Daytona Beach-Ormond Beach	448	494,593	3.36	0.85
Gainesville	310	264,275	2.73	1.77
Homosassa Springs	354	141,236	1.06	0.21
Jacksonville	1,184	1,345,596	4.27	1.41
Lakeland-Winter Haven	406	602,095	2.84	1.31
Miami-Fort Lauderdale-Pompano Beach	3,949	5,564,635	13.54	2.81
Naples-Marco Island	264	321,520	4.24	1.17
North Port-Bradenton-Sarasota	516	702,281	4.28	1.39
Ocala	315	331,298	1.54	0.35
Orlando-Kissimmee-Sanford	1,155	2,134,411	4.83	1.47
Palm Bay-Melbourne-Titusville	447	543,376	4.43	1.15
Palm Coast	146	95,696	2.44	0.44
Panama City-Lynn Haven-Panama City Beach	296	168,852	2.58	1.41
Pensacola-Ferry Pass-Brent	518	448,991	2.65	0.98
Port St. Lucie	429	424,107	3.51	0.87
Punta Gorda	165	159,978	2.56	0.71
Sebastian-Vero Beach	115	138,028	2.51	0.87
Sebring	274	98,786	1.95	0.61
Tallahassee	617	367,413	2.48	1.31
Tampa-St. Petersburg-Clearwater	2,160	2,783,243	6.35	1.74
The Villages	105	93,420	1.94	0.28

NOTES:

To more accurately account for household representativeness, analytic weights (NHTS household survey weights) have been considered in the computation of the residential and employment densities reported;

[a] Measured by taking the average of values for the census block group within the CBSA rather than dividing the overall population by the overall area (size of the metropolitan area). The unit is persons per acre;

[b] Measured by taking the average of values for the census block group within the CBSA rather than dividing the overall employment by the overall area (size of the metropolitan area). The unit is jobs per acre.

[19] U.S. Census Bureau, American FactFinder web site: https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

It can be seen from the table that the most highly populated metropolitan areas in the Florida sample are the Miami-Fort Lauderdale-Pompano Beach and the Tampa-St. Petersburg-Clearwater metropolitan areas, respectively. In terms of average employment density, Miami-Fort Lauderdale-Pompano Beach is the metropolitan area with the most job opportunities per area of land and the Gainesville and Tampa-St. Petersburg-Clearwater metropolitan areas follow next. Table 2 also shows that sample sizes are proportionate to the population, which overall makes this sample a good representative of the population within the state of Florida.

4.1.3 Household-level Nonmotorized Travel Behavior Model Framework

The unit of analysis for the first Florida case study is the household. As indicated previously, a large proportion of Florida nonmotorized trips did not originate from the home location (41%). Also, for considerable proportions of nonmotorized trips, a travel distance over 1.5 miles (>14%) or a travel time of over 30 minutes was reported (>13%); therefore, it is possible that many of these trips did not occur or stay within the residential neighborhood. Consequently, the environmental patterns of geographical areas beyond the neighborhood (e.g., county or metropolitan area) may have played a role in generation of these nonmotorized trips. This implies that potentially multiple levels of built and social environments influenced the extent of nonmotorized travel behavior in the Florida sample.

This is in line with the theoretical principles of the ecological model of behavior, which posits that within the multiple levels of influence on behavior, concepts that themselves operate at multiple levels are sociocultural and built environment factors (Sallis et al. 2008). In this case, focusing only on the attributes of the neighborhood-level built or social environment for their influence on nonmotorized travel behavior will not be a comprehensive analysis. Therefore, based on the ecological model of behavior, a multilevel model framework has been conceptualized for the Florida household-level analysis, which relates the extent of households' nonmotorized travel to the attributes of the built and social environments at various levels of influence.

Figure 5 shows the ecological model framework as conceptualized and applied to the Florida household-level nonmotorized travel behavior models.

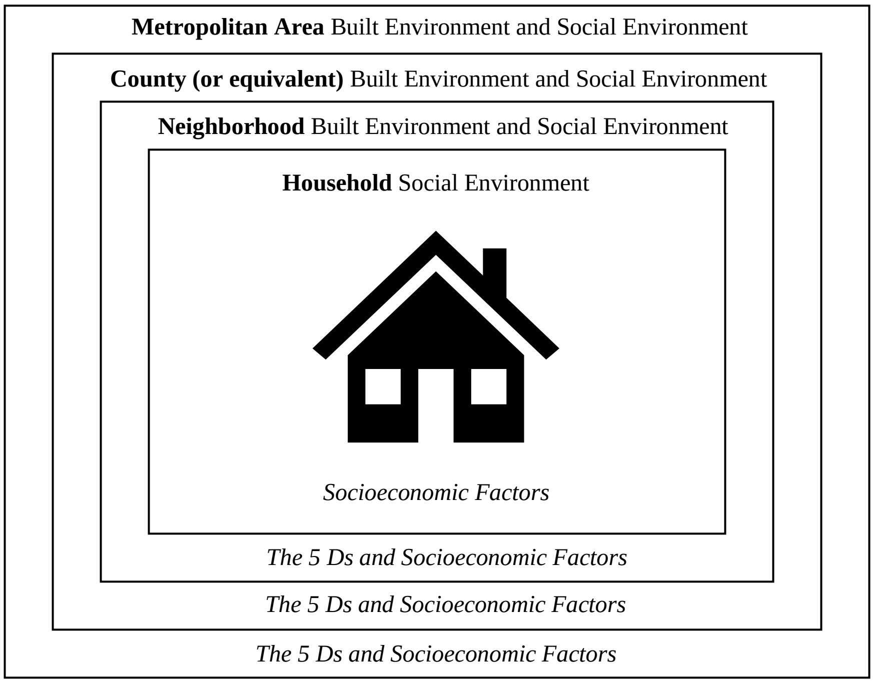

Figure 5. Ecological Framework for Levels of Influence on Nonmotorized Travel Behavior (Florida Household-level Models)

As depicted in the figure, to capture the impact of the built environment at multiple levels of influence, built environment characteristics have been measured utilizing three geographical units of analysis (i.e., neighborhood, county, and metropolitan area). These levels correspond to a three-level hierarchy of the influence of the built environment attributes: the micro level, the meso level and the macro level. Also, to capture the influence of the social environment on nonmotorized travel behavior at multiple levels, the household-level models incorporate the micro-meso-macro level range for social environment characteristics. These levels correspond to a three-level hierarchy for the influence of the social environment on walking and bicycling behavior—namely, the household (i.e., micro level), the neighborhood (i.e., the meso level), and the metropolitan area (i.e., the macro level). Although considered in the initial model framework (Figure 5), county-level socioeconomic factors have not been included in the final Florida household models mainly to keep the hierarchy for the influence of the social environment at three levels.

4.1.4 Household-level Nonmotorized Travel Models: Dependent Variables

The nonmotorized trips of the 2009 NHTS Add-on households located in metropolitan areas within the state of Florida have been considered for statistical modeling in the Florida household-level case study. Florida was selected as the study area due to availability of geocoded information on respondents' household location in the 2009 NHTS Add-on data for that state, which allowed operationalization of the neighborhood built environment attributes at a fine scale. Four separate models for walking and bicycling trips have been developed based on four dependent variables:

1) household's number of daily per capita walking trips;

2) household's number of daily per capita bicycling trips;

3) household's total number of daily walking trips; and

4) household's total number of daily bicycling trips.

The total numbers of a household's walking (or bicycling) trips were computed by aggregating the number of walking (or bicycling) trips recorded in the 2009 NHTS Add-on travel survey during the travel day for all members of that household.

To obtain the household's number of daily per capita walking trips, the total number of household's daily pedestrian trips was divided by the total number of household members. Similarly, the household's number of daily per capita bicycling trips was computed by dividing the total number of household's daily bicycling trips by the total number of household members.

Table 3 provides information on the frequency and percentage of Florida households' total number of household's daily walking and bicycling trips. The table indicates that the maximum number of household trips was 22 and 11 for walking and bicycling trips, respectively.

Table 3. Number and Proportion of Florida Household Nonmotorized Trips

Number of Household Trips	Frequency		Percent	
	Walking	Bicycling	Walking	Bicycling
0	11,607	14,463	77.50	96.57
1	421	59	2.81	0.39
2	1,787	339	11.93	2.26
3	161	19	1.08	0.13
4	584	63	3.90	0.42
5	63	12	0.42	0.08
6	185	10	1.24	0.07
7	24	3	0.16	0.02
8	82	4	0.55	0.03
9	10	1	0.07	0.01
10	28	2	0.19	0.01
11	4	1	0.03	0.01
12	4	—	0.03	—
13	—	—	—	—
14	7	—	0.05	—
15	2	—	0.01	—
16	3	—	0.02	—
17	—	—	—	—
18	1	—	0.01	—
19	1	—	0.01	—
20	—	—	—	—
21	1	—	0.01	—
22	1	—	0.01	—
Total	14,976	14,976	100.00	100.00

NOTE: — = Not applicable; Source of data: 2009 NHTS Add-on data.

Also, a sizable percentage (77.5%) of Florida households did not report any walking trips. This percentage is much higher in the case of bicycling trips as almost 97% of households did not report any bicycling trips during the day of travel survey. The average number of daily household walking and bicycling trips were 0.65 trips and 0.08 trips, respectively. These low figures are consistent with the literature that suggests nonmotorized trips occur at very low rates (see e.g., Friedman et al. 1994; Agrawal and Schimek 2007; Marcus 2008; Kuzmyak et al. 2014) as well as the statistics obtained from the Baltimore-DC case study (presented in Appendix C). Also, Florida households' average lower in the number of daily household walking trips compared to the Baltimore-DC case study where the average number of daily household walking trips was 0.99 (see Appendix C).

4.1.5 Household-level Nonmotorized Travel Models: Independent Variables

The independent variables for the Florida statistical models were chosen based on the theoretical principals of the ecological models of behavior, previous empirical research (elaborated in Chapter 2 and Appendix B), and the results of the Baltimore-D.C. case study (reported in Appendix C). The independent variables for the Florida household-level case study are categorized as follows:

4.1.5.1 Social Environment Variables

Social environment factors have been included in the models at three levels of influence: the household (i.e., the micro level), the neighborhood (i.e., the meso level), and the metropolitan area (i.e., the macro level). The household is considered the most important setting among the social environment levels of influence that determines an individual's behavior (Gochman 1997; Van Acker et al. 2010). Therefore, household control variables have been included in the Florida models to represent the first level of influence (micro level) of the social environment on nonmotorized travel behavior. These variables provide information on socioeconomic status (SES) of each Florida 2009 NHTS Add-on household including the household's:

- number of adult members;
- annual income;
- number of workers; and
- number of vehicles.

The values for these variables are taken directly from the Florida 2009 NHTS Add-on data. Many past studies (see Chapter 2) highlighted the crucial role of car ownership in nonmotorized travel behavior[20]. Thus, variables representing car ownership were included in the models at influence levels higher than the household (i.e., the micro-level social environment).

To represent the meso-level social environment, a variable representing the percentage of households in the neighborhood that own no cars has been included in the nonmotorized travel behavior models. The macro-level social environment has been represented by a CBSA-level car ownership variable (i.e., the average percentage of households in the CBSA that own more than two cars) as well as a CBSA-level income-related variable (i.e., the average percentage of low-wage workers in the CBSA).

These variables allow controlling for socioeconomic factors within the area where the household was located, in addition to those of the household itself. Table 4 provides additional information about the three-level (micro, meso, macro) social environment variables included in the Florida models.

4.1.5.2 Built Environment Variables

As mentioned previously, built environment characteristics of the household location have been considered at various levels of geography to control for the impact of micro-, meso- and macro-level built environment on walking and bicycling travel behavior. These variables include:

Micro-level (i.e., Neighborhood-level) Built Environment Variables

The micro-level built environment variables provide information on the neighborhood-level built environment for each household location. The SLD provides these data at the census block group (CBG) level, which is a fine-scale geographical area. According to the U.S. Census Bureau, CBGs

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[20] Household vehicle ownership also proves to be one of the most influential socioeconomic factors in determining walking and bicycling trips in the Baltimore-D.C. case study (see Appendix C).

typically contain between 600 to 3,000 people[21]. Therefore, the census block group is a relatively small area that approximates a neighborhood (Zick et al. 2013). In the Florida case study, the neighborhood-level built environment variables are represented by the attributes of the census block group where the household was located. This provides a much better resolution for the neighborhood built environment characteristics than the one utilized in the Baltimore-D.C. case study, which used TAZs as neighborhoods (see Appendix C). The SLD neighborhood-level (i.e., CBG-level) built environment variables included in the Florida household-level models are:

- activity density;
- entropy;
- intersection density;
- pedestrian-friendly network density;
- local transit accessibility (frequency of service); and
- distance to local transit (proximity to transit).

These variables represent the *D*s of the built environment at the neighborhood level. Table 4 provides additional information about the micro-level built environment variables.

Meso-level (County-level) Built Environment Variables

The meso-level built environment variables have been defined based on the county where the household was located. Block group-level built environment and land use measures provided by the SLD were aggregated to obtain the average county-level built environment measures for each household's location. Aggregation of data at smaller scales to obtain the mean of the explanatory variables at larger scales provides a meaningful contextual variable (i.e., the group mean) for inclusion in the multilevel mixed-effects models (Snijders and Bosker 2012). This method of

[21] "Geographic Terms and Concepts – Block Groups": https://www.census.gov/geo/reference/gtc/gtc_bg.html

calculation of the built environment for larger level scales prevents measurement biases (Nasri and Zhang 2014). Meso-level regional accessibility measures have also been derived from the SLD data. Interzonal (i.e., census block group to census block group) accessibility measures provided in SLD have been aggregated to obtain average county-level accessibility measures for the nonmotorized travel behavior models developed in this case study. The meso-level (i.e., county-level) built environment variables included in the household-level nonmotorized travel models are:

- average activity density;
- average entropy;
- average regional diversity;
- average intersection density;
- average pedestrian-friendly network density;
- average transit service frequency;
- average automobile accessibility; and
- average transit accessibility.

These variables represent the *D*s of the built environment at the county (meso) level in the models. Table 4 provides more information about the meso-level built environment variables.

Macro-level (Metropolitan Area-level) Built Environment Variables

To examine the role of various levels of geography on nonmotorized travel behavior, the Florida case study adds the macro-level (i.e., metropolitan area-level) geographical scale to the analysis. The travel profile in many metropolitan areas shows a mix of patterns ranging from high levels of automobile trips in the suburban areas to high levels of nonmotorized trips in the core of the urban area (Murga 2004). Therefore, the role of the metropolitan area-level built environment characteristics in nonmotorized travel behavior is examined by including variables representing these macro-level built environment attributes in the Florida models.

Metropolitan area-level built environment variables have been defined based on the Core Based Statistical Area (CBSA) where the household was located. Past studies also defined metropolitan areas based on the CBSA designation (Cidell 2010).

Census block group-level built environment and land use measures provided by the SLD have been aggregated to obtain the average metropolitan area-level (macro-level) built environment measures for each household location. This was done based on arguments by Snijders and Bosker (2012) who suggested that obtaining the mean of the explanatory variables at larger scales by aggregation of data at smaller scales provides a meaningful contextual variable (i.e., the group mean) for inclusion in multilevel mixed-effects models. The macro-level (i.e., CBSA/metropolitan area-level) built environment variables included in the models are:

- average activity density;
- average entropy;
- average total road network density;
- percentage of small blocks;
- average automobile accessibility; and
- average transit accessibility.

Table 4 provides additional information about the macro-level built environment variables, and the *D*s of the built environment they represent in the models.

Additional Notes on Built Environment Variables

As seen from Table 4, a few of the built environment variables have been included at all three levels of geography (i.e., micro, meso, and macro levels). For example, the *Activity Density* variable at the micro level measures employment and residential density at the neighborhood level, whereas the *Mean Activity Density* variables at the meso and macro levels quantify the level of residential and employment activities in the corresponding level of geographical areas (e.g., county and metropolitan area).

Also, the *Entropy* variable has been included in the model to represent the extent of mixed-use development (i.e., land use diversity) in the respective area (i.e., neighborhood, county, metropolitan area). This variable uses the 5-tier employment categories (i.e., retail, office, industrial, service, and entertainment) and the entropy formula[22] in computation of entropy at each level of geography.

Variables representing intersection density and total road network density have been included to account for street network design and automobile-oriented intersection density. Intersection density have been used in the past studies as an indicator of smaller block sizes and a more walkable urban design (see e.g., Kerr et al. 2007). However, the intersection density variable provided by the SLD measures the intersection density in terms of automobile-oriented intersections. Additionally, the SLD User Guide states that the source data for this variable "provides no information regarding the presence or quality of sidewalks"[23]. Therefore, this variable it is not expected to be an indicator of more pedestrian-friendly designs or to have a positive correlation with walking in this analysis.

The pedestrian-friendly network density variables have been included to capture the influence of pedestrian-oriented urban designs on nonmotorized travel behavior. These variables are hypothesized to have a positive association with walking.

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[22] Entropy = $-\sum_j \frac{P_j * ln(P_j)}{ln(J)}$ where, $J =$ number of land use classes within the area; and $P_j =$ proportion of land use in the *j*th class (Frank and Pivo 1994; Cervero and Kockelman 1997; Cervero 2001; and Cervero and Duncan 2003);

[23] See page 20 of Ramsey and Bell (2014).

Local transit proximity and accessibility are represented by variables measuring distance to transit stops and frequency of transit service. Frequency of transit service has been aggregated to the county level to represent the transit accessibility at the meso level of the built environment.

The inclusion of destination accessibility variables allows for capturing the role of regional accessibility in nonmotorized travel behavior at both the county and the metropolitan area levels. The destination accessibility variables measure the average number of employment opportunities in the county or metropolitan area that are within a 45-minute automobile or transit travel time, respectively. These variables focus on employment accessibility and have been considered for inclusion in the models based on the use of similar measures in past research. For example, Cervero and Murakami (2010) used an employment accessibility index computed based on the mean number of jobs within 30 minutes travel time on highway networks. Employment accessibility was also measured in terms of number of jobs within a distance from the origin in the analysis of walking and bicycling by Cervero and Duncan (2003).

The final integrated database is included in Table 4, which lists all the independent variables used in the Florida nonmotorized travel behavior models along with brief descriptions, the effect they represent in the model, and information about data sources.

Together, the variables listed in Table 4 provide a comprehensive set of factors that can be used to examine the effects of the five *D*s of the built environment as well as the social environment attributes at hierarchical levels of influence as posited by the principles of the ecological model of behavior.

Tables 5 and 6 present the weighted descriptive statistics for household-level social environment variables as well as a few of the main built environment independent variables at the neighborhood level (CBG level) for Florida metropolitan areas included in the models.

Table 4. Florida Household-level Model Variable Descriptions and Data Sources

Independent Variable	Represented Effect	Variable Description/Units	Data Source	Data Field (Computation)[24], [a]
Social Environment				
Micro Level: The Household				
Number of Adults	SES	Persons over 18 in household	NHTS	NUMADLT[c]
Number of Vehicles	SES	Vehicles owned by household	NHTS	HHVEHCNT[c]
Number of Workers	SES	Employed persons in household	NHTS	WRKCOUNT[c]
Annual Income	SES	Household annual income (midpoint of category)	NHTS	Based on "HHFAMINC"[c]
Meso Level (Census Block Group): The Neighborhood				
Percentage of HHs with No Cars	SES	Percentage of HHs in CBG with zero cars	SLD	Pct_AO0
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of HHs with 2+ Cars	SES	Percentage of HHs in CBSA with more than two cars	SLD	Pct_AO2p (Averaged)
Average Percentage of Low-Wage Workers	SES	Percentage of workers in CBSA earning $1250/month or less	SLD	R_PctLowWage (Averaged)
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density	<u>D</u>ensity	(Employment + housing units) on unprotected land area (acres)	SLD	D1d
Entropy	Land use <u>D</u>iversity	5-tier employment entropy	SLD	D2b_E5Mix
Intersection Density	Urban <u>D</u>esign	Auto-oriented intersections/mi^2	SLD	D3bao
Pedestrian-friendly Network Density	Urban <u>D</u>esign	Facility miles of pedestrian-oriented links/mi^2	SLD	D3apo
Local Transit Service	Local Transit Accessibility	Aggregate frequency of transit service/mi^2	SLD	D4d
Local Transit Accessibility	<u>D</u>istance to Local Transit	Distance from centroid to the nearest transit stop (meters)	SLD	D4a
Meso Level: The County				
Mean Activity Density	<u>D</u>ensity	Ave. (employment+ housing units) on unprotected land in county	SLD	D1d (Averaged)
Mean Entropy	Land use <u>D</u>iversity	Ave. 5-tier employment entropy for county	SLD	D2b_E5Mix (Averaged)
Mean Regional Diversity	Regional <u>D</u>iversity	Ave. deviation of jobs/population ratio from the regional[b] average	SLD	D2r_JobPop (Averaged)
Mean Intersection Density	Urban <u>D</u>esign	Ave. auto-oriented intersections/mi^2 for county	SLD	D3bao (Averaged)
Mean Pedestrian-friendly Network Density	Urban <u>D</u>esign	Ave. facility miles of pedestrian-oriented links/mi^2 for county	SLD	D3apo (Averaged)
Mean Transit Service	Transit Accessibility	Ave. aggregate frequency of transit service/mi^2 for county	SLD	D4d (Averaged)

[24] The variables provided in the SLD have been computed using various established methodologies, which have been extensively described in the SLD User Guide document. Therefore, the computation methods for the SLD variables are not discussed in this dissertation. The Smart Location Database User Guide can be found at: https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf

Mean Temporal Automobile Accessibility	Destination Accessibility	Ave. number of jobs in county within a 45-minute auto travel time	SLD	D5ar (Averaged)
Mean Temporal Transit Accessibility	Destination Accessibility	Ave. number of jobs in county within a 45-minute transit commute	SLD	D5br (Averaged)
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density	Density	Ave. (employment+ housing units) on unprotected land in CBSA	SLD	D1d (Averaged)
Mean Entropy	Land use Diversity	Ave. 5-tier employment entropy for CBSA	SLD	D2b_E5Mix (Averaged)
Mean Total Road Network Density	Urban Design	Ave. total road network density for CBSA	SLD	D3a (Averaged)
Percentage of 0.01 Blocks	Urban Design	Percent blocks with an area smaller than 0.01 square miles	Census TIGER Block Shapefiles	
Mean Temporal Automobile Accessibility	Destination Accessibility	Ave. number of jobs in CBSA within a 45-minute auto travel time	SLD	D5ar (Averaged)
Mean Temporal Transit Accessibility	Destination Accessibility	Ave. number of jobs in CBSA within a 45-minute transit commute	SLD	D5br (Averaged)

NOTES:
[a] Measure was computed by averaging values of the referenced field provided in data source over the relevant geographical area;
[b] CBSA;
[c] Variable was obtained from 2009 NHTS Add-on Household File;
Ave. = Average; HH = Household.

Table 5. Descriptive Statistics: Socioeconomic Status (SES) Characteristics

Florida Metropolitan Area (CBSA)	**Number of HH Adults**		**Number of HH Vehicles**		**Number of HH Workers**		**HH Annual Income** (1,000 dollars)	**% HHs in CBG with No Cars**	
	Mean	SD	Mean	SD	Mean	SD	Mean	Mean	SD
Cape Coral-Fort Myers	1.82	0.74	1.66	0.95	0.96	0.86	50 - 55	4.44	6.52
Crestview-Fort Walton-Destin	1.89	0.72	2.12	1.21	1.13	0.73	50 - 55	3.05	3.56
Deltona-Daytona Beach-Ormond	1.85	0.77	1.79	1.01	0.82	0.85	40 - 45	5.18	6.85
Gainesville	1.84	0.69	1.82	1.05	1.16	0.84	50 - 55	7.21	7.03
Homosassa Springs	1.88	0.71	1.87	1.08	0.84	0.92	40 - 45	3.71	3.81
Jacksonville	1.85	0.74	1.74	1.01	1.01	0.82	50 - 55	6.80	10.1
Lakeland-Winter Haven	1.86	0.72	1.62	1.01	0.90	0.84	40 - 45	5.53	6.99
Miami-Fort Lauderdale-Pompano	1.91	0.84	1.58	0.97	1.00	0.84	45 - 50	8.66	11.2
Naples-Marco Island	1.74	0.68	1.62	0.92	0.89	0.75	45 - 50	4.75	5.44
North Port-Bradenton-Sarasota	1.75	0.65	1.56	0.89	0.75	0.84	45 - 50	5.56	6.42
Ocala	1.90	0.88	1.73	1.02	0.78	0.88	40 - 45	4.36	5.06
Orlando-Kissimmee-Sanford	1.95	0.79	1.71	0.96	1.09	0.86	45 - 50	5.13	6.69
Palm Bay-Melbourne-Titusville	1.85	0.76	1.71	0.91	0.99	0.87	45 - 50	4.27	5.17
Palm Coast	2.07	0.69	2.01	0.94	1.02	0.88	50 - 55	3.80	4.73
Panama City-Lynn Haven	1.74	0.64	1.78	0.88	0.97	0.76	45 - 50	4.31	4.05
Pensacola-Ferry Pass-Brent	1.77	0.69	1.78	1.20	0.99	0.80	40 - 45	5.93	7.09
Port St. Lucie	1.89	0.61	1.78	0.96	1.02	0.86	50 - 55	4.43	6.30
Punta Gorda	1.78	0.69	1.65	1.05	0.79	0.90	35 - 40	5.57	9.31
Sebastian-Vero Beach	1.71	0.62	1.77	1.04	0.97	0.83	50 - 55	6.82	7.71
Sebring	1.77	0.63	1.75	1.08	0.81	0.97	40 - 45	5.62	6.40
Tallahassee	1.82	0.71	1.82	1.03	1.16	0.82	50 - 55	6.44	8.48
Tampa-St. Petersburg-Clearwater	1.81	0.71	1.62	0.94	0.98	0.83	45 - 50	6.45	8.16
The Villages	1.62	0.50	1.37	0.79	0.43	0.69	35 - 40	2.76	3.38

NOTES: HH = Household; CBG = Census Block Group (i.e., neighborhood).

The information in Table 5 shows that the Palm Coast metropolitan area has the largest mean of number of adults in the household (2.07), whereas the Crestview-Fort Walton-Destin metropolitan area households own the largest number of vehicles (2.12). The metropolitan areas with the largest number of workers in the household are Gainesville and Tallahassee (each with 1.16 workers in the household). Households residing in The Villages and the Punta Gorda metropolitan areas earn the lowest mean annual income. Also, neighborhoods in the Miami-Fort Lauderdale-Pompano metropolitan area have the largest mean percentage of households that do not own any private vehicles (8.66%).

Table 6. Descriptive Statistics: CBG-Level Built Environment Characteristics

Florida Metropolitan Area (CBSA)	**Activity Density** (employment + housing units)/ acre		**Entropy** (dimensionless)		**Intersection Density** (auto-oriented intersections/mi^2)		**Pedestrian-friendly Network Density** (miles of ped-oriented links/mi^2)		**Distance to Local Transit**[a] (meters)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cape Coral-Fort Myers	3.19	3.14	0.58	0.33	0.58	1.24	13.35	5.68	688.41	301.11
Crestview-Fort Walton -Destin	2.79	2.89	0.63	0.31	0.27	0.64	10.52	5.79	667.83	25.96
Deltona-Daytona Beach-Ormond	2.75	3.28	0.65	0.28	0.51	0.75	10.68	5.76	697.47	— [b]
Gainesville	3.06	6.54	0.63	0.24	0.57	1.12	8.22	6.51	665.27	26.44
Homosassa Springs	0.81	0.89	0.54	0.34	0.25	0.43	7.67	4.39	640.49	— [b]
Jacksonville	3.49	4.26	0.66	0.25	1.31	3.05	10.13	5.87	668.82	25.23
Lakeland-Winter Haven	2.59	4.52	0.54	0.31	0.64	1.17	8.99	5.81	729.35	335.53
Miami-Fort Lauderdale-Pompano	9.35	11.6	0.53	0.33	1.41	2.90	17.42	6.13	658.59	285.13
Naples-Marco Island	3.61	3.53	0.65	0.25	0.61	0.89	10.51	5.57	483.22	26.88
North Port-Bradenton-Sarasota	4.04	4.54	0.61	0.29	0.42	1.03	13.61	6.05	725.85	295.08
Ocala	1.17	1.44	0.59	0.31	0.39	0.69	8.29	5.05	665.88	23.47
Orlando-Kissimmee-Sanford	3.64	4.65	0.72	0.23	1.06	1.79	10.88	5.23	667.99	— [b]
Palm Bay-Melbourne-Titusville	3.47	2.99	0.61	0.31	0.56	1.13	12.44	5.26	767.79	274.91
Palm Coast	1.73	1.12	0.51	0.37	0.35	0.62	9.77	5.59	665.43	— [b]
Panama City-Lynn Haven	3.16	3.91	0.62	0.29	0.51	0.97	10.11	5.03	673.15	— [b]
Pensacola-Ferry Pass-Brent	2.19	2.37	0.64	0.29	0.62	1.65	9.36	5.19	667.82	— [b]
Port St. Lucie	2.71	2.82	0.62	0.62	0.49	0.72	10.59	5.86	668.32	— [b]
Punta Gorda	2.27	2.45	0.54	0.35	1.04	2.03	13.15	5.57	987.49	— [b]
Sebastian-Vero Beach	2.31	1.99	0.58	0.34	0.57	1.02	9.92	4.78	697.48	— [b]
Sebring	1.62	1.83	0.53	0.35	0.36	0.75	11.06	6.75	674.98	— [b]
Tallahassee	2.49	4.89	0.61	0.31	0.51	0.98	7.28	5.32	674.44	— [b]
Tampa-St. Petersburg-Clearwater	5.07	5.76	0.53	0.34	1.12	2.59	14.33	6.64	649.78	283.78
The Villages	1.58	1.13	0.54	0.67	0.44	0.42	9.22	5.36	640.08	— [b]

NOTES: [a] Missing values were replaced by the value of the mean of the adjacent CBGs or CBSAs; [b] Not applicable (due to missing data, the average value of the variable from adjacent CBSAs were considered for all CBGs within the entire CBSA).

The descriptive statistics in Table 6 indicate that the mean activity density is highest in the Miami-Fort Lauderdale-Pompano Beach and the Tampa-St. Petersburg-Clearwater metropolitan areas (9.35 and 5.07, respectively). The Orlando-Kissimmee-Sanford and Jacksonville metro. areas have the highest extent of mixed-use development (mean entropies of 0.72 and 0.66, respectively). Miami-Fort Lauderdale-Pompano Beach metro. area has the highest mean of automobile-oriented intersection density (1.41 intersections/mi^2), whereas Homosassa Springs has the lowest (0.25 intersections/mi^2). Also, the Miami-Fort Lauderdale-Pompano Beach and Tallahassee metropolitan areas have the highest and lowest pedestrian-oriented street network density (17.42 and 7.28 facility miles of pedestrian-oriented links/mi^2), respectively.

4.1.6 Household-level Nonmotorized Travel Behavior Models

Using an integrated database as shown in Table 4, nonmotorized travel behavior has been modeled for Florida households. The analysis of household-level nonmotorized travel behavior for the Florida case study is performed by employment of mixed-effects modeling techniques and ordered probit modeling techniques.

First, mixed-effects (i.e., multilevel) models have been developed to relate the number of household's daily per capita walking and bicycling trips to social environment characteristics (i.e., household, neighborhood, and metropolitan area socioeconomic attributes) as well as neighborhood, county, and metropolitan area built environment measures. Then, ordered probit models have been developed to predict the number of household's daily walking and bicycling trips based on the same factors as above. The results of the two types of models are used for comparison purposes.

All Florida models have been developed based on the principles of the ecological model of behavior. Considering these principles, the models examine the association between nonmotorized travel behavior and the social environment attributes as well as the built environment characteristics at three hierarchical levels of influence. For the social environment, these levels of influence include: the micro level (i.e., household), the meso level (i.e., neighborhood), and the macro level (i.e., metropolitan area). For the built environment, the levels of influence considered in the models are: the micro level (i.e., neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan).

The final model specifications have been obtained based on a systematic process of testing and eliminating variables found to be statistically insignificant. This was accompanied by parsimony and intuitive considerations as well as consideration of the results from earlier studies including the Baltimore-DC case study (see Appendix C).

4.1.6.1 Linear Mixed-effects Models (i.e., the Multilevel Models)

Specification of Models: Florida Linear Mixed-effects Nonmotorized Travel Models

Mixed-effects (multilevel) models have been employed in this Florida case study to examine the association between household-level nonmotorized travel behavior and the social as well as the built environment characteristics of the place of residence. The ecological frameworks of the models incorporate variables that operate at multiple hierarchical levels of influence. This makes the multilevel model an appropriate statistical tool to evaluate the influence of built and social environments on nonmotorized travel behavior. Also, literature supports the use of multilevel models in ecological analyses of behavior (Sallis et al. 2008), which can include walking and bicycling behavior. Data for the Florida case study are assumed to be clustered as groups of surveyed households locate within similar geographical areas (e.g., neighborhoods or counties), and there may be correlations between households that locate in the same area. The clustered nature of observations further warrants the use of mixed-effects models for this case study.

Based on the general formula for the linear mixed-effects model (Equations 1 and 2), the Florida household-level nonmotorized travel behavior mixed-effects models are specified as:

$$Y = \beta_0 + \beta_1' \mathrm{SE}_{\mathrm{HH}} + \beta_1 \mathrm{SE}_{\mathrm{CBG}} + \beta_2' \mathrm{SE}_{\mathrm{CBSA}} + \beta_3' \mathrm{BE}_{\mathrm{CBG}} + \beta_4' \mathrm{BE}_{\mathrm{County}} + \beta_5' \mathrm{BE}_{\mathrm{CBSA}} + u_{\mathrm{CBG}} \mathbf{RE}_{\mathrm{CBG}} + \varepsilon \qquad \text{Equation 21}$$

where,

β_0 = model intercept;

$\beta_1' - \beta_5'$ = column vectors of model parameters;

β_1 = model parameter for the meso-level (neighborhood) social environment attribute;

u_{CBG} = vector of iid neighborhood-level random effects;

ε = vector of model error terms;

$\mathrm{SE}_{\mathrm{HH}}$ = column vector of micro-level (household) social environment attributes;

$\mathrm{SE}_{\mathrm{CBG}}$ = the meso-level (neighborhood) social environment attribute;

$\mathrm{SE}_{\mathrm{CBSA}}$ = column vector of macro-level (metropolitan area) social environment attributes;

$\mathrm{BE}_{\mathrm{CBG}}$ = column vector of micro-level (neighborhood) built environment attributes;

$\mathrm{BE}_{\mathrm{County}}$ = column vector of meso-level (county) built environment attributes;

$\mathrm{BE}_{\mathrm{CBSA}}$ = column vector of macro-level (metropolitan area) built environment attributes;

$\mathbf{RE}_{\mathrm{CBG}}$ = matrix of neighborhood-level covariates for random effects; and

Y = vector of observations (household's number of per capita walking or bicycling trips).

As it can be seen from Equation 21, census block groups (i.e., neighborhoods) have been considered as clusters in this case study and random effects of census block groups have been estimated in the models. This model design introduces two levels: the first level is the household, and the second level is the census block group (i.e., CBG). There are households that live in the same census block group (cluster), but individual household characteristics differ from each other.

Therefore, two sources of variation exist in the model: the variation between different census block groups (i.e., interclass variance) and the variation within each census block group (i.e., intraclass variance). These variations are estimated in the model.

It is assumed that the slope of similar covariates contained within the random portion of the model (i.e., $\mathbf{RE}_{\mathrm{CBG}}$) is constant across CBGs. Therefore, the CBG random effects are simplified to a CBG-specific effect, which captures an effect that is common to all households within the same CBG ($u_{0\mathrm{CBG}}$). This makes the specified model a random intercept model, which assumes that CBGs add a random offset to households' nonmotorized travel behavior (i.e., measured as household's number of daily per capita walking or bicycling trips).

The simplified (i.e., random intercept) model formula is:

$$\mathrm{Y} = \beta_0 + \beta_1' \mathrm{SE}_{\mathrm{HH}} + \beta_1 \mathrm{SE}_{\mathrm{CBG}} + \beta_2' \mathrm{SE}_{\mathrm{CBSA}} + \beta_3' \mathrm{BE}_{\mathrm{CBG}} + \beta_4' \mathrm{BE}_{\mathrm{County}} + \beta_5' \mathrm{BE}_{\mathrm{CBSA}} + u_{0\mathrm{CBG}} + \varepsilon \qquad \text{Equation 22}$$

As indicated previously, census block groups (i.e., CBGs) represent the neighborhoods in the Florida case study. Thus, the variance estimates (random effects) computed by the mixed-effects model provide information as to how random differences between neighborhoods affect the walking and bicycling behavior of residents.

The model estimates also provide information on the existence and magnitude of effects exerted by meso-level (county-level) and macro-level (metropolitan area-level) built environment factors on walking or bicycling trips generated from the surveyed households.

The walking and bicycling mixed-effect (multilevel) models relate the dependent variables (household's number of daily per capita walking and household's number of daily per capita bicycling trips) to the independent variables listed in Table 4.

Pearson correlation coefficients have been calculated for all original independent variables and are presented in Appendix E. As built environment factors tend to be highly correlated, some researchers use composite indices to deal with the high correlation between variables. Replacement of highly correlated variables with a composite variable obtained from combining them is considered one way of dealing with extreme collinearity between variables (Kline 2011).

However, composite indices are often difficult to interpret for policy purposes (Lee and Moudon 2006)[25]. To facilitate the interpretation of study results into policies, the present study focuses on objectively measured and individually observable measures of the built environment and avoids the use of composite indices—to the extent possible. This approach, however, introduces the risk of multicollinearity in the models.

Correlation coefficients higher than 0.8 or 0.9 between independent variables are considered as excessively collinear and are indicators of multicollinearity according to Franke (2010). Initial Pearson correlation coefficients computed for all original independent variables that were considered for inclusion in the models showed that variables representing the population and employment densities at the county and metropolitan area level are highly correlated ($r > 0.9$). Some researchers argue that residential density and employment density should be measured separately since most of new developments at the urban outskirts have gained residential density but lack employment opportunities and density (Fan 2007).

Nonetheless, to lower the risk of multicollinearity in the models, the highly correlated population and employment density variables have been replaced with activity density variables, which quantify the density of total population plus employment opportunities within each geographical scale (i.e., neighborhood, county, and metropolitan area). In reality, however, the

[25] See Appendix C (Nonmotorized Travel Behavior: A Baltimore, Maryland and Washington, D.C. Case Study) for a more detailed discussion regarding the issue of high correlation between built environment factors.

effects of many built environment factors are correlated and there is not an easy way to separate these correlations, as Reilly and Landis (2003) argued. Thus, this study uses a correlation threshold of $|p| > 0.70$—suggested by previous research (Kim and Susilo 2013)—to eliminate highly correlated independent variables. Variables with correlation coefficients ≥ 0.70 and < 0.85 were retained in the models if they reached a significance level of 0.05 or if there was a theoretical reason for retaining the variable; for example, if the variable was proved by previous studies to be an important factor in determining nonmotorized travel behavior.

Any continuous variable with a correctable skewed distribution was normalized by transformation into its naturally logged form before inclusion in the model. Many variables however, showed a normal (or nearly normal distribution), while the distribution of a few variables with skewed distributions (including the dependent variables) did not improve by transformation to naturally logged form. Therefore, these variables have been included in the model in their original form. Due to the natural log of zero being undefined, for independent variables with an original value equal to zero, the zero value was changed to 0.25 before the variable was log-transformed—a practice also used in previous research (see e.g., Schauder and Foley 2015).

Discussion of Results: Florida Linear Mixed-effects Nonmotorized Travel Models

Table 7 summarizes the estimation results of the Florida household-level mixed-effects walking and bicycling models. The results show many statistically significant associations between household nonmotorized travel behavior and built environment characteristics at all levels of influence including the micro level (i.e., neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area). The results also indicate that social environment measures at all hierarchical levels of influence have statistically significant associations with nonmotorized travel behavior, especially at the household level.

Table 7. Results: Florida Household-level Mixed-Effects Nonmotorized Travel Models

Dependent Variable: Number of Household's Daily Per Capita Walking/Bicycling Trips				
	Walking Model		**Bicycling Model**	
Independent Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Social Environment				
Micro Level: The Household				
Number of Adults - logged	-.1049554***	0.000	-.0088922*	0.093
Number of Vehicles	-.0292874***	0.000	-.007933***	0.006
Number of Workers	-.0013254	0.886	-.0008806	0.787
Annual Income	.0099911***	0.000	.0010603**	0.037
Meso Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	.150817*	0.093	-.0242312	0.477
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars	-.3428987*	0.073	-.3256664**	0.038
Average Percentage of Low-Wage Workers	.6029278	0.451	-.3282153**	0.047
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density	.0019367*	0.059	-.0003432	0.346
Entropy	.0304338*	0.073	.0116624*	0.091
Intersection Density (Auto-oriented) - logged	-.0016636	0.284	.0007872*	0.085
Pedestrian-friendly Network Density	.0018363***	0.007	.0007049*	0.073
Local Transit Service - logged	.0076436**	0.039	.0004267	0.747
Local Transit Accessibility	-9.40e-06	0.836	-.0000108	0.506
Meso Level: The County				
Mean Activity Density	.0122569*	0.094	-.0053862**	0.040
Mean Entropy	.3974471*	0.092	.0455479	0.592
Mean Regional Diversity	-.2390165	0.215	-.077811*	0.055
Mean Intersection Density (Auto-oriented)	.0335583	0.438	.0221108*	0.069
Mean Pedestrian-friendly Network Density	.0016844*	0.059	.005206**	0.012
Mean Transit Service	.0001846*	0.087	.0000951	0.308
Mean Temporal Automobile Accessibility	-1.12e-06*	0.075	-3.70e-07**	0.049
Mean Temporal Transit Accessibility	-.0000269	0.147	-1.70e-06	0.834
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density	.0017064	0.856	.0026659	0.429
Mean Entropy	-.4171373**	0.026	.0418177	0.731
Mean Total Road Network Density	-.0008827*	0.085	-.0004398	0.325
Percentage of 0.01 Blocks	.5314081***	0.010	.0312544	0.688
Mean Temporal Automobile Accessibility	-1.48e-07	0.843	-1.11e-07	0.679
Mean Temporal Transit Accessibility	-7.73e-06	0.452	-8.99e-06**	0.015
Variance Estimates (Random Effects)				
Census Block Group (i.e., Neighborhood)	.0084544***	0.000	.0022749***	0.000
Residuals	.6152914***	0.000	.0753187***	0.000
Model Goodness Parameters				
Likelihood Ratio Test vs. Linear Regression	χ^2 = 2.89*	0.089	χ^2 = 13.32***	0.000
Log Likelihood	-17714.041		-2101.6548	
R^2 Marginal	0.1087513		0.0448391	
R^2 Conditional	0.2612913		0.0456274	
Observations; Clusters	14,976; 6,956		14,976; 6,956	

NOTE: *, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively.

Social Environment Variables Findings: The results of the Florida household-level nonmotorized travel behavior models show that a few social environment factors at the micro-level (i.e., household level) have significant associations with household's nonmotorized travel behavior. Specifically, the household's number of adults has a significant and negative correlation with household's walking and bicycling travel behavior. This result is expected and consistent with findings of the Baltimore-D.C. case study models (see Appendix C). The variable for household's number of vehicles shows a negative and significant correlation with both household's number of per capita walking and bicycling trips, which corroborates the results of the Baltimore-D.C. case study (see Appendix C) and those of many past studies (e.g., Cervero 1996; Cervero and Radisch 1996; Kitamura et al. 1997; Stinson and Bhat 2004; Plaut 2005; Mitra and Buliung 2012).

Household income shows statistically significant and positive correlations with household's number of per capita walking and bicycling trips. These results confirm the results of the Baltimore-D.C. case study (Appendix C), and in general, may be reflective of recreational nonmotorized travel conducted by members of wealthier households, as also suggested in previous research (see e.g., Pucher et al. 1999; Roshan Zamir et al. 2014). With regards to bicycling, Pucher et al. (1999) argued that although lower income levels may be correlated with more bicycle use, this correlation cannot be generalized because in many cases high bicycle modal shares exist in the wealthiest societies. The finding of the present study, which shows a positive and statistically significant correlation between household income and bicycling, can therefore be indicative of recreational bicycling among wealthier people—perhaps due to factors such as higher levels of affordability and health-consciousness, as also suggested by Heinen et al. (2010).

On another note, Dill and Carr (2003) suggested that in analysis of bicycling trips, income might be significant at the disaggregate level. The results of the Florida case study support that statement as the coefficient of the variable representing the household income is significant in the Florida bicycling model. It should be noted, however, that the coefficient of the household income variable is insignificant in the Baltimore-DC bicycling model (see Appendix C). Thus, when considered in conjunction with the results of that case study, the findings confirm the conclusion of Heinen et al. (2010) that the relationship between income and bicycling remains unclear.

As a social environment factor, car ownership at the meso level (i.e., neighborhood level) exhibits a significant association with household's walking. The results show a positive correlation between the percentage of households within the neighborhood that own no cars and households' number of daily per capita walking trips.

Social environment measures at the macro level (i.e., metropolitan area level) also show significant correlations with household nonmotorized travel behavior. The average percentage of households within the metropolitan area that own more than two cars is significantly and negatively correlated with household's nonmotorized travel behavior—an expected finding. This result reinforces the corresponding results at the household level (i.e., micro level) and neighborhood level (i.e., meso level), suggesting that vehicle ownership at multiple levels of influence (and beyond the household level) plays a key role in nonmotorized travel behavior.

Also, the average percentage of low-wage workers in the metropolitan area is negatively associated with household's per capita bicycling trips. This suggests that living in a metropolitan area where more low-income workers reside is associated with fewer household bicycling trips. In other words, bicycling is occurring more in metropolitan areas with fewer lower-income workers. This result seems counter-intuitive as higher levels of commuting by bicycle and other utilitarian bicycling are expected to be correlated with lower income levels. However, this finding may be an indication of recreational bicycling by wealthier individuals.

Micro-level (Neighborhood-level) Built environment Variables Findings: A few micro-level built environment variables are significantly correlated with household nonmotorized travel behavior. As seen from Table 7, the variables representing activity density (i.e., the *Activity Density* variable) and land use mix (i.e., the *Entropy* variable) at the neighborhood level are positively correlated with households' number of per capita walking trips. The neighborhood-level *Entropy* variable is also positively correlated with households' number of per capita bicycling trips. These results show that higher residential and employment densities at the neighborhood level are associated with increased numbers of walking trips, whereas higher mixed land use at the neighborhood level is associated with increased numbers of both walking and bicycling trips. These findings corroborate those of the Baltimore-D.C. case study (see Appendix C).

The density of the pedestrian-oriented network within the neighborhood shows significant and positive correlations with the number of daily per capita walking and bicycling trips generated from households. These results are expected and corroborate the findings of previous studies that found pedestrian-oriented environments to be encouraging of nonmotorized travel (see e.g., Greenwald and Boarnet 2001).

On the other hand, the coefficient estimate of the *Intersection Density* variable at the neighborhood level in the bicycling model indicates a significantly positive correlation between bicycling and the density of automobile-oriented intersections within the neighborhood. This result might be showing that bicyclists ride their bicycles on automobile-oriented roadways, and that higher intersection density may encourage bicycling and not defer bicyclists. These results are somewhat in line with previous research suggesting that presence and/or higher density of intersections at the neighborhood level positively influence nonmotorized travel (Cervero and Kockelman 1997; Boer et al. 2007; Kerr et al. 2007).

The *Local Transit Service* variable, which measures the frequency of the local transit service, shows a significant and positive correlation with walking. This indicates that a higher frequency of transit service within the neighborhood is associated with more walking trips generated from households within the neighborhood. This result is in line with the results from the Baltimore-D.C. case study, which show a positive correlation between higher accessibility to local transit and the number of daily per capita walking trips by residents (see Appendix C).

Together, these results confirm that neighborhood-level built environment attributes are important factors in estimating nonmotorized travel behavior.

Meso-level (County-level) Built environment Variables Findings: At the meso level (i.e., county level), the *Mean Activity Density* variable shows significant associations with walking and bicycling travel, but the direction of these associations is opposite. More specifically, this variable is positively correlated with walking trips, whereas its correlation with bicycling trips is negative. This is the same pattern observed in the Baltimore-D.C. case study (see Appendix C). These results further emphasize that built environment characteristics can influence walking and bicycling travel behavior differently. With regards to bicycling, literature offers two arguments. One is that of Cervero and Duncan (2003) who suggested that denser urban employment settings create many roadway conflict points, and thereby may deter bicyclists due to safety concerns. The other point of view is that of Pucher et al. (1999) who argued that denser urban environments tend to attract utilitarian bicycling due to more destinations being accessible within a short bicycle ride. The results of the present case study support the former argument.

The *Mean Entropy* variable at the county level shows a significant and positive correlation with walking, and a positive but insignificant one with bicycling. This suggests that increased mixed land use within the county is associated with increased numbers of daily per capita walking trips and potentially increased numbers of daily per capita bicycling trips. County-level entropy shows a negative sign in both the walking model and the bicycling model in the Baltimore-D.C. case study; however, the coefficient estimate of this variable is not significant in the Baltimore-D.C. walking mixed-effects model (see Appendix C).

As mentioned previously, improved mixed-use development throughout the county is expected to increase the extent of nonmotorized travel by residents because past research found a negative association between mean county-level mixed-use development and household VMT (Nasri and Zhang 2012). The findings of the Baltimore-D.C. case study (presented in Appendix C) did not support the hypothesis that higher levels of mixed-use development throughout the county is correlated with increased levels of nonmotorized travel. However, the results of the Florida household-level case study partially support that hypothesis. The results of the Baltimore-D.C. case study (Appendix C) can be revealing an effect related to more variety in destinations. That is, as destination choices within the county increase, individuals may be attracted to destinations located farther away and may choose to drive to these remote destinations for their travel needs instead of walking or bicycling to nearby destinations. The substitution of automobile trips to farther destinations for nonmotorized trips to nearby destinations may negatively influence the number of households' nonmotorized trips. Thus, the role of county-level mixed-use development in nonmotorized travel behavior seems to be a bit unclear. Consequently, additional investigation is probably needed to examine the link between mixed land use at the county level and walking and bicycling travel behavior.

Further the *Mean Regional Diversity* variable shows a significantly negative correlation with bicycling trips. This result indicates that higher regional diversity (in terms of employment opportunities within the county) is associated with fewer daily per capita bicycling trips.

The coefficient estimates of the *Mean Pedestrian-oriented Network Density* variable at the county level show significant and positive correlations with household's daily per capita walking and bicycling trips. The coefficient estimate of the *Mean Intersection Density* at the county level in the bicycling model is also significantly positive. These results complement those estimated for the neighborhood-level variables and indicate that pedestrian-friendly designs may promote both walking and bicycling activities, while higher intersection density may lead to higher levels of bicycling activity.

The significantly positive coefficient of the county-level *Mean Transit Service* variable in the walking model indicates that a higher average transit frequency within the county is associated with increased numbers of walking trips generated from households. However, transit accessibility at the county level (mean number of jobs within 45 minutes of transit travel time) does not seem to be correlated with walking or bicycling trips because the coefficient of the county-level *Mean Temporal Transit Accessibility* variable is insignificant in both models. On the other hand, county-level automobile accessibility (mean number of jobs within 45 minutes of automobile travel time) is negatively associated with nonmotorized travel, as expected. Even though these effects are very small, they are significant in both the walking and bicycling models. Accessibility has been operationalized in terms of number of employment opportunities within a certain travel time or distance in the past. One example is a study by Cervero and Duncan (2003) who examined the effect of an employment accessibility variable measured as the number of jobs within 1 and 5 miles of origin in walking and bicycling, respectively. They found this variable to be positively associated with walking, and negatively associated with bicycling (but not statistically significant).

Overall, these results corroborate those from the Baltimore-D.C. case study (Appendix C) in implying that the county-level built environment plays an important role in nonmotorized travel.

Macro-level (Metropolitan-level) Built Environment Variables Findings: At the metropolitan area level (macro level), the *Mean Entropy* variable shows a negative association with walking and its coefficient is significant. This suggests that a higher level of mixed land use within the metropolitan area is correlated with fewer numbers of daily per capita walking trips generated from households within that metropolitan area. This can be an indication of the effect of additional destination choices. As destination choices—especially those related to employment—increase, people will need to commute long distances across metropolitan areas to reach employment sites and other destinations. This can lead to a reduction in the number of walking trips made by members of the households within the metropolitan area due, in part, to substitution of automobile trips to remote destinations for nonmotorized trips to nearby destinations.

The coefficient of the *Mean Total Road Network Density* variable has a negative sign in both walking and bicycling models, as expected. However, this coefficient is only significant in the walking model. The negative sign indicates that higher roadway network densities within the metropolitan area are associated with fewer walking trips generated from households. Although the effects of the metropolitan area-level built environment factors (including road density) have not been previously tested, the density of major roads at the neighborhood level did not show any impact on walking or bicycling travel in a previous study (Mitra and Buliung 2012).

Another salient result is the coefficient estimate of the *Percentage of 0.01 Blocks* variable in the walking model. This variable represents the percentage of blocks with an area smaller than 0.01 square miles, and has been included in the model to capture the effects of the pedestrian friendliness and connectivity of the street network within the metropolitan area based on previous research (Nasri and Zhang 2014). As expected, this variable exhibits a positive and highly significant correlation with walking, which means increased numbers of walking trips are associated with higher levels of pedestrian friendliness of the network as well as with better street network connectivity. This finding emphasizes the importance of street connectivity throughout the entire metropolitan area in generation of walking trips. However, the coefficient of this variable is not statistically significant in the bicycling model. Previous literature on bicycling travel behavior can be used as support for this latter result. Although the impact of block size at the macro-level scale of geography has not been tested in previous studies, block size at the neighborhood level was found to be insignificant in bicycling travel by Moudon et al. (2005).

Temporal destination accessibility in terms of mean automobile accessibility to jobs within the entire metropolitan area (i.e., the macro-level *Mean Temporal Automobile Accessibility* variable) shows a negative association with walking and bicycling, but its coefficient is not significant in either model. Nonetheless, the negative sign of the coefficient for this variable is consistent with the statistically significant coefficients of the same variable at the meso level (i.e., county level) as well as the results of the Baltimore-D.C. case study (Appendix C) in which the regional automobile accessibility index is negatively associated with walking and bicycling.

The *Mean Temporal Transit Accessibility* variable at the macro-level, which represents the temporal destination accessibility by transit (i.e., the mean number of jobs in the metropolitan area that are within a 45-minute transit commute), has a negative sign in both models, but its coefficient is only significant in the bicycling model. The coefficient, albeit very small (-0.00000899), reaches the 5% significance level. This result shows that higher transit accessibility to employment within the metropolitan area is associated with households generating fewer bicycling trips per person. This finding implies that accessibility at the metropolitan area level has a potential to significantly impact household bicycling travel in a negative way. Although these results at first may seem to be counter-intuitive, further reasoning presents the possibility that the negative direction of the coefficients of the *Mean Temporal Transit Accessibility* can be capturing the effect of driving to transit stations rather than walking or bicycling to them. The importance of macro-level accessibility to transit by means of nonmotorized modes (i.e., walk and bicycle accessibility to transit within the entire metropolitan area) is, therefore, further emphasized by these results. The results of the Baltimore-D.C. case study (see Appendix C) provide support for these statements. In that case study, regional accessibility to transit by means of driving was found to be negatively associated with walking, whereas regional accessibility to transit by means of walking was found to be positively associated with both nonmotorized modes of travel (i.e., walking and bicycling).

As previously mentioned, the *Mean Temporal Automobile Accessibility* and the *Mean Temporal Transit Accessibility* variables in the Florida case study represent the mean number of jobs within 45 minutes of automobile travel or transit commute, respectively. The results of the models potentially indicate that more jobs within relatively longer commutes (i.e., up to 45 minutes) are associated with fewer nonmotorized trips. This is in line with what Rodríguez and Joo (2004) suggested; decreasing commuting distance may result in higher propensity of choosing nonmotorized modes and a lower propensity of choosing motorized modes.

Taken together, these results show that metropolitan area-level built environment attributes are associated with households' number of per capita walking and bicycling trips and their effects should not be overlooked in the analysis of nonmotorized travel behavior.

Interpretation of Results: Florida Linear Mixed-effects Nonmotorized Travel Models

The results presented in Table 7 can be interpreted using standard interpretation methods for regression coefficients. A few specific examples are given here: for instance, the coefficient of the household vehicle ownership in the walking model (-0.0292874) indicates that all else being equal, each additional private automobile that is available to the household is correlated with a decrease of approximately 0.03 in the number of daily walking trips per household adult (0.03 fewer walking trips/person for each additional private vehicle owned by the household).

The coefficient estimate of the log-transformed *Intersection Density* variable at the micro level (i.e., neighborhood level) in the bicycling model is equal to 0.0007872. This estimate means that all else being equal, an increase of 100% in the value of the neighborhood-level *Intersection Density* variable (i.e., doubling of the number of intersections/miles^2 CBG land area) is associated with an increase of approximately 0.08 in the number of bicycling trips per household adult member (0.08 more bicycling trips/person).

The coefficient estimate of the county-level *Mean Pedestrian-friendly Network Density* variable in the walking model (0.0016844) indicates that a one unit increase in the average density of pedestrian-friendly facilities (i.e., one additional mile of pedestrian-oriented facilities/miles^2) within the county is correlated with approximately 0.002 additional walking trips per household adult member for households within that county.

The entropy index is in a proportion form, meaning that its value ranges between 0 and 1. The coefficient of the *Mean Entropy* variable at the metropolitan level in the walking model is equal to -0.4171373, which indicates that all else being equal, an increase of one unit (i.e., 0.01) in the mean entropy within the metropolitan area of residence is associated with a decrease of nearly 0.42 in the daily number of walking trips generated by each adult person in the household.

These interpretations serve as examples for quantifications of the impact of neighborhood-, county-, and metropolitan-level built environment characteristics such as mix land use, network pedestrian friendliness and street network density on nonmotorized travel behavior of residents.

As in the Baltimore-D.C. case study (Appendix C), the random effects of neighborhoods (i.e., census block groups) have been considered in the above mixed-effects models to assess how random differences between neighborhoods affect nonmotorized travel behavior of residents. The between-CBG (level two) component of variance (i.e., the variance component corresponding to the random intercept) is σ_u^2= 0.0084544 in the walking model, and σ_u^2= 0.0022749 in the bicycling model. These estimates are statistically significant, which indicates that after controlling for the various variables listed in Table 7, there remains some CBG-level variance in the models which is unaccounted for. This means that significant variation exists in the means of the number of households' per capita walking/bicycling trips across CBGs.

Additionally, the between-CBG (level two) component of variance in the walking model (σ_u^2= 0.0084544) is much smaller that the within-CBG (level one) component of variance (σ_e^2= 0.6152914). This result is probably because the number of households in each CBG (i.e., number of observations per cluster) is relatively small (an average of 2.15 observations per cluster), whereas the number of CBGs (clusters) that are compared to each other is large (6,956 CBGs)[26].

The total variance for the walking model is $\sigma_u^2 + \sigma_e^2$= 0.0084544 + 0.6152914 = 0.6237458. Thus, the variance partition coefficient (i.e., intraclass correlation coefficient) is equal to 0.0084544/0.6237458 = 0.0136. This indicates that approximately 1.4% of the variance in number of households' daily per capita walking trips is attributable to random differences between CBGs[27] (i.e., neighborhood random effects).

With respect to the bicycling model, Table 7 shows that the between-CBG component of variance (σ_u^2= 0.0022749) is much smaller that the within-CBG component of variance (σ_e^2= 0.0753187). This difference is also attributable to the fact that the number of households in each

[26] The small number of households in each CBG (i.e., number of observations per cluster) further justifies employment of mixed-effects modeling techniques and computing random effects in this analysis. According to Demidenko (2004), having a large number of clusters with a small number of observations per cluster necessitates the treatment of the cluster-specific coefficients as random effects.

[27] Computations based on examples in Leckie (2010), and in Albright and Marinova (2010).

CBG (i.e., number of observations per cluster) is relatively small (an average of 2.15 observations per cluster), but a large number of CBGs (i.e., clusters) are compared to each other (6,956 CBGs). The total variance for the bicycling model is $\sigma_u^2 + \sigma_e^2$= 0.0022749 + 0.0753187= 0.0775936. Thus, the variance partition coefficient (i.e., intraclass correlation coefficient) is equal to 0.0022749/0.0775936 = 0.0293. This indicates that approximately 3% of the variance in number of households' daily per capita bicycling trips is attributable to random differences between CBGs (i.e., neighborhood random effects).

The p-values of the CBG random effects are significant in both the walking and bicycling models. These results suggest that random differences between neighborhoods play a small but statistically significant role in nonmotorized travel behavior of residents. This finding is consistent with the results obtained in the Baltimore-D.C. case study (presented in Appendix C).

The results of the Likelihood Ratio tests in both models are statistically significant as evidenced by the value of chi-squared (χ^2) as well as the p-values. These results mean that in both models, the multilevel (i.e., mixed-effects) modeling technique offers improvements over an ordinary linear regression model with fixed effects only. These results justify taking into consideration the effects of individual CBGs (i.e., neighborhoods) on walking and bicycling trips and using the mixed-effects models instead of ordinary linear regression models. It should be noted, however, that albeit statistically significant at 10% significance level, the improvements offered by the multilevel model in the walking model are not very robust (p-value = 0.089).

The marginal R-squared values provide information on variance explained by fixed factors, and the conditional R-squared is for variance explained by both fixed and random effects. The differences between values of the marginal R-squared and the conditional R-squared reflect the variability that exists in random effects (Nakagawa and Schielzeth 2013). The referenced paper recommended that both marginal and conditional R-squared be reported in publications because each of these R-squared convey unique information.

Elasticities: Table 8 shows the elasticities computed for the multilevel (i.e., mixed-effects) models with all the independent variables set equal to their mean values.

Table 8. Elasticities: Florida Household-level Mixed-Effects Nonmotorized Travel Models

Dependent Variable: Number of Household's Daily Per Capita Walking/Bicycling Trips				
	Walking Model		**Bicycling Model**	
Independent Variable	**Elasticity**	**p-value**	**Elasticity**	**p-value**
Social Environment				
Micro Level: The Household				
Number of Adults - logged	-.1679345***	0.000	-.2237934*	0.095
Number of Vehicles	-.3286707***	0.000	-.365574***	0.007
Number of Workers	-.0031924	0.886	-.0170474	0.787
Annual Income	.3270595***	0.000	.2789398**	0.038
Meso Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	.0250779*	0.091	-.0323814	0.477
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars	-.5623937*	0.073	-4.292675**	0.040
Average Percentage of Low-Wage Workers	.5021738	0.451	-2.19699**	0.048
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density	.0267505*	0.059	-.0385365	0.341
Entropy	.0549636*	0.072	.1692731*	0.093
Intersection Density (Automobile-oriented) - logged	-.0052096	0.284	.0198126*	0.087
Pedestrian-friendly Network Density	.0697464***	0.007	.2151574*	0.075
Local Transit Service - logged	.0239362**	0.039	.0107387	0.747
Local Transit Accessibility	-.0196095	0.836	-.1810229	0.506
Meso Level: The County				
Mean Activity Density	.2150806*	0.094	-.7595931**	0.042
Mean Entropy	.6722402*	0.092	.6191477	0.592
Mean Regional Diversity	-.1321075	0.216	-.3456379*	0.055
Mean Intersection Density (Automobile-oriented)	.1061823	0.438	.56226*	0.067
Mean Pedestrian-friendly Network Density	.0672372*	0.060	1.670148**	0.013
Mean Transit Service	.1188901*	0.089	.4921798	0.308
Mean Temporal Automobile Accessibility	-.2640612*	0.075	-.6979103**	0.050
Mean Temporal Transit Accessibility	-.2000848	0.147	-.1016926	0.834
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density	.031397	0.856	.394206	0.430
Mean Entropy	-.7060062**	0.025	.5688136	0.731
Mean Total Road Network Density	-.0512845*	0.087	-.2053688	0.326
Percentage of 0.01 Blocks	.9494162***	0.010	.4487667	0.688
Mean Temporal Automobile Accessibility	-.0355812	0.843	-.2143855	0.679
Mean Temporal Transit Accessibility	-.0623876	0.452	-.5835221**	0.016

NOTE: *, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively.

The table indicates that among the micro-level (i.e., neighborhood-level) built environment characteristics, the *Pedestrian-friendly Network Density* variable has the highest statistically significant elasticity in both the walking and the bicycling models (0.0697464 and 0.2151574, respectively). These results mean that an increase of 1% in the density of pedestrian-friendly network within the neighborhood (i.e., facility miles of pedestrian-oriented links/mi^2) is associated with an increase by approximately 0.07% in the number of household's daily per capita walking trips and an increase by approximately 0.22% in the number of household's daily per capita bicycling trips. This is an interesting finding that shows bicycling trips may be more sensitive to pedestrian-oriented network designs than walking trips. One reason for such a result may be that the SLD-defined pedestrian-oriented links were also attractive to bicyclists.

The SLD defines pedestrian-oriented facilities as[28]:

- Any arterial or local street having a speed category of 6 (between 21 and 30 mph) where car travel is permitted in both directions;
- Any arterial or local street having a speed category of 7 or higher (less than 21 mph);
- Any local street having a speed category of 6 (between 21 and 30 mph);
- Any pathway or trail on which automobile travel is not permitted (speed category 8);
- For all of the above, pedestrians must be permitted on the link;
- For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction (implied eight lanes bidirectional) are excluded.

[28] Page 22 of Ramsey and Bell (2014), "The Smart Location Database User Guide".

Considering the definition above, it is very likely that bicyclists also used these pedestrian-oriented links—perhaps even to a higher extent than pedestrians—and that resulted in the higher elasticity for this particular variable in the bicycling model as seen in Table 8.

At the meso level (i.e., county level), the *Mean Entropy* variable, which measures the average mixed land use within the county, has the highest elasticity in the walking model (0.6722402). Based on this elasticity, a 1% increase in the value of county-level mean entropy is correlated with a 0.67% increase in the number of daily walking trips generated from each adult member of households within that county. Interestingly, the county-level *Pedestrian-friendly Network Density* variable is again the county-level built environment variable with the highest elasticity in the bicycling model (1.670148), which is consistent with the elasticity obtained for this variable at the neighborhood level (i.e., micro level). In addition, the elasticity of this variable is only 0.0672372 in the walking model, which is considerably less that the highest elasticity at this level of geography (i.e., 0.6722402 for the county-level *Mean Entropy* variable). These results support the statements in the previous paragraph that the pedestrian-friendly networks as defined in SLD potentially facilitate bicycling as well and perhaps are even more inviting to bicyclists than to pedestrians.

At the macro level (i.e., metropolitan area level), the highest statistically significant elasticities belong to the *Percentage of 0.01 Blocks* variable (0.9494162) in the walking model, and the *Mean Temporal Transit Accessibility* variable (-0.5835221) in the bicycling model. Since the *Percentage of 0.01 Blocks* variable represents the percentage of blocks within the metropolitan area that are smaller than 0.01 square miles, the former result shows the importance of smaller block sizes (i.e., street network connectivity) within the entire metropolitan area in generating walking trips. Also, the macro-level *Mean Temporal Transit Accessibility* variable represents the mean number of jobs in the metropolitan area that are within 45 minutes of transit commute. Therefore, the elasticity of this variable indicates that having more jobs located within relatively longer commutes (i.e., up to 45 minutes) are associated with fewer bicycling trips.

Regarding social environment variables, Table 8 shows that the highest elasticity of the number of household's daily per capita walking trips with respect to the household socioeconomic characteristics belongs to the variable representing the number of vehicles owned by the household (-0.3286707). This elasticity indicates that an increase of 100% in the number of vehicles (i.e., if the number of household vehicle doubles) is associated with a decrease of approximately 33% in the number of household's daily per capita walking trips. The elasticity of the number of household's daily per capita walking trips with respect to household vehicle ownership variable obtained from the Baltimore-D.C. case study (see Appendix C) is -0.528005, which albeit higher in value, is consistent with the elasticity obtained here in terms of the negative direction of the effect. Vehicle ownership shows the highest elasticity among the household socioeconomic characteristics in the bicycling model as well (-0.365574).

The elasticities of the social environment variables at the neighborhood and metropolitan area levels are also noteworthy. At both levels of influence, vehicle ownership variables show statistically significant elasticities in the walking model, meaning that daily per capita walking trips generated from households are sensitive to vehicle ownership levels, not just at the household level but also at the neighborhood and metropolitan area levels.

However, the salient finding concerns the elasticities of the social environment variables at the metropolitan area level in the bicycling model. The variables representing the average percentage of 2^{+}-car households and the average percentage of low-wage workers within the metropolitan area show the highest elasticities in the bicycle model (-4.292675 and -2.19699, respectively) even with consideration of the built environment variables.

These results mean that at the macro level (i.e., metropolitan area level) of influence, bicycling trips may be more sensitive to social environment factors than to built environment factors. This finding is in line with previous research, which found that the influence of built environment factors on travel behavior including nonmotorized travel was not greater than that of sociodemographic factors such as car ownership (Wang 2013). The referenced study suggested that this was a reasonable finding because households with different backgrounds and in different life stages may have developed their own travel pattern and they may resist changing that pattern due to external factors (e.g., the characteristics of the built environment).

These results emphasize the role of social environment factors such as vehicle ownership at multiple levels of influence (i.e., household, neighborhood, and metropolitan area) in nonmotorized travel, especially in the case of bicycling. The elasticities also provide further insights into the key determinants of the built environment at multiple levels with respect to nonmotorized trips. The influence of factors such as mixed land use and pedestrian friendliness of the street network on nonmotorized trips potentially goes beyond the neighborhood level (i.e., micro level) as these variables show high elasticities at the county level and metropolitan area levels in nonmotorized travel models.

Also, based on the elasticities obtained, county-level activity density and automobile accessibility are other key meso-level built environment factors to consider in nonmotorized travel behavior analysis. At the metropolitan area level (i.e., macro level), the most influential built environment factors seem to be block size for walking trips and mean transit accessibility for bicycling trips.

4.1.6.2 Ordered Probit Models

Specification of Models: Florida Ordered Probit Nonmotorized Travel Models

In this part of the Florida household-level case study, ordered probit models have been employed to examine the association between nonmotorized trips and built and social environment characteristics at three levels of influence: the micro level, the meso level, and the macro level.

Applying the ordered probit modeling concepts to the Florida household-level case study, the total number of household's daily walking (or bicycling) trips has been defined as the observed ordinal dependent variable (y) in the models. This observed variable is assumed to take on a series of values—from zero to the maximum number of trips in the dataset (22 for walking trips, and 11 for bicycling trips, per Table 3)—depending on the value of the unobserved variable y^*. Based on Equation 10, the Florida household-level ordered probit models can be formulated as:

$$y^* = \beta_1' \mathrm{SE_{HH}} + \beta_1 \mathrm{SE_{CBG}} + \beta_2' \mathrm{SE_{CBSA}} + \beta_3' \mathrm{BE_{CBG}} + \beta_4' \mathrm{BE_{County}} + \beta_5' \mathrm{BE_{CBSA}} + \varepsilon \quad \text{Equation 23}$$

where,

$\beta_1' - \beta_5'$ = column vectors of model parameters;

β_1 = model parameter for the meso-level (neighborhood) social environment attribute;

ε = an iid error term with a normal distribution ($\varepsilon \sim N\ (0, 1)$);

SE_{HH} = column vector of micro-level (household) social environment attributes;

SE_{CBG} = column vector of meso-level (neighborhood) social environment attributes;

SE_{CBSA}= column vector of macro-level (metropolitan area) social environment attributes;

BE_{CBG} = column vector of micro-level (neighborhood) built environment attributes;

BE_{County} = column vector of meso-level (county) built environment attributes;

BE_{CBSA}= column vector of macro-level (metropolitan area) built environment attributes;

y^* = value of the unobserved latent variable.

The probability of a certain number of walking (or bicycling) trips having been generated from a certain household, *i*, is computed by the ordered probit model through relating the observed number of household trips (y) to the unobserved latent variable y^*.

That probability is given by:

Probability $(y_i = y_n) = \Phi(\alpha_n - x_i\beta) - \Phi(\alpha_{n-1} - x_i\beta)$

where,

y_n = an integral number of walking (or bicycling) trips;

Φ = the cumulative normal distribution function;

α_n = the upper threshold for the range of y^* which corresponds to *n* trips;

α_{n-1} = the lower threshold for the range of y^* which corresponds to *n* trips;

x_i = vector of independent variables containing $SE_{HH/CBG/CBSA}$, $BE_{CBG/County/CBSA}$; and

β = column vector of the parameters β_1 and β'_{1-5} (in Equation 23).

Given the representation above, the ordered probit models can be estimated for Florida household's daily number of walking (or bicycling) trips based on built and social environment characteristics at multiple levels of influence.

Discussion of Results: Florida Ordered Probit Nonmotorized Travel Models

Table 9 summarizes the results of the ordered probit models for the Florida household-level analysis. The results of the ordered probit models are generally consistent with those obtained from the multilevel (i.e., mixed-effects) models, which are presented in Table 7.

Therefore, this discussion section only focuses on comparing the results of the Florida household-level ordered probit models with those obtained from the Florida household-level multilevel models (Table 7) as well as with the results estimated by the Baltimore-D.C. ordered probit models (presented in Appendix C).

Table 9. Results: Florida Household-level Ordered Probit Nonmotorized Travel Models

Dependent Variable: Number of Household's Daily Walking/Bicycling Trips				
Independent Variable	**Walking Model**		**Bicycling Model**	
	Coefficient	**p-value**	**Coefficient**	**p-value**
Social Environment				
Micro Level: The Household				
Number of Adults - logged	-.3624788***	0.000	-.2758517***	0.000
Number of Vehicles	-.0521078***	0.000	-.0750995***	0.003
Number of Workers	.0587672***	0.000	.0454139*	0.092
Annual Income	.0188557***	0.000	.0153484***	0.000
Meso Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	.0628375*	0.075	-.2444447	0.465
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars	-.7354391**	0.047	-2.027309*	0.091
Average Percentage of Low-Wage Workers	.5676108	0.674	-.691309	0.111
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density	.003134*	0.051	-.006105	0.198
Entropy	.0496001*	0.066	.128649*	0.060
Intersection Density (Automobile-oriented) - logged	-.0011786	0.650	.0063139*	0.078
Pedestrian-friendly Network Density	.0020931**	0.046	.0047229*	0.070
Local Transit Service - logged	.0141105**	0.026	.008118	0.473
Local Transit Accessibility	.0000264	0.727	.0000228	0.874
Meso Level: The County				
Mean Activity Density	.0313752***	0.010	-.0191985**	0.038
Mean Entropy	.8760413**	0.035	.2806565	0.704
Mean Regional Diversity	-.0832672	0.805	-.5391015	0.358
Mean Intersection Density	-.0009994	0.989	.1361056**	0.048
Mean Pedestrian-friendly Network Density	.0113724**	0.049	.0326989*	0.058
Mean Transit Service	.0005097	0.253	.0005049	0.526
Mean Temporal Automobile Accessibility	-1.52e-06	0.206	-2.37e-06	0.259
Mean Temporal Transit Accessibility	-.0000706*	0.069	-.0000316	0.646
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density	-.0177383	0.271	.0314577	0.282
Mean Entropy	-1.368036**	0.020	-.2736731	0.784
Mean Total Road Network Density	-.0013882*	0.097	-.0008796	0.813
Percentage of 0.01 Blocks	.8381268**	0.020	.3858952	0.532
Mean Temporal Automobile Accessibility	1.29e-06	0.304	-6.90e-07	0.750
Mean Temporal Transit Accessibility	-.0000194	0.267	-.0001004***	0.001
Model Goodness Parameters				
Likelihood Ratio Test	391*** (DF=27)		108*** (DF=27)	
Pseudo R^2	0.015		0.019	
Log likelihood	-12879.027		-2786.517	
Observations (households)	14,976		14,976	

NOTES:
DF=Degrees of freedom;
*, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;
For brevity, the cut point estimates are not reported in the table.

Social Environment Variables Findings: Parallel to the results of the mixed-effects models (Table 7), the Florida household-level ordered probit models show that social environment factors at multiple levels of influence are correlated with household's daily number of nonmotorized trips.

Micro-level (i.e., household-level) social environment attributes such as the number of household adult members and the number of household vehicles exhibit negative correlations with household's number of walking and bicycling trips. These results are consistent with results obtained from the Florida mixed-effects models (Table 7) and those from the ordered probit models for the Baltimore-D.C. case study (Appendix C). However, unlike the case in the mixed-effects models, the variable representing the number of household workers becomes statistically significant in the ordered probit models for both walking and bicycling and it shows a positive correlation with household's number of nonmotorized trips. This is consistent with the Baltimore-D.C. case study (see Appendix C) and indicates that an increase in the total number of employed persons in the household is associated with more nonmotorized trips generated from the household.

Also, consistent with the mixed-effects models (Table 7), household's annual income shows a positive correlation with household's daily number of both walking and bicycling trips. As indicated previously, this finding is probably capturing recreational walking and bicycling trips of members of wealthier households. However, there is inconsistency between the results of the Florida ordered probit models, which show a significant correlation between household income and bicycling, and the results of the Baltimore-D.C. bicycling ordered probit model (see Appendix C), in which, the coefficient of the income variable is insignificant. Thus, the conclusion of Heinen et al. (2010) that the relationship between income and bicycling remains unclear is corroborated.

At the meso level (i.e., neighborhood level) of the social environment, a positive correlation is estimated by the ordered probit model between the percentage of households with no cars within the neighborhood and household's number of daily walking trips. This result is consistent with the results of the Florida mixed-effect models.

At the macro level (i.e., metropolitan area level) of the social environment, the average percentage of 2^+-car households within the metropolitan area is significantly and negatively correlated with household's nonmotorized travel—a finding that is consistent with that of the mixed-effects models. This result also supports the results obtained for the car ownership variables at the household level (i.e., micro level) and neighborhood level (i.e., meso level) and suggests that vehicle ownership at multiple levels of influence is associated with nonmotorized travel.

Micro-level (Neighborhood-level) Built Environment Variables Findings: Considering the micro-level (i.e., neighborhood-level) built environment variables, the ordered probit models indicate that increased daily numbers of household walking trips are correlated with increased levels of compactness (i.e., higher activity density), higher mixed land use (i.e., entropy), higher pedestrian-friendly network density, and more frequent transit service within the neighborhood.

Increased neighborhood-level mixed land use, pedestrian-friendly network density, and intersection density are also positively correlated with the daily number of household bicycling trips. These results are consistent with the results of the Florida mixed-effects models (Table 7). Overall, these findings confirm that neighborhood-level built environment attributes are among the key elements in estimating nonmotorized trips of residents.

Meso-level (County-level) Built Environment Variables Findings: At the county level, increased household's daily number of walking trips are associated with increased compactness (i.e., higher average activity density), higher average entropy (i.e., mixed land use), and higher average pedestrian-friendly network density. These results are consistent with the results of the mixed-effects models and the Baltimore-D.C. case study except in the case of average county-level entropy variable, which shows a negative association with walking trips in the Baltimore-D.C. ordered probit model (see Appendix C). Increased county-level transit accessibility to employment shows a negative correlation with the daily number of walking trips. This variable measures the average number of jobs within a 45 minute-transit commute; thus, the result obtained indicates that having more jobs located within relatively longer transit commutes (i.e., up to 45 minutes) is associated with fewer walking trips generated from households. The coefficient for this variable did not reach a significance threshold in the mixed-effects model.

Consistent with the results of the mixed-effects models and the Baltimore-D.C. case study (see Appendix C), increased county-level compactness (higher average activity density) is negatively correlated with household's daily number of bicycling trips, whereas increased average county-level intersection density and average pedestrian-friendly network density show significant and positive correlations with households' daily number of bicycling trips. Average county-level entropy variable does not reach a significance threshold in the bicycling model—a result consistent with that of the mixed-effects model. However, this variable shows a negative and significant association with bicycling trips in the Baltimore-D.C. ordered probit model (see Appendix C). Also, the county-level *Mean Transit Service* variable in the walking ordered probit model and the county-level *Mean Regional Diversity* variable in the bicycling ordered probit model become insignificant despite showing significant coefficients in the respective mixed-effects models.

Together, these results confirm that county-level compactness (i.e., average activity density) and pedestrian-friendly network density are among key county-level built environment factors in determining nonmotorized travel behavior. The results also indicate that other county-level built environment attributes (e.g., mixed land use, transit accessibility, and automobile accessibility) play a less clear role in nonmotorized travel behavior of residents.

Macro-level (Metropolitan Area-level) Built Environment Variables Findings: At the metropolitan area level (i.e., macro level) of influence, increased numbers of daily household walking trips are associated with better street connectivity (i.e., percentage of small blocks) within the metropolitan area. Conversely, fewer numbers of daily household walking trips are associated with higher levels of mixed land use and higher road network density throughout the metropolitan area. All of these results are consistent with those obtained from the mixed-effects models.

Also consistent with the results of the mixed-effects models (Table 7), the *Mean Temporal Transit Accessibility* variable at the macro level has a negative sign in both ordered probit models but is only significant in the bicycling model. This shows that higher transit accessibility to employment within the metropolitan area is associated with households generating fewer bicycling trips. The *Mean Temporal Transit Accessibility* variables in this case study represent the mean number of jobs within 45 minutes of transit commute. The results of the models potentially indicate that metropolitan areas with more jobs accessible within relatively longer commutes (i.e., up to 45 minutes) are associated with fewer nonmotorized trips by residents.

The negative coefficient of the *Mean Temporal Transit Accessibility* in the bicycling model may be capturing the effect of driving to transit stations rather than bicycling to them (due to longer commute distance). This argument is in line with what Rodríguez and Joo (2004) suggested; decreasing commuting distance may result in higher propensity of choosing nonmotorized modes and a lower propensity of choosing motorized modes.

Taken together, the results of the ordered probit models support the results of the mixed-effects models and indicate that macro-level (i.e., metropolitan-level) built environment factors are associated with walking and bicycling. Therefore, to comprehensively analyze nonmotorized travel behavior, the role of macro-level built environment attributes should not be overlooked.

Interpretation of Results: Florida Ordered Probit Nonmotorized Travel Models

Marginal effects can be computed after the Florida household-level ordered probit models to measure the change in the probability of a certain category of the ordinal dependent variable occurring as a result of a one-unit change in each of the independent variables. In the Florida case study, the ordinal categories of the dependent variable consist of different values of the "total number of daily walking or bicycling trips" (0-22 for walking trips and 0-11 for bicycling trips based on Table 3). Marginal effects can be computed for each specific number of trips to obtain the probability of a household generating that exact number of walking or bicycling trips.

To avoid ambiguity in interpretations of marginal effects for all values of the of the total number of trips, marginal effects are only reported for the case of "zero" daily walking and "zero" daily bicycling trips. This means that average marginal effects have been computed for the case of a household not reporting any walking/bicycling trips during the travel survey day. The marginal effects in this case represent the expected change in the probability of households' reporting no walking/bicycling trips during the travel survey day, associated with a one-unit change in a certain independent variable. Since the ordered probit model is a nonlinear model, that effect varies from household to household. The average marginal effect computes the change in the probability for each observation (i.e., household) and then computes the average for all observations.

Table 10 provides the average marginal effects along with the p-values estimated after the ordered probit models for a total number of "zero" daily walking/bicycling trips generated from a household. The average marginal effects are interpreted as the average probability of the household generating exactly "zero" walking/bicycling trips during a day. The ordered probit model is a nonlinear model; therefore, for interpretation purposes, it is assumed that the average marginal effects of a unit change in a certain independent variable on the probability of the household generating exactly “zero” walking/bicycling trips during a day is conditional on the distribution of all the model variables being as they are in the dataset. The average marginal effects can be interpreted for each of the independent variables as if it represents the response to a unit change[29].

Table 10. Average Marginal Effects: Florida Household-level Ordered Probit Models

Average Marginal Effects for Number of Household’s Daily Nonmotorized Trips = 0				
	Walking Model		**Bicycling Model**	
Independent Variable	**Average Marginal Effects**	**p-value**	**Average Marginal Effects**	**p-value**
Social Environment				
Micro level: The Household				
Number of Adults - logged	.0152792***	0.000	.0055833***	0.004
Number of Vehicles	.1062873***	0.000	.0205083***	0.000
Number of Workers	-.0172319***	0.000	-.0033763*	0.093
Annual Income	-.0055289***	0.000	-.0011411***	0.000
Meso Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	-.0184254*	0.075	.0181733	0.465
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars	.2156481**	0.047	.1507208*	0.091
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density	-.000919*	0.051	.0004539	0.198
Entropy	-.0145439*	0.066	-.0095644*	0.060
Intersection Density (Automobile-oriented) - logged	.0003456	0.650	-.0004694*	0.078
Pedestrian-friendly Network Density	-.0006137**	0.046	-.0003511*	0.070
Local Transit Service - logged	-.0041375**	0.026	-.0006035	0.473
Meso Level: The County				
Mean Activity Density	-.0091999***	0.010	.0014273**	0.035
Mean Entropy	-.256876**	0.035	-.0208655	0.704
Mean Intersection Density	.000293	0.989	-.0101188**	0.048
Mean Pedestrian-friendly Network Density	-.0033347**	0.049	-.002431**	0.058
Mean Temporal Transit Accessibility	.0000207*	0.069	2.35e-06	0.646
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Entropy	.4011405**	0.020	.0203463	0.784
Mean Total Road Network Density	.000407*	0.097	.0000654	0.813
Percentage of 0.01 Blocks	-.2457585**	0.020	-.0286895	0.532
Mean Temporal Transit Accessibility	5.68e-06	0.267	7.46e-06***	0.001
Model Prediction				
Model Prediction for Total Number of Household’s Trips = 0 (all variable set to their mean values)	.7802678***		.9686084***	

NOTES:
*, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;
Variables with statistically insignificant marginal effects in both models have been omitted from the table.

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[29] See Stata 13 Manual “margins — Marginal means, predictive margins, and marginal effects”: https://www.stata.com/manuals13/rmargins.pdf

For example, the average marginal effects on the household vehicle ownership in the walking model (0.1062873) indicates that each additional private vehicle that is available to the household is associated with an increase of approximately 10.6 percentage points in the average probability of the household generating no walking trips (i.e., households are less likely to generate walking trips if they own more vehicles). Consistent with the elasticities computed for the multilevel (i.e., mixed-effects) models, this is the highest average marginal effect on the number of household's daily walking trips with respect to the household socioeconomic characteristics. In addition, this result is consistent with the average marginal effects computed for the household-level vehicle ownership variable in the Baltimore-D.C. case study (see Appendix C). Vehicle ownership also shows the highest average marginal effects among the household socioeconomic characteristics in the bicycling model (0.0205083).

The average marginal effects on the social environment variables at the neighborhood and metropolitan area level further emphasize the role of vehicle ownership in nonmotorized travel behavior. These results show that an increase of one percentage point in the average percentage of zero-vehicle households within the neighborhood is associated with 1.84 percentage points decrease in the average probability of the household generating no walking trips (i.e., walking trips are more likely to occur if the percentage of zero-vehicle households in the neighborhood is higher). Also, an increase of one percentage point in the average percentage of 2^+-vehicle households within the metropolitan area is associated with 21.5 percentage points increase in the average probability of the household generating no walking trips (i.e., walking trips are less likely to occur if the percentage of 2^+-vehicle households in the metropolitan area is higher). The variable with the largest average marginal effect in the bicycling model is the variables representing the average percentage of 2^+-vehicle households within the metropolitan area (0.1507208). These results emphasize the role of social environment factors such as vehicle ownership at multiple levels of influence (i.e., household, neighborhood, and metropolitan area) in nonmotorized travel.

Furthermore, among the micro-level (i.e., neighborhood-level) built environment characteristics, the *Entropy* variable has the largest average marginal effects in both the walking and the bicycling models (-0.0145439 and -0.0095644, respectively). This result is consistent with the results of the Baltimore-D.C. case study (see Appendix C). The average marginal effects can be interpreted as: a one-unit increase in the neighborhood-level entropy value (i.e., mixed land use) is associated with a decrease of 1.45 and 0.95 percentage points in the average probability of the household generating no walking or no bicycling trips, respectively (i.e., households are more likely to generate walking/bicycling trips if land use mix within the neighborhood increases).

At the meso level (i.e., county level), the *Mean Entropy* variable is again the variable with the largest average marginal effects in the walking model (-0.256876). This means that a one-unit increase in the county-level entropy value (i.e., mixed land use) is associated with a decrease of approximately 26 percentage points in the average probability of the household generating no walking trips. This result is consistent with the results of the elasticities computed for the multilevel (i.e., mixed-effects) models (Table 8), but it stands in contrast with the results of the Baltimore-D.C. case study, which shows positive correlations between county-level entropy variable and nonmotorized trips (see Appendix C). The county-level *Mean Intersection Density* variable has the largest statistically significant average marginal effects in the bicycling model (-0.0101188) with respect to county-level built environment variables. This indicates that a one-unit increase in the value of the county-level *Mean Intersection Density* variable is associated with a decrease of 1.01 percentage points in the probability of the household generating no bicycling trips. This result implies that increased intersection density within the county may encourage bicycling trips.

At the macro-level (i.e., metropolitan area level), the largest statistically significant average marginal effect in the walking model belongs to the *Mean Entropy* variable (0.4011405). This result means that a one-unit increase in the metropolitan-level entropy value is associated with an increase of 40 percentage points in the average probability of the household generating no walking trips. This shows the importance of mixed-use development within the entire metropolitan area in walking. It should be noted, however, that compared with the sign of the average marginal effects of the entropy variables at the micro and meso level (negative signs), the sign of the average marginal effect of the entropy variable at the macro level is reversed (positive sign). Considering that the average marginal effects are computed for “zero” walking/bicycling trips, these results suggest that higher levels of mixed land use within the metropolitan area are correlated with a higher probability of fewer walking trips generated from households within that metropolitan area.

The only significant average marginal effects at the metropolitan level (i.e., macro level) in the bicycling model belongs to the *Mean Temporal Transit Accessibility* variable. This effect indicates that an increase of 1,000 jobs in the mean number of jobs within 45 minutes of transit commute in the metropolitan area is associated with an increase of 0.75 percentage points in the average probability of the household generating no bicycling trips. Therefore, consistent with what the elasticity of this variable showed (Table 8), this result implies that having more jobs located within relatively longer transit commutes is associated with fewer household bicycling trips.

The probability of a household generating no walking trips given that the rest of the variables are at their mean values is 78% (model prediction is 0.7802678). The probability of a household generating no bicycling trips given that the rest of the variables are at their mean values is 97% (model prediction is 0.9686084). In sum, the results of the ordered probit models emphasize the role of social and built environment at multiple levels of influence in nonmotorized travel.

4.1.7 Person-level Nonmotorized Travel Behavior Model Framework

The Florida household-level nonmotorized travel behavior models in Subsection 4.1.6 were developed based on the ecological model of behavior, which stems from the social cognitive theory. Applying the concepts of the ecological model to physical activity as a health behavior in general, and to its travel-related forms (i.e., walking and bicycling) in particular, one can state that:

i) in examining walking and bicycling behavior, the role of various factors across multiple levels of influence (intrapersonal, interpersonal, environmental, community, and policy) should be considered; and

ii) levels of walking or bicycling are expected to be maximized when: the individuals have pro-walking/pro-bicycling attitudes (i.e., the intrapersonal level); the social and cultural norms within the community as well as family and friends are supportive of walking and bicycling (i.e., the interpersonal and the community levels); the built environment—at various spatial scales—and the natural environment are conducive to nonmotorized travel (i.e., the environmental level); and policies are in place to promote walking and bicycling (i.e., the public policy level).

This is also in line with the conceptual model of travel behavior proposed by Van Acker et al. (2010), which considered travel behavior as the outcome of a decision hierarchy based on three levels of "opportunities and constraints": 1) spatial (i.e., built/natural environment characteristics); 2) social (i.e., sociodemographic/socioeconomic factors such as age and income, as well as sociocultural characteristics such as ethnicity backgrounds); and 3) individual (i.e., personal sociopsychological characteristics such as attitudes and perceptions).

The household-level models met some of the above criteria as they incorporated the emphasis of the ecological model on the influence of built environment factors on behavior as well as the emphasis of the social cognitive theory on the influence of social environment factors on behavior, especially the role of household as the most important setting among social environment factors. Further, the household-level models were conceptualized based on the ecological models' multiple level of influence framework—relating household-level walking and bicycling behavior to built and social environment characteristics, each at three levels: the micro, the meso, and the macro levels. Nonetheless, the household-level models have limitations that can be further improved. Particularly, the following two limitations exist in the household-level models:

1) Noninclusion of the Intrapersonal Level: Although the household-level models include various levels of influence for the social and built environments in their framework, they do not fully incorporate all the levels conceptualized by the ecological model of behavior. Based on the principles of that model, an important level of influence on behavior is the *intrapersonal level*.

The intrapersonal level of influence encompasses individual-level attributes that drive or impede behavior. These characteristics include biological factors such as genetic characteristics, demographic factors such as age and gender, socioeconomic factors such as employment status and college education, and psychological factors such as attitudes and perceptions.

Incorporation of these factors is, therefore, essential in development of comprehensive model frameworks for examination of human behavior including travel behavior. Literature supports person-level analyses and argues that "the individual" is a more proper unit of analysis since: a) physical activity (e.g., walking and bicycling) manifests itself at the person level; and b) aggregate data may not show causal links (National Research Council 2005);

2) Noninclusion of the Self-selection Effect: Residential self-selection is a crucial element in nonmotorized travel behavior, which has received much scholarly attention—as elaborated in Chapter 2 (and Appendix B). Understanding the role of self-selection is the key to understanding the causal relationship between the built environment and travel behavior (Handy et al. 2005).

Residential self-selection can confound the analysis of the link between nonmotorized travel behavior and the built environment due to uncertainty in spuriousness or causality of the link. Since existence of a correlation cannot confirm existence of a causal link, controlling for residential self-selection bias is essential in determining whether the correlation observed between nonmotorized travel behavior and the built environment is the result of spuriousness or causality.

If the choice of residential location is influenced by unobserved attitudes and preferences toward nonmotorized modes of travel, then variables representing the built environment attributes can be correlated with the error term resulting in endogeneity bias in the analysis. Thus, in research concerning the link between the built environment and travel behavior, residential self-selection bias is considered the manifestation of the endogeneity bias. The issue of residential self-selection should be accounted for in the analysis of the link between the built environment and nonmotorized travel behavior to establish causality and to address the endogeneity bias.

Although the analytical structure of the household-level models allowed for examining the statistical association between nonmotorized travel and the built environment, it imposed limitations on capturing self-selection bias as well as making inferences about causality.

The results of household-level models confirmed existence of many statistically significant correlations between nonmotorized travel behavior and built environment factors at various levels of influence; however, as Kelloway (1998) argued, "finding the expected patterns of correlations is a necessary, but not sufficient condition for the validity of theory". Since residential self-selection was not considered in the household-level model frameworks, the models developed in the present research thus far do not provide any insights into the role of self-selection and the causality of correlations observed. Therefore, the links between built environment attributes and walking/bicycling travel as estimated by the household-level models should not be construed as casual ones. In other words, the results of the household-level models merely confirm existence of a correlation between the built environment and nonmotorized travel behavior but not causality.

To improve upon the nonmotorized travel behavior models, the two limitations of the household-level models (discussed above) are addressed in the framework of the person-level nonmotorized travel behavior models as follows:

First, in consideration of the intrapersonal level of influence as posited by the ecological model of behavior, the principles of this model have been used to conceptualize a multilevel model framework that relates nonmotorized travel behavior at the individual level to attributes of the built and social environments of the residential location. Figure 6 shows the ecological framework applied to the Florida person-level nonmotorized travel behavior models. The framework is similar to that of the household-level models (Figure 5); however, as depicted in the figure, person-level characteristics have been added in the new models as the framework of the person-level models focuses on nonmotorized travel behavior of individuals.

In developing the model framework for person-level nonmotorized travel behavior, it should be borne in mind that each individual belongs to a social network of family, friends, and colleagues and resides within a particular location, which can influence her/his behavior. Thus, the ecological model should include the individual level, the social environment level, and the spatial environment level (Van Acker et al. 2010). Accordingly, these levels have also been included in the person-level model framework. The theory of the ecological model posits that within the multiple levels of influence on behavior, the social and built environment levels operate at multiple levels themselves (Sallis et al. 2008). Thus, built environment characteristics in the person-level models have been measured utilizing a three-level hierarchy of influence: the micro level (i.e., neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area).

Also, the person-level models incorporate a three-level hierarchy for the influence of the social environment on walking and bicycling behavior: the micro level (i.e., the household and the neighborhood), the meso level (i.e., the county), and the macro level (i.e., the metropolitan area).

It should be noted, however, that although the core concept of the ecological model includes a policy level as a key level of influence on behavior (see Sallis et al. 2008), due to lack of data on policy measures, a policy level was not included in the person-level ecological models developed in this study.

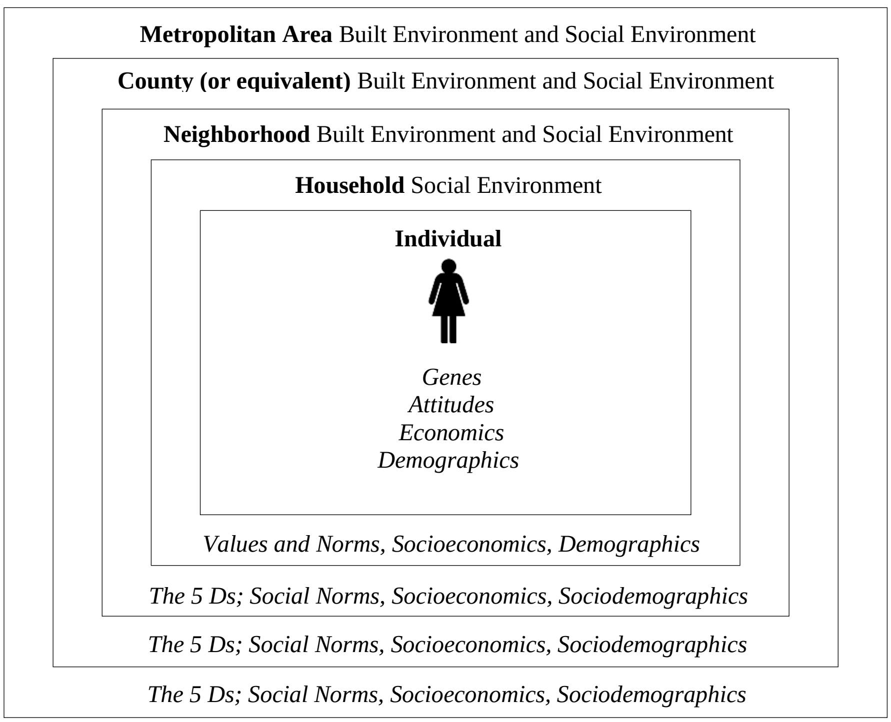

Figure 6. Ecological Framework for Levels of Influence on Nonmotorized Travel Behavior (Florida Person-level Models)

<u>Second</u>, by addressing residential self-selection in the analysis of the link between nonmotorized travel behavior and the built environment, the frameworks of the person-level models are designed to test the causality of correlations observed and reduce the risk of endogeneity bias in the analysis.

4.1.8 Person-level Nonmotorized Travel Models: Dependent Variables

The 2009 NHTS Add-on data from the metropolitan areas within the state of Florida have been used to conduct the analysis of nonmotorized travel behavior at the individual level. Nonmotorized trip mode share for each individual traveler has been considered for statistical modeling. Separate models for walking and bicycling have been developed based on two dependent variables:

1) individual's daily walking mode share (i.e., number of daily walking trips by the individual divided by the number of all trips made by the individual);

2) individual's daily bicycling mode share (i.e., number of daily bicycling trips by the individual divided by the number of all trips made by the individual).

The 2009 NHTS Add-on data for the person-level models provide information on a total of 24,550 individuals who resided in Florida metropolitan areas. Table 11 lists the frequency of the total number of individuals' daily walking and bicycling trips. The table indicates that the maximum numbers of walking and bicycling trips for Florida residents were 18 and 10, respectively. Consistent with what the literature suggests, most individuals did not make any walking or bicycling trips.

Owing to most individuals not making any nonmotorized trips, the two dependent variables are extremely skewed. However, since the data distribution curve did not show any improvement by transforming the data values to their naturally logged form, the dependent variables were retained in the models in their original form.

Also, the average numbers of daily person-level walking and bicycling trips in the Florida study area were 0.40 and 0.05 trips, respectively. The average person-level walking mode share was 8.3%, whereas the average person-level bicycling mode share was 1.1%.

Table 11. Frequency of Florida Nonmotorized Person Trips

Number of Individual's Trips	Frequency	
	Walking	Bicycling
0	20,369	23,972
1	640	74
2	2,705	426
3	155	20
4	469	39
5	43	10
6	107	3
7	13	2
8	32	2
9	2	1
10	9	1
11	2	—
12	2	—
13	—	—
14	1	—
15	—	—
16	—	—
17	—	—
18	1	—
Total	24,550	24,550

NOTES: — = Not applicable; Source of data: 2009 NHTS Add-on data.

4.1.9 Person-level Nonmotorized Travel Models: Independent Variables

The independent variables for the Florida person-level models have been chosen based on the principals of the ecological models of behavior. Most of the independent variables for the Florida person-level models are the same as those included in the Florida household-level models (Table 4). However, since the person-level models expand the influence level to the individual traveler, person-level data have also been included in the models to account for the role of each individual's characteristics in his/her nonmotorized travel behavior. Further, additional independent variables have been added to better capture the influence of the built and social environment surrounding the residence location of individual trip-makers. The final database for the Florida person-level models was constructed by merging various datasets as depicted in Appendix F. Table 12 lists all the independent variables for Florida person-level nonmotorized travel behavior models.

Table 12. Florida Person-level Model Variable Descriptions and Data Sources

Independent Variable (Exogenous or Endogenous[30])	Represented Effect	Variable Description/Units	Data Source	Data Field/ Computation
Individual (i.e., Person) Characteristics				
Age	Intrapersonal	Person's age (years)	NHTS	R_AGE[d]
Race	Intrapersonal	Person's race: 1 = White, 0 = otherwise	NHTS	HH_RACE[d]
Gender	Intrapersonal	Person's gender: 1 = male, 0 = female	NHTS	R_SEX[d]
Employment Status	Intrapersonal	Employed? 1 = yes, 0 = no	NHTS	WORKER[d]
College Education	Intrapersonal	College degree? 1 = yes, 0 = no	NHTS	Based on "EDUC"[d]
Social Environment				
Micro Level: The Household				
Number of Members	Interpersonal	Count of household members	NHTS	HHSIZE[c]
Number of Vehicles	Interpersonal	Vehicles owned by the household	NHTS	HHVEHCNT[c]
Number of Workers	Interpersonal	Employed persons in the household	NHTS	WRKCOUNT[c]
Annual Income	Interpersonal	Household annual income (midpoint of category)	NHTS	Based on "HHFAMINC"[c]
Number of Daily Transit Trips	Interpersonal	Number of daily transit trips made by all members of the household	NHTS	TRPTRANS[e]
Number of Daily Nonmotorized Trips	Interpersonal	Number of daily [walking + bicycling] trips made by all members of the household	NHTS	TRPTRANS[e]
Micro Level (Census Block Group): The Neighborhood				
Percentage of HHs with No Cars	Interpersonal	Percentage of households (in CBG) with zero cars	SLD	Pct_AO0[f]
Meso Level (County): The County				
Average Walking (or Bicycling) Density	Interpersonal (sociocultural)	Number of walking (or bicycling) trips in CBG divided by area of CBGs in acre (averaged for county)	SLD and NHTS	AC_TOT (SLD)[a,f] and TRPTRANS[e] (NHTS)
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of HHs with 2+ Cars	Interpersonal (socioeconomics)	Average percentage of households (in CBSA) with more than two cars	SLD	Pct_AO2p (Averaged)[a,f]
Average Percentage of Low-Wage Workers	Interpersonal (socioeconomics)	Average percentage of workers (in CBSA) earning $1250/month or less	SLD	R_PctLowWage (Averaged)[a]
Average Walking (or Bicycling) Density	Interpersonal (sociocultural)	Number of walking (or bicycling) trips in CBG divided by area of CBGs in acre (averaged for CBSA)	SLD and NHTS	AC_TOT (SLD)[a] and TRPTRANS[e] (NHTS)

[30] Endogenous variables in a SEM are defined as variables that need to be explained or predicted, and exogenous variables are those that can potentially offer the explanation or prediction (Kelloway 1998). In a SEM model, independent variables can be either exogenous or endogenous, whereas dependent variables are always endogenous.

Public Transportation Annual Passenger-Miles	Interpersonal (sociocultural)	Public transportation annual passenger-miles in CBSA (millions)	TTI	Public Transportation[g]
Average State Gasoline Cost	Interpersonal (socioeconomics)	Average state gasoline cost ($/gallon) for CBSA	TTI	Cost Components[g]
Average Median Age	Interpersonal (sociodemographics)	Median age for the entire population in CBSA (years)	ACS	Median Age[g]
Average Percent Foreign-Born	Interpersonal (sociocultural)	Percentage of population in CBSA that was not born in the U.S.	ACS	Foreign Born[g]
Average Crime Rate	Interpersonal (crime)	Annual number of violent crimes per 100,000 population in CBSA	FBI and CDC	Violent Crime Rate[h]
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density [i]	Density	(Employment + housing units) on unprotected land area (acres)	SLD	D1d[f]
Entropy [i]	Land use Diversity	5-tier employment entropy	SLD	D2b_E5Mix[f]
Intersection Density [i]	Urban Design	Auto-oriented intersections/mi^2	SLD	D3bao[f]
Pedestrian-friendly [i] Network Density	Urban Design	Facility miles of pedestrian-oriented links/mi^2	SLD	D3apo[f]
Local Transit Service	Local Transit Accessibility	Aggregate frequency of transit service/mi^2	SLD	D4d[f]
Local Transit Accessibility	Distance to Local Transit	Distance from centroid to the nearest transit stop (meters)	SLD	D4a[f]
Meso Level: The County				
Mean Activity Density	Density	Average (employment +housing units) on unprotected land in county	SLD	D1d (Averaged)[a,f]
Mean Entropy	Land use Diversity	Average 5-tier employment entropy for county	SLD	D2b_E5Mix (Averaged)[a,f]
Mean Regional Diversity	Regional Diversity	Average deviation of jobs/population ratio from the regional[b] average	SLD	D2r_JobPop (Averaged)[a,f]
Mean Intersection Density	Urban Design	Average auto-oriented intersections/mi^2 for county	SLD	D3bao (Averaged)[a,f]
Mean Pedestrian-friendly Network Density	Urban Design	Average facility miles of pedestrian-oriented links/mi^2 for county	SLD	D3apo (Averaged)[a,f]
Mean Transit Service	Transit Accessibility	Average aggregate frequency of transit service/mi^2 for county	SLD	D4d (Averaged)[a,f]

Mean Temporal Automobile Accessibility (to Jobs)	Destination Accessibility	Average number of jobs in county within a 45-minute automobile travel time	SLD	D5ar (Averaged)[a,f]
Mean Temporal Transit Accessibility (to Jobs)	Destination Accessibility	Average number of jobs in county within a 45-minute transit commute	SLD	D5br (Averaged)[a,f]
Mean Walk Score	Destination Accessibility	Average Walk Score for county	Walk Score®	Averaged for county
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density	Density	Average (employment+ housing units) on unprotected land in CBSA	SLD	D1d (Averaged)[a,f]
Mean Entropy	Land use Diversity	Average 5-tier employment entropy for CBSA	SLD	D2b_E5Mix (Averaged)[a,f]
Mean Total Road Network Density	Urban Design	Average total road network density for CBSA	SLD	D3a (Averaged)[a,f]
Percentage of 0.01 Blocks	Urban Design	Percent blocks with an area smaller than 0.01 mi^2 in CBSA	Census TIGER Block Shapefiles	
Mean Temporal Automobile Accessibility (to Jobs)	Destination Accessibility	Average number of jobs in CBSA within a 45-minutes automobile travel time	SLD	D5ar (Averaged)[a,f]
Mean Temporal Transit Accessibility (to Jobs)	Destination Accessibility	Average number of jobs in CBSA within a 45-minute transit commute	SLD	D5br (Averaged)[a,f]
Mean Walk Score	Destination Accessibility	Average Walk Score for CBSA	Walk Score®	Averaged For CBSA
Average Roadway Congestion Index	Mobility	Average roadway congestion index for CBSA	TTI	Roadway Congestion Index[g] (Averaged)

NOTES:

[a] Measure was computed by averaging values of the referenced field provided in data source over the relevant geographical area;
[b] CBSA;
[c] Variable was obtained from 2009 NHTS Add-on Household File;
[d] Variable was obtained from 2009 NHTS Add-on Person File;
[e] Variable was obtained from 2009 NHTS Add-on Day Trip File;
[f] The variables provided in the SLD have been extensively discussed in the SLD User Guide document, which can be found at: https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf;
[g] Average of years 2008 and 2009;
[h] For CBSAs where FBI crime data were available, the data were averaged over years 2008 to 2010. For CBSAs for which FBI data were not available, the county-level crime data from CDC (CHR&R 2005-2007 data and CHSI 2010-2012 data) were averaged to obtain the CBSA average crime rates;
[i] Endogenous variable.

Table 13 presents the weighted descriptive statistics for the continuous independent variables in the person-level nonmotorized travel behavior models. Cumulatively, the variables listed in Table 13 provide a comprehensive set of factors that can be used to examine the effects of interpersonal (i.e., individual) attributes, intrapersonal (i.e., social environment) attributes, as well as the community physical environment (i.e., built environment) attributes at hierarchical levels of influence as posited by the principles of the ecological model of behavior.

Most of the independent variables were discussed in Subsection 4.1.5. The new independent variables considered for inclusion in the person-level models are discussed below.

4.1.9.1 Person-level Variables (Individual Characteristics)

To satisfy the ecological model of behavior's emphasis on the intrapersonal level of influence on behavior, person-level characteristics such as biological, demographic, socioeconomic factors, as well as measures representing attitudes and perceptions were considered for inclusion in the models. However, using a complete set of person-level variables that represented all of the above-mentioned characteristics was not possible due to the following data limitations:

- the NHTS Add-on Person File did not include biological data on individual trip-makers; therefore, no variable representing the person's genetic attributes was included in the models due to unavailability of these data;
- although the NHTS Add-on Person File provided some data on person's attitudes and perceptions, which can potentially influence one's nonmotorized travel behavior, these data were missing for most of the data records. Appendix G lists the data fields in the NHTS Add-on Person File that were considered to represent a person's attitudes and perceptions along with the number of available and missing observations.

To retain as many observations as possible and reduce the risk of bias in the models, a decision was made to not include these attitudinal data in the models. Consequently, the person-level variables only include the following demographic and socioeconomic characteristics:

- age;
- race;
- gender;
- employment status; and
- college education.

As discussed in the Literature Review Chapter (Chapter 2), previous studies have proved that all of the above factors play important roles in nonmotorized travel behavior.

4.1.9.2 Social Environment Variables

Social environment factors have been included in the models at multiple levels of influence including the household and the neighborhood (i.e., micro level), the county (i.e., the meso level), and the metropolitan area (i.e., the macro level).

Micro-level (i.e., Household and Neighborhood-level) Social Environment Variables

As in the Florida household-level nonmotorized travel behavior models, the household variables provide information on the household's social environment for each of the Florida 2009 NHTS Add-on respondents including the household's:

- number of members (household size);
- annual income;
- number of workers;
- number of vehicles; and
- number of daily transit trips.

The variable representing the number of daily household transit is a new variable, which has been included in the person-level analysis to examine the effects of the household's transit trip levels on nonmotorized trip levels of the household members.

The variable measuring the percentage of zero-vehicle households in the neighborhood has been included in the models to represent the neighborhood-level social environment.

Meso-level (County-level) Social Environment Variable

To represent the meso-level social environment, a new variable has been included in the models that measures the average walking or bicycling density within the county of residence. The inclusion of this variable is intended to operationalize two important behavioral concepts within a nonmotorized travel behavior context: 1) the concept of observational learning—defined by the social cognitive theory; and 2) the concept of contagion perspective—defined by Ross (2000). Representing social norms and sociocultural values, both of these concepts posit that human behavior can be influenced by seeing others perform a certain behavior. Past research showed an association between recreational walking and perceptions of others being physically active (e.g., people walking or bicycling) (Nehme et al. 2016).

Therefore, for the person-level models, it is hypothesized that levels of walking and bicycling densities within the county of residence influence an individual's walking and bicycling travel behavior due to a "cultural" effect. Mitra and builing (2012) who used a measure for walking density in modeling children's nonmotorized trips to school found that children were more likely to walk or bicycle in locations where others also walked (i.e., locations with higher walking densities).

Thus, it is hypothesized that individuals who frequently see others walk and bicycle (i.e., live in counties with higher walking/bicycling densities) engage in such activities at higher rates.

Macro-level (Metropolitan area-level) Social Environment Variables

As in the Florida household-level models, the macro-level social environment is represented by a CBSA-level car ownership variable (the average percentage of households in the CBSA that own more than two cars) and a CBSA-level income variable (the average percentage of low-wage workers in the CBSA). Moreover, a few new CBSA-level variables are included in the Florida person-level nonmotorized travel behavior models to better represent the macro-level social environment. The new macro-level (i.e., CBSA-level) variables include:

- average walking (or bicycling) density;
- annual public transportation passenger-miles;
- average gasoline cost (within the state where the CBSA was located);
- average median age;
- average percentage of population that was born outside of the U.S.;
- average violent crime rate.

The macro-level social environment variables are intended to capture three different features of the social environment within a metropolitan area including the:

1) Sociodemographic and Socioeconomic Characteristics: Together with the CBSA-level car ownership variable and the CBSA-level income variable, variables measuring the CBSA-level average median age and average gasoline cost control for the effects of macro-level sociodemographic and socioeconomic attributes on nonmotorized travel behavior of individuals;

2) Social Norms and Sociocultural Characteristics: As previously mentioned, walking and bicycling density variables have been included in the models to represent social norms and sociocultural values within the metropolitan area and to capture the effects of these concepts on nonmotorized travel behavior of residents. It is hypothesized that where walking/bicycling have higher densities, individuals may be encouraged to walk or bicycle more due to a "cultural" effect.

The variable measuring the percentage of foreign-born individuals within the CBSA has also been included to control for any cultural differences that may exist among immigrants and the U.S.-born population with respect to nonmotorized travel behavior. This variable has been considered for inclusion in the models based on findings by two previous studies: 1) McMillan (2003) who found that having a U.S.-born parent lowered the likelihood of children's nonmotorized travel to school; and 2) McDonald (2005) who found that neighborhoods with larger immigrant population had higher levels of walking to school among children.

Further, the variable measuring the annual public transportation passenger-miles has been included in the analysis to represent the levels of public transit usage within the CBSA—an indicator for a potential "public transportation culture" within the metropolitan area.

3) Crime-related Characteristics: A variable measuring the average CBSA-level violent crime rate has been included in the Florida person-level nonmotorized travel behavior models to examine the impact of violent crime levels within the metropolitan area on nonmotorized travel behavior of residents. This variable has been included in the models based on previous research suggesting that crime rates within an area may play a role in walking or bicycling of individuals (see e.g., Joh et al. 2009).

4.1.9.3 Built environment Variables

Variables representing the built environment characteristics of the household location at various levels of geography have been included in the Florida person-level nonmotorized travel behavior models to control for the impact of micro-, meso-, and macro-level built environment on walking and bicycling of individuals. These include:

Micro-level (i.e., Neighborhood-level) Built Environment Variables

The micro-level built environment variables are based on the SLD data and provide information on the neighborhood-level (CBG-level) built environment and land use for each household location. The neighborhood-level built environment variables include:

- activity density;
- entropy;
- intersection density;
- pedestrian-friendly network density;
- local transit service frequency; and
- distance to local transit (proximity to transit).

These variables represent the *D*s of the built environment at the neighborhood level. Table 13 provides additional information about the micro-level built environment variables.

Meso-level (County-level) Built Environment Variables

The meso-level built environment variables are defined based on the county where the household was located. Block group-level built environment and land use measures provided by the SLD were aggregated to obtain the average county-level built environment measures for each household location. The meso-level (i.e., county-level) built environment variables included in the person-level nonmotorized travel behavior models are:

- average activity density;
- average entropy;
- average regional diversity;
- average intersection density;
- average pedestrian-friendly network density;

- average transit service frequency;
- average local transit accessibility (i.e., average distance to local transit);
- average automobile accessibility to employment opportunities;
- average transit accessibility to employment opportunities; and
- average Walk Score.

The county-level Walk Score variable is a new variable that has been added in the person-level analysis to further examine the effects of county-level destination accessibility as well as walkability on nonmotorized trip levels by residents.

These variables represent the *D*s of the built environment at the county (meso) level in the models. Additional information about the meso-level built environment variables is provided in Table 13.

Macro-level (Metropolitan area-level) Built Environment Variables

Census block group-level built environment measures provided by the SLD were aggregated to obtain the average metropolitan area-level (macro-level) built environment measures for each household location. The macro-level (i.e., CBSA level) built environment variables include:

- average activity density;
- average entropy;
- average total road network density;
- percentage of small blocks;
- average automobile accessibility to employment opportunities;
- average transit accessibility to employment opportunities;
- average Walk Score; and
- average roadway congestion index.

The CBSA-level Walk Score variable is a new variable that has been added in the person-level analysis to further examine the effects of macro-level destination accessibility as well as walkability on nonmotorized trip levels by residents of each metropolitan area. The average roadway congestion index is also a new variable that has been added in the person-level models to account for levels of mobility within the metropolitan area. As an indicator of speed at which a person can travel within a specific timeframe, mobility has a potential to indirectly impact nonmotorized travel behavior through influencing motorized travel choices including mode and destination choices. It is hypothesized in this study that increased congestion (i.e., decreased mobility) within the metropolitan area has a positive association with walking and bicycling.

Table 13 provides more information about the macro-level built environment variables.

Additional Notes on Built Environment Variables

As seen from Table 13, a few of the built environment variables—such as the activity density and the entropy variables—have been included at all three levels of geography (i.e., micro, meso, and macro levels). The entropy variable uses the 5-tier employment categories (i.e., retail, office, industrial, service, and entertainment) and the entropy formula[31] in the computation of entropy at each level of geography. The intersection density variable provided by the SLD measures the intersection density in terms of automobile-oriented intersections. Thus, this variable it is not expected to be an indicator of more pedestrian-friendly designs or to have a positive correlation with walking. Additional information about the Florida built environment variables are provided in Subsection 4.1.5.2. The final integrated database is included in Table 13, which summarizes all the independent variables used in the Florida person-level nonmotorized travel behavior models.

[31] Entropy = $-\sum_j \frac{P_j * ln(P_j)}{ln(J)}$ where, $J =$ number of land use classes within the area; and P_j = proportion of land use in the *j*th class (Frank and Pivo 1994; Cervero and Kockelman 1997; Cervero 2001; and Cervero and Duncan 2003).

Table 13.Descriptive Statistics: Florida Person-level Nonmotorized Travel Model Variables

Independent Variable (Units)	Mean	SD	Min.	Max.
Individual (i.e., Person) Characteristics				
Age of the Individual (years)	46.53	21.89	5	100
Social Environment				
Micro Level: The Household				
Number of Members	2.95	1.45	1	10
Number of Vehicles	1.94	1.02	0	14
Number of Workers	1.27	.91	0	5
Annual Income (1,000s of dollars)	50 - 55	—	≤ 5	≥ 100
Number of Daily Transit Trips (count of daily transit trips by all members of the household)	0.11	0.61	0	12
Micro Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	5.67	7.90	0	90.45
Meso Level (County): The County				
Average Walking Density [average (number of walking trips in CBG/CBG area in acres)]	0.0032	0.0025	0	0.0085
Average Bicycling Density [average (number of bicycling trips in CBG/CBG area in acres)]	0.0003	0.0001	0	0.0014
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars (%)	52.40	2.58	43.35	60.64
Average Percentage of Low-Wage Workers (workers earning ≤ $1250/month) (%)	26.32	1.86	24.31	34.16
Average Walking Density [average (number of walking trips in CBG/CBG area in acres)]	0.0031	0.0021	0.0007	0.0062
Average Bicycling Density [average (number of bicycling trips in CBG/CBG area in acres)]	0.0003	0.0001	0	0.0008
Annual Public Transportation Passenger-Miles (millions)	331.26	408.60	5.70	972.70
Average State Gasoline Cost (dollars/gallons)	2.80	0.05	2.66	2.92
Average Median Age (years)	39.92	3.69	29.4	52.75
Average Percentage of Foreign-Born Population (%)	18.54	11.98	5.19	36.73
Average Violent Crime Rate (annual crimes/100,000 population)	821.67	355.51	180.27	1314.43
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density [(employment + housing units)/acres)]	4.79	7.04	0	177.16
Entropy (dimensionless)	0.59	0.31	0	0.99
Intersection Density (automobile-oriented intersections/mi^2)	0.98	2.17	0	28.83
Pedestrian-friendly Network Density (facility miles of pedestrian-oriented links/mi^2)	12.89	6.71	0	46.42
Local Transit Service (aggregate frequency of transit service/mi^2)	126.03	272.75	0	11760.5
Local Transit Accessibility (distance from centroid to the nearest transit stop in meters)	662.10	162.97	1.87	1205.42
Meso Level: The County				
Mean Activity Density [average (employment + housing units)/acres)]	6.29	4.41	0.02	15.86
Mean Entropy (dimensionless)	0.54	0.06	0.30	0.70
Mean Regional Diversity (average deviation of jobs/population ratio from the regional average)	0.18	0.05	0	0.31
Mean Intersection Density [average (automobile-oriented intersections/mi^2)]	1.12	0.54	0.06	1.99
Mean Pedestrian-friendly Network Density [average (facility miles of ped.-oriented links/mi^2)]	13.38	3.59	1.63	18.74
Mean Transit Service [average (aggregate frequency of transit service per mi^2)]	278.09	277.20	0	728.72
Mean Local Transit Accessibility [average (distance to the nearest transit stop in meters)]	659.18	68.30	481.40	987.49
Mean Temporal Automobile Accessibility (ave. number of jobs within 45-min. auto. commute)	85896.1	59076.8	804.61	172539
Mean Temporal Transit Accessibility (ave. number of jobs within a 45-minute transit commute)	3750.35	3327.53	0	8834.1
Mean Walk Score (dimensionless)	10.71	17.58	0	75
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Activity Density [average (employment + housing units)/acres)]	6.17	3.51	0.18	11.55
Mean Entropy (dimensionless)	0.54	0.05	0.44	0.64
Mean Total Road Network Density [average (total road network miles/mi^2)]	18.83	8.39	4.35	45.69
Percentage of 0.01 Blocks (% blocks with an area smaller than 0.01mi^2)	58.43	8.63	38.66	67.25
Mean Temporal Automobile Accessibility (ave. number of jobs within 45-min. auto. commute)	83615.8	50055.7	6257.5	149675
Mean Temporal Transit Accessibility (ave. number of jobs within a 45-minute transit commute)	2572.9	2073.9	0.91	5388.9
Mean Walk Score (dimensionless)	41.52	15.06	0	91
Mean Roadway Congestion Index (dimensionless)	1.12	0.20	0.82	1.36

4.1.10 Person-level Nonmotorized Travel Behavior Models

Based on the principles of the ecological model of behavior, the Florida person-level models have been developed to comprehensively analyze the relationships between measures representing multiple levels of influence (e.g., intrapersonal, interpersonal, and built environment levels) and nonmotorized travel behavior. Previous research suggests that a key element of such relationships is the influence of intrapersonal level's psychological factors such as attitudes and perceptions (see Chapter 2 and Appendix B). However, as indicated previously, the attitudinal data from the Florida 2009 NHTS Add-on Person File were unusable for the present study due to the large proportions of missing data (see Appendix G). The unavailability of attitudinal survey data limits the ability to control for residential self-selection bias (i.e., endogeneity bias) as residential self-selection is interwoven with attitudes. In addition, owing to lack of attitudinal data, the question of correlation or causality remains unaddressed. This is because attitudes may simultaneously influence travel choices and residential location choices, which means any correlation observed between nonmotorized travel and the built environment can be the effect of a spurious relationship and not a causal one. Further, the available data are cross-sectional, which limits the ability to test for the causality of the links between nonmotorized travel behavior and built environment factors.

Due to the cross-sectional nature of data and lack of attitudinal data, a more sophisticated methodology is needed to more comprehensively analyze the link between nonmotorized travel behavior and the built environment and to control for residential self-selection bias (i.e., endogeneity bias). As indicated in prior chapters, the Structural Equations Modeling (SEM) technique has the capability to simultaneously estimate coefficients for multiple interrelated regression equations and test for the self-selection effect. The SEM methodology has been used in previous travel behavior research to control for self-selection bias and causality in analyses using cross-sectional data and in absence of personal attitudinal data (see e.g., He and Zhang 2012; Wang 2013; Nasri and Zhang 2014). Further, with regards to spatial data, the multilevel structure of the models causes a clustered structure for data. This introduces interdependencies within the data, which can potentially subject the analysis to spatial autocorrelation. Literature suggests that using hierarchical (i.e., multilevel) models can help in statistical treatment of any spatial autocorrelation problem, which may exist due to the clustered nature of the data (see e.g., Moudon et al. 2005).

For the above reasons, multilevel Structural Equation Modeling (multilevel SEM) techniques have been employed in the Florida person-level nonmotorized travel behavior models to explain the complex relationships among person-level walking/bicycling activities and built as well as social environments, while accounting for interdependency among data from multiple hierarchical levels of influence (i.e., micro, meso, and macro levels) in the model framework.

The multilevel SEM approach is a suitable modeling methodology to handle the hierarchical nature of the data as well as the multilevel conceptual model framework used in this analysis. It offers the capability of concurrently analyzing the effect of factors from various levels including those from the individual level and those from the cluster/group level (i.e., contextual effects) on the dependent variable (Kline 2011).

Employment of the multilevel SEM techniques to examine the link between person-level nonmotorized travel behavior and built and social environment factors at multiple levels provides many methodological advantages. Most importantly, the application of the advanced statistical analysis tools offered by the multilevel SEM to the comprehensive person-level ecological model framework allows for controlling for self-selection bias and examining the causal links between nonmotorized travel behavior and the built environment at multiple levels of influence. Further, spatial autocorrelation can be accounted for by using the multilevel analysis capabilities embedded in the multilevel SEM. Moreover, the SEM nature of the multilevel SEM can deal with potential multicollinearity problems that may exist in the models. Literature suggests that by testing causal paths through a sequence of correlated variables or by treating highly correlated variables as indictors of a common underlying construct, SEM may deal with collinearity issues (Franke 2010).

Past research suggests that the advanced capabilities of the multilevel SEM, which allow for addressing various interdependencies within the model—whether resulting from numerous relationships (i.e., direct and indirect effects) or from a nested data structure (e.g., households nesting within neighborhoods)—makes it an appropriate methodology to disentangle the complexity of travel behavior (Van Acker et al. 2010). However, despite having a tremendous potential for application in travel behavior research, this approach has not been taken full advantage of in empirical studies. The author has found only two papers that employed multilevel SEM to examine travel behavior (see Chung et al. 2004 and Kim et al. 2004). Both the referenced papers suggested that although either SEM or multilevel modeling tools have been applied to travel behavior research, a model combining the SEM and multilevel techniques is rarely found in travel behavior research or even within other aspects of transportation research.

Considering the arguments above and based on the proposed ecological model framework (Figure 1), the multilevel SEM models developed in this subsection examine the causality of the links between nonmotorized travel behavior and the built environment, while simultaneously controlling for self-selection bias.

These models relate an individual trip maker's daily walking and bicycling mode share to person-level characteristics, social environment characteristics at multiple hierarchal levels (i.e., household, neighborhood, county, and metropolitan area) as well as built environment characteristics at multiple hierarchal levels (i.e., neighborhood, county, and metropolitan area).

4.1.10.1 Specification of the Florida Person-level Multilevel Structural Equation Models

Data for the Florida person-level models are assumed to be clustered as individuals are nested within households and households are nested within similar geographical areas (e.g., neighborhoods, counties, or metropolitan areas). Due to the clustered nature of data, there may be correlations between observations within the same households or observations within the same spatial area (i.e., spatial autocorrelation). These data interdependencies are accounted for by employing a hierarchical modeling technique (i.e., the multilevel SEM) as well as by considering random effects for two clusters: the household and the neighborhood (i.e., census block group).

From a theoretical standpoint, the importance of consideration of random effects at the household-level in this analysis is further strengthened by the fact that the household is considered the most important social environment setting that determines an individuals' behavior (Gochman 1997; Van Acker et al. 2010).

The theoretical basis for consideration of neighborhood random effects comes from literature providing evidence that neighborhood-level built environment attributes influence nonmotorized travel behavior (see Chapter 2 and Appendix B) as well as the findings of the present study on the role of neighborhood random differences in nonmotorized travel behavior of residents (as evidenced in the Florida household-level nonmotorized travel behavior analysis).

With respect to the multilevel modeling, this model design introduces three levels: the first level is the individual, the second level is the household, and the third level is the census block group (i.e., neighborhood). The household-level and the neighborhood-level random effects are represented by specifying random intercepts at the household level and the neighborhood level (i.e., census block group).

Variations in the models can be divided into two components for the household taste: within-household variation and between-household variation, as well as two components for differences in neighborhoods: within-neighborhood variation and between-neighborhood variation. These variations can be captured by the household-level and neighborhood-level random intercepts[32]. Based on Kline (2011), this model specification allows for simultaneous analysis of the effect of factors from multiple hierarchical levels including those from the individual level and those from the cluster/group level (i.e., contextual effects) on nonmotorized travel.

With respect to the structural equation modeling, the concepts of dependent and independent variables as defined in an ordinary regression modeling context become blurred. Instead, the SEM specification consists of endogenous and exogenous variables representing logical cause-effect relationships between them. Endogenous variables in an SEM context are defined as variables that need to be explained or predicted, whereas exogenous variables are those that are determined by causes outside of the model and can potentially offer the explanation or prediction desired for endogenous variables in the model (Kelloway 1998; Heck 2001).

A path diagram is often drawn for the SEM, which depicts the structural relationships among variables of interest. Unidirectional arrows represent presumed causal links in the path diagram. The causal links hypothesized in the path diagram should be justified based on theoretical grounds. The path diagram can also include latent variables (i.e., variables that are not observed or measured directly) allowing factor analysis to be embedded in the model.

Figure 7 shows the multilevel SEM model structure (i.e., proposed path diagram) describing the hypothesized causal links among endogenous variables as well as between

[32] The Stata software package provides two formulations for the multilevel random-intercept modeling: the single-equation formulation and the within-and-between formulation. If there are no missing data values, results from both formulations are equivalent (StataCorp 2013, Page 370). Since there are no observations with missing values in the present study's database, the single-equation formulation is used for random-intercept modeling in this analysis.

exogenous and endogenous variables for the Florida person-level models. Through incorporation of both measurement and structural models, the path diagram presents a latent variable path analysis (Kelloway 1998). Appendix H provides variable labels as depicted in Figure 7.

Per conventions of SEM, latent (i.e., unobserved) variables are represented in ovals (i.e. ellipses), whereas observed variables are represented in squares or rectangles (see Kelloway 1998; Kline 2011). Accordingly, the path diagram used in the multilevel SEM (Figure 7) is shown with rectangles representing observed variables, and ovals representing latent variables.

Further, endogenous and exogenous variables are connected by arrows indicating the direction of influence coming from the exogenous variables and heading toward the endogenous variables. For instance, the direction of an arrow coming from variable *X* and heading toward variable *Y* (i.e., $X \rightarrow Y$) represents the presumed causal effects (i.e., effect priority) of *X* on *Y*—implying that *X* is causally prior to *Y* and affects it (Kline 2011).

Variables with a double-ringed representation in the path diagram indicate random intercept variables at the household and neighborhood levels. The household-level double-ringed variable stays constant within the same household but varies across different households. Similarly, the neighborhood-level double-ringed variable stays constant within the same neighborhood but varies across different neighborhoods. These variables represent the random effects at the household and neighborhood levels.

Pearson correlation coefficients have been calculated for all original independent variables (i.e., exogenous variables). According to Franke (2010), correlation coefficients higher than 0.8 or 0.9 between independent variables are considered as excessively collinear and are indicators of multicollinearity.

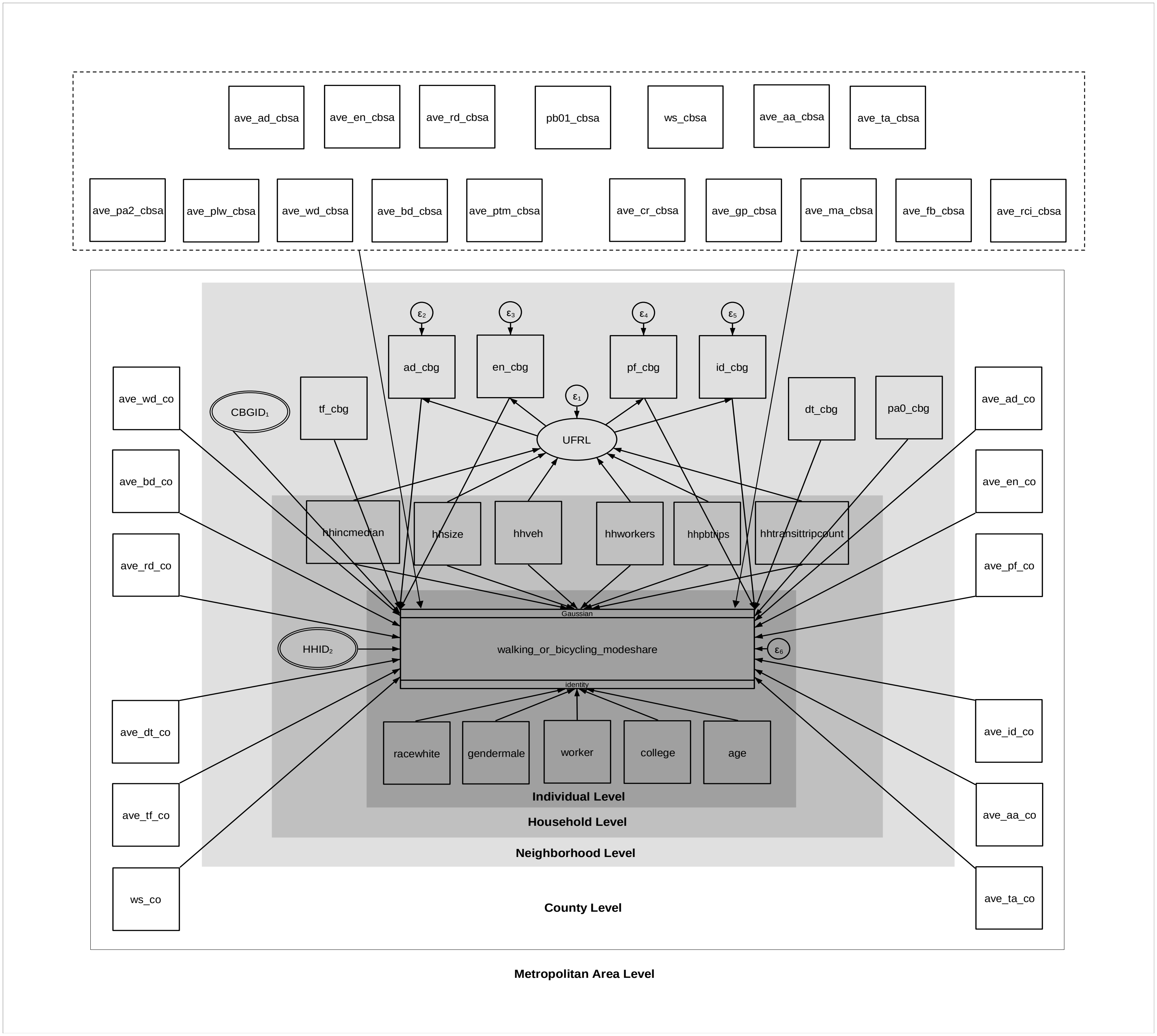

Figure 7. Multilevel SEM Structure

(Florida Person-level Nonmotorized Mode Share Models)

Therefore, as in the household-level models developed in this dissertation, a correlation threshold of $|p| > 0.7$ was used to eliminated highly correlated independent variables (i.e., exogenous variables) as suggested by Kim and Susilo (2013). However, variables with correlation coefficients ≥ 0.70 and < 0.85 were retained in the models if they reached a significance level of 0.05 or if there was a theoretical reason for retaining the variable. Nevertheless, according to Franke (2010), one of the capabilities of SEM techniques is that they may deal with collinearity; therefore, it is assumed that the SEM nature of the developed models handles any multicollinearity problems that may exist after elimination of variables based on a correlation threshold of $|p| > 0.7$.

Also, any continuous variable with a correctable skewed distribution was normalized by transformation into its naturally logged form before inclusion in the model. Most of the variables however, either showed a normal (or nearly normal distribution) or did not show any improvement in their distribution curve by transformation to naturally logged form (including the dependent variables); therefore, these variables have been included in the model in their original form. Similar to previous studies (see e.g., Schauder and Foley 2015), for independent variables with an original value equal to zero, the zero value was changed to 0.25 before their log-transformation. This is because the natural log of zero is undefined.

The path diagram in Figure 7 can be represented by a simplified regression equation for the person-level daily walking or bicycling mode shares (Equation 24) and a simplified equation for the latent variable representing the urban form of the residential location as a function of household-level social environment (i.e., household-level socioeconomic factors as well as transit and nonmotorized travel behavior factors as measures of household travel culture) (Equation 25).

Equations 24 and 25 constitute the structural model, which is formulated as:

$$\mathrm{Y} = \beta_0 + \beta_1'\mathrm{ED}_{\mathrm{Person}} + \beta_2'\mathrm{SE}_{\mathrm{HH}} + \beta_3\mathrm{SE}_{\mathrm{CBG}} + \beta_4\mathrm{SE}_{\mathrm{County}} + \beta_3'\mathrm{SE}_{\mathrm{CBSA}} + \beta_4'\mathrm{BE}_{\mathrm{CBG}} + \beta_5'\mathrm{BE}_{\mathrm{County}} + \beta_6'\mathrm{BE}_{\mathrm{CBSA}} + u_{\mathrm{HH}}\mathbf{RE}_{\mathrm{HH}} + u_{\mathrm{CBG}}\mathbf{RE}_{\mathrm{CBG}} + \varepsilon_6 \quad \text{Equation 24}$$

$$\text{Urban Form of Residential Location}_{(Latent\ Endogenous\ Variable)} = \beta_7'\mathrm{SE}_{\mathrm{HH}} + \varepsilon_1 \quad \text{Equation 25}$$

where,

β_0 = model intercept;

$\beta_1' - \beta_7'$ = column vectors of model path coefficients;

β_3 = model parameter for the micro-level (i.e., neighborhood-level) social environment attribute;

β_4 = model parameter for the meso-level (i.e., county-level) social environment attribute;

u_{HH} = vector of iid household-level random effects;

u_{CBG} = vector of iid neighborhood-level random effects;

$\varepsilon_1, \varepsilon_6$ = model error terms;

$\mathrm{ED}_{\mathrm{Person}}$ = column vector of person-level socioeconomic and sociodemographic attributes;

$\mathrm{SE}_{\mathrm{HH}}$ and $\mathrm{SE}_{\mathrm{CBG}}$ = column vectors of micro-level (i.e., household and neighborhood) social environment attributes (including household-level travel culture attributes);

$\mathrm{SE}_{\mathrm{County}}$ = the meso-level (i.e., county) social environment attribute;

$\mathrm{SE}_{\mathrm{CBSA}}$ = column vector of macro-level (i.e., metropolitan area) social environment attributes;

$\mathrm{BE}_{\mathrm{CBG}}$ = column vector of micro-level (i.e., neighborhood) built environment attributes;

$\mathrm{BE}_{\mathrm{County}}$ = column vector of meso-level (i.e., county) built environment attributes;

$\mathrm{BE}_{\mathrm{CBSA}}$ = column vector of macro-level (i.e., metropolitan area) built environment attributes;

$\mathbf{RE}_{\mathrm{HH}}$ = matrix of household-level covariates for random effects;

$\mathbf{RE}_{\mathrm{CBG}}$ = matrix of neighborhood-level covariates for random effects; and

Y = vector of observed endogenous variable (i.e., person-level walking or bicycling mode share).

As a requirement of the multilevel SEM models, the within-cluster covariance matrices are assumed to be equal across all groups (clusters), allowing for a single pooled within-cluster matrix to be used for estimating the model. Therefore, the assumption for random effects modeling in this type of model is that the relations between variables is the same across all clusters (Stapleton 2006). Accordingly, it is assumed here that the slopes of similar covariates contained within the random portions of the model (i.e., $\mathbf{RE}_{\mathrm{HH}}$ and $\mathbf{RE}_{\mathrm{CBG}}$) are constant across various similar groups (i.e., households or CBGs). Therefore, the random household effects are simplified to a household-specific effect, which captures an effect that is common to all individuals within the same household ($u_{0\mathrm{HH}}$). Similarly, the CBG random effects are simplified to a CBG-specific effect, which captures an effect that is common to all households within the same CBG ($u_{0\mathrm{CBG}}$).

This makes the specified model a random intercept model, which assumes that households and CBGs add random offsets to individuals nonmotorized travel behavior (i.e., person-level daily walking/bicycling mode share).

The simplified (i.e., random intercept) formulation for Equation 24 is:

$$\mathrm{Y} = \beta_0 + \beta_1'\mathrm{ED}_{\mathrm{Person}} + \beta_2'\mathrm{SE}_{\mathrm{HH}} + \beta_3\mathrm{SE}_{\mathrm{CBG}} + \beta_4\mathrm{SE}_{\mathrm{County}} + \beta_3'\mathrm{SE}_{\mathrm{CBSA}} + \beta_4'\mathrm{BE}_{\mathrm{CBG}} + \beta_5'\mathrm{BE}_{\mathrm{County}} + \beta_6'\mathrm{BE}_{\mathrm{CBSA}} + u_{0_{\mathrm{HH}}} + u_{0_{\mathrm{CBG}}} + \varepsilon_6 \qquad \text{Equation 26}$$

Owning to lack of attitudinal survey data and the cross-sectional nature of data used for the analysis, the ability to thoroughly capture the effect of residential self-selection bias (i.e., endogeneity bias) on person-level nonmotorized travel behavior is restricted. However, the SEM techniques allow for testing for existence of residential self-selection effect and estimation of its magnitude relative to the effect of built environment factors with a reasonably close approximation (Nasri and Zhang 2014).

Accordingly, the *Urban Form of Residential Location* (*UFRL*) latent variable is measured by using the main neighborhood-level attributes that represent the overall urban form of the individual trip-maker's residential neighborhood area. Inclusion of this latent variable allows for estimation of the residential self-selection effect in absence of attitudinal data.

In construction of the *Urban Form of Residential Location* (*UFRL*) latent variable, causal links are hypothesized between the household's urban form of residential location and the household-level social environment characteristics (i.e., household taste) including households' socioeconomic and travel culture characteristics. These causal links are included in the model based on the theoretical assumption that the household-level social environment influences both nonmotorized travel behavior and residential location choice—an assumption supported by previous studies (see Chapter 2 and Appendix B).

For instance, wealthier individuals who can afford expenses associated with owning private vehicles and long travel distances are more likely to select a low-density suburban neighborhood to reside in, where they can take advantage of cleaner air and spacious land. In contrast, low-income individuals who own no private vehicles may prefer to reside in dense urban neighborhoods conducive to the less costly modes of transportation such as transit (Wang 2013) as well as walking and bicycling.

The measurement model for the *Urban Form of Residential Location* (*UFRL*) latent variable is formulated by the following equations:

$$\mathrm{AD}_{\mathrm{CBG}} = \alpha_1 \mathrm{UFRL} + \varepsilon_2 \qquad \text{Equation 27}$$

$$\mathrm{EN}_{\mathrm{CBG}} = \alpha_2 \mathrm{UFRL} + \varepsilon_3 \qquad \text{Equation 28}$$

$$\mathrm{PF}_{\mathrm{CBG}} = \alpha_3 \mathrm{UFRL} + \varepsilon_4 \qquad \text{Equation 29}$$

$$\mathrm{ID}_{\mathrm{CBG}} = \alpha_4 \mathrm{UFRL} + \varepsilon_5 \qquad \text{Equation 30}$$

where,

UFRL = *Urban Form of Residential Location* latent variable;

AD_{CBG} = neighborhood-level activity density (the "ad_cbg" variable in Figure 7);

EN_{CBG} = neighborhood-level mixed land use score (the "en_cbg" variable in Figure 7);

PF_{CBG} = neighborhood-level pedestrian-friendly network density ("pf_cbg" in Figure 7);

ID_{CBG} = neighborhood-level intersection density (the "id_cbg" variable in Figure 7);

α_{1-4} = measurement model pattern coefficients; and

ε_{2-5} = measurement errors.

In the measurement model specified above (Equations 27 – 30), there are four observed built environment characteristics that record an individual's urban form of residential location and form the latent variable (*UFRL*). Observed variables used to measure a latent variable are referred to as *indicators* (Kline 2011). The minimum number of indicators to be included in the measurement model for a latent variable (i.e., factor) in a SEM analysis is three (Kelloway 1998), with three or four indicators being deemed as a better target (Kline 2011). Therefore, the present analysis uses four indicators in the measurement model of the latent variable *UFRL*.

Equation 25 along with Equations 27 – 30 represent a MIMIC model where the household-level observed social environment variables (i.e., the SE_{HH} variables) determine the *UFRL* latent variable, and *UFRL* in turn, determines the observed built environment indicator variables (i.e., built environment characteristics of the residential location neighborhood).

The household-level observed social environment variables are treated as predictors of *UFRL*, and thereby give an estimate of the residential self-selection effect.

Through Equations 24 – 30, the model structure allows for the nonmotorized (i.e., walking or bicycling) trip mode shares and the urban form of residential location to be estimated jointly.

This means that all components of the path diagram depicted in Figure 7 are simultaneously estimated by the model[33,34].

4.1.10.2 Discussion of Results: Florida Person-level Multilevel Structural Equation Models

Table 14 summarizes the estimation results of the multilevel SEMs for the Florida person-level nonmotorized travel behavior models. As mentioned previously, the direction of arrows in a SEM path diagram represents the effect priority as hypothesized in the theory for which the model is specified. That is, $X \rightarrow Y$ in the path diagram represents the presumed causal effects of variable X on variable Y, which means that it is hypothesized that X is causally prior to Y, and thus, $X \rightarrow Y$ can be interpreted as X affects Y (Kline 2011). Therefore, the results of the multilevel SEMs are discussed assuming such links as causal ones.

The results of the Florida person-level multilevel SEMs indicate that individuals' nonmotorized travel behavior is linked with their personal characteristics as well as the social environment within their household. The results also show many statistically significant paths between individuals' nonmotorized travel behavior and the built as well as the social environment characteristics of their residential location at all spatial levels of influence including the micro level (i.e., neighborhood), the meso level (i.e., county), and the macro level (i.e., metropolitan area).

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[33] The maximum likelihood estimation (MLE)—commonly used in practice (Cao et al. 2007)—is used to develop the multilevel SEMs in the present study. Model estimation is undertaken using the Generalized Structural Equation Modeling (GSEM) mode of the Stata software. The GSEM mode fits multilevel mixed-effects models in Stata. In standard linear SEMs, the validity of MLE depends on the SEM meeting the assumption of multivariate (i.e., joint) normality of all model variables, observed and latent. However, the MLE method used in GSEM is applied to a different likelihood function that assumes only conditional normality and does not require the full joint-normality assumption of the standard linear SEMs. The conditional normality assumed in MLE means that latent variables are still assumed to be normally distributed (StataCorp 2013, Pages 43-45).

[34] Since data used in this analysis are clustered with some non-normal distributions, a generalized form of the Huber/White/sandwich estimator method for robust calculations of standard errors (i.e., the "vce (cluster clustvar)" option in Stata's GSEM mode) is used to calculate robust standard errors. In this generalized form of standard errors calculations, the errors are independent across clusters (i.e., neighborhoods) but are allowed to be correlated within clusters.

Table 14. Results[a]: Florida Person-level Nonmotorized Travel Models (Multilevel SEMs)

Endogenous Response Variable (Observed): Person-level Daily Nonmotorized Trip Mode Share				
	Walking Model		**Bicycling Model**	
Exogenous and Endogenous Predictor Variables	**Path Coefficient**	**p-Value**	**Path Coefficient**	**p-Value**
Individual (i.e., Person) Characteristics				
Age (years)	-.0676293***	0.000	-.0257986***	0.000
Race (1 = White, 0 = otherwise)	1.065734***	0.044	.1914605NS	0.281
Gender (1 = male, 0 = female)	.0278688NS	0.916	.9399146***	0.000
Employment Status (employed? 1 = yes, 0 = no)	-3.245868***	0.000	-.394663***	0.013
College Education (1 = yes, 0 = no)	.6977489***	0.037	.0062927NS	0.957
Social Environment				
Micro level: The Household				
Number of Vehicles	-1.492666***	0.000	-.3505599***	0.000
Annual Income	.0463946*	0.099	-.0074726NS	0.561
Number of Daily Transit Trips	.9352254**	0.026	.3848374***	0.002
Micro Level (Census Block Group): The Neighborhood				
Percentage of Households with No Cars	.0594356*	0.063	.0056245NS	0.556
Meso Level (County): The County				
Average Walking Density - logged	.5498248*	0.082	—	—
Average Bicycling Density - logged	—	—	.211758**	0.018
Macro Level (Core Based Statistical Area): The Metropolitan Area				
Average Percentage of Households with 2+ Cars	-.0366042*	0.099	-.0616712*	0.080
Average Percentage of Low-Wage Workers	.5566391*	0.087	.0592485NS	0.552
Average Walking Density - logged	2.68457*	0.057	—	—
Public Transportation Annual Passenger-Miles	.0048983**	0.035	.0019688*	0.063
Average State Gasoline Cost	1.112083**	0.044	2.564236**	0.041
Average Median Age	-.1547878NS	0.402	-.1226676**	0.012
Average Percent Foreign-Born Population	.1388364*	0.091	-.0164406NS	0.608
Built Environment				
Micro Level (Census Block Group): The Neighborhood				
Activity Density [b]	.0661413**	0.026	-.0032872NS	0.545
Entropy [b]	.0840489*	0.063	.3595972**	0.049
Intersection Density (Automobile-oriented) [b]	-.0418847NS	0.653	.0938886**	0.023
Pedestrian-friendly Network Density [b]	.000602**	0.043	.0013923*	0.089
Local Transit Service - logged	.1775506*	0.093	-.0098804NS	0.778
Meso Level: The County				
Mean Activity Density	.4101298*	0.085	-.0573349*	0.078
Intersection Density (Automobile-oriented)	.9860214NS	0.461	.3474463*	0.080
Mean Regional Diversity	-.4809108NS	0.399	-.4206712*	0.053
Mean Pedestrian-friendly Network Density	.1227838*	0.087	.0848946**	0.030
Mean Temporal Automobile Accessibility (to Jobs)	-.0000302*	0.085	-.0000113*	0.086

Macro Level (Core Based Statistical Area): The Metropolitan Area				
Mean Entropy	-.1270356**	0.049	.7166568^{NS}	0.841
Percentage of 0.01 Blocks	.0327152**	0.048	-.0018981^{NS}	0.937
Mean Temporal Automobile Accessibility (to Jobs)	6.09e-07^{NS}	0.989	-.0000201*	0.084
Mean Temporal Transit Accessibility (to Jobs)	-.0006749*	0.099	-.0001225*	0.069
Mean Walk Score	.037621*	0.087	—	—
Average Roadway Congestion Index	.6284358*	0.051	3.428704**	0.018
Variance Estimates				
Households [c] (Random Effects)	130.3447***	0.000	7.32847***	0.000
Census Block Groups [d] (Neighborhood Random Effects)	9.84e-30^{NS}	0.903	.4755464^{NS}	0.359
Variance of ε_1 (error term of the *UFRL* Latent Variable)	9.587172***	0.000	9.586853***	0.000
Variance of ε_6 (error term of the Nonmotorized Trip Mode Share Endogenous Variable)	317.116***	0.000	48.73677***	0.000
Other Model Factors				
Log pseudolikelihood	-313179.15		-291360.83	
Observations; Households [c]; Neighborhoods [d]	24,550; 13,509 [c]; 6,613 [d]		24,550; 13,509 [c]; 6,613 [d]	

NOTES:

[a] In the interest of brevity, only variables whose path coefficients were statistically significant in at least one model (i.e., in either walking or bicycling model) are listed in the table;

[b] Endogenous observed variable used in the measurement model of the *UFRL* latent variable;

[c] Clusters: households;

[d] Clusters: neighborhoods;

*, **, *** = Path coefficient is significant at the 10%, 5% and 1% significance level, respectively;

NS = Not significant;

— = Not included in the model.

It should be borne in mind that although the results of the multilevel SEMs provide coefficient estimates on the effects of various factors on individuals' nonmotorized travel behavior, elasticities cannot be computed for these effects.

This is because in the complex structure of the SEM models, different equations represent different effects of variables on one another (i.e., direct and indirect effects). These effects cannot be computed as a single elasticity (Ewing and Cervero 2010).

Person-level (Individual Characteristics) Variables Findings

The results of both the walking and bicycling multilevel SEM models show that as measures of the intrapersonal level of influence on behavior, an individual's demographic and socioeconomic characteristics affect his/her nonmotorized travel behavior. Specifically, individuals' age is negatively linked with their daily nonmotorized mode share. As an individual gets older, physical activity such as walking and bicycling may get more difficult to perform. Many studies in the past also found age to be negatively correlated with nonmotorized travel behavior (see e.g., Hess et al. 1999; Pucher et al. 1999; Ross 2000; Handy and Clifton 2001; Troped et al. 2001; Zhang 2004; Targa and Clifton 2005; Zacharias 2005; Clifton and Dill 2005; Handy et al. 2006; Dill and Voros 2007; Boarnet et al. 2008; Merom et al. 2010; Siu et al. 2012; Ma and Dill 2015).

An individual's race being White is positively linked with his/her daily nonmotorized travel mode share; however, the path coefficient of the race variable does reach a statistical significance threshold in the bicycling model. This means that race may be a more influential factor in walking than in bicycling of individuals.

In terms of gender, the results of the present case study indicate that a higher bicycling mode share is linked with being male, as also suggested by many previous studies (see e.g., Troped et al. 2001; Moudon et al. 2005; Dill and Voros 2007; Gatersleben and Appleton 2007; Ma and Dill 2015). However, gender does not appear to be a statistically significant determinant of individuals' walking mode share.

The results also suggest that being employed is linked with lower levels of nonmotorized mode shares (both walking and bicycling) for individuals. This may be an indication of time limitations that workers face in performing recreational walking and bicycling activities. Further, having a college education has a positive impact on individuals' walking mode share. This is consistent with previous findings that suggested higher education was positively associated with walking (see e.g., Ross 2000; Ewing et al. 2003b, 2008; Targa and Clifton 2005; Siu et al. 2012; Wasfi et al. 2016). The results indicate that the effect of having a college education on an individual's daily bicycling mode share is not statistically significant.

Micro-level (Household/Neighborhood-level) Social Environment Variables Findings

Consistent with the results of the household-level models, the results of the person-level models suggest that household-level socioeconomic characteristics affect nonmotorized travel behavior. A higher number of private vehicles owned by the household has a negative effect on both walking and bicycling mode shares at the person level. This result corroborates findings by many previous studies (see e.g., Cervero 1996; Cervero and Radisch 1996; Kitamura et al. 1997; Plaut 2005; Stinson and Bhat 2005; Mitra and Buliung 2012).

Higher household income levels are positively linked with walking mode share, which is consistent with the results of the household-level models developed in the present study. This result may be an indication of recreational walking by individuals from higher-income households as suggested by previous research (see e.g., Roshan Zamir et al. 2014).

A notable result is the positive direction of influence of the variable representing household's number of daily transit trips on an individual's nonmotorized mode shares (both walking and bicycling). Literature suggests a sizable proportion of all public transit trips involve walking at both ends of the trip, and bicycling can also be a potentially important mode of access to public transit (Pucher et al. 2011). The results of the person-level nonmotorized mode share models show that as hypothesized, more transit trips encourage more nonmotorized trips. This finding implies that a travel culture within a household that is more oriented toward transit usage leads to higher levels of nonmotorized travel by individuals living within that household.

The car ownership variable at the neighborhood level exhibits a statistically significant path coefficient with person-level walking mode share. The positive sign of this variable, which represents the percentage of households within the neighborhood that own no cars, indicates a positive direction of influence on the walking mode share by an individual. This means that the higher the percentage of zero-car households within the neighborhood, the higher the walking mode share is for residents of that neighborhood. This result also implies that the influence of car ownership has a potential to go beyond the household level.

Meso-level (County-level) Social Environment Variable Findings

As measures of the social environment at the county level, the variables representing the average walking and bicycling density within the county show significant effects on individuals' nonmotorized travel behavior. The path coefficients of these variables exhibit a significant positive direction of influence on walking and bicycling mode shares of individuals.

These variables are intended to operationalize two important behavioral concepts: the concept of observational learning—defined within the social cognitive theory—and the concept of contagion perspective—defined by Ross (2000). Both of these concepts postulate that human behavior can be influenced by seeing others perform a certain behavior. In that sense, the average walking and bicycling density variables are considered proxies for social norms and sociocultural values with respect to nonmotorized travel behavior.

Thus, the results imply that walking and bicycling are influenced by "cultural effects" within the county of residence. The results confirm past findings of a positive correlation between individuals' level of nonmotorized travel and higher densities of nonmotorized trips within an area (Mitra and builing 2012), as well as a positive association between walking and perceptions of others being physically active (e.g., walking, bicycling, playing sports) (Nehme et al. 2016).

Macro-level (Metropolitan Area-level) Social Environment Variables Findings

Based on the model results, many metropolitan area-level social environment variables (i.e., variables representing sociodemographic, socioeconomic, sociocultural and crime factors) are influential in an individual's nonmotorized travel (i.e., walking and bicycling mode shares). The effects of macro-level social environment factors on nonmotorized travel behavior of individuals are discussed for three different features of the social environment in a metropolitan area including:

1) Sociodemographic and Socioeconomic Variables Effects: The results indicate that as the average median age within the metropolitan area increases, the person-level nonmotorized mode share declines. Although the effect is not significant in the walking model, the negative direction of influence is in line with the path coefficient estimate for the *Age* variable at the individual level (i.e., -0.0676293). These results further emphasize the role that age plays in physical activity such as walking and bicycling.

As expected, the metropolitan area-level car ownership variable (i.e., average percentage of households within the metropolitan area that own more than two cars) is negatively linked with walking and bicycling mode share of individuals. Also, the metropolitan area-level income variable (i.e., the *Average Percentage of Low-Wage Workers* variable) exhibits a significant positive effect in the person-level walking mode share model, indicating that lower income levels within the metropolitan area are linked with higher walking mode share by residents.

Also, as hypothesized, the average gasoline price affects nonmotorized travel behavior in a positive direction meaning as the gasoline price increases within the state where the metropolitan area is located, person-level walking and bicycling mode shares for residents of that metropolitan area increase. It should be noted that past research found a negative link between increased gasoline price and household-level Vehicle Miles Traveled (VMT) (see e.g., Nasri and Zhang

2014). The finding of the present study that higher fuel costs promote the nonmotorized mode share compliments such past empirical findings in suggesting that the cost of gasoline can act as a disincentive in motorized travel, whereas it can be considered an incentive for nonmotorized travel. On the other hand, this finding is also in line with the literature suggesting that the low user-cost of using private vehicle is crucial in discouraging other modes such as walking (Pucher et al. 1999).

The path coefficient of the *Average State Gasoline Cost* variable is larger in the bicycling model (2.564236) than in the walking model (1.112083), which implies that higher gasoline prices may lead to generation of more bicycling trips than walking trips. One possible explanation for this can be the effect of trip distance. Longer distances can be traveled by bicycling compared to walking; therefore, individuals may substitute more vehicular trips with bicycle trips if they deem gasoline costs as high. However, further research is needed in this area to examine any substitution effects of gasoline prices on bicycling trips for vehicular trips considering travel distances.

2) Social Norms and Sociocultural Variables Effects: Reinforcing the model estimations at the county-level, the path coefficient of the *Average Walking Density* variable at the metropolitan level implies a positive effect of social norms and sociocultural factors on individual's walking. Also, higher percentages of foreign-born population living within the metropolitan area seem to positively influence individuals' walking mode share. This finding is supported by McMillan (2003) who found that the likelihood of children walking and bicycling to school decreased if they had a parent born in the U.S., as well as by McDonald (2005) who found that neighborhoods with higher percentages of immigrants had higher levels of walking to school by children.

These results provide further support for the influence of cultural norms—in this case, the cultural norms of the country of origin—on nonmotorized travel behavior. The differences between the social norms and travel cultures in the U.S. (which has an automobile-dominated travel culture) and other countries have been discussed in previous studies (see e.g., Pucher et al. 1999; McMillan 2003; McMillan 2005; Giles-Corti et al. 2009). These cultural differences seem to exert a statistically significant effect on individuals' walking mode share, as suggested by the model estimates in the present analysis.

Further, the variable measuring the annual public transportation passenger-miles within a metropolitan area has a statistically significant path coefficient in both the walking and bicycling mode share models. The observed positive influence suggests that as transit use within a metropolitan area increases, so does the person-level nonmotorized trip mode share for residents.

In the present study, this variable is considered as a proxy for a "public transportation culture" within the metropolitan area. Therefore, this result implies that metropolitan areas with a travel culture that is more oriented toward public transportation promote nonmotorized trips.

3) Crime-related Effects: The variable representing the average metropolitan area-level violent crime rate does not reach a statistical significance threshold in the Florida person-level nonmotorized travel behavior models. Previous studies argued that crime rates may play a role in walking or bicycling (see e.g., Joh et al. 2009). However, the results of the present case study suggest that any impact that crime levels within the metropolitan area may have on nonmotorized travel behavior diminishes after the effects of other metropolitan area-level factors (e.g., socioeconomic, demographic, sociocultural factors) are controlled for. This result is in line with empirical findings by Nehme et al. (2016) who found that walking behavior and the number of violent crimes within the neighborhood were not significantly associated.

Cumulatively, these findings lend more credibility to the argument that social environment at multiple levels of influence (i.e., micro, meso, and macro levels) plays a key role in nonmotorized travel behavior.

Micro-level (i.e., Neighborhood-level) Built Environment Variables Findings

Consistent with the results of the household-level models developed in this study as well as many past studies (see Chapter 2 and Appendix B), the results of the Florida person-level models suggest that neighborhood-level built environment attributes impact nonmotorized travel behavior.

Particularly, the results indicate that neighborhoods with higher activity (i.e., residential and employment) densities, a higher extent of land use mix (entropy), higher densities of pedestrian-friendly street networks, and higher frequencies of local transit service are linked with higher walking mode shares for residents. Also, neighborhoods with a higher extent of land use mix, higher levels of street connectivity (higher intersection density), and denser pedestrian-oriented network designs are linked with higher bicycling mode share for residents.

Meso-level (County-level) Built Environment Variables Findings

The models' estimations suggest that built environment characteristics at the county level also influence nonmotorized travel behavior. Specifically, higher activity density and more pedestrian-friendly network designs at the county level are related to higher person-level walking mode share, whereas higher levels of accessibility to employment by mean of automobile are related to lower walking mode shares. These results are consistent with the results of the household-level nonmotorized travel behavior models (see Table 7).

On the other hand, higher county-level activity density negatively affects bicycling mode share. This result is consistent with that of the household-level models[35] and further lends support to the hypothesis that built environment characteristics can impact walking and bicycling travel behavior in different directions. Further, higher county-level regional diversity as well as higher levels of accessibility to employment by mean of automobile within the county lead to a lower

[35] This applies to both the Florida and Baltimore-D.C. case studies, the latter of which is presented in Appendix C.

person-level bicycling mode share, whereas higher pedestrian friendliness and connectivity of the county street network promote the bicycling mode share for individuals. These results are also consistent with the results of the household-level models (see Table 7).

The path coefficient of the county-level *Mean Entropy* variable shows insignificant effects in both the Florida person-level walking and bicycling models. This variable exhibited significant correlations with walking and bicycling in the Florida household-level models as well as the Baltimore-D.C. case study (see Appendix C); however, those correlations fluctuated in directions. Therefore, it can be inferred that the role of county-level mixed-use development in nonmotorized travel behavior stays unclear and requires further examination.

Macro-level (Metropolitan Area-level) Built Environment Variables Findings

The results of the person-level mode share models suggest that higher mixed-use development within the entire metropolitan area is related to lower walking mode shares for residents. As previously mentioned, the negative direction of influence can be capturing a substitution effect; residents may be driving to additional and more remote destination options (provided by the higher extent of mixed land use within the metro. area) instead of walking to nearby local destinations.

As hypothesized, higher Walk Scores and higher percentages of small blocks within the metropolitan area affect person-level walking mode share in a positive direction. These results indicate that increased walking mode shares for residents are related to higher walkability, increased destination accessibility by means of walking, and better street connectivity within the metropolitan area.

Moreover, higher transit accessibility to jobs within the entire metropolitan area leads to lower walking and bicycling mode shares. The negative direction of influence can be capturing the effect of driving to transit stations rather than walking or bicycling to stations. The results further indicate that higher automobile accessibility to jobs within the metropolitan area discourages bicycling, which is an expected result.

Also expected is the positive signs of the path coefficients of the *Average Roadway Congestion Index* in the models. This variable represents mobility within the metropolitan areas in this study. Literature suggests that the speed (i.e., extent of mobility) of alternative modes influences travel behavior such as modal choice (Pucher et al. 1999). Therefore, it was hypothesized that increased roadway congestion levels (which indicate lower levels of speed and mobility) lead to increased levels of nonmotorized mode shares. Model estimations confirm that hypothesis and indicate that increased congestion (i.e., decreased mobility) within the metropolitan area positively affects walking and bicycling mode shares of residents. Past empirical research found that increased congestion levels lead to lower household-level VMT (Nasri and Zhang 2014). This lends support to the finding of the present study that lower levels of mobility within a metropolitan area promote nonmotorized travel—perhaps through discouraging vehicular trips.

Random Effects[36]

The variances of the household-level random intercepts are estimated by the walking and bicycling mode share models to be 130.3447 and 7.32847, respectively. Despite being less than the corresponding estimated error variances (317.116 in the walking model and 48.73677 in the bicycling model), the estimated variances are sufficiently large to not be disregarded. These results indicate that after controlling for the various variables in the models (as listed in Table 14), there remains some household-level variance in the model that is unaccounted for. Thus, there appears to be significant variation in averages of the person-level walking/bicycling mode shares across

[36] In the person-level models, the coefficients of the household and neighborhood random intercept variables are constrained to be 1. Such constraints are automatically supplied by the Generalized Structural Equation Modeling (GSEM) mode of the Stata software to identify the latent variables in the model.

households. These results indicate that household-level random effects (i.e., random differences across households) play a significant role in nonmotorized travel behavior of individuals.

However, the variances of the neighborhood-level random intercepts are small and statistically insignificant. Therefore, it can be inferred that neighborhood-level random effects (i.e., random differences between neighborhoods) do not play a crucial role in nonmotorized travel behavior of individuals. This finding stands in contrast to the results of the household-level models, which suggested that random differences between neighborhoods played a small but statistically significant role in nonmotorized travel behavior. One possible explanation can be that the statistical significance of the neighborhood random effects as estimated by the household-level models in fact captured the household-level random effects, which were not accounted for in those models. Thus, it could be the case that once household-level random effects are controlled for, the neighborhood-level random effects become statistically insignificant. Further research is probably needed to clarify the role of neighborhood random effects in nonmotorized travel behavior. Nonetheless, the present results emphasize the key role that the household—as the first and the most influential social environment setting—plays in nonmotorized behavior of individuals.

The Self-selection Effect

As the model path diagram shows (Figure 7), the latent variable *UFRL* was created to represent the overall urban form of the residential location of the individual trip-makers. This latent variable is measured from four observed land use and built environment variables at the neighborhood level through Equations 27 – 30. It is hypothesized that the *UFRL* latent variable is influenced by households' social environment characteristics (i.e., SE_{HH} variables). Together, Equations 25 along with Equations 27 – 30 represent the MIMIC model specified to examine the self-selection effect in Florida person-level nonmotorized travel behavior models.

Table 15 presents estimation results of the measurement model for the *UFRL* latent variable (i.e., results of Equations 27 – 30) as well as those of the related structural model, which is assumed to quantify the self-selection effect (Equation 25)[37]. In measurement models with a MIMIC factor (i.e., latent variable), some observed indicators are specified as effects of the latent variable, whereas other indicators are specified as causes of the latent variable (see Kline 2006).

Accordingly, the built environment variables in the measurement model (i.e., the AD_{CBG}, EN_{CBG}, PF_{CBG}, ID_{CBG} variables) were specified as the effects of the *Urban Form of Residential Location* (*UFRL*) latent variable, while the household-level social environment variables (i.e., number of members, number of workers, vehicle ownership, annual income, level of transit usage, and level of nonmotorized travel) were specified as the cause of *UFRL*. Thus, the results of the model are interpreted in such way to reflect these cause-effect considerations.

Table 15. Self-selection Effects: Florida Person-level Nonmotorized Travel Models

To (Variable)	From (Variable)	Pattern Coefficient	p-value
Measurement Model: Latent Variable - Urban Form Residential Location (UFRL)			
AD_{CBG} (neighborhood-level activity density)	UFRL	1 (constrained)	—
EN_{CBG} (neighborhood-level entropy score)	UFRL	.0189522***	0.000
PF_{CBG} (neighborhood-level ped-friendly network density)	UFRL	1.473815***	0.000
ID_{CBG} (neighborhood-level intersection density)	UFRL	.0739489***	0.000
Structural Model: Self-selection Effect			
UFRL	Number of members (household size)	-.033423NS	0.475
UFRL	Number of household vehicles	-.7028294***	0.000
UFRL	Number of household workers	.3229689***	0.000
UFRL	Annual income of the household	-.0250406***	0.008
UFRL	Number of daily transit trips	.6475415**	0.011
UFRL	Number of daily nonmotorized trips	.0899426***	0.001

NOTES:

*, **, *** = Path coefficient is significant at the 10%, 5% and 1% significance level, respectively; NS = Not significant.

[37] Owing to utilization of the same data and same variables, the estimation results of the measurement model for the *UFRL* latent variable and the structural model that captures the self-selection effect are almost identical in the walking and bicycling mode share models.

The direction of the hypothesized causal effects from household social environment variables to the *UFRL* latent variable (which is itself measured from the built environment variables) represents the residential self-selection behavior (see Wang 2013). The results of the self-selection effect analysis (Table 15) show that household social environment characteristics—often termed households' taste in transportation research—influence households' residential location choice. Most notably, the exogenous variables representing household's number of daily transit and nonmotorized trips exhibit positive effects on the *UFRL* latent variable. The positive direction of the effects implies that households with more transit and nonmotorized trips choose to live in more walkable and bikeable urban neighborhoods, which often also foster transit use.

Despite not being able to make direct inferences about the influence of individuals' travel attitudes and preferences on their residential locations (due to the unavailability of attitudinal survey data in this study), it can be inferred from the SEM estimations that households' travel culture impacts their residential location choice. The results confirm that households with a travel culture that is more oriented toward nonmotorized and transit trips self-select into residential locations that facilitate their travel culture (which most likely represents their travel attitudes and preferences).

In addition, the exogenous household-level socioeconomic variables show statistically significant effects on households' residential location choice. The variables representing the number of vehicles owned by the household and the household's annual income have negative effects on the *UFRL* latent variable, suggesting that households with more private vehicles and higher annual income levels choose to reside in suburban neighborhoods where they can enjoy cleaner air, ample parking space, larger homes, as well as less congested and noisy streets. These results confirm an argument by Wang (2013) who suggested that individuals with a higher household income may be willing to live in low-density suburban neighborhoods. In contrast, the variable representing the number of household workers exerts a positive effect on *UFRL* latent variable. This implies that households with more employed members tend to locate closer to dense urban neighborhoods where higher levels of mixed-use development provide better access to more destinations including employment centers.

With respect to the measurement model estimations, one should be mindful that due to *UFRL* being a latent variable, it requires a normalization constraint because latent variables do not have natural scales (StataCorp 2013)[38]; thus, by SEM conventions, the pattern coefficient of the activity density variable in the *UFRL* measurement model (i.e., the AD_{CBG} variable) is constrained to be equal to 1. This scale is related to that of the explained variance of the AD_{CBG} variable, and the constrained coefficient makes this variable the reference variable for the latent variable *UFRL* (see Kline 2006). All other variables from which the *UFRL* latent variable is measured show statistically significant pattern coefficients with positive signs. This means that urban neighborhoods are neighborhoods that are more compact with higher levels of mixed-use development, increased density of pedestrian-friendly network, and better street connectivity.

These results are in line with how literature characterizes an urban neighborhood (see Chapter 2), particularly with the definition of "urban neighborhood" as provided by Wang (2013). The referenced study considered an urban neighborhood a neighborhood with high density, high mixed land use, high intersection density (i.e., better street connectivity) as opposed to a low-density, residential-only suburban neighborhood with not much street connectivity (see Wang 2013).

[38] See Stata Structural Equation Modeling Reference Manual Release 13, Page 58 "Identification 2: Normalization constraints (anchoring)".

The direction of effects of household characteristics including car ownership, number of workers, and number of transit trips on residential location choice (i.e., *UFRL* variable) and the direction of the pattern coefficients in the measurement model of *UFRL* from the neighborhood built environment variables corroborate findings by past research (Nasri and Zhang 2014). This consistency in findings lends a degree of confidence to the results obtained in the present study.

Coefficients can be interpreted using standard linear regression interpretations. Theoretically, since variables used in this analysis have different scales, standardized coefficients can be used to compare the magnitude of the coefficients. It should be noted, however, that due to the limitations of the Generalized Structural Equation Modeling (GSEM) techniques, which perform the multilevel SEM analyses in Stata, standardized path coefficients cannot be computed for the models developed. As a result, direct comparison of path coefficients in terms of magnitude is not possible. Thus, it cannot be concluded from the results obtained which variable exerts the largest effect on nonmotorized travel mode share or on the residential location choice.

4.2 Chapter Conclusions

The main hypothesis of this chapter was that nonmotorized travel behavior has become more dependent on environmental factors from larger-scale spatial areas. Thus, the present study considered the role of county-level (i.e., meso-level) and metropolitan area-level (i.e., macro-level) built and social environment factors in nonmotorized travel behavior.

More specifically, the main purpose of this chapter was twofold: 1) to examine the role of larger-scale (i.e., county-level and metropolitan area-level) environmental factors in nonmotorized travel behavior; and 2) to investigate the role of self-selection in nonmotorized travel behavior as well as the causal links between nonmotorized travel and the environment within a comprehensive model framework that incorporates factors from various spatial scales of geography.

It is imperative for any research into human behavior to consider psychological theories of behavior. Thus, the principles of the ecological model—a variant of the social cognitive theory (Bandura 1986)—were employed to develop the conceptual framework for this study. Due to travel behavior being affected by opportunities and constraints at multiple levels, the ecological model framework, which includes factors representing multiple levels of influence on behavior, can be considered a suitable theoretical framework for analysis of nonmotorized travel behavior.

Advanced statistical methods such as mixed-effects modeling and multilevel SEM techniques were utilized to estimate models capturing the link between nonmotorized travel behavior and built as well as social environment factors at multiple levels (i.e., micro, meso, and macro levels) of influence. The analysis was conducted using two units of analysis: the household and the individual. Data from several metropolitan areas in the state of Florida as well as in Washington, D.C. and Baltimore, Maryland were used in the analysis[39].

Considering that the study utilized datasets, which are either available from most MPOs (e.g., household travel surveys, land use data, and skimming OD matrices) or are publicly available (e.g., SLD, Walk Score, U.S. Census Bureau's TIGER/Line data, ACS), similar models can also be developed for other metropolitan areas using the approach proposed in this study.

In practice, more effective operational models can be developed by incorporating the proposed approach (i.e., consideration of hierarchical levels of environmental influence within an ecological model framework) to capture nonmotorized travel patterns and demand in U.S. cities, and to develop policies as well as planning and design processes accordingly.

The chapter conclusions are discussed next in terms of research findings and policy implications as well as research contributions and limitations.

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[39] As mentioned previously, due to similarities in the analysis of the two case studies, the Baltimore-Washington, D.C. case study analysis and model results are presented in Appendix C.

4.2.1 Research Findings

Findings in this chapter reveal that nonmotorized travel behavior of individuals can be influenced not just by the character of their neighborhood but also by the spatial structure and the context of the county or metropolitan area which their neighborhood is a part of. In other words, the research findings provide evidence that in analyzing walking and bicycling trips, going beyond the neighborhood boundaries is okay! and may even be essential.

The main conclusions reached, and the knowledge obtained from this research can be presented as follows:

On Correlations: Nonmotorized travel behavior is correlated with built and social environment factors at multiple spatial levels

From results of the household-level nonmotorized travel behavior models, it can be inferred that nonmotorized trips are correlated with built and social environment attributes at multiple levels of influence.

Among neighborhood-level (i.e., micro-level) built environment attributes, nonmotorized trips are associated with the extent of: compactness, mixed-use development, pedestrian- and bicyclist-friendliness of the street network, connectivity of the street network, and access to public transit within the neighborhood. Neighborhood mixed-use development and the pedestrian friendliness of the street network show the highest elasticities with respect to nonmotorized trips.

Walking or bicycling trips are also correlated with measures of the built environment at the county level (meso level) including the extent of: compactness, mixed-use development, connectivity and pedestrian friendliness of the street network, access to public transit, automobile as well as transit accessibility to employment opportunities within the county. County-level mixed-use development has the highest elasticity with respect to walking, whereas pedestrian friendliness of county street network has the highest elasticity with respect to bicycling.

Macro-level built environment attributes associated with nonmotorized trips—particularly walking trips—include distance to the CBD, road network density, and the extent of: regional accessibility to highways and transit, mixed-use development, connectivity and pedestrian friendliness of the street network, and transit accessibility to employment opportunities within the metropolitan area. Among macro-level built environment factors, the highest elasticities with respect to walking belongs to the variables measuring the connectivity and pedestrian friendliness of the street network as well as those measuring the extent of mixed-use development.

These findings highlight the roles of pedestrian-friendly designs and land use diversity within the county as well as the entire metropolitan area in nonmotorized travel of residents.

The social environment attributes associated with walking and bicycling are household-level (i.e., micro-level) characteristics such as size, number of students, number of workers, vehicle as well as bicycle ownership status, and level of income. In addition, vehicle ownership levels within the neighborhood (i.e., meso level) as well as vehicle ownership and income levels within the metropolitan area (i.e., macro level) are also associated with nonmotorized trips.

Also, based on the elasticity analysis, it is concluded that at various levels of influence, the most important social environment factor determining the extent of household nonmotorized travel—particularly bicycling—is vehicle ownership. This suggests that the role of vehicle ownership in nonmotorized travel behavior may be far more critical and complex than previously considered. The highest elasticities in the Florida household-level bicycling model are exhibited by the metropolitan area-level car ownership and income variables. These findings also emphasize the key role that macro-level (i.e., metropolitan area-level) social environment plays in bicycling trips. This role should not be overlooked in examining bicycling travel behavior.

Overall, findings of the analyses presented in this chapter support the research hypothesis of this dissertation that the residential location's built and social environment characteristics at multiple levels (i.e., micro, meso, and macro levels) are correlated with nonmotorized travel behavior (see Hypothesis 1a in Table 1).

These findings accentuate the importance of examining the relationship between nonmotorized travel behavior and environmental factors within an ecological model framework, which allows assessing the role of multiple levels of the built as well as social environment on observed behavior (e.g., nonmotorized travel behavior).

On Causality: Causal links may exist between nonmotorized travel behavior and built as well as social environment factors at multiple spatial levels

By definition, the direction of arrows in a SEM path diagram represents the effect priority as hypothesized in the theory for which the model is specified. Thus, the employment of multilevel SEM techniques in the person-level nonmotorized travel behavior models was assumed to allow for testing the causality of correlations observed between nonmotorized travel behavior and the environmental factors. Considering the results of the models, it can be concluded that causality may play a role in the links between individuals' nonmotorized travel behavior and the built (as well as social) environment attributes—at multiple levels of influence—of their place of residence.

The findings imply that within this sample, causal links exist between individuals' nonmotorized trip mode share and the extent of: compactness, mixed-use development, pedestrian friendliness and connectivity of the street network, and access to public transit service within the neighborhood (i.e., micro level).

Further, the effect of a few of these factors spills over the neighborhood boundaries, as hypothesized in this research. Nonmotorized travel behavior is linked with a few meso-level (i.e., county-level) built environment attributes including the extent of: compactness, regional diversity, connectivity and pedestrian friendliness of the street network, and automobile accessibility to employment opportunities within the county. The macro-level built environment attributes with potential causal relations with nonmotorized travel behaver include the extent of: mixed-use development, connectivity of the street network, pedestrian friendliness and walkability of the streets, roadway congestion (i.e., proxy for mobility levels), and automobile as well as transit accessibility to employment opportunities within the metropolitan area.

Nonetheless, considering the study findings, it can be concluded that the stimulating effect of mixed-use development on nonmotorized travel, which exists at lower spatial scales such as the neighborhood, diminishes at higher spatial scales. One explanation can be that more land use diversity within metropolitan areas may encourage residents to make more vehicular trips to various, more remote destinations rather than using nonmotorized modes to visit local destinations. Therefore, an optimal threshold may exist for cities to become mixed in terms of land use to promote nonmotorized travel.

The findings also indicate that contextual effects—such as those of the social environment (i.e., the interpersonal level of ecological influence) at multiple levels (i.e., micro, meso, macro levels)—play a role in people's nonmotorized travel behavior.

Micro-level social environment attributes such as households' level of vehicle ownership, annual income, and daily transit trips influence individuals' nonmotorized travel. Vehicle ownership levels within the neighborhood also have an impact, particularly on walking trips. The findings provide additional support for concluding that the impact of vehicle ownership and income levels go beyond the household and neighborhood boundaries as these factors measured at the macro level (i.e., metropolitan area level) are also influential in nonmotorized travel behavior. Other macro-level sociodemographic and socioeconomic attributes such as the median age and the gasoline price within the metropolitan area also impact nonmotorized travel behavior.

Furthermore, based on the findings, important conclusions can also be drawn regarding the role of sociocultural factors at various levels of influence in nonmotorized travel behavior. As representatives of the social environment, sociocultural factors such as the travel culture within the household, county, or metropolitan area of residence also prove influential in individuals' walking and bicycling activities.

At the micro level, the extent of household's daily transit trips is linked with nonmotorized travel behavior. This is perhaps capturing the positive influence of the "transit travel culture" within a household on walking/bicycling trips of household members. Further, the densities of nonmotorized trips within the county (i.e., the meso level) and the metropolitan area (i.e., the macro level) are linked with nonmotorized travel behavior. Moreover, the annual public transportation passenger-miles—considered a proxy for a "public transportation travel culture" within the metropolitan area in this study—is also influential in levels of nonmotorized travel. The percentage of foreign-born population living within the metropolitan area (i.e., macro level) also affects individuals' walking behavior, which can be capturing the influence of the cultural norms of the country of origin on nonmotorized travel behavior.

Therefore, it can be concluded that nonmotorized travel behavior is influenced by "sociocultural effects". These include social norms concerning nonmotorized travel and public transit that exist within the household as well as the area of residence at multiple spatial levels.

On a related note, the impact of household-level random effects proved to be significant in the models, emphasizing the importance of households' tastes in individuals' nonmotorized travel behavior. This conclusion is supported by the literature suggesting that the most important setting within the individual's social environment is the household (Gochman 1997; Handy 2005; National Research Council 2005; Van Acker et al. 2010).

Overall, these findings support the hypotheses of this study that in addition to the built and social environment of the neighborhood (i.e., micro level), built (and social) environment at the meso and macro levels also play a causal role in shaping individuals' nonmotorized travel behavior (see Hypotheses 1a and 3 in Table 1). Considering the hierarchical nature of these levels of influence, the importance of using an ecological model framework in examining the link between nonmotorized travel and the environment is, therefore, re-emphasized through these findings.

Further, the findings reveal that the relationship between the residential location's built environment and nonmotorized travel behavior may be a causal one. In other words, the effects of the built environment on nonmotorized travel go beyond the neighborhood boundaries (as they are significant at higher spatial levels), and the links between the two go beyond mere correlations (as they imply causality—at least in this sample). It should be borne in mind that although the results of the person-level nonmotorized travel behavior imply existence of casual links between the built environment and nonmotorized travel, evidence for existence of the causality is only supported by the results estimated for the sample examined in this research. Thus, caution should be exercised with generalizing the results and implying "proof of causality" based on findings. As Kline (2011) argues, it is impractical for a single study to meet all the conditions required for inference of causality; therefore, it is more appropriate to regard structural models as seemingly causal models with a potential to correspond to the real-world causal processes (Kline 2011).

On Self-selection: Residential self-selection plays a decisive role

Nonmotorized travel behavior literature is increasingly emphasizing on the role of residential self-selection in walking and bicycling. This is because nonmotorized travel behavior, car ownership, and residential location choice are integrally linked (Salon 2006), which introduces the self-selection bias in the analysis. As understanding the role of self-selection is the key to understanding the causal links between the built environment and travel behavior (Handy et al. 2005), the frameworks of the person-level nonmotorized travel behavior models developed in this chapter were designed to address the residential self-selection bias (i.e., endogeneity bias) in the analysis.

The self-selection effect can be best accounted for by using attitudinal survey data, which provide information on respondents' attitudes and preferences toward travel. Absent attitudinal survey data, however, the advanced capabilities of structural equation modeling techniques can be employed for analyzing the link between nonmotorized travel and the built environment, while controlling for residential self-selection bias. Due to lack of attitudinal data, self-selection was addressed in this analysis by using the latter methodology (i.e., SEM).

The results show that self-selection of individuals is shaped by household social environment attributes—often termed household's taste in transportation research. These attributes were defined in the present study based on household's socioeconomic attributes as well as attributes representative of households' travel culture. Further, the findings indicate that individuals' self-selection influences their choice of residential location. More specifically, the findings suggest that households with a travel culture more oriented toward nonmotorized and transit trips self-select into neighborhoods that facilitate their travel culture (which probably represents their attitudes and preferences toward travel). Based on these findings, it can be inferred that both the built environment and self-selection influence nonmotorized travel behavior, as suggested by several past studies (see Chapter 2 and Appendix B). These findings provide support for the hypotheses of this dissertation that self-selection plays a role in nonmotorized travel behavior and the link between nonmotorized travel behavior and the built environment is a causal one (see Hypotheses 2 and 3 in Table 1). In drawing conclusions with regards to causality and self-selection, however, one should be mindful of two caveats in this analysis: 1) the use of cross-sectional data (which limits the ability to make causal inferences); and 2) the unavailability of attitudinal survey data (which limits the ability to make inferences about self-selection).

The alternative to using cross-sectional data is to collect and use longitudinal data—an effort that poses challenges in terms of cost and resources. This is probably the reason for SEM studies often featuring concurrent rather than longitudinal measurement (Kline 2011).

Nevertheless, it is assumed that the capabilities offered by the multilevel SEM techniques combined with the comprehensive ecological framework of the person-level nonmotorized travel behavior models allowed for adequate examination of the causal links between nonmotorized travel behavior and the built environment as well as controlling for self-selection bias. Thus, it is concluded that the successful estimation of the multilevel SEM models in this study, which controlled for self-selection effects, have yielded policy-relevant findings.

4.2.2 Policy Implications

Analyses presented in this chapter of the dissertation provide a useful and systematic approach for researchers and policy analysts to determine the most effective interventions for promoting walking and bicycling trips. The ecological models developed in this study highlight the role of the built environment—at various spatial levels—in nonmotorized travel behavior. As a key strength of the ecological model of behavior, this focus on multiple hierarchical levels of influence broadens options for interventions (Sallis et al. 2008).

To infer policy conclusions and develop suitable interventions, the effect of each level of influence can be considered separately or in combination with the effects of other levels as estimated in the analysis. As regards the built environment, findings from the present study provide compelling evidence that modifications to the *D*s of the built environment at multiple spatial levels can influence nonmotorized travel behavior. These findings imply that policies concentrating on interventions that target the built environment within the neighborhood (i.e., micro level), the county (i.e., meso level), and the metropolitan area (i.e., macro level) to make them more supportive of nonmotorized and transit trips can promote walking and/or bicycling by residents.

At the neighborhood (i.e., micro) level, such interventions include changes to the built environment within the neighborhood that:

- increase compactness (i.e., density in terms of activities);
- increase mixed-use development (i.e., land use diversity);
- increase walkability and bikeability (i.e., destination accessibility);
- increase pedestrian friendliness of the street network (i.e., design);
- increase connectivity of the street network (i.e., design); and
- increase access to transit facilities and services (e.g., shorter distance to transit stations, more frequency of service).

At the county (i.e., meso) level, key interventions to promote walking and/or bicycling include changes to the built environment within the county that:

- increase compactness (i.e., density in terms of activities) in areas with existing low residential and employment densities—to promote walking trips;
- increase pedestrian friendliness of the street network (i.e., design); and
- improve connectivity of the street network (i.e., design).

Further, a salient finding of this study is that the built environment characteristics of the metropolitan area (i.e., macro level) influence nonmotorized travel behavior of residents. Therefore, these characteristics should also be considered in decisions regarding policy and intervention development. With this respect, findings suggest that walking and bicycling can be promoted through interventions to modify the built environment within the entire metropolitan area in such ways that:

- improve connectivity of the street network (i.e., design);
- increase walkability (i.e., destination accessibility);
- facilitate accessibility to transit by means of nonmotorized modes, particularly by walking (e.g., shorter distance to transit stations); and
- build residential or other activity locations closer to the core activity center of the city (i.e., CBD). This is, basically, moving away from decentralization of urban areas—a development pattern which is associated with longer travel times and discouragement of nonmotorized modes of travel.

According to the study findings, the social environment characteristics within the residential area are also influential in promoting nonmotorized trips. More specifically, the findings provide evidence that walking and bicycling trips are influenced by factors representing the socioeconomic status and sociocultural values—particularly with respect to travel culture—within the county and/or metropolitan area. Thus, interventions targeting these characteristics can also be considered in policy decisions.

Based on the study findings, stimulating walking and bicycling trips through changes to the social environment within the area of residence include interventions that:

- encourage more use of nonmotorized modes of travel through observational learning (i.e., seeing others engage in walking and bicycling activities);
- encourage more use of public transportation modes;
- discourage automobile ownership; and
- discourage the use of the automobile mode through increasing gasoline costs.

Overall, evidence found in this study supports the idea that nonmotorized trips can be promoted through interventions that target the environment, built and social.

Findings imply that a built environment inimical to nonmotorized modes of travel can discourage walking and bicycling trips, whereas an amenable one can foster these trips. To promote nonmotorized modes of travel, therefore, policies and interventions that can make the built environment more supportive of walking and bicycling activities should be pursued, while policies encouraging sprawling urban developments and automobile-oriented urban designs should be avoided.

In terms of the social environment, the study findings imply that communities with travel cultures more oriented toward nonmotorized and public transportation modes foster walking and bicycling trips. Thus, policies and programs that incentivize non-automobile mobility and disincentivize automobile dependency within the society can be developed. This includes policies that can potentially increase the cost of automobile ownership and use. An argument by Pucher et al. (1999) is well-suited here: the low cost of using automobiles in the U.S. (e.g., low gasoline costs) is a key factor in discouraging other modes of travel including the nonmotorized ones, whereas higher costs of automobile use in Europe is a factor that makes car ownership less essential and increases the tendency to use nonmotorized modes (Pucher et al. 1999).

The analysis framework and findings of the present study can assist policy decision-makers aiming to increase levels of walking and bicycling within their communities in assessment of interventions that involve changes to the built and/or social environment. Yet, the main point of the study findings must be re-emphasized: more effective policies to promote walking and/or bicycling seem to be the ones that consider the overall form of the metropolitan area in addition to that of the county and the neighborhood of residence. Put differently, to promote nonmotorized trips, interventions to modify the built environment should be considered not just within the neighborhood but also in combination with those within the county as well as throughout the whole metropolitan area. In addition, interventions targeting the built environment should be considered in combination with those targeting social environment and not in isolation.

This provides a seamless and integrated policy framework, which can help urban/transportation planning professionals and decision-makers to find more potent intervention strategies to create urban environments that are more amenable to walking and bicycling. Policies developed based on such a comprehensive framework can yield the most efficient use of resources and the most optimized solutions.

4.2.3 Contributions

This chapter contributes to the body of knowledge on the role of the environment (i.e., built and social environments) in nonmotorized travel behavior in terms of theoretical framework as well as methods, empirical evidence, and policy implications.

With respect to theoretical contributions, this research derives a comprehensive theoretical framework from the principles of the ecological model of behavior to systematically examine the link between nonmotorized travel behavior and built environment factors. Up to the present, the research probing this link has been focused on the micro-level (i.e., neighborhood-level) built environment. This study hypothesizes that built and social environment factors at larger scales may also be influential in nonmotorized travel behavior due to the complex interrelations between environmental factors and travel behavior. The integrated theoretical framework derived in this study allows for simultaneous examination of the influence of environmental attributes at various levels on nonmotorized travel behavior within an ecological framework.

The hierarchical levels included in the theoretical framework of this study for the built environment are: the micro level (i.e., the neighborhood), the meso level (i.e., the county), and the macro level (i.e., the metropolitan area). The hierarchical levels for the social environment are: the micro level (i.e., the household or the neighborhood), the meso level (i.e., the neighborhood or the county), and the macro level (i.e., the metropolitan area).

To the best of the author's knowledge, this research is one of the first to move beyond the neighborhood by including several measures of macro-level (i.e., metropolitan area-level) built and social environments in addition to those of the meso level (i.e., county level) and the micro level (i.e., neighborhood level) within an integrated theoretical framework in analysis of walking and bicycling trips. Such research framework advances the body of knowledge on nonmotorized travel behavior by assisting researchers and policymakers in determining the role of the overall context and structure of metropolitan areas in walking and bicycling activities of residents.

Macro-level built environment characteristics have rarely been tested for their link with nonmotorized travel behavior. Thus, the main contribution of this chapter is looking at the bigger picture—the position of the neighborhood with respect to the region and the metropolitan area it is located in—when analyzing nonmotorized travel behavior. The knowledge developed from this study can be integrated with past research that focused on the impact of micro-level (i.e., neighborhood-level) built environment on walking and bicycling to provide a more comprehensive understanding of how the environment (i.e., built and social) influences nonmotorized travel behavior, especially in large metropolitan areas.

Further, the conceptual framework of the person-level nonmotorized travel behavior developed in this chapter allows for controlling for residential self-selection bias (i.e., endogeneity bias) in the analysis. In terms of the relationship between the built environment and activities such as walking and bicycling, literature suggests that a more comprehensive conceptual model that accounts for the possibility of endogeneity bias is needed since the observed link between the built environment and physical activity (e.g., walking and bicycling) may be an outcome of residential location choices (Handy 2005). The body of knowledge on nonmotorized travel behavior is furthered on the role of self-selection and causality in nonmotorized trips by the comprehensive framework of the person-level nonmotorized travel behavior models developed in this study, which allow for addressing self-selection bias, while incorporating various hierarchical levels (i.e., micro, meso, macro) of built environmental influence.

In terms of the methodology, this study contributes by examining the causality of the links between nonmotorized travel behavior and the built environment as well as by addressing spatial autocorrelation using a more solid methodology. As elaborated in Chapter 2 (and Appendix B), the existing empirical evidence indicates that built environment factors and nonmotorized travel behavior are correlated. However, evidence supporting the causality of this correlation is currently sparse due to few studies controlling for self-selection bias or demonstrating a causal link using reliable methodologies. Further, the clustered structure of the data introduces interdependencies within the data, which can potentially subject the analysis to spatial autocorrelation issues. Self-selection and causality can be controlled for by employing Structural Equation Modeling (SEM) techniques, whereas spatial autocorrelation can be accounted for by employing multilevel (i.e., hierarchical) modeling techniques.

To elucidate these issues empirically within the integrated ecological framework of this research, multilevel modeling techniques should be combined with SEM techniques so that any potential self-selection and spatial autocorrelation issues are addressed and any causal links between nonmotorized travel behavior and the built environment are better understood. Therefore, this study examines the utility of the multilevel Structural Equation Modeling (i.e., multilevel SEM) techniques—rarely applied in a transportation context—to investigate the relationship between nonmotorized travel behavior and environmental factors. Employment of the multilevel SEM techniques to such analysis provides several methodological advantages:

First, the advanced statistical analysis capabilities offered by such techniques conform to the ecological framework of the models. This allows for addressing residential self-selection bias as well as for examining the causal links between nonmotorized travel behavior and the built environment in a more methodologically rigorous manner. Moreover, employment of multilevel SEM can account for any potential spatial autocorrelation issue in the analysis as using hierarchical models can help in statistical treatments of spatial autocorrelation problems, which may exist due to the clustered nature of the data (see e.g., Moudon et al. 2005). In addition, the SEM nature of the multilevel SEM can deal with any potential multicollinearity problems in the models. This is because by examining causal paths through a sequence of correlated variables or by treating highly correlated variables as indictors of a common underlying construct, SEM may deal with collinearity problems (Franke 2010).

Despite having these advanced capabilities and a tremendous potential to be used in travel behavior research, the application of multilevel SEM in a transportation context remains scarce, as also noted previously (see Chung et al. 2004). In fact, only two empirical studies were located by the author that used multilevel SEMs in conducting travel behavior research (Chung et al. 2004; Kim et al. 2004). In proposing a conceptual model for travel behavior, Van Acker et al. (2010) also argued that the complexity of travel behavior can be better understood by employment of multilevel SEM techniques. The referenced study suggested that the capabilities of multilevel SEM can account for various interdependencies within the model including those resulting from numerous relationships (i.e., direct and indirect effects) as well as those resulting from a nested data structure (e.g., individuals nesting within households, and households nesting within neighborhoods) (Van Acker et al. 2010).

However, to the best of the author's knowledge, multilevel SEM techniques have never been applied to empirical data to investigate the link between nonmotorized travel behavior and environmental factors. Thus, the present study contributes to the body of knowledge by employment of multilevel SEMs to test the causal pathways between nonmotorized travel behavior and the built environment and by reintroducing the capabilities of such techniques to the travel behavior field of research.

With respect to empirical contributions, this study systematically tests the link between nonmotorized travel behavior and the built as well as the social environment, using two units of analysis: the individual (i.e., person-level nonmotorized travel behavior models) and the household (i.e., household-level nonmotorized travel behavior models). The findings add to the existing empirical knowledge on the link between nonmotorized travel behavior and the environment by providing insights into the consistency between results from the two different analyses (i.e., person-level model results vs. household-level model results).

Further, the relationship between the built environment and physical activity such as walking and bicycling is often not systematically examined due partly to variables included in the studies not comprehensively capturing the characteristics of the built environment (Lee and Moudon 2004). One example of this can be the absence of factors representing the overall form of the region (i.e., macro-level built environment) in the analysis.

As little empirical knowledge exists on the influence of the environment at larger scales than the neighborhood (i.e., micro level) on nonmotorized travel behavior, this study empirically tested the under-investigated role of macro-level environmental factors in explaining walking and bicycling trips. The study results provide evidence that macro-level environmental factors play a crucial role in residents' nonmotorized travel behavior.

Of particular importance is the model results indicating that nonmotorized travel behavior is influenced by the macro-level (i.e., metropolitan area-level) built environment in addition to the micro-level (i.e., neighborhood-level) built environment. These findings enhance and complement existing empirical knowledge on the role of built environment factors in walking and bicycling, and thereby contribute to the research on the topic of nonmotorized travel behavior.

Moreover, compared with walking, bicycling travel behavior can be considered an under-studied topic as empirical research on nonmotorized travel behavior often focuses on walking trips or combines walking and bicycling trips into one category (see Chapter 2). Nonetheless, past research also suggests that bicycling and walking are distinct activities (see e.g., Porter et al. 1999; Pikora et al. 2003; Schlossberg et al. 2006). Therefore, this study analyzes walking and bicycling trips separately to further elucidate the role of built and social environments on bicycling behavior.

The results provide empirical evidence that built environment characteristics, particularly the extent of compactness (i.e., measured as activity density)—affect walking and bicycling travel behavior differently. This finding is another empirical contribution of this dissertation considering the importance of gaining a deeper understanding about the specific factors that influence bicycling trips and isolating these factors from those that influence walking trips.

Also, the present study follows recommendations of previous research that suggests the use of objectively measured, individually observable measures of the environment—instead of subjective measures or composite indices—to facilitate the interpretation of results for policy and interventions (Moudon et al. 2005; Lee and Moudon 2006). By including objective and independent measures of the built environment, this study contributes to facilitated interpretation of empirical findings to draw more effective policy strategies and interventions that can promote nonmotorized travel.

In terms of contributions to policy and practice, the study findings contribute to the ongoing policy debates concerning the role of the built environment in nonmotorized travel behavior. As this research focuses on the influence of macro-level environment (i.e., built and social environment), the research findings particularly shed light on the most promising policy interventions that can promote walking and bicycling through modifications to the built (and social environment) within metropolitan areas.

Overall, the implications of these findings can provide insights for those who are tasked with making and executing decisions related to improving the equity and affordability of the transportation opportunities within communities. This can assist policy decision-makers as well as urban/transportation planning and engineering professionals who aim at enhancing sustainability and livability of their communities to more appropriately and more efficiently allocate available resources toward that goal.

4.2.4 Study Limitations and Future Research

Analyses presented in this chapter, albeit significant contributions to the research on the link between nonmotorized travel behavior and the built environment, have a few limitations.

Main data-related limitations include the use of cross-sectional data, and lack of useable data on attitudes and perceptions. First, cross-sectional data were used in the analyses, which provide a snapshot of the information at a single point in time. By nature, cross-sectional analyses can capture correlations but do not allow for a full examination of causal relationships.

The employment of Structural Equation Modeling (SEM) techniques—to a degree—allowed for examination of causal links between nonmotorized travel behavior and built environment factors in the present analysis. One should be mindful, however, that although causality is implied by the results obtained from samples analyzed for this research, "proof of causality" for broader, real world processes is not provided by findings of this study. This is—according to Kline (2011)—due to the impracticality of any single study to meet all the conditions required for inference of causality[40]. Therefore, as put by Kline "it is better to view the structural models as being "as if" models of causality that may or may not correspond to causal sequences in the real word" (Kline 2011).

Most importantly, the use of cross-sectional survey data limits the ability to draw inferences about true causal links at work as cross-sectional data do not provide information regarding the temporal precedence of events. For instance, it most likely takes a period of time for changes in the built environment to lead to changes in travel behavior and these effects are not instantaneous. On the other hand, some researchers posit that the relationship between the built environment and travel behavior is bidirectional even though changes in the built environment

[40] Refer to page 98 of Kline (2011) for a list of general conditions that must be met to infer a cause-effect relation.

may not be immediately affected by changes in travel behavior (e.g., nonmotorized travel behavior) (Cao et al. 2009). For these reasons, the use of cross-sectional data often causes researchers and policy decision-makers to interpret research findings cautiously.

In contrast, using longitudinal data allows for examining bidirectional links between the built environment and travel behavior (Cao et al. 2009). By clearly establishing temporal precedence, longitudinal data can enhance the ability to infer causality (Bagley and Mokhtarian 2002). Therefore, future research can benefit from utilization of longitudinal data, which allow for a more intensive investigation of causal relationships and can provide more reliable evidence of the causal links between nonmotorized travel behavior and the built environment.

Second, owing to lack of attitudinal data, the effect of residential self-selection may have not been thoroughly captured in this study. As previously mentioned, the attitudinal data from the Florida 2009 NHTS Add-on Person File were unusable for this analysis due to the large proportions of missing data. In absence of attitudinal data, a sophisticated model framework and advanced statistical methods were used in an attempt to capture self-selection bias. This included application of the latent variable approach within a SEM model structure and defining the self-selection effect as a function of households' social environment (i.e., households' tastes), which can influence residential location choices.

The SEM methodology has been used in previous travel behavior research to control for self-selection bias in analysis of cross-sectional data and in absence of personal attitudinal data (see e.g., He and Zhang 2012; Wang 2013; Nasri and Zhang 2014). However, as residential self-selection is intertwined with attitudes, using attitudinal survey data can undoubtedly improve the analysis, and allow future research to fully control for any potential self-selection bias.

Attitudinal survey data, however, remain rarely available, probably due to two main reasons: 1) collection of such data is costly and time-consuming; and 2) even when questions about attitudes and preferences are included in travel surveys, most respondents skip answering those questions, resulting in large proportions of missing data in such fields (as in the case of the Florida 2009 NHTS Add-on data).

Further, due to data limitations and the scope of this research, several other built and social environment factors (at various levels of influence) that potentially impact walking and bicycling were not included in the models. Among such factors are: extent of toll roads and amount of toll fees as well as parking availability and fees (which can affect nonmotorized trips in CBD areas).

In addition, although this study controlled for the influence of built and social environments on nonmotorized travel behavior, it did not address an equally important aspect of the environment, which can potentially impact walking and bicycling—the natural environment. Weather and climate, topography, and extent of vegetation—all may influence the decision to walk or bicycle and the levels of such activities. Future research can extend the scope of the study by including such potentially contributing factors to gain a deeper and more comprehensive understanding of the impact of the environment on nonmotorized travel behavior.

Moreover, although policy has been identified as one of the key levels of influence on human behavior based on the core concept of the ecological model (see Sallis et al. 2008), due to lack of data on policy measures, a policy level was not included in the person-level ecological models developed in this dissertation. Future research can examine the effects of policy (e.g., parking, housing, bicycling policies) on nonmotorized travel in an integrated model framework with multiple levels of influence such as the one proposed and tested in the present study.

Additionally, although the ecological model of behavior was considered as a comprehensive and integrated framework for modeling nonmotorized travel behavior in this study, literature suggests that borrowing insights on the discrete choices that underlie behavior from the utility-maximizing framework may enhance the analysis by consideration of different conceptualizations of behavior (Handy 2005). Therefore, a research framework that conceptualizes nonmotorized travel behavior by combining principles of the ecological model and those of the utility-maximization demand theory may enhance the analysis and provide a better understanding of mechanisms that influence nonmotorized travel behavior.

Also, utilitarian and recreational nonmotorized trips were analyzed together in this research and not separately. However, work trips and non-work trips may respond differently to environmental factors (Frank and Pivo 1994); therefore, future research can separate commute and recreational trips in analyzing the influence of multiple levels of environmental factors in nonmotorized travel behavior.

Furthermore, the data used for developing the nonmotorized travel behavior models in this study came only from a few metropolitan areas and may not be fully representative of the U.S. metropolitan areas. Thus, it may be best to apply some caution with respect to the potential transferability of the results to other cities. Data from additional metropolitan areas and other states within the U.S. can be analyzed in the future to investigate the link between nonmotorized travel behavior and various levels (i.e., micro, meso, macro levels) of the built and social environment within an ecological model framework. An analysis based on such enhanced data—which offer more variation, particularly with regards to macro-level environmental factors—can provide insights into the generalizability of the findings of the present study.

Lastly, the empirical evidence presented in this chapter proves inconclusive in a few cases, which indicates potential avenues for further research.

For instance, the examination of the effects of mixed-use development in nonmotorized travel behavior yielded inconsistent results in different models. More specifically, a higher extent of mixed land use at the meso level (i.e., county level) in household-level models resulted in contradictory estimations between the Florida case study (presented in this chapter) and the Baltimore-D.C. case study (presented in Appendix C). This is while meso-level mixed land use shows insignificant effects in the Florida person-level nonmotorized travel behavior models. Therefore, the role of meso-level mixed land use (i.e., extent of mixed-use development within the county) in nonmotorized travel behavior stays unclear and requires further examination.

Also, the results of the Florida household-level nonmotorized travel behavior models and the Baltimore-D.C. household-level nonmotorized travel behavior models (see Appendix C) showed that random differences between neighborhoods may play a small but statistically significant role in the extent of walking and bicycling trips. However, random differences between neighborhoods exhibited statistically insignificant effects in the Florida person-level nonmotorized travel behavior. One possible explanation can be that the statistical significance of the neighborhood random effects as estimated by the household-level models in fact captured the household-level random effects, which were not accounted for in those models. Nonetheless, further research is needed to clarify the role of household as well as neighborhood random effects (i.e., random neighborhood contextual effects) on nonmotorized travel behavior.

Chapter 5: Health Impacts of Active Travel and Built Environment

"It is health that is real wealth and not pieces of gold and silver."

—*Mahatma Gandhi*

Human health is an invaluable quality and probably the greatest asset one can poses. There are numerous benefits of being healthy. Healthy individuals can live free of pain, discomfort, or suffering; can regain their health quicker in case of illness; and can perform to the best of their ability in every sphere of life. Through being at their best state of being, healthy individuals can help shaping healthy communities. Healthy communities are more prepared, provide more resources for promoting healthy habits, and are more resilient after a disaster occurs[41].

Health starts with the individual and extends to the community. Thus, identification of factors that impact individuals' health status and understanding the extent of the effects of those factors are essential tasks for development of transportation planning policies and urban designs that promote public health within communities.

Physical activity—in both its general form as well as its active travel form (i.e., walking and bicycling)—and the built and social environments of the residential location are among the factors that can influence health, both at the individual and community levels (see Chapter 2).

While it is evident from the literature that neighborhood-level (i.e., micro-level) and county-level (i.e., meso-level) built environment play important roles in individuals' health, the role of metropolitan area-level (macro-level) built and social environment characteristics in individual and population health has not been thoroughly examined in the past.

[41] Centers for Disease Control and Prevention "Public Health Matters Blog": https://blogs.cdc.gov/publichealthmatters/2015/09/a-healthy-community-is-a-prepared-community/

Further, the complex interrelationships between health outcomes, health behavior, and the built environment introduce the possibility of endogeneity bias to the analysis. A review of health literature (see Chapter 2) revealed that endogeneity bias is often neglected in examination of the link between health outcomes, health behavior (e.g., walking and bicycling), and the built environment—which may result in biased estimates, as also argued by Schauder and Foley (2015).

In addition, little empirical knowledge exists on the effects of other travel-related behavior on health. For instance, although a few studies investigated the link between telecommuting and psychological health, the role of telecommuting in physical health has not been thoroughly tested. Further, the role of teleshopping behavior in health remains largely unclear as there are no empirical studies on the health impacts of teleshopping.

This chapter contributes to the existing knowledge on the links between health outcomes, health behavior (in terms of both general physical activity and active travel), travel behavior (including telecommuting and teleshopping behavior), and the built and social environments by developing advanced statistical models to predict physical and psychological health outcomes. These models incorporate individual and household characteristics, as well as built and social environment attributes—at hierarchical levels of geography—for the place of residence. Additionally, all health models developed account for a potential endogeneity bias in the analysis.

Person-level models have been developed to examine the link between indicators of individuals' health status and health behavior (e.g., physical activity), measures of built as well as social environment at multiple levels of influence, and measures of travel behavior including active travel, telecommuting, and teleshopping behavior. The person-level models have been estimated for various different health indicators representing both the physical and the psychological health status for residents. These health indicators include obesity, diabetes, asthma, general health status, as well as the average numbers of physically and mentally unhealthy days. Health behavior such as physical activity has also been examined to model the level of physical activity performed by individuals. Due to the possibility of reverse causality (i.e., reciprocal causation) between individuals' health and their health behavior (e.g., physical activity such as walking and bicycling), (see e.g., Lee and Moudon 2004; Schauder and Foley 2015; van Wee and Ettema 2016), the health outcome models are susceptible to endogeneity bias. Reverse causality and endogeneity bias have been addressed in the person-level health models by employment of instrumental variable analysis as well as inclusion of bidirectional links between health outcomes and health behavior (i.e., physical activity) within a SEM model structure. Person-level health outcome models are developed using data from residents of several metropolitan areas within the state of Florida.

County-level health outcome models have also been developed as part of this dissertation research, but in the interest of brevity, are presented in Appendix I[42]. The county-level models examine the link between county-level health status indicators and built and social environment attributes at two levels of geography: the county level (i.e., meso level), and the CBSA within which the county lies (i.e., macro level). The county-level models are estimated for six different health indicators representing both the physical and the psychological health status for county residents. These health indicators include prevalence of obesity, prevalence of diabetes, prevalence of fair or poor health, prevalence of premature death, as well as the average number of physically and mentally unhealthy days experienced by residents of the county. To account for reverse causality and endogeneity bias, the SEM framework of the county-level models includes bidirectional links between health outcomes and measures of nonmotorized (i.e., active) travel behavior. This model design allows for examining causal pathways between health outcomes,

[42] Results from the county-level health models are used in the main body of the dissertation for comparison purposes and are referred to as corroborating evidence for the findings of the person-level health outcome models.

health behavior (i.e., active travel), and built environment factors—while concurrently addressing any potential endogeneity bias. County-level health models are developed using data from counties within the U.S. states of Florida, Maryland, Virginia, Washington, D.C., and West Virginia.

The health outcome models have been specified in such way to include the elements of the main conceptual framework (see Figure 1), which follows an ecological model framework. The proposed ecological framework allows for testing the effects of the built as well as social environment at multiple levels of influence on health behavior and health status of residents.

It should be noted that while the role of genetic factors in individuals' health is very important, it is not within the scope of this study—partly due to limitations in data. This analysis focuses on the built and social environment attributes as well as transportation-related factors that can potentially influence health outcomes. As Corburn (2015) puts it "health begins where we live, learn, work and play, and transport has a critical role in providing access to healthy communities, schools and workplaces for all".

As previously mentioned, walking and bicycling are often referred to as *active travel* in health literature. Therefore, the terms nonmotorized travel and active travel are used interchangeably in this part of the dissertation.

5.1 Person-level Health Outcome Models

The county-level health impact models, which are developed and discussed in Appendix I, provide insights into the role of meso- and macro-level built and social environments as well as the travel culture of communities in shaping the health profile of those communities. Nonetheless, health is a person-level quality and the collective health profile of each community is inevitably formed by the health status of each individual resident. Thus, to better understand the health of a population, examining the factors that influence individuals' health status seems to be a reasonable step.

As noted in Chapter 3, the world's largest and most important source of person-level health data is the BRFSS dataset. This dataset has been used in this section to develop person-level health outcome models. Due to confidentiality reasons involving health data, the smallest geographic area for which BRFSS data are available is the county. Consequently, the smallest geographical unit of analysis for the person-level health models has been selected as the county where the respondent resided in. The models have been developed using the 2009 BRFSS data from respondents living in the state of Florida. Florida was selected as the study area because it is the same state from which data were utilized in the analysis of nonmotorized travel behavior (presented in Chapter 4).

The person-level health models examine the link between individual-level health status indicators; travel behavior including nonmotorized travel, telecommuting, and teleshopping behavior; built environment attributes at two levels of geography: the county of residence (i.e., the meso level), and the CBSA within which the county of residence lies (i.e., the macro level); and social environment attributes at three levels of influence: the household (i.e., the micro level), the county (i.e., the meso level), and the CBSA (i.e., the macro level).

5.1.1 Person-level Health Outcome Models: Data

The database for the person-level health outcome models consist of the following datasets:

- Behavioral Risk Factor Surveillance System (BRFSS);
- National Household Travel Survey (NHTS)—2009 Florida Add-on data;
- American Community Survey (ACS);
- Smart Location Database (SLD);
- Community Health Status Indicators (CHSI);
- County Health Rankings & Roadmaps (CHR&R);
- Woods & Poole Complete Economic and Demographic Data Source (CEDDS);

- Urban Mobility Information data—Texas A&M Transportation Institute (TTI);
- Uniform Crime Reporting Program data—Federal Bureau of Investigation (FBI);
- Walk Score data;
- Point of Interest (POI) data; and
- Census Bureau's TIGER/Line Shapefiles.

The BRFSS provided self-reported data on individuals' socioeconomic and sociodemographic characteristics (e.g., age, gender, race, household income level), health-related behavior (e.g., physical activity, consumption of fruits and vegetables, and consumption of tobacco products), as well as the health status of respondents with respect to various health indicators.

The NHTS and the ACS data provided information on travel behavior within the county. These included the county-level: automobile, public transit, and nonmotorized travel mode shares as well as levels of: telecommuting, online purchasing, and delivery of online purchases within the county. ACS also provided data on social environment factors for the counties (i.e., socioeconomic and sociodemographic attributes such as median age, median household income, and the racial composition within each county).

The TTI Urban Mobility Information data provided information about the mobility level within the CBSA of residence (e.g., congestion level). The FBI Uniform Crime Reporting (UCR) data provided information on the levels of violate crimes within the CBSA of residence. Garmin Point of Interest (POI) data provided information on the location of fast food establishments within the counties. Also, Walk Score data provided information on the Walk Score within the counties and CBSAs where the Florida respondents of 2009 BRFSS lived.

Information provided by the data included in the SLD, the CHSI, the CHR & R, the Woods and Poole's CEDDS datasets, and the TIGER/Line Shapefiles is elaborated in Appendix I.

GIS tools were utilized to spatially link travel behavior, telecommuting and teleshopping behavior, as well as social and built environment data to person-level health data and obtain the final integrated database for statistical modeling of individual-level health outcomes. Detailed information on the datasets used in this analysis can be found in Chapter 3.

5.1.2 Person-level Health Outcome Models: Dependent Variables

The dependent (i.e., endogenous) variables for the person-level health outcome models have been selected based on health outcomes provided in the BRFSS dataset, which represent measures of mortality and morbidity for each respondent.

Seven separate models have been developed for the following seven person-level health outcomes and health behavior indicators:

1) overweight or obese;
2) diabetes;
3) asthma;
4) general health;
5) poor physical health days;
6) poor mental health days;
7) participation in 150 minutes of moderate physical activity per week (as recommended by CDC and DHHS[43]).

Maps presented in Appendix I show the prevalence of a few of the above indicators for each county within the study area based on the data available from the 2012 CHR & R datasets.

[43] Centers for Disease Control and Prevention (CDC) "Physical Activity Basics": https://www.cdc.gov/physicalactivity/basics/index.htm, and DHHS (2018).

5.1.3 Person-level Health Outcome Models: Independent Variables

The independent (i.e., exogenous) variables for the statistical models in the person-level health impact analysis have been considered based on previous research (Chapter 2 and Appendix B) as well as the results of the county-level health models (Appendix I). These variables represent health behavior and health status at the individual level as well as the built and social environments at two different geographical levels: the county and the metropolitan area of residence.

The independent (i.e., exogenous) variables included in the person-level health modes are categorized as follows:

5.1.3.1 Person-level Variables (Characteristics of Individuals and their Households)

The person-level variables represent the socioeconomic and sociodemographic characteristics for the respondents and their households as well as the health behavior of the BRFSS respondents. These variables include respondent's:

- age;
- race;
- gender;
- employment status;
- college education status;
- number of children in the household;
- annual household income;
- level of physical activity;
- level of consumption of fruits and vegetables;
- level of consumption of alcoholic beverages; and
- smoking status.

5.1.3.2 Built Environment Variables

Built environment variables have been included in the person-level health models to account for the most important built environment factors that—according to the literature—can influence the health status of an individual. The built environment variables have been chosen in such manner to capture the physical environment profile of the residential area with respect to the extent it promotes or restricts: 1) physical activity; 2) social interaction; and 3) access to healthy food. These are the three main domains identified by Kent and Thompson (2012) through which the built environment can influence human health.

As mentioned previously, the BRFSS health data, which are used to develop the person-level health outcome models, do not provide information at the neighborhood level (i.e., micro level) due to confidentiality concerns. Thus, the county of residence was the smallest scale at which this analysis could be conducted. As a result, built environment characteristics have been included in the person-level health models at two spatial levels: the meso level (i.e., county level) and the macro level (i.e., CBSA level).

Meso-level (County-level) Built Environment Variables

Census block group-level built environment and land use measures provided by the SLD were aggregated to obtain the average county-level built environment measures. Other built environment variables at the county level are related to health factors and come from the CHSI and the CHR&R datasets. These variables include data on the levels of: access to clinical healthcare, access to healthy and unhealthy food, and access to parks for the population residing within a county as well as the air quality within the county.

The meso-level (i.e., county-level) built environment variables included in the person-level health outcome models are:

- average activity density;
- average entropy (i.e., mixed land use);
- average intersection density;
- average local transit accessibility (i.e., average distance to local transit);
- average automobile accessibility to employment opportunities;
- average transit accessibility to employment opportunities;
- prevalence of fast food restaurants;
- access to parks;
- access to primary care physicians;
- access to healthy food outlets;
- ambient air pollution; and
- average Walk Score.

Together, these variables represent the *D*s of the built environment as well as other important built environment factors at the county (i.e., meso) level that—based on the literature (and the findings from the county-level health models presented in Appendix I)—may play a role in the health of the residents. Table 16 provides more information about the meso-level built environment variables included in the person-level health outcome models.

Macro-level (CBSA-level) Built Environment Variables

The macro-level variables are defined based on the Core Based Statistical Area (CBSA) of residence. For the person-level health models, CBSAs include only metropolitan areas (and not micropolitan areas). Census block group-level built environment measures provided by the SLD were aggregated to obtain the average CBSA-level (macro-level) built environment measures.

The macro-level built environment variables included in the models are:

- average activity density;
- average entropy;
- average intersection density;
- average transit accessibility (i.e., average distance to local transit);
- average automobile accessibility to employment opportunities;
- average transit accessibility to employment opportunities; and
- average roadway congestion index.

These variables capture a good picture of the overall physical environment (i.e., built environment and land use characteristics) of the CBSAs in the study area including the extent of: compactness, mixed land use, street network connectivity, and access to transit as well as levels of mobility within those urbanized areas. Table 16 provides additional information about the macro-level built environment variables included in the person-level health outcome models.

5.1.3.3 Social Environment Variables

Social environment factors have been included in the person-level health models at two spatial levels: the county (i.e., the meso level) and the CBSA (i.e., the macro level).

Meso-level (County-level) Social Environment Variables

County-level socioeconomic and sociodemographic attributes have been included in the person-level health outcome models to represent the meso-level (i.e., county-level) social environment. The county-level social environment variables are:

- median age;
- median household income;
- percentage of population of the White race; and
- percentage of industry employment that can be performed by telecommuting.

These variables provide information on key socioeconomic and sociodemographic characteristics of a county that—based on the literature (and results from the county-level health models presented in Appendix I)—can play a role in residents' health outcomes.

Macro-level (CBSA-level) Social Environment Variables

CBSA-level socioeconomic and sociodemographic characteristics have been included in the person-level health models to represent the macro-level social environment.

The CBSA-level (i.e., metropolitan area-level) social environment variables are:

- average walking and bicycling density;
- annual public transportation passenger-miles;
- average commuter stress index;
- average percentage of low-wage workers;
- average percentage of households with no cars;
- average percentage of the minority population;
- average gross regional product (GRP); and
- average violent crime rate.

These variables control for the effects of macro-level (i.e., metropolitan area-level) sociodemographic, socioeconomic, and sociocultural factors on person-level health outcomes. It should be noted that in a way, the first three variables (average walking and bicycling density, annual public transportation passenger-miles, average commuter stress index) represent the "travel culture" within the CBSAs (i.e., metropolitan areas).

These variables are intertwined with travel behavior measures for the residential areas; thus, they can be considered as factors representative of travel behavior within urbanized residential communities—a subject discussed next.

5.1.3.4 Travel Behavior and Telecommuting Behavior Variables

The travel behavior measures included in the models provide information about the extent of travel by each travel mode within each county in the study area as well as the extent of telecommuting and teleshopping-related activities within the county.

The county-level travel behavior measures include:

- nonmotorized travel mode share;
- private vehicle mode share;
- public transit mode share;
- average frequency of telecommuting events per month;
- average percentage of household members with telecommuting option;
- average number of online purchases per month; and
- average number of monthly deliveries related to online purchases.

As potentially influential—but to some degree, subtle travel behavior factors—online shopping-related activities have notably been overlooked in health impact studies. To fill that gap in empirical analysis, measures of teleshopping behavior have been included in the present study to account for the impact of the prevalence of an "online shopping culture" within the area of residence on individuals' health outcomes.

It should be kept in mind that although categorized under separate categories of variables, the travel behavior as well as the telecommuting and teleshopping behavior variables potentially represent another aspect of the social environment within the county of residence. Cumulatively, these measures characterize each county in terms of its "travel culture", and thereby they can be considered sociocultural characteristics of the county—or in other words, measures of the county's social environment. Table 16 lists the final variables included in the person-level health models.

Table 16. Person-level Health Models Variables: Descriptive Statistics and Data Sources

Model Variables	Mean	SD	Data Source
Endogenous (i.e., Dependent) Variables: Person Level			
Overweight or Obese (individual had a BMI ≥ 25 – 1: yes, 0: otherwise)	0.63	0.48	BRFSS
Diabetes (individual was diagnosed with diabetes – 1: yes, 0: otherwise)	0.14	0.34	BRFSS
Asthma (individual was diagnosed with asthma – 1: yes, 0: otherwise)	0.12	0.32	BRFSS
Good General Health (individual reported good or better health – 1: yes, 0: otherwise)	0.78	0.41	BRFSS
Number of Poor Physical Health Days (in the past 30 days)	4.65	9.27	BRFSS
Number of Poor Mental Health Days (in the past 30 days)	3.45	8.18	BRFSS
CDC Physical Activity (individual participated in 150 minutes of physical activity/week per CDC – 1: yes, 0: otherwise)	0.62	0.49	BRFSS
Independent (i.e., exogenous) Variables			
Person and Household Characteristics			
Age (individual's age in years)	58.98	16.27	BRFSS
Race (individual's race: – 1: White, 0: otherwise)	0.82	0.38	BRFSS
Gender (individual's gender: – 1: male, 0: female)	0.38	0.49	BRFSS
Employment Status (individual was employed – 1: yes, 0: otherwise)	0.42	0.49	BRFSS
College Education (individual had college degree – 1: yes, 0: otherwise)	0.61	0.48	BRFSS
Physical Activity (individual's total minutes of moderate physical activity per week) [a]	58.79	82.21	BRFSS
Fruit and Vegetable (individual's fruit and vegetable servings per day)	3.96	3.04	BRFSS
Smoking Status (1: everyday smoker, 2: someday smoker, 3: former smoker, 4: non-smoker)	3.23	1.09	BRFSS
Drinking Status (total number of alcoholic beverages consumed per month)	11.92	41.34	BRFSS
Household Income Category [b]	3.48	1.44	BRFSS
Number of Children in Household (number of children under 18 years of age in individual's household)	0.42	0.92	BRFSS
Social Environment			
Meso Level: The County			
Median Age (years)	39.19	4.85	ACS
Median Annual Household Income (dollars)	43,842	6,292	ACS
Percent White (%)	76.70	7.59	ACS
Percent of Telecommutable Jobs [c] (%)	56.40	5.82	Woods and Poole [d]
Macro Level (Core Based Statistical Area): The Metropolitan Area			
Average Walking and Bicycling Density [average (number of walking and bicycling trips in CBG/CBG area in acres)]	0.0024	0.0016	NHTS and SLD
Annual Public Transportation Passenger-Miles (millions)	129.14	262.00	TTI
Average Commuter Stress Index	1.18	0.064	TTI
Average Percentage of Low-Wage Workers (workers earning ≤ $1250/month) (%)	27.44	1.93	SLD
Average Percentage of Households with No Cars (%)	6.43	1.19	SLD
Average Gross Regional Product (GRP) (in millions of 2004 dollars)	49,829	63,022	Woods and Poole [d]
Average Crime Rate (annual violent crimes/100,000 population)	700.83	363.17	FBI and CDC

Travel Behavior			
Meso Level: The County			
Nonmotorized Travel Mode Share (%)	8.10	2.38	ACS
Private Vehicle Travel Mode Share (%)	87.16	3.60	ACS
Public Transit Travel Mode Share (%)	1.21	0.79	ACS
Average Frequency of Telecommuting Events per Month	4.05	2.03	NHTS
Average Percentage of Household Members with Telecommuting Option (%)	11.46	4.83	NHTS
Average Number of Online Purchases per Month	1.80	0.37	NHTS
Average Number of Monthly Deliveries Related to Online Purchases	3.00	0.48	NHTS
Built Environment			
Meso Level: The County			
Mean Activity Density [average (employment + housing units)/acres)]	3.41	2.99	SLD
Mean Entropy (dimensionless)	0.54	0.07	SLD
Mean Intersection Density [average (automobile-oriented intersections/mi^2)]	0.72	0.55	SLD
Mean Local Transit Accessibility [average (distance to the nearest transit stop in meters)]	735.45	69.64	SLD
Mean Temporal Automobile Accessibility (average number of jobs within a 45-minute automobile travel time)	44,173	46,063	SLD
Mean Temporal Transit Accessibility (average number of jobs within a 45-minute transit commute)	1,488	1,666	SLD
Density of Fast Food Restaurants [e] (number of fast food restaurants/10,000 population)	1.97	0.63	POI and ACS
Access to Parks (percentage of population living within half miles of park features) (%)	20.54	15.21	CHSI
Primary Care Physician Rate (primary care providers per 100,000 population)	68.10	31.11	CHR&R
Access to Healthy Food Outlets [f] (percent of zip codes in county with healthy food outlets) (%)	47.68	11.21	CHR&R
Ambient Air Pollution (annual number of unhealthy air quality days due to Ozone and Fine Particulate Matter)	7.23	4.89	CHR&R
Mean Walk Score (dimensionless)	11.23	18.94	Walk Score®
Macro Level (Core Based Statistical Area): The Metropolitan Area			
Mean Activity Density [average (employment + housing units)/acres)]	4.39	2.40	SLD
Mean Entropy (dimensionless)	0.56	0.05	SLD
Mean Intersection Density [average (automobile-oriented intersections/mi^2)]	0.88	0.42	SLD
Mean Local Transit Accessibility [average (distance to the nearest transit stop in meters)]	669.51	46.33	SLD
Mean Temporal Automobile Accessibility (average number of jobs within a 45-minute automobile travel time)	53,611	40,868	SLD
Mean Temporal Transit Accessibility (average number of jobs within a 45-minute transit commute)	1,703	1,450	SLD
Mean Roadway Congestion Index (dimensionless)	0.98	0.18	TTI
Number of Observations (i.e., BRFSS Respondents): 9,427 – Number of Counties: 51 – Number of CBSAs: 23			

NOTES: [a] BRFSS defines moderate physical activity as “brisk walking, bicycling, vacuuming, gardening, or anything else that causes some increase in breathing or heart rate”;

[b] Based on household income categories listed in BRFSS (1= less than $15,000; 2= $15,000 to less than $25,000; 3= $25,000 to less than $35,000; 4= $35,000 to less than $50,000 and 5= $50,000 or more);

[c] Percentage of county jobs that fall into the “Information”, “FIRE” (Finance, Insurance, Real Estate), “Services”, and “Government” sectors;

[d] Source: Woods & Poole Economics, Inc. Washington, D.C. Copyright 2018. Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusion drawn from it are solely the responsibility of the author of this dissertation;

[e] In computation of the values of this variable, the following establishments have been considered fast food restaurants: Burger King, Domino Pizza, KFC, McDonalds, Papa John’s Pizza, Pizza Hut, Roy Rogers, Subway, Taco Bell, and Wendy’s;

[f] Data on healthy food outlets in the 2010 CHR&R data come from the County Business Patterns (CBP) economic data. According to the CHR&R “healthy food outlets include grocery stores (NAICS 445110) with > 4 employees and produce stands/farmers’ markets (NAICS 445230)”; CBG = Census Block Group.

As seen from Table 16, the table summarizes all the endogenous (i.e., dependent) and exogenous (i.e., independent) variables used in the person-level health outcome models. The Florida metropolitan areas included in the person-level health models are the same as the ones included in the Florida nonmotorized travel behavior models. Information about social and built environment attributes of those metropolitan areas was listed in Tables 2, 5, and 6 (Chapter 4).

Table 17 provides descriptive statistics by CBSA (i.e., metropolitan area) for a few of the county-level variables that come from health datasets and have not been previously described.

Table 17. Descriptive Statistics: Health-related Data for Florida Metropolitan Areas

Metropolitan Area	**Crime Rate**		**Ambient Air Pollution**		**Primary Care Provider Rate**		**Access to Healthy Food Outlets**		**Access to Parks and Green Spaces**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cape Coral-Fort Myers	556.2	—	7.0	—	62.9	—	51.1	—	23.0	—
Crestview-Fort Walton -Destin	342.9	28.5	5.7	0.6	54.3	35.6	36.9	11.8	8.0	5.2
Deltona-Daytona Beach-Ormond	563.9	—	5.0	—	69.8	—	42.55	—	30.0	—
Gainesville	470.4	362.9	4.5	1.0	65.9	94.5	46.1	7.8	3.5	2.9
Homosassa Springs	293.3	—	3.0	—	52.7	—	40.0	—	14.0	—
Jacksonville	723.3	423.2	7.4	5.7	68.2	31.7	46.3	13.5	21.8	10.6
Lakeland-Winter Haven	519.0	—	8.0	—	55.3	—	41.8	—	8.0	—
Miami-FortLauderdale-Pompano	774.3	202.0	0.3	0.6	90.6	15.7	58.9	3.0	44.3	17.6
Naples-Marco Island	436.0	—	5.0	—	70.7	—	60.1	—	16.0	—
North Port-Bradenton-Sarasota	681.6	388.8	12.0	4.2	79.3	12.5	56.5	0.3	21.5	17.7
Ocala	698.1	—	4.0	—	56.0	—	44.7	—	13.0	—
Orlando-Kissimmee-Sanford	670.4	333.1	9.3	2.2	68.6	18.2	46.9	6.1	11.5	5.8
Palm Bay-Melbourne-Titusville	669.5	—	5.0	—	74.3	—	44.7	—	36.0	—
Palm Coast	313.1	—	4.0	—	31.8	—	50.0	—	19.0	—
Panama City-Lynn Haven	452.9	307.8	6.0	2.0	50.4	10.2	52.6	18.7	17.5	14.5
Pensacola-Ferry Pass-Brent	523.5	400.9	16.5	4.9	76.2	11.4	45.0	7.1	7.0	2.8
Port St. Lucie	515.2	114.5	3.5	2.1	62.1	29.6	60.7	3.4	32.0	2.8
Punta Gorda	458.6	—	5.0	—	61.3	—	58.8	—	25.0	—
Sebastian-Vero Beach	358.1	—	4.0	—	79.7	—	43.8	—	32.0	—
Sebring	413.1	—	4.0	—	62.0	—	36.4	—	8.0	—
Tallahassee	653.6	330.5	6.7	3.5	39.7	28.5	40.5	16.9	10.3	14.9
Tampa-St. Petersburg-Clearwater	612.5	231.7	10.3	6.8	71.7	21.4	48.9	7.4	27.0	19.5
The Villages	377.8	—	5.4	—	18.9	—	40.0	—	8.0	—

NOTE: SD = Standard deviation; — = Data not available; Source of data: 2010 CHR&R data.

The descriptive statistics show that the Miami-Fort Lauderdale-Pompano and Jacksonville metropolitan areas have the highest crime rates (774.3 and 723.3 violent crimes per 100,000 population, respectively), whereas Homosassa Springs has the lowest crime rate (293.3 violent crimes per 100,000 population) in Florida. The Pensacola-Ferry Pass-Brent metro. area has the highest annual average number of ambient air pollution days (approximately 17 days), but data indicates that with only 0.3 days, the Miami-Fort Lauderdale-Pompano metro. area has the lowest average number of unhealthy air quality days in Florida. In terms of access to clinical care, the Miami-Fort Lauderdale-Pompano metro. area provides the largest number of primary care providers per 100,000 population (over 90 providers), whereas access to clinical healthcare seems to be limited to fewer than 20 providers per 100,000 population in The Villages metropolitan area.

Access to healthy food outlets is highest in the Port St. Lucie and Naples-Marco Island metropolitan areas as the average percentage of zip codes with healthy food outlets in counties within those metropolitan areas are above 60%. However, the residents of the Sebring metropolitan area do not seem to enjoy the same healthy food access advantages since based on data, only 36.4% of them have access to healthy food outlets.

Poor diet is one of the accepted causes leading to poor health (Samimi et al. 2009). The difference in having access to healthy food outlets between the highest level of access (in Port St. Lucie) and the lowest level (in Sebring) is over twenty-four percentage points (60.7% - 36.4%), which is somewhat high and may have health implications for the residents of Sebring.

Further, access to green spaces and parks may contribute to residents' health—as suggested by past studies (see e.g., Lund 2003; Timperio et al. 2010)—in part, by facilitating physical activity. Table 17 shows that the Miami-Fort Lauderdale-Pompano metropolitan area offers the best opportunity in Florida for residents to enjoy a healthier lifestyle as related to having access to green spaces. With over 44% of its population living within half miles of parks, the Miami-Fort Lauderdale-Pompano is the metro. area in Florida where the highest level of access to parks and green spaces exists. The Gainesville metropolitan area lies on the other end of the access-to-parks spectrum in Florida, with only 3.5% of its population living near parks and green spaces.

5.1.4 Person-level Health Outcome Models: Methodology and Results

The person-level health outcome and health behavior models have been developed based on variables included in Table 16. Several other built and social environment variables were considered for inclusion in the person-level health outcome models. At the end, the most parsimonious model specifications representing logical cause-effect relationships were selected with consideration of reducing the risk of multicollinearity in the models.

The analysis of person-level health outcomes is susceptible to endogeneity bias. This is due to the possibility of reverse causality between health outcomes and physical activity (including walking and bicycling) or omission of an underlying unmeasurable variable, such as internal motivation that influences both the propensity to be physically active (e.g., engage in active travel) as well as the health status (Schauder and Foley 2015).

To account for any potential endogeneity bias in the person-level health outcome models, two advanced statistical techniques have been employed in this chapter of the dissertation:

1) instrumental variable analysis; and

2) multilevel SEM analysis.

Instrumental variable analysis has been used by other researchers as an appropriate methodology to address endogeneity bias in estimating health outcomes (see e.g., Zick et al. 2013; Schauder and Foley 2015) and can provide more comprehensive and less biased results.

Further, as discussed previously, the employment of SEM techniques allows for examination of the causal links between health outcomes, health behavior (including physical activity and active travel), and built as well as social environment factors—while controlling for any potential endogeneity, multicollinearity, or spatial autocorrelation problems (the latter may exist due to usage of clustered data).

5.1.4.1 Specification of Models: Person-level Health Outcome Models

Instrumental Variable Binary Probit Models

In developing person-level health models, the assumption is that individuals' level of physical activity (including walking and bicycling) impacts their health status, but that the reciprocal effect can also exist; individuals' health status may influence their levels of physical activity. This reciprocal causation effect—also termed r*everse causality* in the literature—has been rationalized by researchers to exist because having a better health status makes individuals more likely to perform physical activity such as active travel (Schauder and Foley 2015). In addition, there may exist at least one omitted variable in the models that influences both an individual's physical activity level and his/her health status. In this situation, the physical activity variable becomes an endogenous independent variable in the model, meaning that after controlling for all the other independent variables, there is a non-zero correlation between physical activity and the error term. Such a correlation may lead to biased coefficient estimates in the model (see Subsection 3.3.3). To account for this potential endogeneity bias in the person-level health models, instrumental variables have been used for the endogenous physical activity independent variable.

Several health outcome variables are in a binary form, indicating the diagnosis (or lack thereof) of a specific health outcome for an individual. This requires the employment of binary choice models. As in many past studies (see e.g., Samimi et al. 2009; Samimi and Mohammadian 2009), binary probit modeling has been selected in the present study as the regression technique to model several health outcomes. Five models have been developed for five binary endogenous variables representing person-level health outcomes including the individual being overweight or obese, the individual having ever been diagnosed with diabetes, the individual having ever been diagnosed with asthma, the individual having good general health, and the individual having met the CDC recommendations of participating in 150 minutes of physical activity per week.

The person-level instrumental variable binary probit health models can be formulated as:

$$y_{1i}^* = c_{1i} + \beta y_{2i} + \gamma_{1i}' \mathrm{ED}_{\mathrm{Person}} + \gamma_{2i}' \mathrm{SE}_{\mathrm{County}} + \gamma_{3i}' \mathrm{SE}_{\mathrm{CBSA}} + \gamma_{4i}' \mathrm{TB}_{\mathrm{County}} + \gamma_{5i}' \mathrm{BE}_{\mathrm{County}} + \gamma_{6i}' \mathrm{BE}_{\mathrm{CBSA}} + \mu_i \qquad \text{Equation 31}$$

$$y_{2i} = c_{2i} + \mathbf{\Pi}_1 \mathrm{ED}_{\mathrm{Person}} + \mathbf{\Pi}_2 \mathrm{SE}_{\mathrm{County}} + \mathbf{\Pi}_3 \mathrm{SE}_{\mathrm{CBSA}} + \mathbf{\Pi}_4 \mathrm{TB}_{\mathrm{County}} + \mathbf{\Pi}_5 \mathrm{BE}_{\mathrm{County}} + \mathbf{\Pi}_6 \mathrm{BE}_{\mathrm{CBSA}} + \mathbf{\Pi}_7 \mathrm{Z}_{\mathrm{Person}} + \vartheta_i \qquad \text{Equation 32}$$

where,

y_{1i}^* = value of the unobserved endogenous person-level health outcome variable *i*;

y_{2i} = value of the observed endogenous person-level physical activity variable (for outcome *i)*;

c_{1i}, c_{2i} = model intercepts;

β = model structural parameter for the instrumented endogenous variable (i.e., person-level physical activity variable);

$\gamma_{1i}' - \gamma_{6i}'$ = column vectors of model structural parameters;

$\mathbf{\Pi}_1 - \mathbf{\Pi}_7$ = matrices of reduced-form parameters;

$\mathrm{ED}_{\mathrm{Person}}$ = column vector of exogenous person-level (and person's household) attributes;

$\mathrm{SE}_{\mathrm{County}}$ = column vector of exogenous meso-level (i.e., county) social environment attributes;

$\mathrm{SE}_{\mathrm{CBSA}}$ = column vector of exogenous macro-level (i.e., CBSA) social environment attributes;

$\mathrm{TB}_{\mathrm{County}}$ = column vector of exogenous meso-level (i.e., county) travel behavior attributes;

$\mathrm{BE}_{\mathrm{County}}$ = column vector of exogenous meso-level (i.e., county) built environment attributes;

$\mathrm{Z}_{\mathrm{Person}}$ = column vector of additional person-level instrumental variables;

μ_i and ϑ_i = model error terms; and

i = (overweight or obese, diagnosed with diabetes, diagnosed with asthma, good general health).

It should be noted that the equation for y_{2i} (Equation 32) is written in the reduced form. Also, by assumptions of the model, $(\mu_i, \vartheta_i) \sim$ N (0, Σ), where σ_{11} is normalized to one to identify the model. The model is derived under the assumption that (μ_i, ϑ_i) is iid multivariate normal for all observations (in the model for health outcome *i)*. In addition, while y_{1i}^* is not observable, the observed value of the endogenous health outcome variable, y_{1i}, changes as follows:

$$y_{1i} = \begin{cases} 0 & y_{1i}^* < 0 \\ 1 & y_{1i}^* \geq 0 \end{cases}$$

Thus, the instrumental variable analysis formulated above consists of two stages: in the first stage, the endogenous independent variable (i.e., physical activity variable) is modeled as a function of control variables plus the instrumental variables, Z_{Person} (which are assumed to be strongly correlated with the physical activity variable but have zero correlation with the error term in the health outcome model). In the second stage, the observed value of the physical activity variable is replaced with its predicted value obtained from the first stage of analysis and the health outcome binary probit model is estimated based on the predicted values of the physical activity variable plus the control variables. The instrumental variable analysis isolates the variation in the instrumented variable (in this case the physical activity variable) that is not due to reverse causality or omitted variables, and thereby achieves a more accurate estimate for its coefficient in the model (Schauder and Foley 2015).

According to Wooldridge (2010), the instrumental variables contained in column vector Z must satisfy two conditions: 1) exogeneity; and 2) correlation. Exogeneity implies that the instrumental variable must be uncorrelated with the error term in the health models (μ_i). Correlation implies that the instrumental variable must be partially correlated with the endogenous independent variable (i.e., physical activity variable, y_{2i}, in this case).

Three person-level variables have been selected as instrumental variables in this analysis:

- employment status (1: individual is employed, 0: otherwise);
- educational status (1: individual has college degree, 0: otherwise); and
- children (number of children under 18 years of age in individual's household).

These variables have been chosen as instrumental variables because they can be correlated with an individual's propensity and level of physical activity (the correlation condition) but should not theoretically be correlated with the error term in the health outcome models (μ_i) after controlling for other factors (the exogeneity condition).

Findings of past research is inconsistent in terms of existence of a correlation between the health outcomes for individuals and their educational attainment, employment status, or living-with-children status. For instance, while some studies suggested that individuals' level of education is significantly correlated with BMI (Plantinga and Bernell 2007) and being obese (Frank et al. 2004; Samimi and Mohammadian 2009), others found no significant correlation between individuals' education and being obese or having asthma (Langerudi et al. 2015).

Also, no significant correlation was found between having children and being obese or having asthma (Samimi and Mohammadian 2009; Langerudi et al. 2015). Further, although both latter studies found a correlation between having children and individuals' general health condition, their findings should be treated with caution due to inconsistency in the direction of effects. The direction of the correlation between having children and individuals' general health was found to be positive in the first study (Samimi and Mohammadian 2009), whereas it was found to be negative in the second one (Langerudi et al. 2015)—making the end result inconclusive.

Overall, the inconsistencies in past findings suggest that educational status, employment status, and number of children can be suitable instrumental variables to model the specific health outcomes of interest in this section of the analysis (i.e., obesity, diabetes, asthma, general health).

Multilevel Structural Equation Models (i.e., Multilevel SEMs)

Two person-level health outcomes are in the form of continuous endogenous variables: the number of poor physical health days and the number of poor mental health days. Therefore, binary probit modeling as used for estimating the other health outcomes (i.e., obesity, diabetes, asthma, general health) is not a suitable technique to model these health outcomes.

To control for endogeneity bias due to omitted variables or potential reverse causal effects between the health outcomes represented by the continuous endogenous variables (i.e., the number of poor physical or mental health days) and the level of physical activity, multilevel SEM techniques have been employed to estimate the number of physically or mentally unhealthy days.

The multilevel SEM model structure for these health outcomes includes bidirectional arrows to incorporate the reciprocal causation (i.e., reverse causality), which may potentially exist between physical activity levels and these particular health outcomes (i.e., the number of poor physical or mental health days).

Employment of multilevel SEM has the bonus of dealing with any potential multicollinearity or spatial autocorrelation problems in the person-level health outcome models. Consistent with the county-level health models (see Appendix I), CBSAs (i.e., metropolitan areas) are considered clusters in the person-level multilevel SEM health models and CBSA random effects are estimated by these models.

The person-level multilevel SEMs can be represented by the following two regression equations for: 1) the person-level health outcomes (i.e., the number of poor physical health days or the number of poor mental health days); and 2) the person's level of physical activity (i.e., total minutes of moderate physical activity per week):

$$\text{Number of poor physical (or mental) health days}_{(Observed\ Endogenous\ Variable)} = \beta_0 + \beta_1' \mathrm{ED}_{\mathrm{Person}} + \beta_2' \mathrm{SE}_{\mathrm{County}} + \beta_3' \mathrm{SE}_{\mathrm{CBSA}} + \beta_4' \mathrm{TB}_{\mathrm{County}} + \beta_5' \mathrm{BE}_{\mathrm{County}} + \beta_6' \mathrm{BE}_{\mathrm{CBSA}} + u_{0\mathrm{CBSA}} + \varepsilon_1 \quad \text{Equation 33}$$

$$\text{Minutes of moderate physical activity per week}_{(Observed\ Endogenous\ Variable)} = \alpha_0 + \beta_7' \mathrm{HO}_{i\ (\mathrm{Person})} + \beta_8' \mathrm{SED}_{\mathrm{Person}} + \varepsilon_2 \quad \text{Equation 34}$$

where,

α_0, β_0 = model intercepts;

$\beta_1' - \beta_8'$ = column vectors of model path coefficients;

ED_{Person}, SE_{County}, SE_{CBSA}, TB_{County}, BE_{County}, and BE_{CBSA} = as defined for the person-level instrumental variable binary probit health models (Equations 31 and 32);

u_{0CBSA} = the CBSA-level random intercept (i.e., random effects);

$HO_{i\ (Person)}$ = the person-level health outcome *i*;

SED_{Person} = a subset column vector containing person-level characteristics as well as the characteristics of the person's household;

$\varepsilon_1, \varepsilon_2$ = model error terms;

i = (number of poor physical health days, number of poor mental health days).

Considering the arguments presented in Kline (2011), the above multilevel SEM model specification allows for simultaneous analysis of the effect of factors from multiple hierarchical levels—including those from the individual level and those from the cluster level (i.e., contextual effects) on individuals' health outcome of interest being modeled.

In this case, the health outcomes of interest are those represented by the continuous endogenous variables, which include: the individual's number of poor physical health days or the individual's number of poor mental health days.

Variable Transformation and Estimation Methods

Most of the variables included in the models are normally distributed; however, to simplify interpretation of the results, a few of the built environment variables were normalized by transformation into a naturally logged form before inclusion in the models. The MLE estimation method has been used to estimate the person-level health outcome models.

For the instrumental variable binary probit models, application of the MLE method allows for computation of marginal effects after model estimation using the Stata software. With respect to multilevel SEMs, applying the MLE method deals with endogeneity bias in the models since in estimating bidirectional relationships, potential endogeneity bias can be statistically corrected by using MLE (Cervero and Murakami 2010).

In addition, to account for spatial autocorrelation, all standard errors have been adjusted for lack of independence among observations due to being located within a certain geographical area (i.e., county). That is, the standard errors have been calculated under the relaxed assumptions of a generalized Huber/White/sandwich estimation method.

These assumptions relax the assumption of independence of the errors and replace it with the assumption of independence between clusters. Therefore, the errors are allowed to be correlated within clusters (i.e., counties in this case)[44]. This estimation method for standard errors, therefore, is robust to heteroskedasticity of the errors as well as any spatial autocorrelation problems, which may exist in the models. The AIC and the BIC were used for model evaluation and to select the best model for each of the health outcomes.

The results of the person-level health outcome models are discussed next.

[44] See Stata Structural Equation Modeling Reference Manual Release 13, Pages 96-97 "intro 8 — Robust and clustered standard errors": https://www.stata.com/manuals13/sem.pdf and Stata's "ivprobit — Probit model with continuous endogenous regressors", Page 5 "Technical note": https://www.stata.com/manuals13/rivprobit.pdf

5.1.4.2 Discussion of Results: Person-level Health Outcome Models

Table 18 summarizes the estimation results of the instrumental variable binary probit models and multilevel SEM models for the seven person-level health indicators of interest (obesity, asthma, diabetes, general health, poor physical health days, poor mental health days, and participation in at least 150 minutes of moderate physical activity per week).

With regards to the binary probit models, average marginal effects have been computed for each independent variable to facilitate interpretation of the coefficients. Table 19 provides the average marginal effects, estimating the probability of: being overweight or obese; having asthma, diabetes, a good or excellent health; and meeting the CDC-recommended physical activity levels.

With regards to the multilevel SEM models, the direction of arrows in the path diagrams represents the effect priority as hypothesized and specified in the model (i.e., $X \rightarrow Y$ implies that X affects Y) (Kline 2011). Thus, the results of the multilevel SEMs are discussed considering such links as causal relations.

Through their comprehensive frameworks, the econometric models for which the results are presented in Tables 18 and 19 link individuals' physical and psychological health[45] indicators to their personal and household characteristics as well as travel behavior characteristics (i.e., active travel behavior, motorized travel behavior, telecommuting behavior, and teleshopping behavior) and built and social environment factors of their place of residence at different spatial levels.

The results show that person-level health outcomes are linked with person and household attributes, health-related behavior, travel behavior as well as built and social environment attributes of place of residence at the meso level (i.e., county) and the macro level (i.e., CBSA).

[45] Psychological health status is perceived to be a result of environmental factors or social circumstances (external factors), whereas mental health status is perceived to be formed partly by individual's biological factors (internal factors). Although often perceived in different ways, the terms psychological and mental are sometimes used interchangeably. Thus, the phrases psychological health and mental health are used interchangeably in this research.

Table 18. Results: Person-level Health Outcome Models

Health Outcome Response Variables / *Predictor Variables*	*Overweight Or Obese*		*Asthma Diagnosis*		*Diabetes Diagnosis*		*Good or Excellent General Health*		*Number of Poor Physical Health Days*		*Number of Poor Mental Health Days*		*Participation in ≥ 150 Min. Moderate Physical Activity*	
	Coefficient	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*	*Path Coefficient*	*p-value*	*Path Coefficient*	*p-value*	*Coefficient*	*p-value*
The Health Outcome Equation														
Person and Household														
Age (*years*)	.002257*	0.087	.0058397***	0.000	.0045403***	0.002	-.004757***	0.000	NS	NS	.091115***	0.000	-.0113326***	0.000
Race (*1: White, 0: otherwise*)	-.1855208***	0.001	NS	NS	-.0860503**	0.030	.2192878***	0.000	NS	NS	NS	NS	.2454019***	0.000
Gender (*1: male, 0: female*)	NS	NS	NS	NS	-.1197435***	0.000	NS	NS	NS	NS	-.680052***	0.004	.2160422***	0.000
Physical Activity [b, c] (*minutes per week*)	-.0105765***	0.000	-.0119303***	0.000	-.0124975***	0.000	.001614***	0.000	-.0222596**	0.036	-.0151169*	0.088	—	—
Fruit and Vegetables (*servings per day*)	-.019859**	0.013	-.0141154***	0.008	-.014526***	0.002	.0319202***	0.000	-.064054*	0.097	-.0685074**	0.035	.0898337***	0.000
Smoking Status (*base: nonsmoker*)														
everyday smoker	-.265297***	0.000	.1402861***	0.005	-.1300801***	0.008	-.3827534***	0.000	2.149076***	0.000	3.034778***	0.000	NS	NS
someday smoker	-.240904***	0.001	.2390436***	0.001	-.1716818***	0.007	-.388848***	0.000	2.954808***	0.000	1.920725***	0.003	-.1425182*	0.062
former smoker	NS	NS	.0975375***	0.050	NS	NS	-.2126278***	0.000	1.263961***	0.000	.8654087***	0.000	NS	NS
Drinking Status *(number of alcoholic beverages per month)*	—	—	—	—	.0006407*	0.087	—	—	—	—	—	—	—	—
Household Income (*base: < $15,000*)														
$15,000 to less than $25,000	NS	NS	NS	NS	NS	NS	.3398008***	0.000	-3.279143***	0.000	-1.820816***	0.000	.1562742***	0.005
$25,000 to less than $35,000	NS	NS	NS	NS	NS	NS	.5259056***	0.000	-3.981217***	0.000	-2.531651***	0.000	.1643225***	0.009
$35,000 to less than $50,000	NS	NS	NS	NS	NS	NS	.7404188***	0.000	-4.74856***	0.000	-3.356317***	0.000	.2960195***	0.000
$50,000 or more	NS	NS	-.2009064*	0.099	NS	NS	1.044106***	0.000	-5.304316***	0.000	-4.018764***	0.000	.383828***	0.000
Employment Status [d] (*1: employed, 0: not employed*)	NA		NA		NA		.4421719***	0.000	-2.622018***	0.000	-1.534643***	0.000	NS	NS
College Education [d] (*1: yes, 0: no*)	NA		NA		NA		.1382413***	0.000	-.5393645***	0.010	NS	NS	.0963694**	0.023
Children [d] (*number of children in the household*)	NA		NA		NA		.0511261**	0.016	-.3354186***	0.006	NS	NS	NS	NS
Social Environment														
Meso Level: The County														
Median Age	NS	NS	.0277286***	0.002	.0134414*	0.082	-.0583641***	0.001	.1395475*	0.072	.1548975**	0.025	-.0476338***	0.000
Median Annual Household Income	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Percent of White Population	NS	NS	NS	NS	NS	NS	.0261994***	0.000	-.0947322***	0.008	NS	NS	.0127899***	0.002
Percent of Telecommutable Jobs	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Macro Level (Core Based Statistical Area): The Metropolitan Area														
Average Walking and Bicycling Density [a]	NS	NS	NS	NS	-.0414568*	0.084	.1916424*	0.066	NS	NS	-1.373881***	0.000	NS	NS
Annual Public Transit Passenger-Miles [a]	NS	NS	.1228535***	0.010	-.0897097**	0.042	-.2888749***	0.003	1.128578**	0.020	NS	NS	NS	NS
Average Commuter Stress Index	NS	NS	NS	NS	NS	NS	-4.742522***	0.004	10.59153*	0.087	NS	NS	NS	NS
Average Percent of Low-Wage Workers	NS	NS	NS	NS	NS	NS	-.104597***	0.000	NS	NS	.3987882***	0.003	-.0800193***	0.000
Average Percentage of Households with No Cars	NS	NS	NS	NS	NS	NS	-.1048387*	0.067	.7688444***	0.008	.4256389*	0.062	NS	NS
Average Gross Regional Product (GRP) [a]	-.1058054**	0.029	-.0756389*	0.093	NS	NS	.2993636***	0.000	-.5321078*	0.095	-2.16883***	0.000	NS	NS
Average Crime Rate	.0003399***	0.004	-.0005537***	0.000	.000346***	0.002	-.000874***	0.001	NS	NS	NS	NS	-.0004294**	0.019
Travel Behavior														
Meso Level: The County														
Nonmotorized Travel Mode Share	-.0075641**	0.047	NS	NS	NS	NS	.0054944*	0.069	-.1295234**	0.049	-.1406948**	0.029	NS	NS
Private Vehicle Travel Mode Share	NS	NS	.0139775***	0.000	.0118146***	0.000	NS	NS	NS	NS	-.0842479***	0.007	NS	NS
Public Transit Travel Mode Share	-.0597685***	0.002	.0788665***	0.000	-.053574***	0.000	-.0703956**	0.019	NS	NS	.1904615*	0.092	.0996205***	0.000
Ave. Frequency of Telecommuting Events per Month	NS	NS	-.0100291*	0.073	.0089899*	0.059	-.0282205*	0.097	NS	NS	NS	NS	-.0165912*	0.077
Ave. Percent of HH Members with Telecommuting Option	NS	NS	-.0081331*	0.049	NS	NS	NS	NS	NS	NS	.0811453***	0.003	-.0069587*	0.089
Ave. Number of Online Purchases per Month	.1019967**	0.021	-.0466664*	0.099	NS	NS	-.4156456***	0.000	1.883836***	0.000	.6604995*	0.077	NS	NS
Ave. Number of Monthly Deliveries Related to Online Purchases	NS	NS	NS	NS	.1015846**	0.017	NS	NS	NS	NS	NS	NS	-.252159***	0.000

Built Environment														
Meso Level: The County														
Mean Activity Density [a]	.0774713***	0.002	-.0908846**	0.021	.0496282***	0.003	-.126384**	0.047	NS	NS	.4590626*	0.084	.0915875**	0.019
Mean Entropy [a]	-.5076122***	0.004	.7426236***	0.004	.2912284**	0.047	NS	NS	NS	NS	2.166756**	0.074	.5677244***	0.005
Mean Intersection Density [a]	NS	NS	NS	NS	NS	NS	.3569469***	0.003	NS	NS	NS	NS	-.0922825**	0.030
Mean Local Transit Accessibility	NS	NS	-.0013313*	0.065	NS	NS	-.0024025**	0.047	NS	NS	NS	NS	.0026825***	0.000
Mean Temporal Automobile Accessibility [a]	NS	NS	.0509068*	0.059	NS	NS	NS	NS	NS	NS	-.8602602***	0.001	-.1099844**	0.021
Mean Temporal Transit Accessibility [a]	-.0190041***	0.000	.0167732***	0.000	-.0121438***	0.001	NS	NS	-.1119116**	0.039	NS	NS	NS	NS
Density of Fast Food Restaurants	.095305***	0.000	.1475638***	0.000	.1039651***	0.000	-.1124666***	0.008	.6907523***	0.006	NS	NS	-.0771437***	0.003
Access to Parks	-.0026208*	0.095	.0056172***	0.004	-.002919***	0.004	NS	NS	-.0436033***	0.007	-.0221404*	0.075	.0088919***	0.000
Primary Care Physician Rate	-.0015728**	0.020	NS	NS	NS	NS	.00129*	0.087	-.0124352*	0.054	NS	NS	NS	NS
Access to Healthy Food Outlets	-.0028061*	0.061	-.0054182***	0.000	-.0037962***	0.000	.005718***	0.005	NS	NS	-.0258053***	0.005	.0077523***	0.000
Ambient Air Pollution	—	—	.0040683*	0.067	—	—	-.0428995***	0.000	.1640947***	0.002	.0767465*	0.085	—	—
Mean Walk Score	-.0027107***	0.001	-.0025144**	0.037	-.0020266***	0.005	.0063055***	0.001	-.0240459**	0.037	NS	NS	NS	NS
Macro Level (Core Based Statistical Area): The Metropolitan Area														
Mean Activity Density [a]	NS	NS	-.2119958***	0.008	.1914216**	0.017	NS	NS	NS	NS	1.817649***	0.004	NS	NS
Mean Entropy [a]	NS	NS	.8071199***	0.004	.2790995*	0.085	1.445422***	0.006	NS	NS	NS	NS	1.040943***	0.001
Mean Intersection Density [a]	.2101968**	0.012	.1859524*	0.068	.1503409**	0.029	.3920485**	0.020	-2.112958**	0.029	NS	NS	NS	NS
Mean Local Transit Accessibility	.0014559**	0.016	NS	NS	.000788**	0.044	NS	NS	.0171399***	0.001	.0053337*	0.070	NS	NS
Mean Temporal Automobile Accessibility [a]	.2972497***	0.003	.2766411***	0.004	.1759324**	0.022	-.4232195**	0.030	NS	NS	-3.467102***	0.000	NS	NS
Mean Temporal Transit Accessibility [a]	NS	NS	.0411097***	0.005	-.0243627*	0.088	.0784013***	0.001	NS	NS	.1600574*	0.059	.0830311***	0.000
Mean Roadway Congestion Index	NS	NS	NS	NS	NS	NS	-.8122739**	0.020	5.979551***	0.004	NS	NS	-.5009632*	0.083
The Weekly Minutes of Moderate Physical Activity Equation (in multilevel SEM Models only)														
Person and Household														
Number of Poor Physical Health Days [c]	NA		NA		NA		NA		NS	NS	—	—	NA	
Number of Poor Mental Health Days [c]	NA		NA		NA		NA		—	—	NS	NS	NA	
Age (*years*)	NA		NA		NA		NA		-.2988571***	0.000	-.1684047*	0.095	NA	
Gender (*1: male, 0: female*)	NA		NA		NA		NA		11.13582***	0.000	11.42947***	0.000	NA	
Employment Status (*1: employed, 0: not employed*)	NA		NA		NA		NA		NS	NS	NS	NS	NA	
College Education (*1: yes, 0: no*)	NA		NA		NA		NA		4.656244**	0.038	5.541723**	0.013	NA	
Children (*number of children in the household*)	NA		NA		NA		NA		NS	NS	NS	NS	NA	
Warm Season	—		—		—		—		NS	NS	NS	NS	—	
Other Model Factors														
Wald test of exogeneity [(corr = 0): χ^2 (1)] for IV Probit Model	10.12***	.0015	11.02***	.0009	7.49***	.0062	see Note " e "		NA		NA		see Note " f "	
Amemiya-Lee-Newey minimum χ^2 test for the equivalent model estimated using the twostep method (test of overidentifying restrictions, Baum et al. 2006)	.241	.8866	1.619	.4451	1.787	.4092	NA		NA		NA		NA	
Model	IV Binary Probit		IV Binary Probit		IV Binary Probit		Binary Probit [e]		Multilevel SEM		Multilevel SEM		Binary Probit [f]	
CBSA Random Effects	—		—		—		—		NS		NS		—	
Pseudo R^2	NA		NA		NA		0.1673		NA		NA		0.0652	
Log pseudolikelihood	-44672.516		-43961.596		-43214.583		-3026.1687		-65655.726		-65409.793		-4415.5681	

NOTES:
a Variable was log-transformed; **b** Instrumented variable in IV probit models (on instruments *Employment Status*, *College Education*, and *Children*); **c** Endogenous variable in multilevel SEM models; **d** Instrumental variable in in IV probit models; **e** Instrumental variable analysis showed no endogeneity bias in the model (the Wald test of exogeneity was not significant for the IV probit model—indicating the null hypothesis of no endogeneity cannot be rejected); therefore, a regular binary probit model was estimated instead of an instrumental variable (IV) probit model; **f** No endogeneity was assumed in this model; therefore, a regular binary probit model was estimated instead of an instrumental variable (IV) probit model; HH = Household; NA = Not applicable; NS = Not statistically significant; — = Not included in the model; *, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;
Also, standard errors were adjusted for 51 clusters (i.e., counties);
The process of model selection is not discussed in this dissertation; therefore, the values of the minimum AIC and BIC for each health outcome model are not reported in the table. As Fabozzi et al. (2014) suggested, AIC/BIC estimates for just one model and in isolation are meaningless.

Table 19. Average Marginal Effects: Person-level Health Outcome Models

Predictor Variables \ Health Outcome Response Variables	Overweight Or Obese		Asthma Diagnosis		Diabetes Diagnosis		Good or Excellent General Health		Participation in ≥ 150 Min. Moderate Physical Activity	
	Average Marginal Effects	***p-value***	***Average Marginal Effects***	***p-value***	***Average Marginal Effects***	***p-value***	***Average Marginal Effects***	***p-value***	***Average Marginal Effects***	***p-value***
Person and Household										
Age	NS	NS	.0016064***	0.001	.0031978***	0.002	-.0011288***	0.000	-.0039874***	0.000
Race (*1: White, 0: otherwise*)	-.0879356***	0.001	NS	NS	-.0734162***	0.002	.0520407***	0.000	.0863445***	0.000
Gender (*1: male, 0: female*)	.168422***	0.002	-.0461154***	0.000	NS	NS	NS	NS	.0760143***	0.000
Physical Activity [b] (*minutes per week*)	-.0001527*	0.063	-.0000951**	0.028	-.0001283**	0.039	.000383***	0.000	—	—
Fruit and Vegetables (*servings per day*)	-.0053932*	0.095	NS	NS	NS	NS	.0075752***	0.000	.0316079***	0.000
Smoking Status (*base: non-smoker*)										
everyday smoker	-.0973157***	0.000	NS	NS	NS	NS	-.0908339***	0.000	NS	NS
someday smoker	-.063421***	0.002	.0408043**	0.035	NS	NS	-.0922802***	0.000	-.0501449*	0.062
former smoker	.0303125*	0.080	.0411301***	0.000	.0276464***	0.010	-.0504602***	0.000	NS	NS
Drinking Status (*number of alcoholic beverages per month)*	—	—	—	—	.0011031***	0.002	—	—	—	—
Household Income (*base: < $15,000*)										
$15,000 to less than $25,000	NS	NS	-.0672238***	0.001	NS	NS	.1129422***	0.000	.058242***	0.005
$25,000 to less than $35,000	NS	NS	-.0863357***	0.000	NS	NS	.1670949***	0.000	.061196***	0.009
$35,000 to less than $50,000	NS	NS	-.1015195***	0.000	NS	NS	.2212181***	0.000	.1086166***	0.000
$50,000 or more	NS	NS	-.1237543***	0.000	-.0652509***	0.006	.2818209***	0.000	.1390636***	0.000
Employment Status [c] *(1: employed, 0: not employed)*	NA		NA		NA		.1049349***	0.000	NS	NS
College Education [c] (*1: yes, 0: no*)	NA		NA		NA		.032807***	0.000	.0339075**	0.023
Children[c] (*number of children in the household*)	NA		NA		NA		.0121331**	0.016	NS	NS
Social Environment										
Meso Level: The County										
Median Age	NS	NS	.0048621*	0.076	NS	NS	-.0138508***	0.001	-.0167599***	0.000
Median Annual Household Income	NS	NS	-2.16e-06***	0.007	-2.24e-06**	0.034	NS	NS	NS	NS
Percent of White Population	NS	NS	.0020337*	0.056	NS	NS	.0062176***	0.000	.0045001***	0.002
Percent of Telecommutable Jobs	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Macro Level (Core Based Statistical Area): The Metropolitan Area										
Average Walking and Bicycling Density [a]	NS	NS	-.027676**	0.019	-.0109178*	0.097	.04548*	0.064	NS	NS
Annual Public Transit Passenger-Miles [a]	-.0492583*	0.092	NS	NS	-.0081668*	0.073	-.0685549***	0.003	NS	NS
Average Commuter Stress Index	.7558689*	0.049	NS	NS	NS	NS	-1.125481***	0.005	NS	NS
Average Percent of Low-Wage Workers	.0144142**	0.045	NS	NS	NS	NS	-.0248226***	0.000	-.0281547***	0.000

Average Percentage of Households with No Cars	NS	NS	NS	NS	NS	NS	-.02488*	0.069	NS	NS
Average Gross Regional Product (GRP) [a]	-.0442002**	0.093	-.016817*	0.078	NS	NS	.071044***	0.000	NS	NS
Average Crime Rate	NS	NS	-.0000583*	0.085	NS	NS	-.0002074***	0.001	-.0001511**	0.020
Travel Behavior										
Meso Level: The County										
Nonmotorized Travel Mode Share	-.0015181**	0.089	NS	NS	NS	NS	.0013039*	0.070	NS	NS
Private Vehicle Travel Mode Share	NS	NS	.002202*	0.097	NS	NS	NS	NS	NS	NS
Public Transit Travel Mode Share	-.0041469**	0.055	.0183288***	0.001	-.0126945**	0.049	-.0167061**	0.019	.0350514***	0.000
Ave. Frequency of Telecommuting Events per Month	.0062141*	0.061	-.0011821*	0.093	NS	NS	-.0066972*	0.096	-.0058376*	0.076
Ave. Percent of HH Members with Telecommuting Option	NS	NS	-.0030147**	0.012	NS	NS	NS	NS	-.0024484*	0.089
Ave. Number of Online Purchases	.0633425**	0.014	-.0261397*	0.052	NS	NS	-.0986397***	0.000	NS	NS
Ave. Number of Monthly Deliveries Related to Online Purchases	.0714118**	0.042	NS	NS	NS	NS	NS	NS	-.088722***	0.000
Built Environment										
Meso Level: The County										
Mean Activity Density [a]	.0176133*	0.067	-.0381007***	0.001	NS	NS	-.0299931**	0.047	.032225**	0.019
Mean Entropy[a]	-.1795927*	0.097	.2355872***	0.000	.2121117***	0.004	NS	NS	.1997535***	0.005
Mean Intersection Density [a]	NS	NS	.0487475***	0.000	NS	NS	.0847095***	0.003	-.0324695**	0.030
Mean Local Transit Accessibility	.0003067*	0.076	-.0006379***	0.000	.0003539**	0.013	-.0005702**	0.046	.0009438***	0.000
Mean Temporal Automobile Accessibility [a]	.0360363*	0.095	NS	NS	.0223294**	0.019	NS	NS	-.0386979**	0.021
Mean Temporal Transit Accessibility [a]	-.0035077***	0.084	.0026601*	0.091	NS	NS	NS	NS	NS	NS
Density of Fast Food Restaurants	.0001297**	0.044	.0199601**	0.014	.0131376*	0.099	-.0266902***	0.008	-.027143***	0.003
Access to Parks	NS	NS	.0019291***	0.000	-.0014158*	0.095	NS	NS	.0031286***	0.000
Primary Care Physician Rate	-.0009547**	0.027	NS	NS	NS	NS	.0003062*	0.085	NS	NS
Access to Healthy Food Outlets	NS	NS	-.0009925***	0.006	-.0012867*	0.069	.001357***	0.005	.0027277***	0.000
Ambient Air Pollution	—	—	.0020361*	0.095	—	—	-.0101808***	0.000	—	—
Mean Walk Score	-.000044**	0.038	-.0005676*	0.094	NS	NS	.0014964***	0.001	NS	NS
Macro Level (Core Based Statistical Area): The Metropolitan Area										
Mean Activity Density [a]	.1444978**	0.015	NS	NS	NS	NS	NS	NS	NS	NS
Mean Entropy[a]	NS	NS	.2336963***	0.002	.1106682*	0.054	.3430231***	0.006	.3662552***	0.001
Mean Intersection Density [a]	NS	NS	.0413187*	0.063	.0443029*	0.063	.0930397**	0.020	NS	NS
Mean Local Transit Accessibility	.0003777*	0.087	-.0007915***	0.000	.0003052*	0.096	NS	NS	NS	NS
Mean Temporal Automobile Accessibility [a]	NS	NS	NS	NS	NS	NS	-.1004371**	0.030	NS	NS
Mean Temporal Transit Accessibility [a]	-.0213517**	0.031	NS	NS	NS	NS	.0186059***	0.001	.0292144***	0.000
Mean Roadway Congestion Index	.2272241*	0.080	.1200605**	0.024	NS	NS	-.1927663**	0.019	-.1762636*	0.083
Model	IV Binary Probit		IV Binary Probit		IV Binary Probit		Binary Probit [d]		Binary Probit [e]	

NOTES: [a] Variable was log-transformed; [b] Instrumented variable in IV probit models; [c] Instrumental variable in IV probit models; [d] Instrumental variable analysis showed no endogeneity in the model (the Wald test of exogeneity was not significant for the IV probit model); therefore, a regular binary probit model was estimated instead of an instrumental variable (IV) probit model; [e] No endogeneity was assumed in this model; therefore, a regular binary probit model was estimated instead of an instrumental variable (IV) probit model; HH = Household; Ave.=Average; NS = Not statistically significant; — = Not included in the model; *, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively.

The Health Outcome Equation Findings

Person-level Variables (Individual and Household Characteristics) Findings

The results of the person-level health outcome models emphasize the influential role of characteristics related to individuals as well as their households in person-level health outcomes. These characteristics represent sociodemographic and socioeconomic status of the Florida 2009 BRFSS respondents as well as their health behavior in the models.

Among sociodemographic characteristics, an individual's age, race, gender, as well as the number of children in individual's household have been included in the models. Not surprisingly, older age is associated with adverse health outcomes including a higher likelihood of having been diagnosed with asthma, a higher likelihood of having been diagnosed with diabetes, a lower likelihood of meeting the CDC recommendation on physical activity levels and having a good or excellent general health. The *Age* variable is also linked with a higher number of poor mental health days and might have a positive association with being overweight or obese (marginal effect not statistically significant). These findings are consistent with past studies suggesting that older age is associated with lower likelihood of participation in physical activity as well as lower levels of physical activity (see e.g., Ross 2000; Trost et al. 2002; Frank et al. 2005; Ewing et al. 2014), and poorer health outcomes (see e.g., Frank et al. 2004; Plantinga and Bernell 2007; Lindström 2008; Ewing et al. 2014; Langerudi et al. 2015; Barr et al. 2016; Tajalli and Hajbabaie 2017).

Additionally, race proves to be an influential factor in individuals' health status and outcomes. The results show that being of the White race is associated with an increased likelihood of participating in at least 150 minutes of physical activity per week, an increased likelihood of having a good or excellent general health status, and a lower likelihood of having been diagnosed with diabetes or being overweight or obese. These findings are in line with those of previous studies suggesting that the likelihood of engaging in physical activity and meeting the recommended physical activity levels are greater for Whites than other races (see e.g., Ross 2000; Ewing et al. 2003b; Frank et al. 2005; Ewing et al. 2008) and that being of the White race is generally associated with having better health outcomes, especially with respect to obesity and diabetes (see e.g., Ewing et al. 2008; Joshu et al. 2008; Ewing et al. 2014).

Further the individuals' gender plays a key role in their health status and physical activity levels. The model results presented in Tables 18 and 19 indicate that males are more likely to be overweight or obese, but they have a lower likelihood of being diagnosed with asthma and perhaps even diabetes (average marginal effect is not statistically significant in the diabetes model). In addition, males have a lower number of poor mental health days and are more likely to meet the CDC recommendation on physical activity levels. Lending support to these findings are many previous studies suggesting that males are more likely to be physically active and typically have higher physical activity levels (see e.g., Ross 2000; Trost et al. 2002; Ewing et al. 2003b, 2008; Frank et al. 2005; Ewing et al. 2014). A few studies found that BMI was higher for males than females (see e.g., Ewing et al. 2003b, 2008; Plantinga and Bernell 2007; Ewing et al. 2014) and that diabetes and other physical health problems were more prevalent in males than females (Ewing et al. 2014)—all of which are consistent with findings of the present study.

Also, the more children living in an individual's households, the higher the likelihood of that individual having a good or excellent general health and the lower the number of his/her poor physical health days. These results are consistent with findings of Samimi and Mohammadian (2009) who reported that individuals' general health was positively correlated with having children. However, the results stand in contrast with findings of Langerudi et al. (2015) who found a negative correlation between general health and having children. The inconsistencies in these findings suggest that further research may be needed to elucidate the role of having children or living with children in individuals' general health.

Among socioeconomic characteristics, an individual's employment status and educational attainment as well as the income level of the individual's household have been included in the models. Results show that being employed is linked with better physical and psychological health outcomes such as increased likelihood of having good or excellent general health as well as having fewer numbers of poor physical and poor mental health days. In addition, higher education is related to higher likelihood of meeting the CDC recommendations on physical activity levels, a higher likelihood of having a good or excellent general health, and fewer numbers of poor physical health days. These results are consistent with previous findings suggesting that higher levels of educational attainment were associated with a higher likelihood of engaging in physical activity as well as with higher levels of physical activity (see e.g., Ross 2000; Ewing et al. 2003b; Frank et al. 2005). The results are also consistent with studies that found higher levels of educational attainment at the person level were associated with physical healthiness (Tajalli and Hajbabaie 2017), and are in line with those that reported county-level higher educational attainment measures were associated with lower prevalence of diabetes (Braun and Malizia 2015)[46].

Further, increased household income levels are linked with favorable physical and psychological health outcomes. Higher incomes show positive associations with lower likelihood of being diagnosed with asthma or diabetes (average marginal effect is statistically significant for the highest income group), and increased likelihood of meeting the CDC-recommended physical activity levels and having a good or excellent general health status. Higher household incomes are

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[46] Also, see discussion under the "*Endogeneity and Reverse Causality between Health Outcomes and Physical Activity*" part on page 306 of this dissertation.

also linked with fewer numbers of poor physical and mental health days. These results corroborate past findings that indicated higher incomes were associated with higher levels of physical activity (see e.g., Ross 2000; Ewing et al. 2014), better physical and psychological health outcomes, as well as a better general health status (see e.g., Frank et al. 2004; Samimi and Mohammadian 2009; Ewing et al. 2014; Langerudi et al. 2015; Tajalli and Hajbabaie 2017). The results imply that lower-income households may bear a greater burden of health disparities.

The health behavior of the individuals has been controlled for by including variables representing their fruit and vegetable consumption, alcoholic beverages consumption, smoking status, and physical activity levels. These variables are postulated to be influential in personal health and well-being, and several prior studies have considered some of them in their analysis (e.g., Ewing et al. 2003b, 2008; Ewing et al. 2014; Liao et al. 2016; Tajalli and Hajbabaie 2017).

Based on the results, more servings per day of fruits and vegetables are linked with having more favorable health outcomes including a lower likelihood of being overweight or obese, a higher likelihood of having a good or excellent general health, as well as having fewer numbers of poor physical and mental health days. Moreover, a higher likelihood of meeting the CDC recommendation on physical activity levels is associated with higher consumption levels of fruits and vegetables. Lower probabilities of being diagnosed with asthma and diabetes may also be associated with higher consumption levels of fruits and vegetables (although, the average marginal effects are not statistically significant in the asthma and diabetes models).

These findings corroborate those of past research, which reported that lower BMI was associated with higher daily levels (i.e., three or more servings) of consumption of fruits and vegetables (Ewing et al. 2003b, 2008; Ewing et al. 2014), and that having a healthy diet was associated with better physical and mental health outcomes (Tajalli and Hajbabaie 2017).

The smoking status of the individual also proves a crucial factor in individual's health outcomes. Results indicate that compared to nonsmokers, individuals who smoke cigarettes (i.e., everyday smokers and someday smokers) have a lower likelihood of being overweight or obese and may have a lower likelihood of having diabetes. Albeit somewhat counter-intuitive, these results corroborate past research that found BMI, obesity levels, and diabetes levels to be lower for smokers compared to nonsmokers (Ewing et al. 2003b, 2008; Plantinga and Bernell 2007; Ewing et al. 2014). As expected, however, current smokers suffer from adverse health effects including a higher likelihood of being diagnosed with asthma, a lower likelihood of having a good or excellent general health, as well as increased numbers of poor physical and mental health days.

Current smokers also are less likely to meet the CDC-recommended physical activity levels, which is consistent with findings of prior research suggesting that participation in physical activity and physical activity levels were lower among smokers compared to nonsmokers (Ewing et al. 2003b, 2008). Former smokers, on the other hand, have a higher likelihood of being overweight or obese and a higher likelihood of being diagnosed with diabetes compared to individuals who have never smoked (i.e., the nonsmoker category, which is the base category). Compared to nonsmokers, former smokers are also more likely to have been diagnosed with asthma, are less likely to have a good or excellent general health, and have increased numbers of poor physical and mental health days. These results suggest that smoking, even if only in the past, has adverse health effects—an anticipated finding.

The drinking status of individuals, which represents the level of consumption of alcoholic beverages by them, shows a positive association with increased likelihood of having been diagnosed with diabetes. This implies that as the number of alcoholic beverages consumed per month by the individual increases, so does the risk of developing diabetes. This result is consistent with those obtained from the county-level health outcome models, which indicate that higher liquor store density within the county (proxy for alcohol consumption by residents) may lead to higher rates of diabetes for residents (see Appendix I). These findings are also in line with the literature suggesting that high levels of liquor intake are associated with increased risk of diabetes (Rimm et al. 1995; Wannamethee et al. 2003; Howard et al. 2004).

As regards physical activity, results show that higher levels of moderate physical activity (i.e., more minutes per week) are linked with better physical and psychological health outcomes including a lower likelihood of: overweight or obese, asthma diagnosis, and diabetes diagnosis; lower numbers of poor physical and mental health days; and an increased likelihood of good or excellent general health. These findings corroborate findings of previous research, which suggested that: *i*) participation in physical activity was associated with better physical health outcomes including better general health, a lower likelihood of obesity, and a lower likelihood of asthma (Langerudi et al. 2015); *ii*) higher physical activity levels were associated with lower probabilities of being obese, having diabetes, and having mental health problems (Tajalli and Hajbabaie 2017); and *iii*) higher levels of physical activity in the form of active travel were correlated with lower BMI, a lower likelihood of being overweight/obese, and having other adverse health outcomes as well as an increased likelihood of having a good general health (Schauder and Foley 2015).

Built Environment Variables Findings

The effects of the built environment on person-level health outcomes have been controlled for at two spatial levels: the meso level (i.e., county level) and the macro level (i.e., metropolitan level). Several built environment factors show statistically significant effects in the person-level health outcome models. These effects are discussed below.

Meso-level (County-level) Built Environment Variables Findings: County-level built environment variables represent the *D*s of the built environment in the health outcome models. These variables characterize each county based on levels of compactness (i.e., activity density), mixed-use development (i.e., entropy), connectivity and walkability of the street network, employment accessibility, access to local transit, access to clinical healthcare, access to recreational facilities, access to healthy and unhealthy food outlets, as well as ambient air pollution. The model estimates and marginal effects show that many of these county-level built environment factors play an important role in health status of residents.

The results indicate that despite being positively associated with higher probabilities of the individual meeting the CDC recommendation of participation in at least 150 minutes of moderate physical activity per week, the county-level *Mean Activity Density* variable (which represents population and employment densities combined) also shows positive association with the probability of the individual being overweight or obese, probability of having been diagnosed with diabetes, and with having more mentally unhealthy days. In addition, this variable is negatively associated with the probability of having a good or excellent general health status.

The results imply that despite their potential pedestrian- and bicyclist-friendly designs and providing a better opportunity for physical activity, higher densities—as suggested by many past studies—may adversely affect individuals' health due to creating potentially stressful environments (Kelly-Schwartz et al. 2004; Samimi and Mohammadian 2009; Langerudi et al. 2015). Although, a few previous studies found that residents of more compact counties have lower BMIs (Ewing et al. 2003b; Plantinga and Bernell 2007; Ewing et al. 2014) as well as lower probabilities of obesity and diabetes (Ewing et al. 2014), it should be borne in mind that these studies operationalized compactness based on a sprawl index, which combined factors representing different dimensions of the built environment (i.e., density, land use mix, centering of jobs and population, and street network design). Thus, further research may be needed based on consistent definitions to clarify the role of compactness (i.e., population and employment density) in obesity and diabetes. Also, the effect of the county-level activity density variable on asthma diagnosis shows a negative direction, indicating that a lower probability of asthma is associated with an increased activity density within the county. This result is counter-intuitive as based on past research (Langerudi et al. 2015), one would expect dense urban areas to also be the more polluted ones—residing in which may lead to more respiratory health problems such as asthma.

Tables 18 and 19 indicate that the *Mean Entropy* variable at the county level has a positive association with the probability of meeting the CDC physical activity recommendations, and a negative association with the probability of being overweight or obese. Nonetheless, this variable exhibits a positive association with the probability of having been diagnosed with asthma and diabetes, as well as a positive link with having more mentally unhealthy days. With respect to asthma, the results may be capturing the effects of availability of additional destinations. As mixed land use within a county increases, additional destinations become available at farther distances. This may encourage additional vehicular trips, which may lead to higher pollution levels within the county and an increased risk of asthma for residents. The coefficient and the average marginal effects for this variable show a statistically insignificant effect in the probability of having a good or excellent general health status. This is somewhat inconsistent with findings of a prior study, which suggested that presence of various land uses within a neighborhood is associated with better general health (Langerudi et al. 2015). In terms of mental health, the finding of the present study is consistent with that of a previous study, which found an inverse association between sense of community (a proxy for mental health state) and mixed land use (Wood et al. 2010). Considering these findings, additional research may be needed to further clarify the impact of county-level mixed land use on health outcomes for residents.

Model estimates and average marginal effects also indicate that increased intersection densities throughout the county are associated with higher probabilities of having a better general health status. This is while previous research did not find a statistically significant association between intersection density and the status of population's general health (Samimi and Mohammadian 2009; Samimi et al. 2009). Also, the average marginal effects computed for the county-level *Mean Intersection Density* variable indicates that increased intersection density throughout the county is associated with higher probabilities of being diagnosed with asthma. Results also show that higher levels of county-level intersection density are associated with lower probabilities of meeting the CDC physical activity recommendations. Since the *Mean Intersection Density* variable in this study represents intersection density in terms of automobile-oriented intersections, these results are reasonable. More automobile-oriented intersections within an area can mean higher levels of air pollution due to vehicle emissions—an externality that may lead to lung diseases (Mackett and Thoreau 2015) such as asthma.

In addition, an increased number of automobile-oriented intersections may mean fewer pedestrian and bicyclist facilities, which can lead to lower levels of active travel and other forms of physical activity. However, this variable does not show a statistically significant effect on the other health outcomes including obesity. This result is consistent with that of Samimi and Mohammadian's (2009), but it stands in contrast with the findings of Samimi et al. (2009) who reported a negative association between obesity and county-level intersection density. The inconsistent findings warrant further research into the role of intersection density at the county level in individuals' health outcomes, particularly obesity.

The model estimate and the average marginal effects of the county-level *Mean Local Transit Accessibility* variable suggest that although associated with lower probabilities of having been diagnosed with asthma, increased distances to the nearest local transit stop are also correlated with adverse health effects such as a higher likelihood of being overweight or obese, a higher likelihood of having been diagnosed with diabetes, and a lower likelihood of having a good or excellent general health status. Residential areas farther away from transit stops are most likely the sprawled suburban areas, which provide cleaner air to breath, and thereby can lower the probability of an asthma infection. However, these suburban areas are also the ones that typically restrict activities such as walking and bicycling. This can lead to lower levels of active travel, which in turn, may lead to higher levels of obesity and other health problems for residents. As literature suggests that sprawl is related to higher obesity rates (see e.g., McCann and Ewing 2003; Handy et al. 2006; Ewing et al. 2014), these results imply that living in sprawled suburban areas with lower levels of access to transit may lead to obesity and other adverse health effects.

With regards to physical activity, it can be seen from Tables 18 and 19 that an increased distance to transit stops is associated with a higher probability of participating in at least 150 minutes of moderate physical activity per week. This result may seem counter-intuitive at first since one would expect to see lower levels of physical activity such as active travel performed by residents of suburban areas, which are also typically areas located farther away from transit stops. However, it should be borne in mind that the BRFSS defines moderate physical activity as activities including “brisk walking, bicycling, vacuuming, gardening, or anything else that causes some increase in breathing or heart rate”. Therefore, the results might be an indication of residents of suburban areas engaging in other physical activities, and not necessarily active travel.

The effects of regional accessibility have been examined in the person-level health models by including two county-level variables: *Mean Temporal Automobile Accessibility* and *Mean Temporal Transit Accessibility*. These variables were defined based on accessibility to employment opportunities within 45 minutes of automobile or transit travel times.

The results suggest that higher accessibility to jobs within the county by means of automobile is associated with an increased probability of residents being overweight or obese, whereas higher accessibility to jobs by means of transit is associated with a lower probability of being overweight or obese for residents. In terms of automobile accessibility, the results can be capturing the effect of long commutes. Longer commutes by means of automobile can mean additional commute-related stress and/or lower levels of physical activity; both of which can lead to obesity. Car commuting has been linked with higher levels of stress (Wener and Evans 2011) and long commutes have been suggested to limit physical activity levels by cutting into leisure time (Ewing et al. 2014). Coefficient estimates and the average marginal effects of the county-level *Mean Temporal Automobile Accessibility* variable in the present study confirm that higher temporal accessibility to jobs by means of automobile (proxy for long commutes) is related to a lower likelihood of participating in at least 150 minutes of moderate physical activity per week. With respect to transit accessibility, the results are in line with findings of a previous study, which suggested that increased transit use can lead to lower obesity rates (Samimi et al. 2009).

Further, model estimates provide evidence that higher levels of accessibility to jobs by automobile is linked to a lower number of poor mental health days, which can mean that higher automobile accessibility may lead to better psychological health for residents.

In addition, the average marginal effects of the *Mean Temporal Automobile Accessibility* variable in the *Diabetes Diagnosis* model is statistically significant, suggesting that increased automobile accessibility to jobs is associated with a higher likelihood of being diagnosed with diabetes. The coefficient estimate of the *Mean Temporal Transit Accessibility* variable in the diabetes model is also statistically significant, suggesting that increased transit accessibility to jobs is associated with a lower likelihood of being diagnosed with diabetes. It should be noted, however, that the average marginal effects of this variable does not reach a statistical significance threshold in the *Diabetes Diagnosis* model; therefore, additional research may be needed to clarify the role of transit accessibility to jobs in being diagnosed with diabetes.

Results also show that increased levels of accessibility to jobs by both automobile and transit are associated with an increased likelihood of asthma diagnosis (although the average marginal effects of the *Mean Temporal Automobile Accessibility* variable is not statistically significant in the *Asthma Diagnosis* model). These results are expected as increased levels of accessibility to jobs by automobile and transit can mean increased levels of use of these modes of travel. Increased use of automobiles means higher levels of vehicle emissions, which can affect respiratory health and lead to asthma. Widespread car usage—during both idle and moving times—has been suggested to lead to increasing rate of asthma in past research (Jackson 2003).

With respect to transit, the results of the present study confirm the findings of a previous study that found a significant, positive association between increased use of transit and being diagnosed with asthma (Samimi and Mohammadian 2009). One reason can be additional exposure to harmful particles in the air due to increased time spent outdoors when walking to and from transit stops or while waiting for the vehicle to arrive. Literature suggests that transit accessibility can promote active travel (Ryan and Frank 2009; Barnes et al. 2016), and that most public transit users arrive at and depart from transit stops via walking (Durand et al. 2016). On the other hand, past studies link higher walkability of the area to higher levels of traffic-related pollution (Marshall et al. 2009); thus, additional walking due to additional transit use may lead to inhaling increased amounts of harmful vehicle emissions, which can lead to asthma—as also suggested by Samimi and Mohammadian (2009). Other prior research argued that rail transit users may be exposed to high concentrations of particulate matter (PM) originating from mechanical friction processes, which can lead to negative health effects including respiratory health problems such as asthma (van Wee and Ettema 2016).

Together, these results suggest that in general, increased levels of accessibility to jobs by means of automobile may lead to better psychological health, whereas higher levels of accessibility to jobs by means of transit may lead to better physical health (except in the case of asthma). The latter argument is further supported by the negative direction of the path coefficient estimate of the *Mean Temporal Transit Accessibility* variable in the *Number of Poor Physical Health Days* multilevel SEM model.

Consistent with the county-level health outcome models (see Appendix I), access to clinical care within the county seems to contribute to a better health status for residents. The results indicate that an increased number of primary care physicians per 100,000 county population is associated with a lower likelihood of the residents being overweight or obese. This variable is also linked with individuals experiencing fewer numbers of physically unhealthy days. In addition, higher levels of access to clinical care within the county is associated with residents having good or excellent general health status. These results further support the hypothesis that increased access to healthcare within an area contributes to the betterment of the health status of residents.

Additionally, the results of the person-level health models provide further evidence for the role of the food environment in human health. The results show that higher densities of fast food restaurants within the county are associated with a higher likelihood of: being obese or overweight, having been diagnosed with asthma and/or diabetes, and with a lower likelihood of: meeting the CDC recommendations on physical activity and having a good or excellent general health status. Moreover, higher densities of fast food restaurants within the county are linked to increased numbers of poor physical health days for residents.

With respect to obesity, these results are consistent with those obtained from the county-level models (see Appendix I) and corroborate the findings of past research (Maddock 2004). Also, the results provide evidence for arguments by: *i*) Joshu et al. (2008) who suggested that physical environments that promote unhealthy food choices can also promote obesity; *ii*) Plantinga and Bernell (2007) who suggested that prevalence of fast food restaurants is one of the factors that may explain the rise in obesity rates in the U.S.; and *iii*) Croucher et al. (2012) who after conducting a review of literature, suggested that empirical evidence supports a link between the density of fast food outlets and obesity. Considering diabetes, at least one previous study found that more fast food restaurants within the city were associated with a higher diabetes rates (Marshall et al. 2014) —a finding in line with findings of the present study.

In contrast and as expected, access to healthy food outlets seems to have a favorable influence on health outcomes. Results show that increased levels of access to healthy food outlets within the county is associated with a lower likelihood of: being obese or overweight, having been diagnosed with asthma and/or diabetes, and a higher likelihood of: meeting the CDC physical activity recommendations and having a good or excellent general health status. Higher access to healthy food outlets is also linked with having fewer poor mental health days for residents. It should be noted that the average marginal effects of the *Access to Healthy Food Outlets* variable in the *Overweight or Obese* model does not reach a statistically significance threshold, which means that further examination of the role of access to healthy food in weight-related health outcomes may be needed. Nevertheless, these results imply that access to healthy food plays an important role in physical and psychological health of individuals and confirm arguments by past studies that access to healthy food can influence health outcomes (Frank et al. 2004; Mackett and Thoreau 2015). The findings provide further evidence that access to healthy food—as suggested by Kent and Thompson (2012)—is one of the main domains through which the built environment influences human health. Access to healthy food may be a challenge in sprawling environments (Ewing et al. 2014). Nonetheless, the results of the present study imply that lack of or limited access to healthy food can lead to poor health outcomes in terms of both physical and psychological health. Therefore, access to healthy food is a key element in retaining good health.

Also, living in the vicinity of parks seems to be associated with a lower likelihood of: being overweight or obese (bear in mind, however, that the corresponding average marginal effects is not significant) and having been diagnosed with diabetes, a higher likelihood of meeting the CDC physical activity recommendations. This variable (i.e., the *Access to Parks* variable) is also linked with fewer numbers of poor physical and mental health days. These results are reasonable as living near parks can encourage people to get out of their houses, exercise, and enjoy the outdoors—which can lead to a better state of physical health as well as improved quality of life and psychological health. Literature suggests that lower BMI is associated with more of the county land devoted to parks (Ewing et al. 2014) and that access to green spaces can affect health (Mackett and Thoreau 2015). The results of the present study confirm those hypotheses and further corroborates arguments by previous studies that parks and green spaces play a decisive role in providing neutral environments for social interaction and "de-stressing" (Croucher et al. 2012). However, based on the results, access to parks is also associated with a higher likelihood of being diagnosed with asthma. This is a reasonable finding as spending time near plants and vegetation increases exposure to environmental triggers and allergens such as pollen. Exposure to pollen may lead to respiratory allergic illness and/or exacerbation of asthma (D'amato et al. 2015).

On a related note, exposure to air pollution—particularly transportation and traffic-related air pollution—can adversely affect health (WHO 2006; Marshall et al. 2009; BTS 2016). Although the *Ambient Air Pollution* variable (which in this study represents the annual number of ambient air pollution days due to Ozone and Fine Particulate Matter) did not show a statistically significant association with most health outcomes in the county-level models (see Appendix I), this variable indicates unfavorable, statistically significant health effects in the person-level health models. Most notably, and as expected, an increased number of air pollution days is positively associated with the probability of having been diagnosed with asthma. This result is consistent with the literature suggesting that air pollution is related to asthma and outdoor air pollution exacerbates asthma in individuals who already have the condition (D'amato et al. 2015). Other results suggest that increased exposure to air pollution is associated with a lower probability of having a good or excellent general health as well as increased numbers of physically and/or mentally unhealthy days. Together, these findings are supported by statements in a report published by the World Health Organization (WHO 2006) suggesting that air pollutants such as Ozone and Fine Particulate Matter are associated with adverse health effects.

Results also provide evidence that living in a county with a higher Walk Score is associated with a lower likelihood of having undesirable health outcomes and a higher likelihood of having a good or excellent general health status. These results corroborate results obtained from the county-level health outcome models (see Appendix I) as well as past research (see e.g., Smith et al. 2008) and highlight the importance of walkability and pedestrian friendliness of the street network within the residential area in individuals' health status.

Macro-level (Metropolitan Area-level) Built Environment Variables Findings: The results of the person-level health outcome models provide further evidence that the macro-level (i.e., metropolitan area level) built environment plays an important role in residents' health.

The metropolitan area-level *Mean Activity Density* variable shows positive associations with the probability of the individual being overweight or obese and the probability of having been diagnosed with diabetes. The average marginal effects for this variable is only statistically significant in the *Overweight or Obese* model. Nonetheless, the direction of effects is consistent with those for the county-level *Mean Activity Density* variable and corroborate those findings. In addition, the metropolitan area-level *Mean Activity Density* variable shows a positive link with reporting an increased number of poor mental health days. These results indicate that higher densities (i.e., higher compactness) within a metropolitan area may lead to unfavaroable physical and psychological health outcomes. These findings are in line with arguments presented in past research that higher densities may adversely affect health due to creating potentially stressful environments (see e.g., Kelly-Schwartz et al. 2004; Samimi and Mohammadian 2009; Langerudi et al. 2015).

In terms of psychological health effects, the results of the present study do not provide support for an argument by Melis et al. (2015) who suggested that dense urban structures may lower the risk of depression by providing residents with the opportunity to have a more active social life. Thus, further research may be needed on the role of compactness of metropolitan areas in residents' mental and psychological health.

Results further indicate that similar to its counterpart at the county-level, the *Mean Entropy* variable at the metropolitan area level shows a positive association with the probability of meeting the CDC physical activity recommendations. This variable is also positively associated with the probability of reporting good or excellent general health. This means that a higher extent of mixed-use development within metropolitan areas is associated with increased likelihood of higher levels of physical activity and better general health status for residents.

With respect to general health, these results are counter to those obtained from the county-level health models (see Appendix I). This inconsistency warrants additional research into the role of macro-level mixed-use development in residents' general health status. Nonetheless, the results of the present study are somewhat in line with past findings such as those of Langerudi et al. (2015) who found that presence of various land uses within a neighborhood was associated with better general health. Further, the results provide evidence that the effect of mixed land use on general health go beyond the county, and this dimension of the built environment has a potential to affect residents' health at the metropolitan area level as well.

Also, as in the case for the county-level variable, the metropolitan area-level mixed land use variable is positively associated with the probability of having been diagnosed with asthma and diabetes. In the case of asthma, one explanation can be that as mixed land use increases within a metropolitan area, additional destination options become available at remoter locations, which may encourage more vehicular trips. The increased number of vehicular trips may lead to higher pollution levels within the metropolitan area, and thereby increase the risk of asthma for residents.

Model estimates and average marginal effects also indicate that an increased intersection density throughout the metropolitan area is associated with higher probabilities of having a better general health status. This variable is also linked with reporting fewer numbers of poor physical health days. As intersection density is a proxy for street network connectivity, these results may be capturing the effect of network connectivity on general health status of residents. However, the *Mean Intersection Density* variable in this study represents intersection density in terms of automobile-oriented intersections an increase of which may mean fewer pedestrian and bicyclist facilities and lower levels of active travel and other forms of physical activity. Also, previous research found that smaller average block sizes (proxy for intersection density) may cause poorer general health but did not find a significant relationship between intersection density and the status of population general health (Samimi and Mohammadian 2009; Samimi et al. 2009). Therefore, the results obtained here should be treated with caution and further research may be needed to clarify the role of metropolitan area-level intersection density in individuals' general health status.

On another note, the results indicate that intersection density at the macro-level (i.e., metropolitan area-level) may be more influential in general health than at the meso-level (county-level). In other words, compared to those of the county-level *Mean Intersection Density* variable, the coefficient estimates and average marginal effects for the macro-level *Mean Intersection Density* variable are larger in magnitude in the *Good or Excellent General Health* model as well as the *Number of Poor Physical Health Days* model. This means that better general health status is associated with living in compact metropolitan areas (in terms of intersection density), which is partly consistent with findings of Marshall et al. (2014) who suggested that city-level intersection density was more important in determining health outcomes than the same variable at the neighborhood level. This, as the referenced study also suggested, can mean that better general health outcomes may be associated with residing in a more compact, better connected city than a compact neighborhood surrounded by a sparse city (Marshall et al. 2014).

The average marginal effects computed for the metropolitan area-level *Mean Intersection Density* variable indicate that increased intersection densities throughout the metropolitan area are associated with higher probabilities of being diagnosed with asthma. The direction of this effect is consistent with that for the county-level *Mean Intersection Density* variable. Due to the *Mean*

Intersection Density variable representing intersection density in terms of automobile-oriented intersections, these results are expected. A previous study found that smaller average block sizes (proxy for higher intersection density) were related to higher asthma rates (Samimi and Mohammadian 2009), which is consistent with findings of the present study. More automobile-oriented intersections within an area can mean higher rates of automobile use and higher levels of air pollution, and thereby may lead to respiratory health problems such as asthma. Consistent with the case for the county-level variable, the average marginal effects of the *Mean Intersection Density* variable at the metropolitan area shows a statistically insignificant effect on obesity.

The model estimate and the average marginal effects of the metropolitan area-level *Mean Local Transit Accessibility* variable suggest that increased distances to the nearest local transit stop are associated with lower probabilities of having been diagnosed with asthma but increased probabilities of being overweight or obese and higher probabilities of having been diagnosed with diabetes. This variable is also linked to increased numbers of poor physical and mental health days. These results are consistent with those obtained from the county-level health outcome models (see Appendix I) and can be capturing the state of health for residents of suburban areas.

Areas with greater distances to transit stops are most likely those farther away from the core of the city where traffic-related pollution levels are high. Living in these sprawled suburban areas where air is cleaner may lead to a lower probability of being diagnosed with asthma. However, suburban areas typically do not provide much opportunities for active travel. This can lead to lower levels of walking and bicycling, which in turn, may lead to higher levels of obesity and other health problems. With respect to mental health, having limited access to transit—a feature common to suburban areas in the U.S.—may lead to social exclusion, particularly for individuals who for whatever reason are not able to drive (e.g., seniors, individuals with disability, individuals who do not own a private vehicle, etc.). Providing support for this statement is an argument by Melis et al. (2015) who suggested that good accessibility to public transit may lower the risk of depression, particularly for women and retired individuals, providing them with the opportunity to travel around, satisfy their daily needs and have a more active social life.

Literature suggests that urban sprawl—another feature common to U.S. suburban areas—has a potential to affect physical and mental health outcomes by promoting or restricting active behavior and social inclusion (see e.g., Cervero and Duncan 2003; Khattak and Rodriguez 2005; Næss 2005; Leslie et al. 2007; Plantinga and Bernell 2007; Melis et al. 2015). Consistent with this literature, the results of the present study imply that living in sprawled suburban areas with lower levels of access to transit may lead to obesity and other undesirable physical and psychological health outcomes.

The results suggest that higher accessibility to jobs within the metropolitan area by means of automobile (i.e., the metropolitan area-level *Mean Temporal Automobile Accessibility* variable) is associated with an increased probability of residents being overweight or obese, increased probability of being diagnosed with asthma, increased probability of being diagnosed with diabetes, and a lower probability of reporting good or excellent general health. The direction of these effects is consistent with those obtained for the county-level automobile accessibility variable. It should be noted, however, that the average marginal effects for this variable is only statistically significant in the general health model (i.e., *Good or Excellent General Health* model), suggesting that further examination of the relationship between metropolitan area-level automobile accessibility and health outcomes may be needed.

In terms of physical health outcomes, the results may be capturing the effect of long automobile commutes, which can mean more commute-related stress and less physical activity;

both of which can lead to adverse health effects. Previous studies suggest that long commutes limit physical activity levels by cutting into leisure time (Ewing et al. 2014) and can have adverse health effects on human health over time due to a number of reasons including fatigue and elevated stress levels related to operating and navigating the vehicle during the rush hour traffic, driving on congested roadways, and having to deal with aggressive driving behavior such as road rage (Jackson 2003; Galovski and Blanchard 2004; Evans and Wener 2006; Wener and Evans 2011; Hansson et al. 2011; Künn-Nelen 2015).

Also, the positive direction of the effect of the metropolitan area-level *Mean Temporal Automobile Accessibility* variable in the asthma model (i.e., *Asthma Diagnosis* model) is expected. Increased levels of automobile accessibility to jobs within a metropolitan area can mean increased levels of use of private vehicle for commuting, and thereby higher levels of vehicle emissions and traffic-generated air pollution. Respiratory health problems such as asthma may then affect the health of residents of such metropolitan areas at higher rates due to higher levels of air pollution within the area. Past research suggests that widespread car usage may lead to increased rates of asthma (Jackson 2003).

In terms of mental health, the results indicate that higher accessibility to jobs within a metropolitan area is linked with fewer poor mental health days, suggesting that higher automobile accessibility to employment opportunities within the urban area of residence may lead to better psychological health for residents.

On the other hand, higher accessibility to jobs by means of transit (i.e., the metropolitan area-level *Mean Temporal Transit Accessibility* variable) is associated with a lower probability of being overweight or obese for residents, a lower probability of being diagnosed with diabetes, as well as a higher probability of meeting the CDC recommendations on physical activity levels, and a higher probability of having good or excellent general health. However, results indicate that higher transit accessibility to jobs is also associated an increased probability of being diagnosed with asthma. It should be noted, however, that the average marginal effects for this variable is statistically insignificant in the *Asthma Diagnosis* and *Diabetes Diagnosis* models.

With respect to physical health outcomes, the results are in line with findings of previous studies suggesting that increased transit use can lead to lower obesity rates (Samimi et al. 2009; Langerudi et al. 2015), and higher asthma rates (Samimi and Mohammadian 2009). The physical activity associated with transit use can lead to lower levels of obesity. Literature suggests that transit accessibility can promote active travel (Ryan and Frank 2009; Barnes et al. 2016) as most transit users arrive at and depart from transit stops via walking (Durand et al. 2016).

However, increased walking and waiting times associated with transit use can mean additional exposure to harmful particles in the air; a factor that may lead to development of asthma. Past studies suggest that transit riders are more exposed to polluted air due to additional walking associated with transit use as well as the mechanical friction processes involved in transit vehicle operations, and therefore, they are at higher risks of having asthma (Samimi and Mohammadian 2009; van Wee and Ettema 2016).

Despite having a statistically significant coefficient in the *Diabetes Diagnosis* model, the average marginal effects of the *Mean Temporal Transit Accessibility* variable does not reach a statistical significance threshold; therefore, additional research is required to clarify the role of transit accessibility to employment opportunities within the metropolitan area in being diagnosed with diabetes.

Regarding mental health, the results indicate that higher transit accessibility to jobs within a metropolitan area is linked to an increased number of poor mental health days, suggesting that higher transit accessibility to employment opportunities within an urban area may lead to adverse psychological health effects for residents. A farther commute distance by means of transit can mean additional transit-specific stress including unpredictability of service, having to wait for the arrival of the vehicle, and interaction with other riders. For instance, a previous study found predictability to be a salient component of commuting-related stress among rail transit users as both perceived stress and cortisol levels were significantly higher among users who perceived their commute as more unpredictable (Evans et al. 2002).

Longer duration of rail commuting was also found in another study to be associated with elevated cortisol levels and higher levels of perceived commuting stress (Evans and Wener 2006). Other researchers suggested that using public transit may lead to lower levels of subjective well-being due to exposure to incidents such as undesired interactions with personnel or other travelers, which may evoke negative emotions (van Wee and Ettema 2016). In the case of recurrent travel such as everyday commute, the chronic stress associated with public transit use may lead to adverse psychological health effects.

Overall, it can be said that with respect to automobile accessibility to jobs, the results are consistent with those obtained from the county-level variable and suggest that increased levels of regional accessibility to jobs by means of automobile may lead to a better psychological health status for residents. The results also imply that higher levels of accessibility to jobs by means of transit may lead to a better physical health status (with exception of asthma).

Further, the *Mean Roadway Congestion Index* variable is positively associated with the probability of being obese or overweight, which is consistent with findings of Joshu et al. (2008) who reported that heavy traffic was moderately associated with obesity among residents of large metropolitan and micropolitan areas.

Additionally, this variable is positively associated with the probability of having asthma and it is negatively associated with having good or excellent general health status and meeting the CDC recommendations on physical activity. Further, the results indicate that higher roadway congestion indices are linked with having an increased number of poor physical health days.

Cumulatively, these results imply that higher congestion levels within metropolitan areas of residence may adversely impact the physical health status of residents. The two main culprits are likely to be: 1) higher levels of stress in residents of such congested urban areas; and 2) less time to engage in physical activity for car commuters who drive on congested roadways.

The above argument is supported by past studies suggesting that driving on congested roads is a contributor to stress (see e.g., Stokols et al. 1978; Evans et al. 2002; Jackson 2003; Evans and Wener 2006; van Wee and Ettema 2016). In addition, higher congestion levels may be an indication of longer automobile commute times, which based on literature, may lead to increased levels of stress in commuters (Wener and Evans 2011) as well as lower levels of physical activity (Ewing et al. 2014), and thereby can have adverse health effects (Jackson 2003; Evans and Wener 2006) including obesity. Also, past research provides evidence that: *i)* additional daily time spent in an automobile is associated with an increased likelihood of obesity (Frank et al. 2004); and *ii)* a longer duration of car commuting is associated with a higher BMI (Lindström 2008).

Concerning asthma, it should be noted that increased congestion levels mean additional exposure to harmful air pollutants due to vehicle emissions, and thereby can lead to respiratory health problems such as asthma. Past research provides support for this argument by suggesting that: *i)* increased car usage may lead to increased rates of asthma (Jackson 2003); and additionally, that *ii)* residential proximity to heavy traffic increases the risk of asthma occurrence and exacerbation (Salam et al. 2008).

Social Environment Variables Findings

Social environment factors have been included in the person-level health models at two spatial levels: the meso level (i.e., the county) and the macro level (i.e., the metropolitan area level). At both geographical scales, several social environment (i.e., sociodemographic and/or socioeconomic) factors prove to play a key role in an individual's health status.

Meso-level (County-level) Social Environment Variables Findings: The effect of meso-level sociodemographic and socioeconomic factors in individuals' health outcomes have been controlled for by including county-level: median age, median annual household income, percent of the population that is of the White race, and the percent of total telecommutable jobs.

With regards to sociodemographic factors, the variable representing the median age of the county population (the *Median Age* variable) shows a positive correlation with the likelihood of having been diagnosed with asthma and having been diagnosed with diabetes (although the average marginal effects is not statistically significant in the case of diabetes). Also, the county-level *Median Age* variable exhibits a negative correlation with the likelihood of having a good or excellent general health status and meeting the CDC recommendations on physical activity levels. Further this variable is positively linked with the number of poor physical health days and the number of poor mental health days. These results further indicate that older age is associated with lower levels of physical activity and adverse health outcomes, which is consistent with past research (see e.g., Trost et al. 2002; Lindström 2008; Ewing et al. 2014; Langerudi et al. 2015).

Results also suggest that the racial composition of the county plays a role in health outcomes for residents as having a higher percentage of White residents within the county is associated with an increased likelihood of participating in at least 150 minutes of physical activity per week, an increased likelihood of having a good or excellent general health status, and a lower number of poor physical health days. These findings are consistent with those of previous studies, which suggested that being White was associated with a higher likelihood of engaging in physical activity and meeting the recommended physical activity levels—and in general—with having better health outcomes, especially as related to obesity and diabetes (e.g., Ewing et al. 2003b, 2008; Ewing et al. 2014). Also, according to Table 19, higher percentages of White residents within the county are associated with an increased likelihood of having asthma. Considering the statistically insignificant coefficient estimate of the *Race* variable, which represents the race of the respondents in the asthma model, the evidence on the role of race in asthma diagnoses can be considered inconclusive. Thus, further research may be required to clarify the link between race and asthma.

The average marginal effects computed for the *Median Annual Household Income* variable show that higher median income levels within the county are correlated with lower probabilities of being diagnosed with asthma and/or diabetes. Past research also found that increased income is associated with lower risk of asthma (Samimi and Mohammadian 2009). However, albeit consistent with the results of the county-level models (see Appendix I), the direction of the effects of this variable in the *Diabetes Diagnosis* model is not consistent with findings of Barr et al. (2016) who suggested that higher household income levels were associated with a higher risk of diabetes.

The model estimates and average marginal effects of the *Percent of Telecommutable Jobs* variable, which represents the level of telecommutability of employment opportunities within a county, does not reach a statistically significant threshold in the person-level health outcome models. These results are not consistent with those obtained from the county-level health models (presented in Appendix I), which suggest that the extent of telecommutability of employment within a county may adversely affect the residents' physical and psychological health status. Therefore, the role of county-level telecommutability of jobs in health outcomes remains unclear.

Macro-level (Metropolitan Area-level) Social Environment Variables Findings: Consistent with the results of the county-level health outcome models (see Appendix I), the results of the person-level health models suggest that macro-level socioeconomic, sociocultural, and crime-related factors can also be influential in the health status of individuals.

As measures of a metropolitan area's economy, *Average Percent of Low-Wage Workers* and *Average Gross Regional Product* variables indicate that higher socioeconomic status and a larger-size economy within a metropolitan area are associated with a lower likelihood of residents being overweight or obese and/or having been diagnosed with asthma as well as with a higher likelihood of them meeting the CDC recommendations on physical activity levels (i.e., participating in at least 150 minutes of physical activity per week) and having a good or excellent general health status. Residents of metropolitan areas with higher socioeconomic status also seem to report a lower number of poor physical and mental health days. These results are consistent with past findings that higher incomes are associated with higher levels of physical activity (e.g., Ross 2000; Ewing et al. 2014) and that the likelihood of obesity and other adverse physical or mental health outcomes declines with higher income levels and living in high-income areas (Samimi and Mohammadian 2009; Ewing et al. 2014; Tajalli and Hajbabaie 2017).

In addition, the coefficient and the average marginal effects of the *Average Percent of Households with No Cars* variable, which measures another aspect of the socioeconomic status (i.e., vehicle ownership levels) of residents of a metropolitan area, indicate that lower levels of vehicle ownership within metropolitan areas are associated with a lower likelihood of residents having a good or excellent general health. This variable is also linked with residents reporting increased numbers of poor physical and mental health days. One explanation for these results can be the limited access to healthcare providers or services imposed by not having access to a car.

Individuals who do not own a private vehicle may not be able to reach a physician's office or pharmacy when they are ill and need treatment. As a result, they may be more likely to suffer from poorer physical health conditions. On the other hand, access to a private vehicle can be psychologically advantageous as Ellaway et al. (2003) found that individuals with car access may experience positive psychological effects, in their words, such as "more protection, autonomy, prestige, self-esteem, and mastery". In addition, literature suggests that lack of transportation may prevent individuals from finding employment (Mackett and Thoreau 2015). Therefore, owning a private vehicle provides the opportunity to find a job or secure a better one, which can also be considered a psychosocial advantage of vehicle ownership. These arguments lend support to the findings of the present study that suggest a positive link exists between lower levels of vehicle ownership within an urban area and a poorer mental health status for residents.

Together, these results suggest that higher socioeconomic status within a metropolitan area is associated with better physical and mental health outcomes for residents, which is a reasonable finding. Higher socioeconomic status (e.g., higher incomes, owning more vehicles, etc.) means higher levels of affordability for better quality goods as well as higher levels of access to services that can impact one's health. For example, high-income individuals can afford organically-grown food items, better health insurance, and gym membership—all of which may favorably influence their health status. Past research found higher income levels to be correlated with better health status (see e.g., Samimi and Mohammadian 2009; Marshall et al. 2014; Langerudi et al. 2015; Braun and Malizia 2015). In addition, literature suggests that higher-income individuals travel further and have an increased level of access to opportunities (Mackett and Thoreau 2015).

The findings are also in line with arguments by Ellaway et al. (2003) who suggested that vehicle ownership was associated with better physical health outcomes (i.e., lower rates of overall mortality, lower rates of long-term illness, and fewer symptoms) as well as with better mental health (e.g., gaining more psychosocial benefits).

Based on the coefficient estimates and average marginal effects of the *Average Crime Rate* variable, it seems that increased rates of violent crime within the metropolitan area are associated with lower probabilities of residents meeting the CDC recommendations on physical activity levels and having a good or excellent general health status as well as with lower probabilities of them having been diagnosed with asthma. One explanation for these findings can be lower levels of outdoor physical activity due to safety concerns. Residents who fear violent crimes in their cities are not likely to spend much time outside of their houses to perform physical activities such as walking or bicycling. Fear and concerns about neighborhood crime and personal safety have been postulated to act as a barrier to walking and other physical activities (CDC 1999; Ross 2000) and empirical research has shown that violent crime rates have a negative impact on walking trips (Joh et al. 2009). Further, chronic exposure to community violence and crime has been argued to be an important social environment factor that can potentially impact physical activity levels (King et al. 2002). The latter study also suggested that the extent of environmental stressors (such as crime) at micro, meso, and macro levels of the environment may lead to reduced levels of individuals' engagement in outdoor recreational physical activities (e.g., walking, bicycling, and use of open spaces for sports).

On the other hand, residents of high-crime cities may be at lower risk of developing asthma due to spending more time indoors and having less exposure to airborne pollutants that are detrimental to respiratory health. Results also show a positive and significant association between the coefficient estimate of the violent crime variable and the probability of residents being overweight or obese and having been diagnosed with diabetes; however, the corresponding average marginal effects are not statistically significant in either model, indicating the need for further investigation of the relationship between metropolitan area-level crime rates and obesity as well as diabetes rates in residents. Nonetheless, the positive direction of the effect of the violent crime variable in the *Overweight/Obese* model is consistent with past findings suggesting that prevalence of obesity is higher in areas with more violent crime (Ewing et al. 2014).

The coefficient estimate and the average marginal effects of the *Average Walking and Bicycling Density* variable indicate that increased densities of active travel within a metropolitan area are associated with better physical health outcomes (i.e., a lower likelihood of asthma and diabetes diagnoses and a higher likelihood of having a good or excellent general health status) as well as better mental health outcomes (i.e., fewer number of poor mental health days). These results are expected as many past studies found an association between higher levels of active travel and physical as well as mental health indicators (see e.g., Leyden 2003; Frank et al. 2004; Lindström 2008; Gordon-Larsen 2009; Schauder and Foley 2015; Tajalli and Hajbabaie 2017).

Further, the results indicate that increased public transit usage within the metropolitan area (represented by the *Annual Public Transit Passenger-Miles* variable) is associated with a lower likelihood of being overweight or obese and a lower likelihood of having been diagnosed with diabetes. However, this variable is also associated with unfavorable physical health outcomes such as a higher likelihood of asthma diagnoses, a lower likelihood of having a good or excellent general health status, and an increased number of physically unhealthy days. These results are in line with studies suggesting that increased public transit use is associated with better weight-based health outcomes such as lower risks of overweight or obesity (Lindström 2008; Samimi et al. 2009; Langerudi et al. 2015; Liao et al. 2016), most likely due to the additional physical activity associated with transit use. The results are also consistent with literature suggesting that increased public transit use is associated with higher risk of asthma (Samimi and Mohammadian 2009; van Wee and Ettema 2016), most likely due to inhalation of more polluted air produced from transit vehicle operations. In addition, crowded transit vehicles provide increased opportunities for diseases to spread, which can negatively affect one's personal health (Widener and Hatzopoulou 2016). The association between increased public transit use within the metropolitan area and poorer general health status for residents can be due to reasons such as increased levels of transit commute-related stress—a subject which brings the discussion to the next factor with a potential to affect human health as hypothesized in this study—commuter stress in urbanized areas.

Tables 18 and 19 show that the *Average Commuter Stress Index* variable is positively associated with the probability of being overweight or obese and negatively associated with the probability of having a good or excellent general health status. Moreover, the path coefficient of this variable is positively linked with the number of poor physical health days. These results imply that, as expected, residing in metropolitan areas with higher levels of commuter stress may adversely affect health outcomes. Lending further credence to this argument is past research suggesting that commute-related stress may be linked to adverse health outcomes (e.g., Galovski and Blanchard 2004; Evans and Wener 2006; Rissel et al. 2014; van Wee and Ettema 2016).

The last three variables (i.e., *Average Walking and Bicycling Density*, *Annual Public Transit Passenger-Miles* and *Average Commuter Stress Index* variables) have been considered proxies for travel-related social norms and sociocultural factors in the present study and in that sense, they have been assumed to represent the "travel culture" within the metropolitan areas. Therefore, the results of the person-level health models provide evidence that the travel culture within the metropolitan area of residence can influence individuals' health outcomes both in terms of physical and psychological health. Metropolitan areas with a travel culture that is more oriented toward active travel can promote this form of physical activity, which can lead to better health outcomes for residents. Indeed, literature suggests that supportive social and cultural norms can promote physical activity as observing others being physically active has encouraging effects on individuals to do the same (see e.g., Trost et al. 2002). On the other hand, sprawled metropolitan areas with a travel culture oriented toward long commutes may induce higher levels of commute-related chronic stress in residents, and as a result, lead to adverse health effects.

These findings further imply that the effects of the macro-level built and social environments on travel culture, and thereby on health outcomes are intertwined. As Joshu et al. (2008) argued, by changing social norms, changes in the macro-level built environment can potentially affect personal attitudes and motivations. Personal attitudes, preferences, and motivations are key factors in shaping the daily travel behavior of individuals and thus, in the long run, these factors can shape the travel culture within communities and the society as a whole.

Therefore, social environment factors such as those representing the travel culture within an urbanized area are closely related with the travel behavior of residents of that area. The role of travel behavior measures in health outcomes based on the results of the person-level health models is discussed next.

Travel Behavior and Telecommuting Behavior Variables Findings

Meso-level (County-level) Travel Behavior Variables Findings: Consistent with the results of the county-level health models (see Appendix I), the results of the person-level health models show that measures of travel behavior of residents of a county play an important role in their health status. The coefficient estimates and average marginal effects of the *Nonmotorized Travel Mode Share* variable are negatively associated with the likelihood of being overweight or obese and positively associated with the likelihood of having a good or excellent general health status.

Further, the path coefficients of this variable in multilevel SEMs is negatively linked with the number of poor physical and mental health days. These results corroborate those obtained from the county-level health models (Appendix I) and are in line with findings of several prior studies, which reported that active travel lowers the risk of morbidity and mortality (see e.g., Andersen et al. 2000; Frank et al. 2004; Smith et al. 2008; Schauder and Foley 2015; Tajalli and Hajbabaie).

More specifically, with respect to weight-related health outcomes and general physical health, these findings are consistent with those of many past studies (see e.g., Frank et al. 2004; Lindström 2008; Gordon-Larsen 2009; Schauder and Foley 2015; Tajalli and Hajbabaie 2017). With respect to mental health outcomes, the findings are consistent with past research as well (see e.g., Leyden 2003; Ohta et al. 2007; Tsunoda et al. 2015; Liao et al. 2016; Tajalli and Hajbabaie 2017). Thus, the results of the present analysis provide evidence that higher rates of walking and bicycling within a county can lead to better physical and psychological health status for residents.

Also, the results indicate that more traveling within the county by means of private vehicle (represented by the *Private Vehicle Travel Mode Share* variable) is associated with adverse physical health outcomes including a higher likelihood of having been diagnosed with asthma and a higher likelihood of having been diagnosed with diabetes (the average marginal effects is statistically insignificant in the case of diabetes). Although results of the county-level health models (presented in Appendix I) suggest that higher levels of private vehicle use within the county are linked to many other unfavorable physical health outcomes such as higher prevalence of obesity and poor/fair general health as well as higher numbers of poor physical days, the coefficient estimates and/or average marginal effects of this variable do not reach statistical thresholds in the corresponding person-level health models. Therefore, further research may be needed to clarify the role of private vehicle use in obesity, diabetes, and general physical health.

Further, the results show a negative link between levels of private vehicle use within a county (the *Private Vehicle Travel Mode Share* variable) and the number of poor mental health days for residents. This result stands in contrast to that obtained from the county-level health models (see Appendix I), which suggest that private vehicle use within a county and the number of poor mental health days are positively linked. Many past studies suggested that increased use of private vehicle—particularly in the form of car commuting—is associated with increased levels of stress and adverse phycological health outcomes such as a negative mood and decline of social capital (see e.g., Leyden 2003; Galovski and Blanchard 2004; Wener and Evans 2011), increased cognitive impairment and lower overall life satisfaction (Rissel et al. 2014), and lower levels of subjective well-being (van Wee and Ettema 2016). On the other hand, others suggested that use of private vehicle may have positive mental health outcomes (see e.g., Ellaway et al. 2003; Tsunoda et al. 2015). Considering the inconsistent results from county-level and person-level health models (the former are presented in Appendix I and the latter in this chapter) as well as the inconsistent arguments in the literature, the role of private vehicle use in mental health status remains unclear.

Tables 18 and 19 show that the coefficient estimates and average marginal effects of the *Public Transit Mode Share* variable are associated with a lower probability of being overweight or obese, a lower probability of having been diagnosed with diabetes, and a higher probability of meeting the CDC recommendations on physical activity levels. However, this variable is also positively associated with having been diagnosed with asthma and it is negatively associated with having a good or excellent general health status. Moreover, it is positively linked with having an increased number of poor mental health days. These results suggest that despite having a potential to promote physical activity and providing some health benefits, increased transit use within the county may be related to adverse general health outcomes. These findings are consistent with literature suggesting that: *i)* a positive association exists between public transit use and physical activity in the form of active travel as using public transit involves walking (and/or bicycling) to, from, and within the transit stations (see e.g., Cervero 2001; National Research Council 2005; Lindström 2008; Liao et al. 2016; Barr et al. 2016; Sener et al. 2016); and *ii)* public transit use is correlated with a lowered risk of being overweight or obese due to the active travel involved in transit trips (see e.g., Langerudi et al. 2015; Liao et al. 2016).

The results are also consistent with those of the past studies that found an association between use of subway and lower probabilities of obesity and diabetes (Tajalli and Hajbabaie 2017) as well as those that reported an association between use of public transportation and better weight-based health outcomes including lower risks of overweight or obesity (Lindström 2008; Samimi et al. 2009; Liao et al. 2016). With respect to general health, however, the results of the present study stand in contrast with those of a few past studies that found higher levels of transit use within a county were correlated with better general health for residents (Samimi and Mohammadian 2009; Samimi et al. 2009). One explanation for the adverse effects of increased transit use within an area on general health status of residents can be conditions that are typically associated with public transit use and have a potential to affect human health. For transit user, these could include long wait times, higher stress levels due to unpredictability of service, exposure to higher levels of air pollution due to transit vehicle operations, exposure to inclement weather conditions, exposure to crowded stations, and interaction with other users who may be ill. Past studies suggest that public transit users experience higher levels of perceived stress, particularly due to factors such as long commutes and unpredictability (Evans et al. 2002; Evans and Wener 2006). The chronic stress experienced by public transit users may lead to adverse physical and mental health outcomes, and thereby to a poorer general health status.

In addition, the general health of transit users may be adversely affected due to increased and frequent exposure to other riders and higher disease diffusion rates among riders, particularly for airborne infectious diseases such as the common cold. Andrews et al. (2013) suggested that densely crowded and often poorly ventilated environments associated with public transportation can provide high respiratory contact rates, and thereby pose a risk of transmission of airborne infections. Widener and Hatzopoulou (2016) suggested that more interactions between individuals provides more opportunities for diseases to spread, which can negatively affect individuals' personal health. With regards to mental health, literature suggests that public transit users may have lower levels of subjective well-being due to negative emotions evoked by exposure to undesired interactions with other users (van Wee and Ettema 2016). Therefore, frequent use of public transit such as in the case of everyday commute may lead to a poorer mental health state for transit commuters due to these negative emotions.

Moreover, and for both users and non-users of transit, the higher air pollution levels due to increased transit use—particularly in the case of bus or other vehicular transit—within the county may lead to negative health outcomes. Past research suggests that air pollution from vehicles has negative health effects including lung disease and other undesirable health conditions (Mackett and Thoreau 2015). With regards to asthma, additional amounts of walking or waiting by transit users may negatively affect respiratory health and lead to asthma due to inhalation of more polluted air. Support for these arguments is provided by Samimi and Mohammadian (2009) who found that increased transit use within a county was correlated with higher rates of asthma. They suggested that this was due to transit riders being more exposed to polluted air because of the additional walking associated with transit use. Nonetheless, non-transit users who live in areas within which transit use is high can also be at increased risk of developing asthma due to higher air pollution levels within their residential areas.

Overall, findings of the present analysis are consistent with those obtained from the county-level health models (see Appendix I) and corroborate some aspects of past research. However, inconsistencies exist among findings of a few previous studies and those of the present study regarding the implications of levels of public transit use within an area for general health outcomes of residents. Thus, additional examination of the role of public transit in general health is needed.

Consistent with the results of the county-level health models (see Appendix I), the results of the person-level health models indicate that a higher of telecommuting mode share within the county is associated with a higher likelihood of being overweight or obese and a lower likelihood of having a good or excellent general health status. Additionally, a higher telecommuting mode share is associated with a lower likelihood of meeting the CDC recommendations on physical activity levels. On a positive note, however, it seems that an increased telecommuting mode share within the county is associated with a lower likelihood of being diagnosed with asthma. The results further suggest that a negative association exists between the percentage of the county population with an option to telecommute and the likelihood of being diagnosed with asthma as well as the likelihood of meeting the CDC recommendations on physical activity levels. Also, increased percentages of the county population with an option to telecommute are linked with more mentally unhealthy days. The results show consistency in terms of the direction of associations between measures of telecommuting behavior and health outcomes.

These findings confirm past arguments that excessive participation in computer-related activities has a potential to reduce physical activity levels (King et al. 2002). Therefore, more telecommuting can mean less physical activity, which can lead to obesity and other adverse physical and psychological health outcomes. Also, facilitated access to food for telecommuters who work from the convenience of their homes can lead to an increased overall food consumption and ultimately, to obesity and other related adverse general health outcomes. Nonetheless, with regards to obesity and physical activity levels, the results of the present study are not consistent with those of Henke et al. (2015) who found that non-telecommuters were at greater risk for obesity and physical inactivity, and those of Tajalli and Hajbabaie (2017) who did not find a statistically significant association between telecommuting and obesity.

One reason for the inconsistency in results can be that in both cases of Henke et al. (2015) and Tajalli and Hajbabaie (2017), telecommuting information was available at the respondent level, which made it possible to examine the association between telecommuting behavior and health outcomes at the individual level. Telecommuting data at the respondent level were not available for the present study; therefore, this analysis examined the role of telecommuting in health outcomes using aggregate telecommuting measures (i.e., county-level measures). Therefore, caution should be taken with respect to the findings bearing in mind the issue of *ecological fallacy*, which is making inferences about correlations at the disaggregate level when data are only available at the aggregate level (Robinson 1950; Snijders and Bosker 2012). Nevertheless, the inconsistency in the results of the present study and past findings suggests that further investigation into the relationship between telecommuting and physical health outcomes may be needed, particularly in the case of obesity and physical activity.

The negative association between telecommuting measures and the likelihood of asthma diagnoses is notable. Increased levels of telecommuting within an area may mean less vehicular commute and less congestion, which can lead to reduced air pollution levels in that area. Past research suggests that telecommuting has a potential to serve as a substitute for commuting, and reduce traffic congestion (see e.g., Mokhtarian 2003; Balaker 2005; Lister and Harnish 2011; Khan 2015). This literature also argues that telecommuting may reduce greenhouse gases and improve air quality in urban areas (see e.g., Balaker 2005; Lister and Harnish 2011; Khan 2015).

The cleaner air within the area of residence due to higher telecommuting rates in that area can then lead to a lower risk of asthma for residents. With regards to diabetes, the average marginal effects for the measures of telecommuting in the *Diabetes Diagnosis* model are statistically insignificant. This is consistent with past empirical research that did not find a statistically significant link between telecommuting and diabetes (Tajalli and Hajbabaie 2017).

From a mental health perspective, the results of the present study suggest that telecommuting may have adverse effects—a finding consistent with those of the county-level health models (see Appendix I) as well as previous research. A few studies in the past suggested that telecommuting may lead to negative psychological health outcomes such as social isolation and mental exhaustion (see e.g., Baruch 2001; Tajalli and Hajbabaie 2017). In particular, empirical findings provide evidence that telecommuting is associated with a higher probability of having mental disorders (Tajalli and Hajbabaie 2017). The results from the present study corroborate those findings as the model estimates indicate that an increased percentage of the county population with an option to telecommute is linked to a higher number of poor mental health days for residents. Yet, Henke et al. (2015) found that employees who telecommuted during regular work hours had a lowered risk for depression over time compared to employees who did not telecommute.

Considering the inconsistencies in the findings of the present study and those of Henke et al. (2015), further research may be needed to clarify the role of telecommuting in mental health outcomes. Nonetheless, the results of the person-level health models provide evidence that telecommuting affects health outcomes in terms of both physical and psychological health.

Model results also provide evidence that the extent of online shopping-related activities within an area is associated with the health status of residents. Most notably, the model estimates and average marginal effects of the *Average Number of Online Purchases per Month* and the *Average Number of Monthly Deliveries Related to Online Purchases* variables indicate that increased online shopping-related activities are associated with a lower likelihood of meeting the CDC recommendation on physical activity and a higher probability of being overweight or obese. These results complement those on the telecommuting variables and are consistent with them in the direction of correlations.

These findings are also in line with past arguments that excessive participation in computer-related activities and time spent online has a potential to reduce physical activity levels (King et al. 2002; Zheng et al. 2016) and may contribute to weight gain (Zheng et al. 2016). Online shopping can be considered a feature of a sedentary lifestyle. Teleshoppers[47] do not need to leave their house (or even their couch) to satisfy their shopping needs. Therefore, it is plausible to assume that if performed habitually, online shopping may lead to lower levels of physical activity and ultimately, to adverse health outcomes such as obesity.

In addition, the model estimates indicate that increased levels of online shopping are linked with increased numbers of poor mental health days. This finding is in line with the very limited literature available on the relationship between online shopping behavior and mental health suggesting that excessive online shopping may be related to adverse mental health outcomes such as low self-esteem, low self-regulation, and a negative emotional state (Rose and Dhandayudham 2014). The results are also consistent with the literature within the broader context of internet

[47] The Oxford Dictionary has an entry for *teleshopper*. According to that dictionary, the word *teleshopper* was first used in the 1940s: https://en.oxforddictionaries.com/definition/teleshopper

dependency discussing the negative mental or psychological health effects of internet overuse (see e.g., Yoo et al. 2014; Rose and Dhandayudham 2014; Zheng et al. 2016).

Considering the above, it is not surprising to see that increased levels of online shopping within a county are also correlated with increased numbers of poor physical health days as well as with a lower likelihood of having a good or excellent general health status for the residents. In a general internet overuse context, these results are consistent with those of Zheng et al. (2016) who found increased frequencies of online activities were strongly associated with higher levels of complaints related to general physical health outcomes.

With respect to physical health outcomes, the only favorable online shopping-related results are those in the *Asthma Diagnosis* model. The coefficient and average marginal effects indicate that increased levels of online shopping-related activities within a county are associated with a lower likelihood of residents being diagnosed with asthma. This finding may be related to the substitution effects of online shopping. Online shopping has a potential to substitute for some vehicular trips, which individuals would otherwise make to stores to satisfy their shopping needs. For instance, literature argues that online shopping and home delivery provide the opportunity to reduce the total vehicular transportation related to grocery shopping and the associated emission levels (Siikavirta et al. 2002; Fichter 2002). Therefore, the negative association between online shopping-related variables and asthma diagnosis may be due to the reduced number of vehicular trips to stores and the associated lower air pollution levels within the county of residence.

Nonetheless, literature related specifically to health impacts of online shopping is scarce and little empirical knowledge exists in this area—making it difficult to compare findings from the present analysis to those of the past studies. The results of the person-level health models fill that gap in research and suggest that online shopping may contribute to adverse physical and psychological health outcomes (except in the case of asthma)—a finding which is open to future and further research.

As noted earlier, the travel behavior as well as the telecommuting and teleshopping behavior measures in this study potentially represent the "travel culture" aspect of the social environment within a county. Therefore, the findings on the association between these measures and the person-level health outcomes can also entail the role of a county's sociocultural environment in the health status of its residents.

The Weekly Minutes of Moderate Physical Activity Equation Findings (in Multilevel SEMs)

In the multilevel SEM equation systems for the two continuous endogenous health outcome variables (i.e., number of poor physical health days and number of poor mental health days), the second equation (i.e., Equation 34) estimates the effects of person and household-level factors on an individual's level of physical activity (i.e., minutes of moderate physical activity per week).

Due to the possibility of reverse causality between health outcomes and health behavior such as physical activity (Schauder and Foley 2015), this equation also includes a direct link to each of the two health outcomes indicated above (i.e., number of poor physical health days and number of poor mental health days). This model framework allows for estimation of bidirectional effects between these physical and psychological health outcomes for individuals and their physical activity levels.

By applying the MLE estimation method for multilevel SEMs, this model framework deals with any endogeneity bias that may exist in the models. This is because in estimating bidirectional relationships, potential endogeneity bias can be statistically corrected by using MLE (Cervero and Murakami 2010). The results of the *Weekly Minutes of Moderate Physical Activity* equation for the two health outcome models are discussed below.

Person-level Variables (Individual and Household Characteristics)

The results of the multilevel SEMs indicate that person-level attributes influence the level of individuals' weekly physical activity.

As expected, older age is linked with fewer minutes of weekly physical activity by individuals. This result supports the results obtained for the *Participation in ≥ 150 Min. Moderate Physical Activity* model (in the *Health Outcome Equation* part) and is consistent with findings of previous research suggesting that age is inversely associated with levels of physical activity (see e.g., Ross 2000; Trost et al. 2002; Frank et al. 2005; Ewing et al. 2014).

Further, being male is linked with more minutes of weekly physical activity by individuals, which is consistent with the results from the *Participation in ≥ 150 Min. Moderate Physical Activity* model (in the *Health Outcome Equation* part) as well as findings of past research suggesting that being male is positively associated with physical activity levels (see e.g., Ross 2000; Trost et al. 2002; Ewing et al. 2003b, 2008; Frank et al. 2005; Ewing et al. 2014).

Additionally, having a college education is related to more minutes of physical activity per week—a result consistent with those obtained from the *Participation in ≥ 150 Min. Moderate Physical Activity* model (in the *Health Outcome Equation* part) as well as findings of past studies that suggested higher educational attainment was associated with a higher likelihood of participation in physical activity and with higher levels of physical activity (see e.g., Ross 2000; Ewing et al. 2003b; Frank et al. 2005).

Being employed and the number of children in the household do not show statistically significant effects in the *Weekly Minutes of Moderate Physical Activity* equations for the number of poor physical health days and the number of poor mental health days multilevel Structural Equation Models (multilevel SEMs).

Endogeneity and Reverse Causality Between Health Outcomes and Physical Activity

An underlying assumption in developing the person-level health outcome models was that the *Physical Activity (minutes per week)* variable is an endogenous independent variable in the models. This means that after controlling for all the other independent variables, there is a non-zero correlation between the *Physical Activity* variable and the error term in the models. This correlation could exist due to reverse causality or the effect of omitted variables. Regarding the former, literature suggests that reverse causality may exist between health outcomes and physical activity (Schauder and Foley 2015) and that individuals with poor health may perform lower levels of physical activity (Joshu et al. 2008). In other words, reverse causality implies that an individual's level of physical activity can impact his/her health outcomes but that the reciprocal effect can also exists, meaning that the individual's health status can affect his/her levels of physical activity. In the case of the latter, there may exist one or more omitted variables in the models that can influence both an individual's physical activity level and health outcomes.

The non-zero correlation between the *Physical Activity* variable and the error term subjects the models to endogeneity bias. To mitigate the potential endogeneity bias in the person-level health models due to reverse causality and omitted variables, two statistical methods were utilized: 1) instrumental variable analysis was employed to model the likelihood of obesity, asthma, and diabetes diagnoses as well as that of having a good or excellent general health; and 2) multilevel SEM analysis with bidirectional links between health outcomes and weekly physical activity levels was employed to model the number of physically or mentally unhealthy days.

The instrumental variable analysis included three instrumental variables (i.e., educational status, employment status, and number of children) for the endogenous physical activity independent variable. The Wald test of exogeneity of the instrumented variable (i.e., *Physical*

Activity variable) shows significant results in the *Overweight or Obese*, *Asthma*, and *Diabetes* models. This indicates that the null hypothesis of no endogeneity can be rejected in these models and employment of an instrumental variable binary probit model is justified to control for endogeneity bias in the models. However, in the case of *Good or Excellent General Health* model, this test statistic is not significant, meaning that there is not sufficient information in the sample to reject the null hypothesis of no endogeneity; therefore, a regular binary probit model was employed instead of an instrumental variable binary probit model to estimate the likelihood of having a good or excellent general health (i.e., *Good or Excellent General Health* model).

Also, the results of the Amemiya-Lee-Newey minimum χ^2 test for validity of instruments are statistically insignificant in the *Overweight or Obese*, *Asthma*, and *Diabetes* models, indicating that educational status, employment status, and number of children are valid instruments for the endogenous physical activity independent variable in these models[48].

Findings of past research lend some degree of confidence to the results of the test for validity of instruments. With respect to educational attainment, some studies suggested that higher education had: *i*) a negative correlation with BMI (Ewing et al. 2003b, 2008; Plantinga and Bernell 2007; Ewing et al. 2014); and *ii*) a negative correlation with the probability of being obese (Frank et al. 2004; Samimi and Mohammadian 2009; Ewing et al. 2014; Tajalli and Hajbabaie 2017); and also *iii*) a negative correlation with the probability of having diabetes (Ewing et al. 2014; Tajalli

[48] Stata does not provide a command for testing the validity of instruments after the ivprobit command with the maximum likelihood estimation option. Therefore, the test of overidentifying restrictions in Stata, which gives the Amemiya-Lee-Newey minimum χ^2 statistic for validity of instruments, was performed after the ivprobit command with the two-step estimation option. It should be noted that no standard error adjustments for clusters (i.e., controlling for a lack of independence between observations) are available with the two-step estimation option; as a result, the two-step estimation method produces different results from those of the maximum likelihood method. Nonetheless, the results of the Wald test of exogeneity for both estimation options are significant, indicating that endogeneity bias exists in these models regardless of the estimation method. Therefore, it is assumed that validity of instruments, which holds true for models estimated with the two-step method, also holds true for corresponding models estimated with the maximum likelihood method.

and Hajbabaie 2017). Conversely, others found either a positive association between higher education and the probability of obesity and diabetes (Barr et al. 2016) or no significant correlation between individuals' educational status and obesity or other health outcomes (Langerudi et al. 2015). Further, in a county-level analysis, Braun and Malizia (2016) found that although an increased proportion of county population with higher educational attainment was not associated with prevalence of obesity within the county, it was correlated with lower prevalence of diabetes.

These findings suggest that there is no consensus in past research regarding the association between educational status and obesity or diabetes. It should also be borne in mind that none of these studies controlled for endogeneity bias in their analysis; therefore, any correlations observed between education and obesity or diabetes could be due to the indirect effects of education on these health outcomes through impacting physical activity levels—a condition enhancing the validity of education as an instrument for physical activity in modeling obesity and diabetes. Moreover, past research has not found a correlation between higher education and having asthma (Samimi and Mohammadian 2009; Langerudi et al. 2015).

The inconsistencies in the statistical significance and direction of the correlations between educational attainment and obesity, diabetes, and asthma can mean that education is not related to these health outcomes. On the other hand, research provides evidence that higher education is associated with higher likelihood of participation in physical activity as well as higher levels of physical activity (see e.g., Ross 2000; Ewing et al. 2003b; Frank et al. 2005); therefore, educational attainment can be considered as a valid instrument for physical activity in modeling obesity, diabetes, and asthma—as done in this dissertation.

The result of the present study, which finds the number of children living in the household as a valid instrument for physical activity in modeling obesity and asthma, can also be further validated based on past findings that reported: *i*) having children was not correlated with obesity or asthma (see e.g., Samimi and Mohammadian 2009; Langerudi et al. 2015); but that *ii*) having more children in the household was positively associated with physical activity in terms of active travel (see e.g., Næss 2005); and *iii*) being in a family with children was not a barrier for physical activity in the form of cycling (Gatersleben and Appleton 2007).

The results of the multilevel SEMs for the number of poor physical health days and the number of poor mental health days indicate that reverse causality does not exist between these health outcomes and the extent of weekly physical activity performed by individuals.

These findings stand in contrast with the results of the county-level health models (presented in Appendix I), which show statistically significant links between county-level physical and mental health outcomes—including prevalence of: obesity, diabetes, and fair/poor health as well as average numbers of unhealthy physical or mental days—and levels of physical activity in the form of active travel within the county.

The inconsistency in the findings may have resulted from the differences in the physical activity and active travel measures in the two health model types (i.e., person-level vs. county-level health models). Physical activity as defined in the person-level health models is much broader than active travel as defined in the county-level health models (see Appendix I).

Albeit somewhat inconsistent, these findings provide insights into the issue of reverse causality between health outcomes and health behavior such as physical activity (in its broader form or in its active travel form), which is often overlooked in research probing the link between physical activity and health outcomes.

Notwithstanding, future research is needed to elucidate the role of reverse causality in the link between health outcomes and health behavior such as physical activity and active travel.

Random Effects

Since individuals reside within counties and counties lie within CBSAs (i.e., metropolitan areas in this sample), CBSAs were considered clusters in the multilevel SEMs models and their random effects were estimated by the models. The variance of the CBSA-level random intercept is estimated to be statistically insignificant by both of the multilevel SEM models.

Consistent with the county-level models (Appendix I), this result implies that CBSA-level random effects (i.e., random differences between CBSAs) do not play an important role in these health outcomes for the residents.

5.2 Chapter Conclusions

Health is a key factor influencing the well-being of individuals and the vitality of communities and for that reason, it has been a topic of great interest in many academic disciplines for many decades. The health benefits of active travel and the role of the built environment in human health have also gained a growing attention recently. Research thus far asserts that health—at both individual and community levels—is affected by several factors including the travel behavior of individuals and the built environment characteristics of their surroundings. However, while many studies in the past examined the relationship between various health outcomes and built environment factors at the neighborhood (i.e., micro level) and county level (i.e., meso level), little attention has been given to the health impacts of built environment characteristics at the higher levels of geography (i.e., macro level) such as those of the metropolitan area of residence.

As increased accessibility and mobility have broadened the destination options of people and their commute distances in recent decades, it is hypothesized in this chapter of the present dissertation that individuals' health status can also be affected by the built and social environment characteristics of a wider geographical area such as the metropolitan area. Literature supports this idea. For instance, Ewing et al. (2014) suggested that sprawling metropolitan areas produce long commutes, which can shorten leisure, exercise, or active travel time and ultimately lead to poorer health outcomes. That study further suggested that access to healthy foods may be more difficult within sprawling metropolitan areas, which can also affect health of residents.

Based on the above arguments, this study tested the hypothesis that built and social environments at two hierarchical levels of geography including the county level (i.e., meso level) and the metropolitan area level (i.e., macro level) influence individuals' and communities' health outcomes. Measures of travel behavior were also included in the analysis framework to capture the effects of travel by various modes of travel on individuals' and communities' physical and psychological health status.

More specifically, the main purpose of this chapter was twofold: 1) to examine the under-investigated influence of macro-level (i.e., metropolitan area-level) environmental factors in health; and 2) to investigate the role of telecommuting and teleshopping behaviors in health.

The chapter conclusions are discussed in the subsections below.

5.2.1 Research Findings

On Correlations: Health outcomes are correlated with built and social environment factors

Results of the analyses presented in this chapter of the dissertation indicate that in addition to personal and household characteristics, human health is affected by the characteristics of the environment (i.e., contextual effects) in terms of the built and social environments. These two aspects of the environment exert their influence on human health through various domains, and at hierarchical spatial levels of influence including the previously under-examined macro level.

The findings suggest that social environment characteristics such as the median age, racial composition, and household income levels within the county of residence can affect residents' physical and psychological health outcomes. Findings further suggest that the social environment's influence on human health extends beyond the county boundaries. One example is the effect of the metropolitan area's gross regional product (GRP), which is considered one of several measures of the size of the economy within the metropolitan area. Results provide evidence that metropolitan areas with a stronger and larger economy (i.e., higher average GRP) can promote residents' health.

In addition, residents of metropolitan areas within which income and car ownership levels are higher enjoy improved health outcomes including better mental health outcomes. The latter effect is an interesting finding, which confirms the hypotheses of this study that the influence of car ownership has a potential to go beyond the household level, and that car ownership can affect psychological health of individuals in addition to their physical health. Other findings imply that residents of metropolitan areas with higher violent crime rates may suffer health implications including poorer psychological health outcomes.

As representatives of the social environment, sociocultural factors such as the travel culture within the county or metropolitan area of residence also play key roles in health status of residents. Living in counties or metropolitan areas where active travel is occurring at higher rates can lead to better physical and psychological health outcomes. Residing in county and metropolitan areas with a travel culture geared toward public transit may help in lowering the risk of obesity and diabetes but can also lead to a higher risk of asthma and a poorer general health status—presumably due to reasons such as increased exposure to polluted air generated from transit vehicles, increased exposure to harsh weather conditions, increased exposure to higher disease diffusion rates due to crowded vehicles, and increased levels of stress related to commuting by public transit.

Also, living in metropolitan areas with higher levels of commuter stress may adversely affect the health status of residents. Further, the study findings show that residents suffer from adverse physical health outcomes where the travel culture is oriented toward more usage of private automobiles. These findings are not surprising and corroborate the findings of past research asserting that the physical inactivity, the sedentary lifestyle, as well as the chronic stress related to operating a vehicle and car commuting contribute to declined physical health.

In terms of the under-investigated effects of telecommuting behavior and the almost nonexistent research on the effects of teleshopping-related behavior on health, the findings suggest that living in counties where telecommuting and teleshopping are prevalent among residents may lead to unfavorable physical and psychological health outcomes.

Results of the present study also corroborate past research findings that county-level (i.e., meso-level) built environment factors influence residents' health. Further, the study provides evidence that metropolitan area-level (i.e., macro-level) built environment factors play a crucial role in individuals' health outcomes. Counties with higher levels of compactness may adversely affect physical and psychological health of residents—potentially due to quintessential characteristics of dense urban areas such as crowded conditions, higher pollution levels, and increased stress levels. Counties with a higher extent of mixed-use development can also lead to some unfavorable physical and psychological health outcomes for residents including a higher risk of asthma. On the other hand, poorer health outcomes are associated with living in sprawled counties where average distances to local transit stops are greater. Considering these findings, there may be an optimal threshold for counties to become dense and mixed (in terms of land use) to promote residents' health.

Findings also indicate that walkability and pedestrian friendliness of the street network within the county can lead to better physical and psychological health. Moreover, increased automobile accessibility to employment opportunities within the county may lead to better psychological health outcomes for residents, whereas increased transit accessibility to employment opportunities within the county may lead to better physical health outcomes. Increased access to clinical healthcare, recreational facilities (e.g., parks), and healthy food outlets within the county contribute to better health outcomes for residents. In contrast, living in counties with higher pollution levels and higher access to unhealthy food outlets may lead to adverse health outcomes.

Past research found meso-level (i.e., county-level) sprawl to be more strongly related to residents' health outcomes than macro-level (i.e., metropolitan area) sprawl and posited that the built environment of the county—rather than that of the overall metropolitan environment—may be more representative of the daily experiences of residents, and thereby more influential in their health (Ewing et al. 2003b, 2008). The results of the present study generally agree with that postulate, while placing emphasis on the existence of the impact of macro-level built environment on health. A salient finding of this analysis is that the influence of a few built environment factors including mixed-use development, intersection density, access to local transit, and accessibility to employment on health extends beyond the county boundaries and into the metropolitan area.

Particularly, higher mixed-use development within the metropolitan areas may lead to poorer physical and psychological health outcomes; a result that does not support the hypothesis that higher extents of mixed land use lead to improved health status. On the other hand, metropolitan areas with increased intersection density (a proxy for compactness in terms of street connectivity) may promote general health of residents and in fact, the effect of macro-level (i.e., metropolitan area-level) intersection density may be more influential in general health than the same effect at the meso level (county level). Based on this finding, it can be inferred that better general health may be linked with residing in a more compact, better connected metropolitan area than a compact neighborhood or county located within a sparse metropolitan area—as also suggested by Marshall et al. (2014). Further, living in sprawled metropolitan areas with lower levels of access to transit may lead to obesity and other adverse health outcomes. These findings imply that to promote health, an optimal threshold may exist for cities with regards to compactness and mixed land use. Considering the study results, it seems that compactness in terms of population and employment density at either county or metropolitan area levels is not among the factors with the most influence on residents' health outcomes. If anything, the meso level (i.e., county) seem to be the geographical scale that exerts the most influence on health outcomes in terms of density measures. However, these effects tend to dissipate at the macro level (i.e., metropolitan area).

Increased levels of regional automobile accessibility to employment (within the entire metro. area) may promote residents' psychological health, whereas higher levels of regional transit accessibility to employment may promote their physical health. Also, residents of metropolitan areas with more roadway congestion may suffer health consequences due partly to higher stress levels and higher physical inactivity levels associated with commuting on congested roadways.

Considering these findings, it can be concluded that although the meso-level (i.e., county-level) built environment may be more influential in health status of residents, the effects of the macro-level (metropolitan area-level) built environment on individuals' health are existent and significant, and therefore, should not be overlooked in analysis of health outcomes.

Overall, findings of the analyses presented in this chapter support the research hypothesis of this dissertation that the residential location's built and social environment characteristics at the macro level play a role in residents' health status (see Hypothesis 1b in Table 1).

Further, the findings also provide empirical evidence for the research hypotheses that telecommuting and teleshopping behaviors impact individuals' health outcomes in terms of both psychological and physical health (see Hypotheses 5 and 6 in Table 1).

Moreover, the findings emphasize the importance of using an ecological model framework in examining the link between health outcomes and environmental factors. Accordingly, it is concluded that in probing such link, assessing the effects of multiple levels of the built and social environments on health outcomes is essential—a conclusion consistent with that reached by previous research (Joshu et al. 2008).

On Correlations: Physical activity is correlated with built and social environment factors Based on the findings of this study, it can further be concluded that health-related behavior such as physical activity can be affected by social and built environments at both meso (i.e., county) and macro (i.e., metropolitan area) levels. This holds true for both the general form of physical activity as defined for BRFSS purposes (i.e., activities including brisk walking, bicycling, vacuuming, gardening, or anything else that causes some increase in breathing or heart rate) or in its transportation-specific form (i.e., active travel).

Factors such as the median age, racial composition, household income levels, and crime rates within the area of residence seem to be key influential social environment characteristics in determining the levels of physical activity and/or active travel by residents.

Other sociocultural factors such as the travel culture within the county of residence also play a role. Counties with a travel culture oriented toward public transit (i.e., increased use of public transit) can promote physical activity. On the other hand, counties with a prevalent telecommuting culture and increased levels of online shopping-related activities may discourage active living, and thereby may lead to lower levels of physical activity by residents. The latter findings provide empirical evidence for the research hypotheses of this dissertation that telecommuting and teleshopping behaviors impact individuals' physical activity levels (see Hypotheses 5 and 6 in Table 1).

Several built environment factors at the meso level (i.e., county level) are key elements in physical activity and active travel levels. These include the extent of county compactness; mixed-use development; connectivity and pedestrian friendliness of street network; level of access to: local transit stops, parks, healthy and unhealthy food outlets, clinical healthcare; and accessibility to employment by means of automobile. Physical activity levels are also influenced by a few built environment factors at the macro level including the extent of mixed land use, accessibility to employment by means of transit, and congestion levels throughout the entire metropolitan area.

On Causality: Reverse causality exists between health outcomes and physical activity—leading to a potential endogeneity bias, which should not be overlooked

Findings of this research reveal that in investigating the links between health outcomes, health behavior, and the environment—particularly in terms of the built environment—complex causal relationships and endogeneity issues cannot be overlooked. In particular, addressing reverse causality between health outcomes and health behavior is crucial. This is because individuals' health status may influence their health behavior such as physical activity or active travel levels, as also concluded in previous research (see e.g., van Wee and Ettema 2016).

The capabilities of sophisticated statistical techniques such as the multilevel Structural Equation Modeling (multilevel SEM) and the instrumental variable analysis provide appropriate tools for estimating such complex interrelationships within a comprehensive model framework. Additionally, the SEM techniques—to some extent—allow examination of the causality of the links between physical activity, the built environment, and health outcomes.

Thus, it is concluded that despite the use of cross-sectional data in this analysis, which limits the ability to draw causal inferences, the relative robustness of the datasets combined with the successful estimation of the multilevel SEM and instrumental variable models provided some evidence of causality (at least in this sample), and thereby have yielded results of policy relevance.

5.2.2 Policy Implications

For research and policy analysts, this study provides a useful and systematic methodology for analyzing the health impacts of travel behavior and the built environment. The ecological models developed in this study highlight the role of built environment factors at various levels of geography in health of individuals and communities (i.e., counties).

The findings imply that policies concentrating on interventions that target the built environment of the county may be effective in promoting essential health provisions. These interventions include modifications to the built environment of the county that make it more conducive to physical activity and active travel.

Other interventions include modifications to the built environment of the county to make it more promotive of healthy food choices (or as described by Joshu et al. 2008, to make it more "nonobesogenic").

Examples of such interventions are changes to the built environment features throughout the county that:

- increase walkability and pedestrian friendliness of the street network;
- increase connectivity of the street network (to support nonmotorized travel);
- facilitate access to healthy food outlets;
- facilitate access to parks, green spaces, and recreational facilities;
- facilitate access to clinical healthcare;
- limit the number of fast food restaurants; and
- lower ambient air pollution levels.

The built and social environment characteristics of the metropolitan area also prove to be influential in individuals' and communities' health outcomes; therefore, these characteristics should also be considered in policy and health intervention decision-making processes.

Based on the findings of the present study, more effective public health policies and interventions seem to be the ones that consider the overall form of the metropolitan area in addition to that of the county. These include interventions that can modify the built and social environments within the entire metropolitan area in such way to:

- promote nonmotorized travel (i.e., active travel);
- increase compactness (in terms of intersection density and street connectivity);
- increase access to transit (in terms of distance to transit stops);
- lower traffic congestion levels and commute durations;
- increase the size and strength of the economy (e.g., a higher GRP); and
- lower violent crime rates.

The conclusion that promoting nonmotorized travel (i.e., walking and bicycling) through changes to the built or social environment can be an effective way to improve public health outcomes is not surprising. Nonetheless, it reaffirms past research conclusions that environments supportive of active travel promote individuals' health status.

In addition, since using public transit involves active travel at either end of a trip, promoting a higher public transit mode share can also serve as an effective policy to improve some public health outcomes by integrating physical activity into the daily routines of individuals.

Particularly, considering the findings of the study, it can be concluded that promoting active travel and public transportation use may be cost-effective interventions in increasing physical activity and preventing obesity. This is crucial information for transportation planning and public health policymakers seeking to improve the health of individuals and communities through modifications to the built or social environment that can lead to more active travel by residents, and thereby to better health outcomes for them.

With respect to compactness measured as the density of intersections, findings of the present study imply that better general health may be linked with residing in a more compact, better connected metropolitan area than a compact neighborhood or county located within a sprawled metropolitan area. This is an important finding with policy implications. Constructing new compact neighborhoods with high intersection densities in the middle of sprawled suburban areas may not provide optimal public health benefits. Instead, it is the overall character of the metropolitan area that is more influential. Residing in a connected neighborhood or county can potentially yield more health benefits in a metropolitan area with similar street network structure than in a metropolitan area with a disconnected street network—a conclusion also reached by Marshall et al. (2014). Thus, city planning strategies and urban design policies aiming at building compact metropolitan areas with better connected street networks can promote public health.

As regards crime rates, interventions that help reduce fear-producing behavior and promote crime-related safety can potentially improve health of residents within a metropolitan area. Examples of such interventions are improving street lighting; improving lighting as well as visibility from surrounding buildings and stores at transit stations, bus stops, and parking lots; reducing the number of vacant lots and dilapidated buildings as well as providing emergency pedestal phones and call boxes along walking and bicycling pathways in parks. Another important strategy to lower crime rates within cities can be increasing surveillance or "number of eyes" on streets (Jacobs 1961) by promoting urban designs that encourage continuous presence of people on city streets. In that respect, mixed land use developments can be effective.

Presence of various establishments such as restaurants, stores, and other public places that are open by later hours of the evening can generate constant presence of people, which by increasing the number of eyes and ears, helps in monitoring the street and reducing the number of crimes. However, as findings of this study indicate an optimal threshold may exist for cities to become mixed in terms of land use and still remain beneficial to public health. Therefore, urban design policies aiming at increasing the extent of mixed-use development within metropolitan areas should be developed based on optimization of such trade-offs.

Overall, evidence found in this study supports the notion that adverse health outcomes can be ameliorated through interventions that target the environment, built and social. The analysis framework and findings presented in this research can assist policy decision-makers in assessment of built and social environment attributes—at various levels of geography—that have a potential to influence health outcomes of residents. This in turn, can help in making more informed decisions and developing more effective policies based on interventions that would yield the most efficient use of resources and the greatest health benefits.

Such policies can improve individuals' health conditions in various ways and lead to a better state of health for the communities and the society as a whole.

The annual societal healthcare cost of lack of physical activity and its resultant negative health outcomes in the U.S. is estimated to be around $117 billion (DHHS 2018). Bearing that in mind, the conclusions of this study can be considered in creating policies that spatially optimize modifications to the built and social environments, and thereby reduce the burden of healthcare costs on the society.

5.2.3 Contributions

The analyses presented in this chapter contribute to the body of knowledge on the interrelationships between physical activity, health, and the environment (built and social) in terms of theoretical framework, methodology, empirical findings, and policy debates.

Regarding theoretical contributions, this research considers the principles of the ecological model of behavior as well as past research that emphasizes the role of multiple levels of the environment in health outcomes (Joshu et al. 2008) to drive a theoretical framework for disentangling the interrelationships among physical activity (e.g., active travel), built and social environments, and health. In probing the role of environmental factors in physical activity levels and health outcomes, prior research has paid a considerable amount of attention to micro-level (i.e., neighborhood) and meso-level (i.e., county-level) built environment attributes.

However, literature suggests that urban structural characteristics, such as urban sprawl, also have a potential to influence the health of residents. Although few previous studies examined the health impacts of macro-level built environment factors, the role of macro-level (i.e., metropolitan area-level) environment in residents' health remains appreciably under-investigated, particularly within an integrated theoretical framework that includes both social and built environment factors at various spatial levels. The theoretical framework presented in this study allows for testing the health impacts of various dimensions of the environment at various spatial levels simultaneously, and thereby offers a comprehensive approach that has rarely been applied to empirical data.

Regarding methodological contributions, this analysis employs sophisticated statistical techniques—scarcely applied in a transportation context—to examine the causality of the links between physical activity (e.g., active travel), health, and the built environment. It should also be borne in mind that the complex interrelationships between these three entities introduce interdependencies resulting from reverse causality as well as from a clustered data structure. Often neglected in analysis of the links between physical activity, health outcomes, and the built environment, the former kind of interdependencies may subject the analysis to endogeneity bias but can be accounted for by using Structural Equation Models (SEMs). The latter kind of interdependencies may subject the analysis to spatial autocorrelation issues and can be controlled for by employing multilevel (i.e., hierarchical) models.

Multilevel modeling techniques can be combined with SEM techniques to form a multilevel Structural Equation Model (multilevel SEM). By employment of a multilevel SEM, both kinds of above-mentioned interdependencies can be accounted for and the complexity of the relationship between physical activity, the built environment, and health can be more thoroughly examined and understood.

Despite having numerous capabilities and a tremendous potential to be used in travel behavior research, multilevel SEMs remain rarely found in a transportation context—as also noted by Chung et al. (2004). Only two empirical studies were located by the author of this dissertation that used multilevel SEMs in conducting travel behavior research (Chung et al. 2004; Kim et al. 2004). The employment of multilevel SEM techniques in travel behavior research has also been proposed in another study (Van Acker et al. 2010); however, to the best of the author's knowledge, multilevel SEM techniques have never been applied to empirical data to investigate the health impacts of physical activity (e.g., active travel) and environmental factors, particularly in terms of the built environment.

The present study contributes to the body of knowledge by employment of multilevel SEMs to test the causal pathways between physical activity and health, as well as by adverting to the potential of such techniques for being applied in travel behavior and public health research.

In terms of empirical contributions, the current study expands on the previous work in a number of ways. First, this study systematically tests the link between travel behavior—including active travel behavior—and health outcomes, using two unit-of-analysis levels: the individual (i.e., person-level health models) and the county (i.e., county-level health models, which are presented in Appendix I).

Findings of the study add to the existing empirical knowledge on the link between measures of travel behavior and health outcomes by providing insights into the extent of comparability and consistency between results from the two different analyses (i.e., person-level model results vs. county-level model results).

Further, by including objectively measured and individually observable measures of the built environment (instead of subjective measures or composite indices) the present study contributes to facilitated interpretation of empirical findings to draw more effective policy strategies and interventions that can promote public health. The use of objective measures also facilitates the generalization and transferability of the findings of this research to other metropolitan areas in the U.S.

The study results provide evidence that in addition to meso level (i.e., county level) built environment factors, macro level (i.e., metropolitan area level) built environment factors play an important role in residents' health status. Therefore, strengthening and complementing the existing empirical knowledge on the role of the built environment in human health is another contribution of this study.

Moreover, this research contributes to the body of empirical knowledge on the link between travel behavior and health by including measures of telecommuting behavior as well as those of teleshopping behavior in the analysis.

More specifically, the study findings shed light on the role of telecommuting behavior in physical health outcomes as very little empirical knowledge exists on that topic. Further, although a few previous studies investigated the relationship between telecommuting and measures of psychological health (e.g., job satisfaction, job performance), the role of telecommuting in psychological health remains somewhat ambiguous due to inconsistent empirical findings. The findings of the present study provide additional insights into the influence of telecommuting behavior on psychological health outcomes.

Further, empirical studies with respect to health impacts of teleshopping are—to the best of author's knowledge—nonexistent. Thus, this study contributes by filling that gap in research by empirically testing the link between measures of teleshopping behavior and physical as well as psychological health outcomes.

In terms of contributions to policy and practice, the study findings contribute to the ongoing policy debates concerning the role of the built environment in health behavior such as physical activity as well as in health outcomes.

As this research focuses on the influence of the macro-level environment (i.e., built and social environments) on health, the research findings particularly shed light on the most promising policy interventions that can improve public health through modifications to the built and social environments within the metropolitan areas.

This will enable transportation planning, urban design, and public health decision-makers to develop more effective policies that optimize the efficiency of resource usage as well as the societal health benefits.

5.2.4 Study Limitations and Future Research

The current study has a few limitations. First, due to lack of a database that provided concurrent data on travel behavior, health, and the built environment, several databases were linked to obtain a combined dataset for this analysis. Also, due to privacy issues with health data, travel behavior data were aggregated to the county level in this study. Using a comprehensive database that provides health status as well as travel behavior information at the person level and location data, preferably at the neighborhood level, can enhance analysis of the links between individuals' health, their travel behavior, and the built and social environment attributes of their residential location.

Such database, however, remains scarce—limiting the boundaries of research. Ideally, national travel and health surveys can be modified in the future in such way to provide data on travel behavior, health outcomes, and the built environment in one database. This will also allow compilation of a rich inventory of travel behavior, health, and built environment data over time, which will facilitate future longitudinal analysis of the interrelationships between the three.

Another data-related limitation was the incomplete consideration of transportation-specific physical activity in the health database used for the person-level health models in this analysis (i.e., 2009 BRFSS) owing to the survey: *i*) not distinguishing between active travel and other forms of physical activity; and *ii*) not including the amount of work-related active travel in its questionnaire.

Concerning the first issue, it should be borne in mind that moderate physical activity has been defined in 2009 BRFSS as "brisk walking, bicycling, vacuuming, gardening, or anything else that causes some increase in breathing or heart rate". The specific amount of walking/bicycling by each respondent, therefore, is not clear as it is combined with other physical activities that the respondent may have engaged in. Previous research suggested that travel-related physical activity may interact with other physical activity, and therefore, substitutions of different forms of physical activity should be considered in probing the link between physical activity (e.g., active travel) in health (van Wee and Ettema 2016). Thus, separating the influence of active travel from that of other forms of physical activity on health outcomes in the person-level health models was an infeasible task due to usage of the BRFSS database in the analysis.

Regarding the second issue, and as also noted in previous research (National Research Council 2005), it seems that the BRFSS is mainly focused on leisure-time physical activity, which results in lack of data on the amounts of work-related active travel. Nonetheless, surveys such as the BRFSS are the most promising sources of physical activity and health data that can be linked to built environment factors (Boarnet 2004). Therefore, future research on the interrelationships among physical activity, the built environment, and health can greatly benefit from refined versions of such surveys that allow recordation of exercise and utilitarian active travel separately from each other, and also separately from other forms of leisure-time physical activity.

Furthermore, the present study relies on self-reported data on health and health-related behavior (i.e., the BRFSS database). For various reasons, survey respondents may not always report the most accurate information about their health, which makes the data collected subjective and not objective.

In addition, the health data used for developing the person-level health outcome models came only from metropolitan areas within the state of Florida. While the metropolitan areas selected for this study are not perfectly representative of the U.S. metropolitan areas, they offer a basis for examining the health status of residents of different urban areas based on differences in their travel behavior and environmental attributes of their residential location. Nevertheless, the macro-level factors will have more variations if they come from various parts of the country. Thus, data from additional metropolitan areas in other U.S. states can be analyzed in the future to investigate the health impacts of travel behavior including nonmotorized travel, telecommuting, and teleshopping behaviors as well as those of the meso- and macro-level built and social environments. Such enhanced database will allow better examination of the effects of various measures of travel behavior and various scales of the environment on individuals' health within an ecological model framework. Future analysis based on data from additional metropolitan areas can also provide insights into the generalizability of the findings of the present study.

Further, as in many previous studies, a major limitation of the current study is the usage of cross-sectional data. The employment of SEM techniques—to some extent—allowed for examination of causal links between physical activity (in both its general form as well as its specific form of active travel) and health outcomes. Nonetheless, the use of cross-sectional survey data is a practical drawback to these techniques, limiting the ability to make true causal inferences.

Since causality is a time-ordered process (National Research Council 2005), consideration of temporal precedence of events is essential in examining causal links. For instance, influences between physical activity and health outcomes most likely do not occur instantaneously; a period of time passes before these influences are fully exerted. Although a bidirectional relationship was assumed between measures of physical activity and health in examining causality, the role of temporal precedence between physical activity and health outcomes was not taken into account due to the cross-sectional nature of data.

In addition, changes in the built environment are slow and may occur over time. Thus, any effect these changes may have on levels of physical activity and health status of residents are not instantaneous. For example, an improvement in the built environment to make it more pedestrian- or bicyclist-friendly may not lead to an increase in active travel levels immediately but may do so within a few months.

It should further be noted that the link between health outcomes and the built environment may also be bidirectional as healthier people may self-select themselves into health-promoting residential areas. The bidirectional effects between health outcomes and the built environment were not accounted for in this study.

All the above limitations are examples of arguments by Kline (2011) who emphasized the impracticality of a single study meeting all the conditions required for inference of causality including temporal precedence of the presumed cause in relation to that of the presumed effect[49]. Kline further suggested that causal links hypothesized in structural models (SEMs) should be deemed as causal links that "may or may not correspond to causal sequences in the real word" (Kline 2011). Hence, although implying causal links between the built environment and health outcomes in this particular sample, the findings of the present study may not have established the causality of such links for the processes occurring in the real world.

On the other hand, research based on longitudinal study designs enables the analyst to evaluate the temporal influence of various factors (Gochman 1997), and strengthens the ability to infer causality by clearly establishing temporal precedence (Bagley and Mokhtarian 2002).

Therefore, future research can benefit from analyzing longitudinal data to better examine causal links between physical activity, the built environment, and health outcomes. Usage of longitudinal data in combination with employment of advanced statistical methods such as the SEM can yield more robust causal inferences on these complex interrelationships. As Cao et al. (2009) suggested research designs that use longitudinal structural equations modeling with control groups would meet all causality requisites; however, those designs would require sizable amount of time and resource allocation.

[49] See page 98 of Kline (2011) for a list of general conditions that must be met to infer a cause-effect relation.

Findings of this study also reveal a few avenues for further research. For instance, in terms of the under-investigated effects of telecommuting and teleshopping behaviors on health, the findings of the present study suggest that living in counties where telecommuting and teleshopping are prevalent among residents may lead to unfavorable physical and psychological health outcomes. Due to little empirical research on the role of telecommuting in health and the almost nonexistent research on the health impacts of activities related to online shopping, these findings remain open to further research and evaluation.

Also, based on the findings of the health outcome models developed in this chapter, it can be concluded that although suggestive, the evidence is not very compelling with respect to the promotive role of increased private vehicle use in obesity, diabetes, and poor physical health. Further, the role of private vehicle use in mental health status remains unclear with findings of the county-level health models (presented in Appendix I) and person-level health models (presented in this chapter) suggesting opposite directions of influence.

Moreover, the findings suggest that albeit related to lower rates of obesity and diabetes, increased public transit use may lead to adverse general health outcomes. Therefore, a conclusion cannot be reached regarding the benefits of transit use and the drawbacks of private vehicle use as related to health outcomes. Future research can focus on examining these effects to more thoroughly evaluate the net health impacts of public transit use and private automobile use.

Further, of notable absence among the factors included in this analysis are biological susceptibility factors. While there is an underlying genetic basis for health status of individuals and their level of susceptibility to disease, the role of genetic predispositions in an individual's health outcomes was not controlled for in the person-level health models presented in this study. The reason for this was unavailability of data on biological factors. An individual's health outcomes including his/her physical activity levels are, nevertheless, dependent on biological factors and heredity (see e.g., Trost et al 2002; Zick et al. 2013; Ewing et al. 2014). Thus, future research can benefit from including genetic factors in the analysis to disentangle the relationships between physical activity levels, built and social environment factors (including those from the macro spatial levels), and health outcomes.

Also, the effects of several other built environment factors on health status of individuals were not considered in this study and can be examined in future analysis. These include, but are not limited to, availability and cost of parking, and existence as well as extent of traffic calming measures within the residential area.

Lastly, the effects of physical activity (e.g., nonmotorized travel), telecommuting, and the built as well as social environments (including at the macro level) on other important health indicators such as high blood pressure, heart disease, stroke, cancer, and safety-related health outcomes (e.g., injuries and fatalities from crashes) can be examined in future work.

Chapter 6: Closing Remarks

Probing the nexus between the environment, active travel, and public health requires a holistic approach that considers various theoretical frameworks and empirical methods from various scientific disciplines including transportation engineering and planning, urban planning and design, psychology, and public health.

Promotion of health can be a common motivator to inspire new collaborations—including in research and data collection efforts—between professionals from these disciplines. In particular, the inadequate link between databases providing data on travel behavior, the built environment, and health highlights the need for close collaborations, which can result in collection of combined data from these fields.

For instance, large-scale health surveys (e.g., BRFSS) can be modified to include more specific questions about walking and bicycling for transportation as well as questions about respondents' travel behavior as related to other travel modes. Similarly, large-scale travel surveys (e.g., NHTS) can be modified to include more questions about the health status of respondents such as their overall health and other key health outcomes[50].

Such collaborated efforts can result in refined surveys and compilation of rich databases, which allow comprehensive analysis and a deeper understanding of the complexities involved in the interrelations between environmental factors, physical activity such as active travel, and public health outcomes. The importance of such research efforts is recognized through reiteration of the alarming physical inactivity and public health trends and the disturbing statistics and facts.

[50] The survey questionnaire of the most recent National Household Travel Survey (2017 NHTS) included questions regarding respondents' general health.

Facts adduced by the U.S. Department of Health and Human Services (DHHS 2018) are that currently:

- nearly half of American adults have one or more preventable chronic diseases;
- most of the common chronic diseases are favorably impacted by regular physical activity;
- about 80 percent of American adults do not meet the recommended physical activity levels; and
- the lack of physical activity is linked to approximately $117 billion in annual healthcare costs and about 10 percent of all premature deaths in the U.S.

Active travel can help! By incorporating physical activity into people's daily routines, walking and bicycling—for both utilitarian and recreational purposes—can contribute to improved public health outcomes and reduced societal healthcare costs.

Research suggests that investment into creating more walkable and bikeable communities is an efficient strategy to increase physical activity levels and improve public health (see e.g., McCann and Ewing 2003). The health-related benefits of active travel (including the lower healthcare costs) should, therefore, be compared to the costs of incentives that stimulate walking and bicycling to determine the cost-effectiveness of policies promoting active travel.

Nonetheless, the challenges of determining what factors encourage people to walk and bicycle are many. In general, disentangling mechanisms of human behavior is a difficult endeavor. The complexity of the maze that is human decision-making process adds to the intricacies of predicting and explaining observed human behavior.

With regards to active travel behavior, the potential theoretical frameworks include the utility-maximization demand theory and the ecological model of behavior. The potential empirical evidence can come from using travel or health survey data.

However, each current source of information allows only certain features of active travel behavior to be examined. Travel surveys provide data on sociodemographic and socioeconomic characteristics and daily trips of individuals but may not fully capture information on personal preferences and attitudes toward travel. Health surveys provide information on health-related behavior and health status of respondents but fail to separate the amount of active travel (i.e., walking and bicycling) from other physical activity performed by the respondents. Moreover, both types of surveys do not provide comprehensive data on the built environment of the respondents' residential and workplace areas. Thus, the many aspects of active travel behavior hardly lend themselves to examination using simple theoretical or empirical methods.

To deduce health-related behavior such as active travel, this research finds the ecological model of behavior the most promising theoretical framework. By conceptualizing multilevel influences on behavior, the ecological model provides the most integrated framework for modeling human behavior and allows for reframing of active travel behavior as the outcome of influences across various ecological levels including internal influences (e.g., preferences and attitudes) as well as external influences (e.g., the built and social environments).

The findings of this research also emphasize the role of the environment in active travel behavior. Considering both the utility maximization theory and the ecological model of behavior, researchers probing to explain active travel behavior can only hope that given full knowledge about alternatives and a supportive environment, most travelers would make the "rational" decision. However, providing full information about each alternative mode of travel is not feasible in the real world. Moreover, even fully informed travelers may not always choose the "rational" decision with regards to the trips they make. This can be due to factors such as attitudes, preferences, or health-related restrictions, which can be powerful influences on trip-making decisions. This means that for instance, there may always be those who would not make the switch to active travel modes regardless of supportive environmental attributes. And then, there are those who may, and that is what makes using environmental interventions as change agents to influence people's active travel behavior as well as their health status an issue worth examining.

Further, due to their dependency on environmental factors, health outcomes can also be more thoroughly examined within an ecological framework. With regards to environmental factors, it should be borne in mind that based on an ecological framework, multiple interacting levels of built and social environments may be at work to impact health-related behavior (such as active travel and other physical activity levels) as well as health outcomes. Parallel to these various levels of influences are various levels of potential interventions that can be implemented to promote active travel and improve public health. For instance, modifications to the built environment can be made not just within neighborhoods but also within the county as well as the entire city to promote a seamlessly healthy urban development.

Examples of such modifications at the smallest level—the neighborhood—can be building more walkable and well-connected street networks, mixing residential and commercial land uses, and constructing more compact developments. The neighborhood has the most potential to increase active travel levels within the city through increased levels of walkability and bikeability. Therefore, the focus of modifications to the built environment at the micro level (neighborhood level) should be pedestrian- and bicyclist-friendly planning and design principles.

At the meso and macro levels, the principles guiding modifications to the built environment should still stress the importance of pedestrian- and bicyclist-friendly designs but also focus on increasing access to a variety of health-promoting land uses, increasing access to public transit, discouraging urban sprawl, and encouraging revitalization as well as promoting infill and retrofit developments. Examples of such modifications can include: building or improving street networks in such ways to make them more bicycle- and pedestrian-oriented; facilitating access to transit stations and bus stops by means of walking and bicycling; building new or facilitating access to parks, green spaces, and other recreational facilities that promote physical activity; building new or facilitating access to healthy food outlets; retrofitting sprawling suburban areas to provide increased access to various destinations, particularly by foot or bicycle; revitalizing high-crime or high-poverty neighborhoods with a potential of being walkable and bikeable by constructing new housing developments for various income levels; productively reusing vacant properties; and similar investments.

Together, these multilevel interventions can encourage healthy travel behavior such as walking and bicycling, facilitate access to various local opportunities, foster daily social life and community engagement by catalyzing interactions between people, create opportunities for spending more time in the nature, and ultimately promote healthier and more livable neighborhoods, communities, and cities. As noted by Smith et al. (2008), the challenges of implementing multilevel interventions targeting the built (or social) environment are, however, not to be under-estimated as most of these changes require time and perhaps a political process.

Evidence from travel behavior research points to a latent demand for active travel. Many travel surveys that include questions on attitudinal factors indicate some inclination by respondents toward walking and bicycling given a supportive built or social environment. Further, the most recent National Travel Survey (NHTS) shows that a considerable percentage (over 21%) of automobile trips in the U.S. are either shorter than or approximately one mile in distance[51]. These trips have a potential to be substituted by nonmotorized trips (i.e., walking and bicycling) as conditioned partly by the features of the surrounding built environment.

On the other hand, evidence from health research reveals that the adverse health effects associated with unhealthful lifestyles are largely due to preventable conditions (e.g., lack of physical activity including active travel) (Gochman 1997). Health research further indicates that the built environment is also influential in promotion of health-related behavior such as physical activity and active travel as well as in prevention of chronic diseases.

Research in the past has provided ample evidence on the factors influencing active travel and health outcomes as noted in Chapter 2 (and Appendix B). The findings of the present study add to the empirical evidence; advance the discussion on the links between active (i.e., nonmotorized) travel behavior, the built environment, and health; and inform policymakers on the most effective strategies for future interventions.

Although the existing knowledge can always be improved by further research, much is already well-known and established regarding the influence of active travel on health and the influence of the built environment on both active travel and health. What is now required is action!

Too long have the city design and development patterns in the U.S. been automobile-oriented and too long have the walking and bicycling modes of travel been marginalized in the U.S. Considering the arguments presented in the preceding paragraphs, it is time to reverse the unhealthy trends of physical inactivity associated with automobile-oriented urban development. It is time to make active modes of travel integral parts of transportation planning and urban planning

[51] 2017 NHTS Popular Vehicle Trips Statistics: https://nhts.ornl.gov/vehicle-trips

processes in the U.S., to increase investments in building pedestrian- and bicyclist-friendly infrastructure within American cities, and to encourage walking and bicycling trips—both for utilitarian and recreational purposes.

These efforts will undoubtedly create urban environments that support a vibrant and active public life; one that will be more promotive of better public health through downstream effects of physical activity and active travel.

Indeed, active living is the nexus of transportation planning, urban design, and public health efforts. This research reveals that the pursuit of wellness and the retreat from illness can be achieved by persuading people to adopt healthier lifestyles and behavior (e.g., more active travel) as well as by providing them with the built environment that facilitates doing so.

All aspire better health. After all, "the groundwork of all happiness is health" (Leigh Hunt). Thus, health is a pillar of happiness, and staying active and living in an area where being active is supported by the built environment are pillars of health. The former part of that argument is intuitive, and research findings—including those presented in this dissertation—provide evidence for the latter part.

The next step should be to close the gap between aspiration and operation. By harnessing the existing empirical evidence and by taking a holistic approach, policymakers can make positive impacts on public health through urban designs that foster active travel and active lifestyles.

Appendices

Appendix A

Nonmotorized Travel Behavior, the Built Environment, and Health:

A More Detailed Discussion on Background and Research Motivations for this Dissertation

A.1 Travel Behavior

Travel behavior as noted by McFadden is a "complex and multifaceted" phenomenon that includes making short-term daily travel decisions about the purpose, frequency, timing, destination, and mode of each trip in the context of long-term lifestyle decisions such as vehicle ownership, housing location, and employment location (McFadden 1974).

To put it more simply, travel behavior is how people get where they need to or desire to be. It is the constant practice of making decisions about whether at all to travel, where to travel, when to travel, how to travel, how many times to travel, and with whom to travel. Travel behavior research usually involves asking questions about these decisions in a survey of travelers. The data obtained through responses provided are analyzed by researchers to quantify and understand the choices that individuals make with regards to the *W*s and *H*s of travel (i.e., whether or not, why, where, when, with whom, how, how many times, etc.)

A.1.1 Travel Behavior Research and Theories

Leipmann's 1945 study (Leipmann 1945) is considered by some researchers a pioneering work on derivation of an organized theory of travel behavior (see e.g., Scuderi 2005). Liepmann analyzed data from 1930s on commuting travel (i.e., daily journey to work) in England and was the first to bring attention to the roles of time, cost, and strain of travel in workers' travel behavior, particularly in their commute mode choice.

Later, McFadden (1974) proposed a utility-maximization demand theory—derived from the fields of psychology and economics—to be applied to travel behavior modeling and research. The fundamental assumption of the utility-maximization demand theory is that people are presented with the choice of different alternatives. The theory's basic proposition is that "people make decisions to advance their self-interest" (McFadden 2002). This self-interest is quantified by an indicator termed *utility*, which is a measure of the satisfaction obtained by a consumer from consuming a good. The theory assumes that in making decisions about what good to consume, consumers act rationally and invariably choose the alternative that maximizes their utility.

Applied to travel behavior research, as proposed by McFadden, the maximization of self-interest (i.e., utility) proposition would mean that given the option and full knowledge of all travel alternatives, rational travelers make travel decisions to maximize their benefits (i.e., self-interest or utility)—usually by minimizing their monetary cost, travel time, or effort. For example, one would assume that individuals would be more likely to use nonmotorized modes if conditions for making such trips become safer or more suitable, or if using alternative modes (e.g., automobile) becomes more expensive or less feasible. Although the assumptions of the theory (i.e., rational decision-making, full knowledge of alternatives, and perfect accuracy in computation of benefits) may not hold in the real world, McFadden's utility-maximizing framework has been heavily employed in travel demand analysis.

However, this framework has been primarily used to model motorized travel demand. To make the framework suitable for modeling nonmotorized travel demand, modifications are needed including specification of benefits for nonmotorized trips and incorporation of built environment attributes into the framework (National Research Council 2005). This would mean that to be maximized, the utility (i.e., benefits) of nonmotorized travel would need to be better defined for the travelers providing them with "full knowledge" of these travel alternatives.

Travel behavior research has also benefitted from the perspectives of behavioral theories from the field of psychology including: *i*) the social cognitive theory (Bandura 1986), which considers the role of social environment in behavior; *ii*) the theory of planned behavior (Ajzen 1991), which considers the role of attitudes, subjective norms, and perceived behavioral control in behavior; and *iii*) the ecological model of behavior (Sallis et al. 2008), which considers the role of multiple-level influences including those of the physical (i.e., built) environment in behavior.

The application of the psychological behavioral theories in travel behavior research has been focused on nonmotorized travel behavior as part of a broader research on health behavior such as physical activity. Thus, these theories and their principles will be further elaborated under the sections discussing health behavior theories (Subsections A.2.3 and B.2.1).

A.1.2 Travel in the U.S.

For several decades, automobile has been the dominant mode of transportation in U.S. metropolitan areas, particularly for commuting (National Research Council 2005; Chen et al. 2008; Schneider 2015). Consequently, levels of highway traffic congestion have been increasing over the past decades in all U.S. urban areas. The Bureau of Transportation Statistics (BTS) estimates that of the nearly 5.4 trillion person-miles of travel (PMT) in the U.S. during the year 2014, almost 70% was in private vehicles (BTS 2016). In addition, between the years of 2000 and 2014, the annual highway vehicle miles traveled (VMT) increased by nearly 10%, while the average annual congestion delay (hours) per commuter increased by approximately 14%. Further, by 2014, travelers in major metropolitan areas had to allow an average of at least 150% more travel time during peak periods to arrive at their destinations on time (BTS 2016).

As a result of statistics such as the ones mentioned above, concerns are growing over the ever-worsening traffic congestion conditions, pollution emission levels, high fuel and energy consumption levels as well as the adverse impact of land development on the natural environment, especially in urbanized and metropolitan areas (Badoe and Miller 2000; Boarnet and Crane 2001; Ewing and Greene 2003; Targa and Clifton 2005; Plaut 2005; Goddard et al. 2006; Fan 2007; Marshall et al. 2009; Cervero and Murakami 2010).

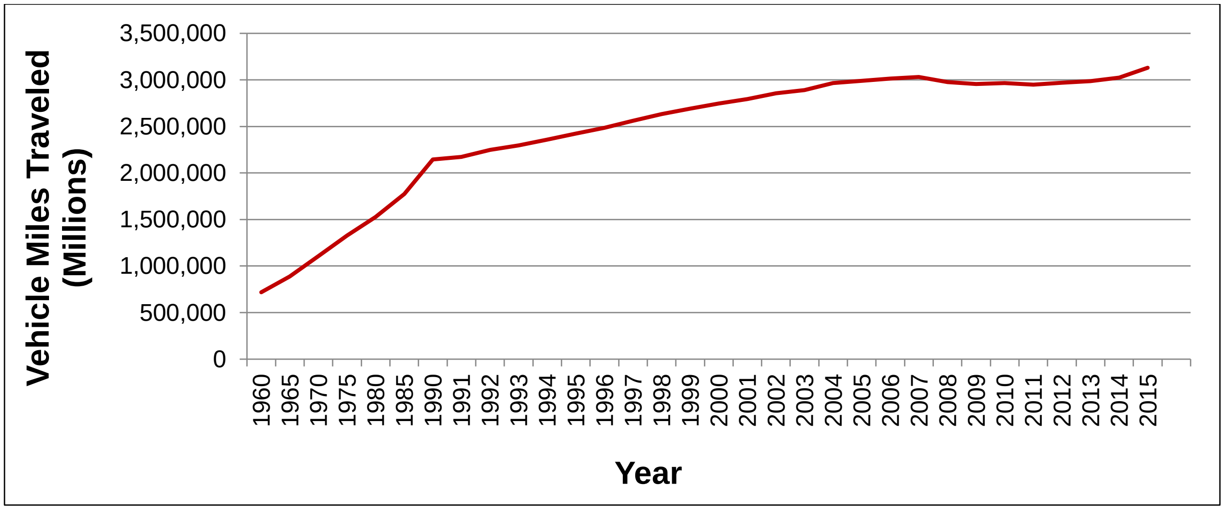

Figure A-1. Highway Vehicle Miles Traveled (VMT) in the U.S. by Year[52]

This is in part due to evidence that shows the U.S. economy has been impacted by traffic congestion, pollution levels, and high energy consumptions—particularly in growing urban areas. Research has shown that in 2011, traffic congestion caused Americans who lived in cities to spend an extra 5.5 billion hours traveling and purchase an additional 2.9 billion gallons of fuel (Milne and Melin 2014). Other statistics reveal that between 2000 and 2014, the economic cost of congestion in urban areas increased by 40% due to the average commuter wasting 19 gallons of

[52] Source of data: Bureau of Transportation Statistics web site - Table 1-35 - U.S. Vehicle-Miles: https://www.bts.gov/archive/publications/national_transportation_statistics/table_01_35

fuel in 2014 as a result of congestion and by 2016, the transportation sector accounted for approximately 70% of the total petroleum consumed in the U.S. (BTS 2016). Moreover, the transportation sector is responsible for a high portion of greenhouse gas (GHG) emissions and other harmful pollutants. According to the U.S. Environmental Protection Agency (EPA), transportation activities accounted for approximately 35% of U.S. carbon dioxide (CO_2) emissions from fossil fuel combustion, and 27% of total GHG emissions in 2015 (EPA 2017).

The recent travel trends not only place mounting pressure on the natural environment, but also can potentially impact the social environment, overall quality of life, and ultimately, human health in a negative way. Obesity, asthma, diabetes, high blood pressure, and many other health problems have reached alarming levels in the U.S. in recent decades (McCann and Ewing 2003; Ewing et al. 2003b; Plantinga and Bernell 2007; Forsyth et al. 2008; Hirsch et al. 2014). Thus, the value of adopting a healthier and more sustainable lifestyle has been increasingly recognized by academics, practitioners, and decision-makers. Concerns over the social costs (i.e., adverse effects of automobile travel externalities on public health, economy, and the environment) have motivated a surge of research efforts and policies to find effective long-term solutions to mitigate these problems. Reduction of the amount of automobile travel seems to be the most popular and promising proposed solution so far (Friedman et al. 1994; Cervero and Radisch 1996; Pucher et al. 1999; Krizek 2003b; Dill and Carr 2003; Lee and Moudon 2004; Goddard et al. 2006; Fan 2007; Ewing and Cervero 2010; Cervero and Murakami 2010; Tajalli and Hajbabaie 2017).

A.1.3 Nonmotorized Travel Behavior

Nonmotorized (i.e., walking and bicycling) modes of travel have received increased scholarly attention as cost-effective, sustainable, viable, low-polluting, and energy-conserving alternatives to driving and appropriate remedies for health issues, which can ultimately improve quality of life (see e.g., Handy 1996b; Porter et al. 1999; Pucher et al. 1999; Lumsdon and Mitchell 1999; Davis and Wicklatz 2001; Dieleman et al. 2002; Lee and Moudon 2004; Leslie et al. 2007; Giles-Corti et al. 2009; Heinen et al. 2010; Pucher et al. 2010; Handy and Xing 2011; Schneider 2015; Mindell 2015; Tajalli and Hajbabaie 2017).

Benefits of nonmotorized travel are not difficult to discern. Nonmotorized modes are deemed as indicators of sustainability, livability, equity, efficiency, and viability. Walking is the most natural way of transportation and both walking and bicycling incorporate the added value of physical activity. In addition to having numerous health and social benefits—at both individual and community levels—nonmotorized travel is inexpensive, enjoyable, and available to almost all (Pucher et al. 1999; Mahmoudi and Zhang 2018a). Yet, the most recent National Household Travel Survey (NHTS), which was conducted in 2009[53], showed that of all trips taken in the U.S., the shares of walking and bicycling trips were only 11% and 1%, respectively compared to automobile travel, which accounted for nearly 83% (Figure A-2). Moreover, approximately 70% of trips shorter than one mile were made by private automobile (Milne and Melin 2014). These statistics provide further support for the claim that automobile is the prevailing mode of travel in America as research in the past also has found (see e.g., National Research Council 2005).

Within a transportation context, the dominance of the private vehicle as the main mode of travel in the U.S. can be considered as a challenge to promoting nonmotorized modes of travel. This is because with the interwoven relationship between transportation and land use, high levels of automobile usage can lead to more automobile-oriented built environment designs and land development patterns, which in turn, can result in more obstacles to using the nonmotorized travel modes (Fan 2007).

[53] At the time this research was conducted, 2009 NHTS was the most recent dataset. The 2017 NHTS data were released in March 2018, and after this study was conducted.

Many researchers are motivated by statistics such as those presented in Figure A-2 to determine the factors that influence one's decision in making a nonmotorized trip. Identification of the factors that play a role in nonmotorized travel behavior, and determination of how to better model nonmotorized trips can greatly deepen the understanding of decision-makers on the most effective policies that can promote bicycle and pedestrian trips (Porter et al. 1999).

Within a public health context, identification of the factors that impact nonmotorized travel behavior is also critical in development of transportation planning policies and urban designs that promote healthier behavior, and thereby lead to healthier citizens, communities and societies.

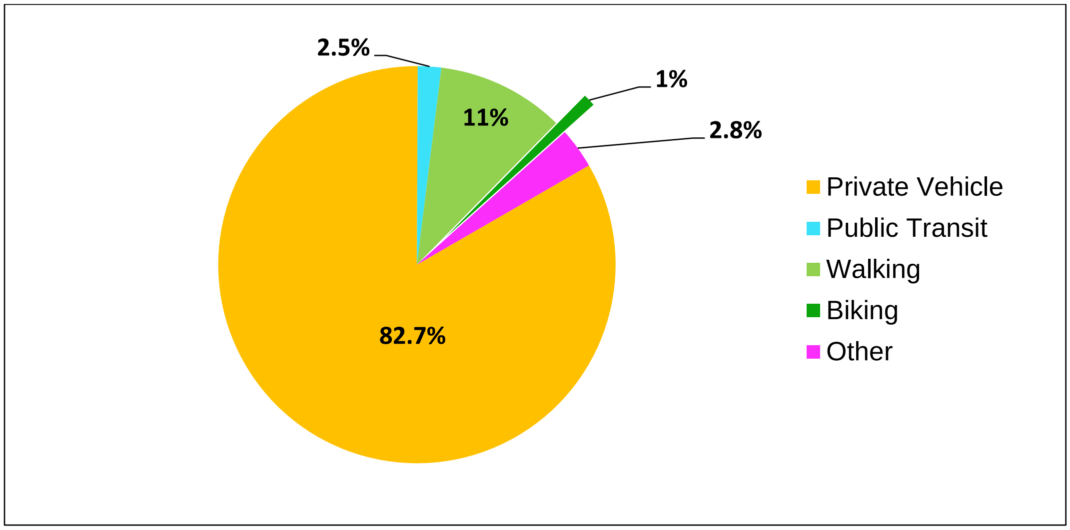

Figure A-2. Percentage of NHTS Trips by Travel Mode (Mode Share)

NOTES:

Percentages calculated from the 2009 NHTS "Weighted Frequency" field;

The "Private Vehicle" mode includes car, van, SUV, pick-up truck, other trucks, recreational vehicle, and motorcycle;

The "Public Transit" mode includes local public transit, commuter bus, charter/tour bus, city to city bus, shuttle bus, Amtrak/intercity train, commuter train, subway, trolley/streetcar;

The "Other" mode includes golf cart, taxicab, ferry, airplane, special-transit-people with disabilities, school bus, and the "other" modes.

Considering the benefits of nonmotorized modes, federal legislations such as the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 and its successors, the Transportation Equity Act of 21st Century (TEA-21) in 1998 as well as the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users (SAFETEA-LU) in 2005 increased public investments and funding for nonmotorized transportation infrastructure improvements. These resources can be used to promote nonmotorized trips in U.S. urban areas.

Although more conducive to motorized trips, most U.S. urban areas have the potential to also provide a reasonably comfortable and safe setting for walking and bicycling trips due to denser designs, which allow pedestrians and bicyclists quickly access destinations. Also, considering that all transit trips (and most vehicular trips) eventually result in walking trips along city streets (Murga 2004), urban areas may be the most suitable candidates for initial and retrofitting designs that are promotive to nonmotorized trips. In fact, urbanized and metropolitan areas have been mentioned in past research as the most promising areas in the U.S. to promote nonmotorized travel modes (Delmelle et al. 2012). Literature specifically underlines the importance of bicycling as a healthy and prominent activity in metropolitan areas despite of its underutilization in U.S. metropolitan areas (Moudon et al. 2005).

A.1.4 Travel Behavior and the Role of the Built Environment

To better understand the factors that influence nonmotorized travel behavior, one should start with gaining a sound understanding of the factors that affect travel behavior in general. The built environment characteristics of the place of residence are among the factors that have been proved to have an impact on travel behavior of individuals. The *built environment* as defined by Cervero and Kockelman (1997) refers to "the physical features of the urban landscape that collectively defines the public realm".

According to Handy (2005), the built environment consists of three components: 1) land use patterns (i.e., spatial distribution of activities); 2) the transportation system (i.e., transportation infrastructure and services); and 3) design features (i.e., design of buildings and public spaces). Each of the built environment components has multiple dimensions. A few examples include location and size of commercial outlets, location and size of employment centers (for land use patterns); sidewalks, bike paths, bus stops (for transportation system); and textures of buildings (for design feature). Together, these elements can facilitate or constrain travel. Specifically, the built environment can provide accessibility or create barriers, provide proximity or create a distance, and provide opportunities for some activities at the expense of some other activities (Næss 2005). Mainly acting as surrogates for unobserved environmental attributes, built environment factors capture characteristics of the environment that even though may not be observed, are essential determinants of travel mode choice (Rodríguez and Joo 2004).

Further, built environment factors can influence travel behavior by affecting the generalized travel cost to various destinations (Boarnet and Sarmiento 1998). For example, the low-density development patterns associated with decentralization of housing and jobs may increase reliance on private automobile, and ultimately, may lead to more automobile travel and more gasoline consumption (Handy 1993; National Research Council 2005). Another example is building neighborhoods with compact development patterns and effective job-housing balance within decentralized metropolitan areas; a practice which may shorten trip and commute distances (by locating employment and home sites close to each other), and thereby facilitate walking and bicycling (Levine 1998; Fan 2007).

Additionally, existing literature on the relationship between the built environment and travel behavior suggests that two built environment-related concepts can be influential in people's travel behavior outcomes, particularly in their mode choice and destination choice. These are: *mobility* and *accessibility*.

Mobility has been defined in literature as the movement of people or goods—typified by highway level of service and speeds (Levine 1998; Handy 2005; Litman 2011). In essence, as

Handy puts it: “mobility is the ability to travel with a reasonable level of performance (i.e., at uncongested and reliable speeds)” (Handy 2005). As an indicator of speed at which an individual can travel through space within a certain time period, mobility has a potential to influence travel behavior through mode and destination choices. For instance, an individual who drives a private vehicle may reach a higher number of destinations during the day than a person who uses a nonmotorized mode of travel (Næss 2005). Mobility concepts assume that increased travel distance or speed benefits the society (Litman 2011). Increased mobility, particularly throughout the urban and metropolitan areas, enables individuals to broaden their destination options by traveling farther and quicker to reach additional desired destinations. Consequently, residents are no longer limited to opportunities in their own locality (or region) as their travel behavior becomes more dependent on the built environment factors of larger-scale spatial areas, such as those of the entire metropolitan area (Nasri and Zhang 2012). Mobility concepts intertwine with accessibility concepts to shape travel choices by residents of metropolitan areas.

Accessibility is the degree to which land use and transportation system enable travel between destinations by a particular travel mode or a combination of travel modes (Geurs and van Wee 2003). Accessibility is an indicator of the level of access to essential societal activities such as employment and social services; hence, it is a major factor in a region’s economic and social development, and it can determine the locational advantage of a region relative to other regions (Schürmann et al. 1997; Geurs and van Wee 2003).

Various definitions have been provided for accessibility in the past. Handy (1996b) defined accessibility as the pattern of activities, which can be operationalized by “quantity, quality, variety, proximity and connectivity”. Other literature suggested that accessibility consists of two factors: 1) an activity factor—which reflects the spatial distribution of activities to be reached—such as employment, shops and residences; and 2) a transportation factor—which reflects the ease of travel to reach those activities—measured by travel distance, time, or cost (Handy 1993; Schürmann et al. 1997). Based on this point of view, accessibility captures the combined effect of a travel impedance factor and an attractiveness factor. Moreover, Litman (2011) defined accessibility as "the ability to reach desired goods, services, activities and destinations (collectively called *opportunities*)", whereas Hansen's definition of accessibility was the "potential of opportunities for interaction" (Hansen 1959). The latter study operationalized accessibility as the number of activities (e.g., employment, residential, commercial) around a zone adjusted for some measure of impedance (e.g., time, distance, cost) for traveling to those activities. Together, these definitions establish that accessibility is the ability to reach opportunities and activities.

Accessibility is often measured within the context of a certain model of travel (or a combination of travel modes). Additionally, accessibility can be measured at local and regional levels where *local accessibility* is considered accessibility to activities within a community and *regional accessibility* is considered accessibility to regional centers of activity from that community (Handy 1993). In that sense, accessibility is considered by some researchers a more descriptive measure of activity intensity than density because accessibility can be regional in scope and not limited to a local area (Kockelman 1997).

Local accessibility is determined by nearby activities. It is associated with distance to destinations and can be represented by the number of establishments (i.e., shopping stores, employment opportunities, banks, restaurants, etc.) within or around one's neighborhood or by having the option and ease of travel to any such desired destination within a specified distance by means of a specific mode of travel—for example, by walking. Increased local accessibility may lead to less vehicular travel (Handy 1993).

Regional accessibility is less dependent on distance to destinations and can be represented by the number of or ease of travel to employment opportunities as well as retail and commercial centers within the region, which can attract customers from a wide geographic area. Higher levels of regional accessibility mean decreased travel distances to regional destinations and may lead to changes in travel modes. However, Handy (1993) suggested that although increased regional accessibility shortens distances, it does little in reducing the frequency of trips, meaning that individuals travel a certain amount regardless of the distance because they may not find everything they need in their local area.

By evaluating both the local and the regional accessibility of a neighborhood, the accessibility characteristics of the neighborhood and the region it is located in as well as the quality of the links between the neighborhood and the region can be accounted for (Handy 1993). This means that together, measures of local and regional accessibility can lay out a good picture of the spatial structure of a metropolitan area and help in differentiating between communities within the region (Handy 1993). Thus, in probing factors that influence travel behavior, the extent of both local and regional accessibility matters.

Like increased mobility, increased local or regional accessibility can influence destination choice or mode choice. In terms of destination choice, the regional structure of a neighborhood may provide more destination opportunities, which can lead to more travel in general, or it can minimize the effects of any destination variations in the neighborhood structure on travel behavior (Krizek 2003b). In other words, having more destination options farther away from the neighborhood may encourage additional and/or longer trips. In fact, Handy (1996b) found that having a greater variety of destination options leads to more frequent trips and longer trip distances. In terms of mode choice, past research suggests that higher local accessibility may lead to less vehicular travel (Krizek 2003a; Handy et al. 2005). For local accessibility to influence travel behavior, variety, location, and type of destinations are critical characteristics (Krizek 2003a).

The above arguments suggest that mobility and accessibility characteristics are linked to built environment and land use patterns and can both play key roles in travel behavior by influencing people's mode and destination choices. For example, by concentrating trip origins near trip destinations (accessibility) and by influencing travel speeds (mobility), compact designs can affect travel cost (Boarnet and Sarmiento 1998), which in turn, can influence mode and destination choices of residents. Accessibility and mobility concepts—as defined by Hansen (1959) and Litman (2011)—were developed for vehicular travel and did not take into consideration the nonmotorized traveler, whose trips are at much lower speeds and shorter distances (National Research Council 2005). Nonetheless, both accessibility and mobility have a potential to indirectly impact nonmotorized travel through influencing motorized travel choices including mode and destination choices, as argued in previous paragraphs.

A.1.4.1 Travel Behavior and the Spatial Scales of the Built Environment

Heinen et al. (2010) described travel as a matter of bridging a gap between locations. One aspect of taking "location" into account is the matter of geographical scales. Past literature suggests that in travel behavior research, consideration of various geographical scales is important (Handy 1993; Boarnet and Sarmiento 1998; Boarnet and Crane 2001; Boarnet 2004; Fan 2007).

The built environment can be measured at various geographical scales including at: the building or site level, the block level, the neighborhood level, and the regional level. Each of these levels can influence travel behavior by facilitating or constraining certain modes of travel. Based on arguments by past research (National Research Council 2005), for example, certain features of buildings or sites such as access to other structures may facilitate the walking travel mode between these structures. On the other hand, lack of these features may make it difficult to walk between structures and require the driving mode to do so. The street block size as well as the built environment attributes of the neighborhood such as network design patterns (i.e., grid-like vs. cul-de-sac designs), extent of mixed land use, and availability of pedestrian and bicycle facilities can also influence travel mode choice and level of nonmotorized travel. Further, the built environment characteristics of the entire region such as its size, distribution of jobs, and supply of transportation facilities can influence travel behavior (National Research Council 2005) including mode choices as well as commute durations.

Thus, with regards to the built environment, the travel behavior of individuals may be most likely influenced by: *i*) the characteristics of the neighborhood of residence (or workplace); *ii*) the position of the neighborhood in the larger region; and *iii*) the spatial structure of the region (Handy 1993; Krizek 2003b).

The various scales of the built environment may also interact with each other to influence travel behavior. That is, the influence of the built environment on travel behavior at one spatial scale may depend on the influence of the built environment at another spatial scale, and the same factor may exert different effects or magnitudes at different scales (National Research Council 2005; Fan 2007). Further, the effect of the built environment at various spatial scales on travel behavior is likely to differ by the type of travel behavior—most importantly—the travel mode. For example, access to various land uses within walking or bicycling distance is likely to promote destination-oriented nonmotorized trips, whereas access to various land uses within the entire metropolitan area may encourage more destination-oriented automobile trips.

It should be noted that although various spatial scales of the built environment have been identified in the literature (e.g., neighborhood, region), there seems to be no consensus among different studies on the exact size of some of these scale categories. For example, the definition of neighborhood in prior travel behavior studies is based on geographical areas ranging from a small buffer zone around the trip origin and/or destination (e.g., Lee and Moudon 2006; Fan 2007; Chatman 2009) to an area as large as a traffic analysis zone (TAZ) (e.g., Cervero 2001; Zhang 2004; Mitra and Buliung 2012). Similarly, the region has been defined as a county in some travel behavior studies (e.g., Nasri and Zhang 2014), whereas others argue that in an urban context, the region may be defined as the metropolitan area (National Research Council 2005).

While the geographical unit of analysis in studies that probe the link between the built environment and travel behavior varies from the street block at the smallest scale to the metropolitan area in its entirety at the largest scale (Ryan and Frank 2009), in general, two distinctive geographical scales for the built environment have been defined in literature. These are: 1) the micro-level built environment, which considers the built environment characteristics of the local or neighborhood; and 2) the macro-level built environment, which examines the built environment characteristics of regional urban areas (Handy 1993; Badoe and Miller 2000; Murga 2004; Joshu et al. 2008; Ryan and Frank 2009; Nasri and Zhang 2012).

A three-level hierarchy for the built environment has been brought to attention by King et al. (2002) and Ewing et al. (2003b), which consists of: 1) the micro level (e.g., immediate local area/neighborhood); 2) the meso level (e.g., neighborhood/community); and 3) the macro level (e.g., metropolitan area or county). Consideration of these hierarchical structures can be useful in conceptualization of study frameworks that are designed to examine the role of various spatial scales of the built environment in travel behavior. These comprehensive frameworks will help researchers to identify the built environment factors that exert the greatest influence on travel behavior—including nonmotorized travel behavior—at each spatial scale.

A.1.5 Why the Macro-level Built Environment Matters in Nonmotorized Travel Behavior Research

As indicated previously, because most nonmotorized travel is spatially constrained, smaller geographic units of analysis (e.g., neighborhoods) have been assumed by researchers to yield more information on the built environment characteristics that impact nonmotorized trips. However, there are reasons to think beyond the neighborhood boundaries in conducting nonmotorized travel behavior research. These reasons are discussed below.

A.1.5.1 The Macro-level Built Environment, Travel Behavior, and Calls in the Literature

Over the past two decades, researchers have been suggesting that the analysis of the link between the built environment and travel behavior can be improved by inclusion of macro-level built environment factors. Early on, this literature suggested that the structure of the metropolitan areas should be considered in travel behavior research (Handy 1996c) as the overall physical form of cities and regions (e.g., the distribution of population and employment within the city and its road and transit networks) can shape people's travel outcomes (Cervero 2002; Bento et al. 2005). Nonetheless, very few empirical studies included built environment measures of larger-scale spatial areas in travel behavior analysis during those years.

An example of the studies that did take into account the role of the built environment at larger scales in travel behavior research is a 1998 study by Boarnet and Sarmiento. The study tested the hypotheses that: *i*) the built environment and land use characteristics of larger-scale spatial areas such as those of the zipcode and metropolitan areas affect travel behavior; and *ii*) compared to those of the neighborhood, land use characteristics of larger geographical areas might be even better determinants of travel behavior. The authors concluded that the effect of zipcode-level land use factors on automobile travel was not different from that of the neighborhood (census block group/census tract)-level factors, and that zipcode-level land use characteristics did not significantly impact the number of non-work automobile trips (Boarnet and Sarmiento 1998). Later, He and Zhang (2012) suggested that by interacting with the neighborhood-level built environment, the overall built environment of the metropolitan area can impact travel behavior over time. Other empirical research showed that metropolitan area-level built environment characteristics influence households' vehicle miles traveled (Nasri and Zhang 2012, 2014).

As regards nonmotorized travel behavior, the issue of geographic scale and the role of macro-level built environment have been underexamined in research (Boarnet 2004; National Research Council 2005). Although too often neglected, there have been calls in the literature for consideration of various levels of geographic context including larger-scale spatial areas in the analysis of nonmotorized travel behavior.

For instance, a 1999 study suggested that larger area/zonal-level factors that represent the relative attractiveness of making nonmotorized trips should be further developed and tested in analysis of such trips (Porter et al. 1999). Another study suggested that in probing the link between the built environment and physical activity (including walking and bicycling as common forms of physical activity), data should provide multiple levels of geographic detail, with special focus on neighborhood-level built environment factors (Boarnet 2004).

Other literature also argued that the built environment at many geographic scales—including the neighborhood, and the region—can influence the propensity of being physically active (e.g., engaging in walking or bicycling activities) (National Research Council 2005). This study characterized the lack of consideration of the built environment at scales larger than the neighborhood and the limited attention given to the role of district or regional-level built environment characteristics a "notable gap" in research concerning nonmotorized travel behavior.

The referenced study then suggested that future research should consider the impact of larger geographical-scale factors on physical activity (e.g., nonmotorized travel behavior) (National Research Council 2005). Further, Mitra and Buliung (2012) argued that in the interaction between human behavior (e.g., walking and bicycling activities) and the built environment, different processes at different spatial scales may be at operation.

These calls in the literature provide grounds for the hypothesis that nonmotorized travel behavior is not just influenced by micro-level built environment characteristics, but also by macro-level built environment characteristics. This means that in influencing nonmotorized travel behavior, neighborhoods are not acting as isolated geographic entities, but as an interwoven part of the larger geographical context of the metropolitan area they belong to.

In a sense, while the built environment of the neighborhood can encourage nonmotorized travel by providing short distances to various destinations, the extent and distribution of opportunities in the metropolitan area and the availability of transportation alternatives (e.g., regional transit) may be the determinant factors for the choice of a nonmotorized mode for regional travel, such as commuting or traveling to malls (National Research Council 2005).

A.1.5.2 Travel Behavior Implications of Sprawl, Decentralization, and Commuting

Although existing research on the role of metropolitan built environment and travel behavior has been focused on vehicular travel behavior, it can be hypothesized that the overall built environment of the metropolitan area has a potential to impact nonmotorized travel behavior—at least through its impact on motorized travel behavior.

Particularly, *urban sprawl* and *decentralization* are important metropolitan area-level built environment factors with the potential to influence nonmotorized travel behavior.

Urban sprawl has been defined as a combination of measures that describe a city's physical shape, spatial distribution of population and employment, and jobs-housing balance as well as its public transit characteristics, which together can influence the VMT and mode choices of households (Bento et al. 2005). For a metropolitan area, sprawling features can be characterized as highly car-dependent designs, suburbanization of activities (e.g., employment), low-density, single-use developments, poor street network connectivity, and polycentric land use (as opposed to monocentric cities). These features lead to increased trip distances, which in turn, can promote automobile use and discourage nonmotorized modes of travel by making them unsafe or impractical. Specifically, as Ewing et al. (2003b, 2008) noted, the most common characteristic of urban sprawl is poor accessibility in term of walking where trip destinations are not within safe and easy walking distance of trip origins. Urban sprawl is now considered the dominant development pattern in the U.S. (Ewing et al. 2014).

Decentralization has been defined in the literature as the movement of people and jobs away from city centers—a trend in urban development for over a century in the U.S. (National Research Council 2005).

By increasing travel distances between origins (e.g., residences) and destinations (e.g., work sites, service locations), decentralization and urban sprawl restrict accessibility based on travel time, and thereby influence travel mode choices (Burbidge and Goulias 2008).

Considering the convenience and mobility offered by the private automobile, decentralization and urban sprawl have been associated with encouraging automobile dependency, and its consequential limited and less feasible non-automobile mobility (i.e., walking and bicycling) as well as sedentary lifestyle patterns (Pucher et al. 1999; Dieleman et al. 2002; King et al. 2002; Stinson and Bhat 2004; Handy et al. 2005; Leslie et al. 2007; Plantinga and Bernell 2007; Cao et al. 2007; Burbidge and Goulias 2008; Cao et al. 2010; Siu et al. 2012; Ewing et al. 2014).

Urban sprawl and decentralization usually produce long commutes for residents. Sprawling metropolitan areas with longer commutes can affect physical activity (e.g., walking for exercise) by cutting leisure times short (Ewing et al. 2014).

Past empirical research has found that longer commute times negatively impact the amount of time allocated to discretionary activities such as leisure activities (Kitamura et al. 1992), which could include recreational walking and bicycling activities. Other research showed that spending more time on work-related activities (e.g., commuting) can lead to spending less time on recreational activities (e.g., walking and bicycling for leisure) (Chung et al. 2004).

Previous studies have also suggested that longer commutes can interfere with having an active lifestyle due to diversion of time from health-promoting activities such as exercise and physical activity (see e.g., Evans and Wener 2006; Plantinga and Bernell 2007; Hansson et al. 2011; Künn -Nelen 2015). In addition to the potential to affect recreational walking and bicycling, longer commute times may also lead to fewer utilitarian nonmotorized trips as past research found that longer commute times negatively correlated with the amount of time allocated to non-work travel (Kitamura et al. 1992), which could include utilitarian nonmotorized travel.

Thus, it is evident that sprawling designs have a potential to promote sedentary behavior by discouraging nonmotorized travel choices, as other studies also argued (see e.g., Leslie et al. 2007; Cao et al. 2009).

In light of these research arguments, consideration of measures representing the level of sprawl and commuting duration within the metropolitan area in the analysis of nonmotorized travel behavior seems a plausible idea.

A.1.5.3 The Origin, the Destination, and the Route Connecting Them

Literature suggests that the overall travel behavior is influenced primarily by the built environment characteristics of the trip origin (most often the home location), and secondarily by the built environment characteristics of the employment location, and thirdly by the characteristics of the route from home to the employment location (Krizek 2003c).

The same argument holds true in the case of nonmotorized travel; the choice and extent of nonmotorized trips are influenced by the quality of the environment (e.g., physical condition, safety, convenience) surrounding the trip origin and destination as well as along the route between the two (see e.g., Handy 1996a; Moudon and Lee 2003; Lee and Moudon 2004, 2006).

Inclusion of macro-level built environment measures in the analysis of nonmotorized travel behavior allows the analyst to account for the effect of the overall built environment of the study area on nonmotorized travel behavior. This allows for conceptualization of nonmotorized travel behavior using a more integrated approach to operationalizing the built environment, which includes the built environment attributes of the origins and the destinations of nonmotorized trips as well as the routes that connect them, all in one analysis framework.

A.1.5.4 Neighborhood Location in the Context of Metropolitan Area

Past research suggests that among factors that influence travel behavior, the location of the neighborhood matters in terms of the surrounding area’s built environment. For instance, if the overall built environment of the metropolitan area (macro-level built environment) is heavily car-dependent, the walkable design of a particular neighborhood (micro-level built environment) may not matter much in promoting the walking mode choice within that neighborhood.

Islands of neotraditional neighborhoods (i.e., dense and mixed-use development neighborhoods that support walking and bicycling) surrounded by typical car-dependent, low-density, suburban neighborhoods in a sprawled metropolitan area may not lead to fundamental changes in the overall travel behavior of residents of those neotraditional neighborhoods (Friedman et al. 1994; Cervero and Gorham 1995).

Further, clusters with just one feature of neotraditional urban design may not change travel behavior in favor of nonmotorized travel. For example, a dense residential-only neighborhood far from nonresidential services does little in discouraging driving and promoting nonmotorized travel due to distances between residences to service land uses, just as a neighborhood with a mix of land uses may not promote walking if it is surrounded by high-speed highways (Krizek 2003b).

The larger geographical context (e.g., regional context) within which a neighborhood locates has been too often neglected in past research (Krizek 2003b). However, as the above literature suggests, larger geographical contexts bear importance in shaping travel behavior of people, and should therefore be considered in the analysis of nonmotorized travel behavior.

A.1.5.5 People Do Not Stay within Their Neighborhoods

Research to date that explored the relationship between nonmotorized travel behavior and the built environment has been almost solely concentrated on neighborhood-level built environment factors. The underlying assumption for this has been that compared to other trips (e.g., bus, car, train trips), walking and bicycling trips are short trips—most often originating and concluding in the neighborhood of residence—and hence, investigation of the factors that affect nonmotorized travel should only include the built environment characteristics of a small geographical area such as that of the neighborhood (see e.g., Cervero and Duncan 2003; Moudon and Lee 2003; Boarnet et al. 2008). However, a recent study referred to this assumption as "just an assumption" as adults spend most of their daily hours away from their home (Ewing et al. 2014).

Moreover, as a report by the National Research Council (2005) suggested, interest in the influence of residential neighborhood's built environment factors on travel behavior is consistent with emphasis on home-based trips. Yet, a simple calculation reveals that "Home" is listed as the trip's destination for approximately 35% of 2009 NHTS trips, meaning these were non-home-based trips. This figure is consistent with Ewing et al. (2014), which estimated that nearly 30–40% of all trips are non-home-based trips. These statistics show that a sizable proportion of trips do not originate at the residence location and may not stay within the neighborhood boundaries.

Other studies suggest that most U.S. metropolitan areas have an extensive transportation network; therefore, the assumption that households select residential locations close to their employment location may not hold (Krizek 2003a). Also, as people's desired activities or consumer goods/services at desired prices are often not located within their neighborhood, their activity space extends well beyond their neighborhood and therefore, they may travel beyond their neighborhood boundaries for their activities or shopping and service needs (Badoe and Miller 2000; Krizek 2003a).

These out-of-neighborhood employment/shopping/service trips may lead to unplanned nonmotorized trips at a location far from the neighborhood of residence. In contrast, the out-of-neighborhood trips may substitute for nonmotorized trips, which would have otherwise occurred within the neighborhood.

In addition, recreational nonmotorized travel behavior may not always occur or stay within the neighborhood. Literature suggests that a substantial proportion of recreational walking trips occurs outside the neighborhood and walking that takes place outside the neighborhood is less likely to be affected by neighborhood built environment characteristics than walking that takes place within the neighborhood (Nehme et al. 2016).

Other literature hints about broadening the scope of walking travel behavior beyond the neighborhood in case the surrounding areas are also walkable (Weinberger and Sweet 2012). Past research has also found that the neighborhood built environment measures were not significant in explaining recreational bicycling and suggested that people may drive to locations far from their residence to bicycle for recreation, and therefore, their neighborhood environment may not matter in their bicycling travel behavior (Ma and Dill 2015).

The above discussion is not to imply that the neighborhood built environment is not important in nonmotorized travel, but rather to impart the importance of the overall built environment of the metropolitan area (i.e., macro-level built environment) in walking and bicycling trips. If the overall built environment of the metropolitan area is supportive of nonmotorized travel, it can influence individuals' choices of travel modes and destinations. In such encouraging environment, residents may go beyond their neighborhoods and travel to farther destinations within their city/urban area to perform walking and bicycling activities.

For example, people may make out-of-neighborhood trips to:

- take advantage of a new walking or bicycling trail in the adjacent county; or
- conduct additional utilitarian activities using nonmotorized modes (such as when students take their bicycle to a school campus, which is located on the other side of the metropolitan area, and ride the bicycle from and to different campus buildings); or
- take advantage of additional social interaction opportunities (such as when people drive to a historic site within their metropolitan area and walk around to visit various tourist attractions that are located there).

In all the above examples, walking and bicycling activities occur regardless of the individual's neighborhood built environment and owing to the supportive nature of the metropolitan area's built environment. Therefore, it is likely that built environment factors at both micro level and macro level are relevant to understanding nonmotorized travel behavior.

In that case, inclusion of macro-level built environment characteristics (such as those of the metropolitan area in which people reside, work, and conduct other activities) can represent the broad settings that shape people's travel choices, and provide a more comprehensive picture of the influence of the built environment on nonmotorized travel behavior.

A.1.5.6 The Potential Influence of Regional Accessibility on Nonmotorized Travel Behavior

As discussed previously, regional accessibility influences travel behavior outcomes such as mode choice and destination choice. Increased regional accessibility (in terms of the number of activities within a given travel time from home) has been found in previous research to reduce a household's vehicular travel (Ewing 1995). Thus, it can be hypothesized that regional accessibility characteristics have a potential to indirectly affect nonmotorized travel behavior through affecting vehicular travel behavior.

For instance, if members of households drive less because they have more regional transit options and more transit-accessible destinations within their region, they may make more transit-related walking trips. Another example is that a pedestrian-friendly neighborhood located in a region without much regional accessibility can encourage more walking trips within the neighborhood. This is because in a region with low regional highway or transit accessibility, residents may find it difficult to travel to farther destinations and so, they may choose destination options within their neighborhoods. If their neighborhood is walkable, these residents may choose to make more walking trips to nearby destinations rather than making vehicular trips to farther, hard-to-reach destinations.

Literature provides support for the arguments above. A 2005 report by the National Research Council (National Research Council 2005) emphasized the importance of considering the effects of regional accessibility on nonmotorized travel and argued that by influencing mode choice and destination choice, accessibility has a potential to influence nonmotorized travel behavior. Scenarios of how increased regional accessibility throughout the metropolitan area of residence can influence nonmotorized travel outcomes by influencing mode and destination options may occur during any typical day.

In terms of the role of regional accessibility in destination choice, for instance, the following scenarios may be considered:

Scenario 1): individual X would like to make a walking trip to a neighborhood restaurant. Individual X has friends who live in a town that locates within the same metropolitan area and is accessible by transit. Individual X's friends ask her to join them at their town for taking a walk around town and to eat at a restaurant there. Individual X takes the train and meets her friends at the other town where they walk for several hours and enjoy shopping and dining together. In this scenario, regional transit accessibility directly influenced individual X's destination choice for her walking activities.

Scenario 2): individual Y drives to a bicycle trail far away from his house to bicycle for exercise. In this case, regional automobile accessibility to the trail directly influenced the choice of destination for individual Y's bicycling activities. This example is in line with past literature that suggested good accessibility can encourage residents to travel beyond their neighborhoods to reach other opportunities for recreation and exercise (National Research Council 2005).

In terms of the role of regional accessibility in mode choice, one can consider the following scenarios:

Scenario 3): individual Z would like to go shopping. She has the option to walk to a few local stores to purchase the goods she desires to buy. However, she thinks that the stores at a shopping mall, which happens to locate far away from her place of residence, offer a more variety of goods. Since this individual resides in a region with high automobile accessibility, the long distance to the shopping mall in combination with ample free parking—a common feature of major shopping centers in the U.S.—encourages her to drive to the mall for shopping instead of walking to the local stores within her neighborhood. In this scenario, good regional accessibility by means of automobile influenced individual Z's travel mode choice. This scenario aligns with what previous studies suggested: *i*) longer distances can encourage people to make the trip using a faster and more convenient mode (such as the automobile) (National Research Council 2005); and *ii*) high accessibility to major shopping centers may promote trips by private cars, in part due to site designs (e.g. abundant free parking) (Cervero and Murakami 2010).

Scenario 4): if the same individual in scenario 3 has the option to take the transit to the shopping mall, this may tip the balance in favor of taking the bus. She takes the bus to the mall where she walks from the mall to subsequent destinations (e.g., a restaurant or a library) nearby because she does not have her automobile with her to drive. In this scenario, regional transit accessibility affected the mode choice of individual Z twice: first, she chose the transit mode over the vehicle mode for traveling to the shopping mall and second, she walked the short distance from the mall to the restaurant/library instead of driving there (a mode choice that she most likely would not have made if she had her car and was able to drive). This scenario aligns with what a previous study suggested; transit accessibility can facilitate nonmotorized travel at trip ends as taking transit to a destination (e.g., workplace or shopping center) requires walking to subsequent destinations instead of driving (De Bourdeaudhuij et al. 2003).

The above scenarios show how increased regional accessibility (by both automobile and transit) throughout the metropolitan area of residence can provide alternative options for travel mode (e.g., transit and walking modes) and alternative activity opportunities (e.g., substitute destinations for eating, recreation, and shopping). Higher regional accessibility to employment can also play a potential role in travel behavior outcomes including the extent of nonmotorized travel. For example, if accessibility to employment opportunities is increased within the entire region or metropolitan area, residents may be encouraged to trade longer commutes for better jobs, and thereby spend more time in a vehicle than conducting walking or bicycling activities.

The preceding paragraphs provide examples of how increased regional accessibility may encourage residents to leave their neighborhoods, and go farther distances to reach additional employment, shopping, recreation, and exercise destinations. In such cases, it is not the local accessibility (a micro-level built environment factor) that affects nonmotorized travel occurring as a result of additional mode and destination options, but instead, it is the regional accessibility throughout the metropolitan area (a macro-level built environment factor). Thus, the role of regional accessibility in influencing nonmotorized travel is critical and merits further investigation.

Moreover, local and regional accessibility may interact to influence nonmotorized travel outcomes (e.g., frequency and mode choice) in a neighborhood. In terms of frequency of trips, a high level of local accessibility may lead to more walking trips within the neighborhood and fewer regional trips by automobile, whereas a high level of regional accessibility may lead to more trips to regional centers and fewer local trips (Handy 1993) including any potential local walking trips. Regarding the trip mode choice, in areas with high regional automobile accessibility, residents may choose the automobile mode due to: a) convenience of the automobile mode; and b) availability of a greater variety of destinations farther away from their residence.

On the other hand, highly accessible areas may also mean shorter distances to local destinations. In this case, residents have the option of choosing the nonmotorized modes and may, for instance, choose to walk to their destination instead of driving to it (Handy 1996b; Kockelman 1997). The possibility of substitution of shorter, within-neighborhood nonmotorized trips for longer, out-of-neighborhood automobile trips in pedestrian-oriented neighborhoods with high local accessibility have been discussed in past research (Handy 1993; Cervero and Radisch 1996; Handy et al. 2005). Hence, consideration of the interaction between local and regional accessibility and the potential resulting trade-offs between trips made by motorized and nonmotorized modes of travel are important in understanding how neighborhood design influences travel behavior of residents, not just on its own, but in the context of the region that it locates in.

The above arguments provide motivation for considering regional accessibility as an essential factor when examining people's nonmotorized travel mode and destination choices.

A.2 Health

In its Preamble of Constitution, the World Health Organization (WHO) defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO 2017). Each of the three dimensions of health is characterized on a continuum with positive and negative directions; positive health is associated with enjoying life even in face of challenges (and not just absence of disease), and negative health is associated with illness or even premature death (DHHS 2008).

Health in both individual and community contexts is a salient and desirable life quality. In a way, every other life quality and function depends on being healthy. Health itself, is a quality that has many complex aspects and depends on many individual-level and community-level attributes. These include factors related to the individual's biology, social and socioeconomic status, race and ethnicity, gender (Ewing et al. 2014) as well as his/her health-related behavior (e.g., physical activity, diet, smoking habits,), the natural and built environments of his/her residence and workplace, and in a transportation context, his/her travel behavior.

From a transportation standpoint, identification of the factors that influence human health, and understanding the extent and direction of these effects are essential to development of transportation planning policies and urban designs that promote health provisions for more livable and healthier communities.

A.2.1 Physical Activity or a Lack Thereof (i.e., Physical Inactivity)

Being an important health-related behavior, physical activity has been identified as a major contributing factor to human health (see e.g., Andersen et al. 2000; Troped et al. 2001; National Research Council 2005; Burbidge and Goulias 2008; Marcus 2008; Sallis et al. 2008; DHHS 2008, 2018). Physical activity has been defined by the U.S. Department of Health and Human Services (DHHS) as “any bodily movement produced by the contraction of skeletal muscle that increases energy expenditure above a basal level” (DHHS 2008).

The health benefits of regular physical activity include reduced levels of weight gain, obesity, and depression, as well as lower risk of diabetes; high blood pressure; breast, colon, and lung cancers; coronary heart disease; stroke; and premature death (see DHHS 2008, 2018).

The DHHS provides comprehensive physical activity guidelines for all age groups of the population (i.e., children and adolescents, adults, older adults) as well as for individuals with special considerations (i.e., pregnant women, adults with disability, and people with chronic medical conditions). These guidelines are also recommended by the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO). The current guidelines on physical activity recommend at least 150 minutes per week of moderate physical activity for adults and at least 60 minutes per day of physical activity for children and adolescents (DHHS 2008, 2018; WHO 2018b).

Despite all the benefits that physical activity offers, statistics on physical activity levels in the U.S. are alarming. The concern is that physical inactivity has become a trend in the U.S. over the past half century—most likely due to factors such as decentralization of metropolitan areas and urban sprawl, technological innovations, as well as a tendency for sedentary activities and lifestyles (King et al. 2002; National Research Council 2005).

Based on annual data available from years 1998 to 2015, Figure A-3 graphs the annual percentage of American adults who reported no leisure-time physical activity.

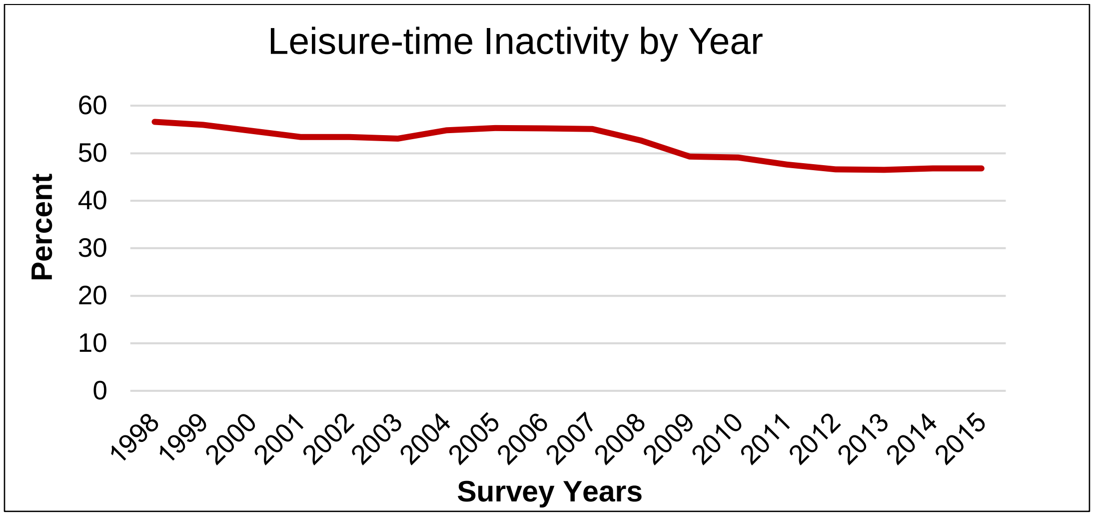

Figure A-3. Trends in Leisure-time Inactivity Among U.S. Adults (Aged 18+)

NOTES:
Inactivity has been measured as the percentage of adults who did not meet the CDC physical activity guidelines;
The graph is based on age-adjusted data (see source of data);
Source of data: Health, United States, 2016 - Individual Charts and Tables, CDC - Table 057: (https://www.cdc.gov/nchs/hus/contents2016.htm).

The figure reveals that during the past two decades, on average, approximately 50% of U.S. adults did not meet the recommended physical activity requirements. Although inactivity levels show a slight decrease around year 2007 and onward, the percentages are still high as they hover around 50%. This indicates that half of the adult population of the U.S. do not meet the recommendations of health agencies (DHHS, CDC, and WHO), which is a minimum of 150 minutes per week of moderate-intensity physical activity, and may be at risk of adverse health effects of physical inactivity. Research in the past two decades echoes that physical inactivity has become a concerning public health issue in the U.S. (see e.g., Sallis et al. 1998; Lumsdon and Mitchell 1999; Troped et al. 2001; King et al. 2002; Hoehner et al. 2005; National Research Council 2005; Leslie et al. 2007; Marcus 2008; Marshall et al. 2009).

There are serious long-term, premature morbidity and mortality-related health risks due to physical inactivity (CDC 1999; McMillan 2003; Anderson et al. 2005). In contrast to benefits of physical activity, physical inactivity and a sedentary lifestyle are known risk factors for many chronic diseases (DHHS 2008; Sallis et al. 2008) including obesity, heart disease, diabetes, stroke, hypertension, depression, and cancer (Ewing et al. 2003b, 2008; National Research Council 2005; Anderson et al. 2005; DHHS 2008; Burbidge and Goulias 2008; Marcus 2008; Kent and Thompson 2012; Frank et al. 2016; Liao et al 2016; Sener et al. 2016).

It is notable that at least four of the ten top leading causes of death in the U.S. are linked to physical inactivity. These are: heart diseases (number 1 cause of death), cancer (number 2 cause of death), stroke (number 5 cause of death), and diabetes (number 7 cause of death). In 2015, these diseases and health conditions accounted for approximately 1.5 million deaths—over 50% of the total number of deaths—in the U.S. (National Center for Health Statistics 2017).

Physical inactivity has also been identified as the fourth leading risk factor for global mortality causing an estimated 3.2 million deaths around the world each year (WHO 2018a). Thus, the DHHS and CDC inform the American public on the health benefits of regular physical activity and recommend that all individuals (including those with disabilities) avoid inactivity by engaging in physical activity, even if a small amount (DHHS 2008, 2018).

A.2.2 Sounding Alarms on Health Issues

In 2003, researchers stated "obesity has reached epidemic levels" (McCann and Ewing 2003; Ewing et al. 2003b). The same year, obesity and physical inactivity were reported to be the cause of for more than 300,000 premature deaths each year (Ewing et al. 2003b). A decade and a half later, the obesity rates and the overall population health are still deteriorating in the U.S.

Figure A-4 depicts the prevalence of obesity by U.S. state in 2017. As seen in the figure, obesity has the highest prevalence in states of Alabama, Arkansas, Louisiana, Mississippi, and West Virginia.

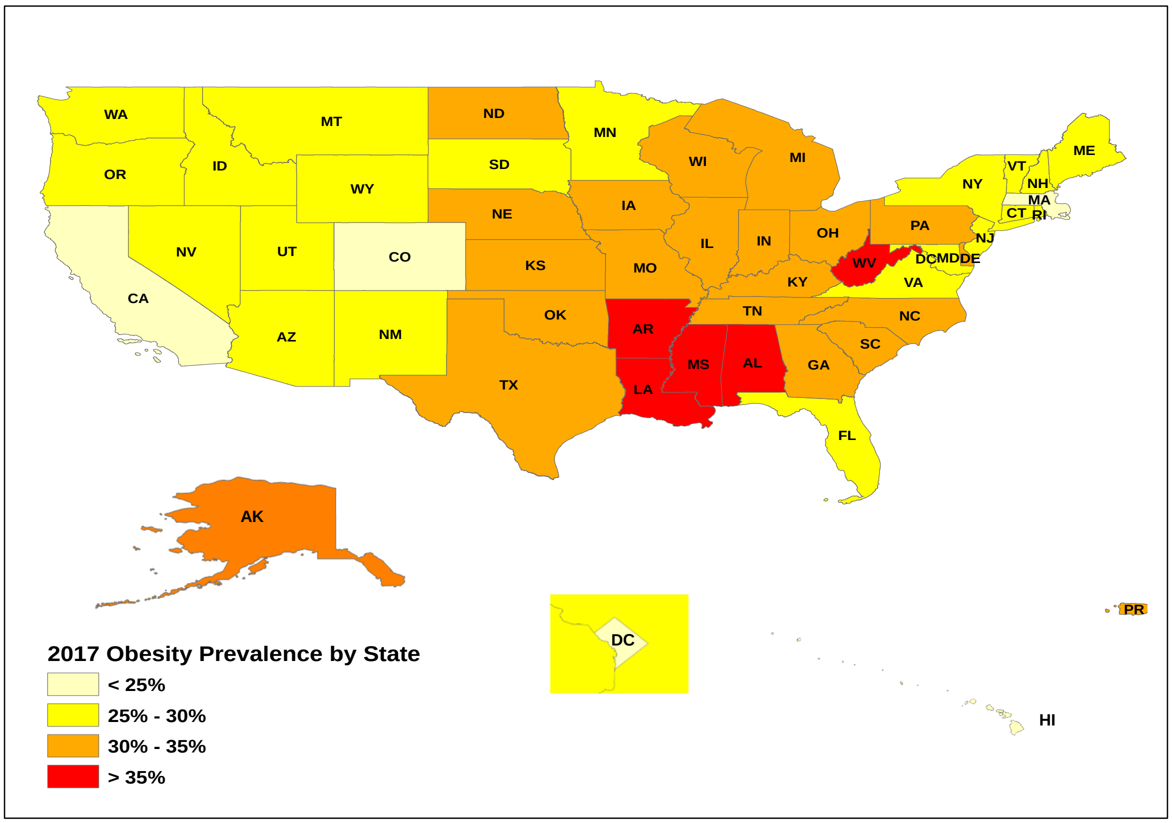

Figure A-4. 2017 Obesity Prevalence by U.S. State

NOTES:

Map is not to scale;

The positions of Alaska, Hawaii, and District of Columbia are not geographically accurate and are for illustration purposed only.

In addition to obesity, which continues to top the list of poor health indicators as nearing "epidemic proportions" (Handy and Xing 2011), the troubling trends in health in U.S. cities include diabetes, hypertension (i.e., high blood pressure), physical inactivity, and stress (Jackson 2003; McCann and Ewing 2003; Dannenberg and Sener 2015). The CDC reports show that during years 2011 to 2014, 36.5% (more than one third) of the U.S. adult population was obese (Ogden et al. 2015); 8.8% suffered from asthma (Akinbami and Fryar 2016); 12% had diabetes; and over 30% lived with high blood pressure (National Center for Health Statistics 2017).

Figure A-5 shows trends in prevalence of these major health problems among adults aged 20 and over in the U.S. during the past three decades.

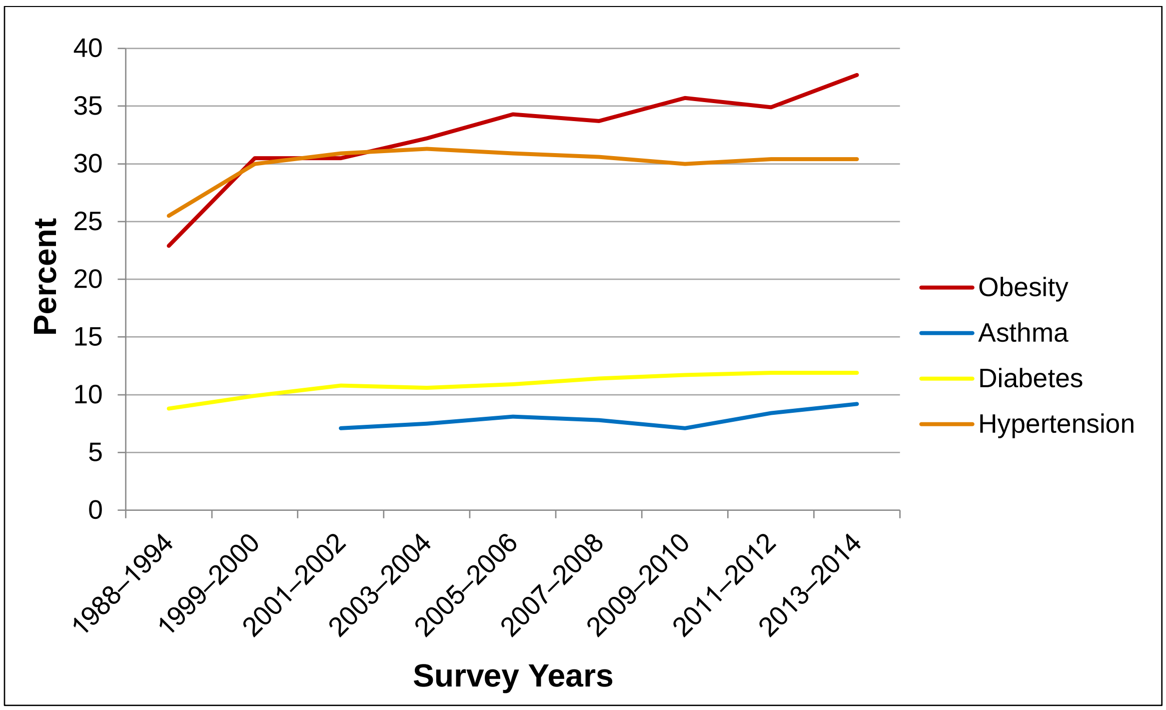

Figure A-5. Trends in Prevalence of Major Health Problems Among U.S. Adults (20+)

NOTES:

The graph is based on age-adjusted data (see source of data);

Source of data:

Diabetes and Hypertension: Health, United States, 2016 - Individual Charts and Tables, CDC – Tables 040 and 054 (https://www.cdc.gov/nchs/hus/contents2016.htm);

Obesity: NCHS Data Brief No. 219, CDC (https://www.cdc.gov/nchs/data/databriefs/db219.pdf);

Asthma: NCHS Data Brief No. 239, CDC (https://www.cdc.gov/nchs/data/databriefs/db239_table.pdf#4).

As seen from Figure A-5, prevalences of almost all health problems graphed above show increasing trends with obesity having the steepest increasing slope. Hypertension prevalence shows a slightly decreasing slope between years 2004 and 2010; however, it regains its increasing trend after year 2010, although at a very slow rate. The slight decrease in asthma prevalence between years 2005 and 2009 also gives way to an increasing slope from 2009 onward.

These trends make these health problems more than just a personal problem!

Aside from the physical and emotional suffering endured by people who are dealing with them, the above health issues impose a financial burden on individuals, families, and the society as a whole. The annual medical expenses of health problems such as obesity have been estimated to be tens of billions in the U.S. by past studies (Cervero and Duncan 2003; Khattak and Rodriguez 2005). A more recent report estimates the annual healthcare cost of lack of physical activity and its resultant negative health outcomes in the U.S. to be around $117 billion (DHHS 2018).

A.2.3 Health Research and Behavioral Theories

As elaborated in preceding sections, being a key health-related behavior, physical activity or lack thereof contributes to human health or lack thereof. Thus, to better understand health, researchers have turned to theories that explain human behavior including health behavior such as physical activity. As a result, research on physical activity has benefited largely from theories in the field of psychology. One such theory is the theory of planned behavior developed by Ajzen.

The theory of planned behavior considers the role of three factors in performing or not performing a certain behavior: *1) attitudes; 2) subjective norms; and 3) perceived behavioral control*. Attitudes toward the behavior are individuals' evaluations of the behavior, which can be favorable or unfavorable toward the behavior. Subjective norms are the perceived social pressure that individuals feel in performing or not performing the behavior (Ajzen 1991). In other words, subjective norms represent the approval or disapproval of the family, peers, society, or other groups deemed important to the individual in performing a certain behavior. In that sense, subjective norms can be representative of the sociocultural characteristics of the social environment in which the individual lives. Perceived behavioral control over the behavior was defined by Ajzen as individuals' "perception of ease or difficulty of performing the behavior of interest". The perceived behavioral control also represents past experience. With regards to a certain behavior, it is assumed that more favorable attitudes, more encouraging subjective norms, and greater perceived behavioral control can lead to higher likelihood of performing the behavior.

The application of the theory of planned behavior to physical activity—and more specifically, to active travel—would mean that whether or not an individual engages in active travel is influenced by the individual's attitudes toward active travel, his/her perceptions of ability to perform active travel, and his/her beliefs about social and cultural norms toward active travel.

The theory of planned behavior also assumes that behavior results from rational decisions (Gochman 1997; Van Acker et al. 2010)—an assumption similar to the assumption of the utility-maximization theory of travel behavior. Attitudes and social norms are notions that are absent from the utility-maximization framework for explaining travel behavior; therefore, the theory of planned behavior may be a better framework to model health behavior such as active travel compared to the utility-maximization framework.

The shortcomings of the theory of planned behavior in explaining health behavior such as physical activity (i.e., active travel in this context) is that two important concepts—the social environment and the physical environment—are not included in the framework of this theory, at least in the sense of objective measures. For instance, although attitudes and perceptions about the physical (i.e., built) environment can be included in the framework (subjective measures), the theory does not consider objective measures of the physical environment in its framework to explain behavior (National Research Council 2005).

Because an individual is a member of the society, lives within a physical neighborhood, and travels to various destinations (Van Acker et al. 2010), the social and physical (i.e., built) environments have a potential to influence individuals' behavior and can play a crucial role in physical activity. Thus, to more comprehensively conceptualize model frameworks that explain physical activity, researchers more often rely on the social cognitive theory (Bandura 1986) and its more recent variant, the ecological model of health behavior.

The social cognitive theory was introduced by Bandura and explains an individual's behavior in terms of reciprocal and interacting relationships between the individual's characteristics, his/her behavior, and the social environment in which the behavior is performed. The most important setting within the individual's social environment is the household (Gochman 1997; Handy 2005; National Research Council 2005; Van Acker et al. 2010). In other words, social cognitive theory posits that both the individual and his/her social environment influence each other (i.e., the concept of reciprocal determinism). In clarifying the concept of reciprocal determinism, Bandura defined reciprocal as "the mutual action between causal factors" (Bandura 1986).

Although reciprocal determinism is a key component of the social cognitive theory, the role of other concepts such as that of "observational learning" in human behavior is also considered within the social cognitive theory. Humans learn and form rules of behavior by observing others and modeling actions based on this observation (Bandura 1986); thus, if an observer's environment is supportive of the new behavior, observational learning may lead to behavioral change (McAlister et al. 2008). The social cognitive theory framework provides a better understanding of the role of various individual and social factors in human behavior as well as those of the behavioral learning processes. This makes the social cognitive theory a suitable framework for modeling health behavior outcomes such as levels of physical activity. Such a model can capture the influence of personal characteristics (e.g., beliefs and attitudes) and observed behavior (e.g., sociocultural norms) on physical activity.

An extension of the social cognitive theory, the ecological model of behavior, conceptualizes multiple interacting levels of various influences for an individual's behavior. These levels often include: the intrapersonal level (e.g., biological, psychological), the interpersonal level (e.g., social environment, sociocultural norms), the organizational level, the community level (e.g., physical environment), and the policy level (Handy 2005; Sallis et al. 2008). Any influence on activity and behavior is thought to interact across these multiple levels of influence.

Since the ecological model of behavior stems from the social cognitive theory, it includes all the components of that theory in its framework (i.e., personal characteristics and behavior as well as the social environment). In addition, the framework of the ecological model of behavior incorporates a policy level as well as additional environmental (both physical and social) levels of influence each of which may operate at various levels. These include the broader community and organizational levels of influence. In a sense, the social cognitive theory focuses on the social environment, whereas the ecological model emphasizes the influence of the spatial environment (Handy 2005; Van Acker et al. 2010).

Equipped with individual, social, and spatial dimensions and multiple levels of influence, ecological models can provide a more integrated and more comprehensive framework for modeling human behavior including health behaviors such as physical activity and its travel-related form, active travel. Based on the ecological model framework, a change in a particular health behavior is expected to be maximized when the change affects all or most of the levels of influence: *i)* the individuals are motivated to make a choice toward that health behavior (i.e., the intrapersonal level); *ii)* the social and cultural norms are supportive of the behavior (i.e., the interpersonal level); *iii)* the environments are conducive to the behavior (i.e., the environmental level); and *iv)* the policies are promotive of the behavior (i.e., the policy level) (Sallis et al. 2008).

Applied to the active travel concept, the ecological model implies that individuals will be more likely to engage in active travel if: *i)* they are motivated to do so; *ii)* there is an encouraging culture toward active travel within the society; *iii)* the built environment is pedestrian- and bicycle-friendly; and *iv)* policies promoting active travel are in place. Ecological models have gained increasing popularity in health research during the past two decades. This is partially due to the ability of these models to guide comprehensive framework and intervention approaches—at each level of influence—for changing health behaviors that can lead to reduced risks of prevalent health problems (Sallis et al. 2008). The simple basic premise of ecological models makes it a promising framework to guide modeling efforts of health behavior and development of more effective multilevel interventions that can encourage individuals to make healthful choices.

A.2.4 Health and Nonmotorized Travel Behavior

As previously indicated, regular physical activity can provide substantial health benefits to all segments of the population including adults, children, and individuals with disabilities. The DHHS, the CDC, and the WHO currently recommend a minimum of 150 minutes per week of moderate-intensity physical activity for adults, and a minimum of 60 minutes per day of moderate-intensity physical activity for children (DHHS 2008, 2018; WHO 2018b). As forms of health-enhancing physical activity recommended by the DHHS, the CDC, and the WHO, walking and bicycling (i.e., nonmotorized travel) can help satisfy these physical activity recommendations to attain health benefits and sustain a healthy lifestyle.

Walking and bicycling are inexpensive (Oja et al. 1998; Lee and Moudon 2004) and available to all people of all ages and socioeconomic status. Therefore, these modes are considered sustainable modes of travel that can be easily incorporated into individuals' daily activities, and thereby contribute to their daily physical activity and health status. Walking and bicycling can help improve the overall health and well-being of individuals by protecting against various types of chronic diseases and health problems such as obesity, diabetes, high blood pressure, metabolic syndrome, and cardiovascular diseases (see e.g., Oja et al. 1991; Ross 2000; Leslie et el. 2007; Gordon-Larsen 2009; Pucher et al. 2011; Oja et al. 2011; Musselwhite et al. 2015; Barr et al. 2016; Sener et al. 2016) and by relieving anxiety and depression and promoting mental well-being (McCann and Ewing 2003; Musselwhite et al. 2015; Tsunoda et al. 2015).

Moreover, walking is the most fundamental form of transportation (Agrawal and Schimek 2007). It is also a natural, common, popular, and low-cost form of physical activity, which may be the predominant form of physical activity for lower income groups (Hovell et al. 1992; Siegel et al. 1995; Lumsdon and Mitchell 1999; Lee and Moudon 2004; Handy et al. 2006; Gordon-Larsen 2009; Nehme et al. 2016; Carver et al. 2016). Bicycling, in turn, has been mentioned as a low-cost, environmentally friendly transportation mode, which can be an important means for reaching destinations and achieving physical activity goals (Handy and Xing 2011; Ma and Dill 2015).

A.2.5 Health and the Role of the Built Environment

Health is a function of health behavior. Thus, to better understand the factors that influence human health, one should start with gaining a better understanding of factors that affect health behavior. Health behavior has previously been defined in many ways. Gochman (1997) defined health behavior as "overt behavior patterns, actions and habits that relate to health maintenance, to health restoration and to health improvement". Based on this definition, health behavior can basically be any activity undertaken by individuals to improve their health and well-being and/or to prevent health problems and disease. Health behaviors can include physician visits and medical screenings, dietary consciousness and consumption of healthy food as well as regulating levels of physical activity, smoking, and alcohol consumption. This makes health behavior research an interdisciplinary and multidisciplinary area of research (Gochman 1997).

Many forms of health behavior are not independent of environmental settings, especially the built environment surrounding the place of residence. Health behavior such as physical activity and active travel can particularly be affected by environmental factors. Literature suggests that travel behavior is the outcome of opportunities and constraints at three levels: 1) the individual level (i.e., personal socio-psychological characteristics such as attitudes and perceptions); 2) the social level (i.e., sociodemographic, socioeconomic, and sociocultural characteristics such as gender, income, and ethnicity); and 3) the spatial level (i.e., quantity and quality of built/natural environment characteristics such as density, diversity, and design) (Van Acker et al. 2010; Harms et al. 2014). Therefore, as a form of travel behavior, active travel can be influenced by built environment factors. In addition, the ecological model of behavior emphasizes the role of the built environment in behavior including health behavior such as physical activity and active travel. The built environment characteristics of the place of residence have been empirically proved to have an impact on health behavior such as physical activity, particularly in its active travel form (i.e., walking and bicycling) (see e.g., Giles-Corti and Donovan 2003; Frank et al. 2004; Rodríguez et al. 2009 among many others as elaborated in Chapter 2). Thus, it can be assumed that the built environment can influence human health through influencing physical activity and active travel.

Further, the built environment has a potential to affect health of individuals more directly. For example, the air quality in a certain area can influence health of residents and depends on various built environment-related factors such as the existence of industrial sites, level of traffic and congestion on roadways, and existence of green spaces. Also access to healthy food options—a built environment factor—can potentially affect individuals' health status. Thus, the built environment has the potential to influence individuals' health both directly by providing or preventing qualities such as standard ambient air and healthy dietary needs as well as indirectly through facilitating or constraining health behaviors such as physical activity (e.g., active travel).

Therefore, built environment attributes are essential components of health research and many researchers include them in modeling health behavior and health outcomes (see e.g., Frank et al. 2004; Smith et al. 2008; Samimi et al. 2009; Samimi and Mohammadian 2009; Ewing et al. 2014; Marshall et al. 2014). Meanwhile, health-promoting elements of the built environment are emerging from these research efforts. Studies are finding that compactness, land use diversity, and design of communities play a role in residents' health and undesirable health trends can be partially caused by the effects of the built environment characteristics of individuals' residential location (see e.g., Ewing et al. 2003b; Frank et al. 2004; Marshall et al. 2014; Ewing et al. 2014).

A.2.5.1 Health and the Spatial Scales of the Built Environment

The built environment as Joshu et al. (2008) puts it is a "multidimensional construct" that can be categorized by scale. As previously stated, the multiple hierarchical dimensions (i.e., spatial scales) of the built environment can include the building or site, the street block, the neighborhood, and the region. In a health context, each of these scales can play a role in individuals' health—either directly or indirectly—through facilitating or constraining health behavior such as active travel or other forms of physical activity.

The building or site may have certain features such as stairwells that facilitate physical activity (National Research Council 2005) and have a potential to indirectly impact the health status of individuals. The street block size as well as the neighborhood's built environment attributes such as network design patterns (i.e., grid-like vs. cul-de-sac), level of land use mix, and availability of recreational facilities can also impact health outcomes directly or indirectly by influencing levels of physical activity and active travel. Further, the built environment characteristics of the region such as the region's size, distribution of employment opportunities, and supply of transportation facilities influence commute times, travel choices, and physical activity levels (National Research Council 2005), and can thereby impact residents' health status.

In addition, the influence of the built environment on health behaviors such as physical activity at one spatial scale may affect the influence of the built environment at another spatial scale (Handy 2005). In other words, the built environment at a certain spatial scale may interact with the built environment at a different scale to influence health outcomes. Literature argues that built environment factors exhibit differing patterns at each geographical scale, and in any analysis of multiple attributes of the built environment, various areas may trade off one attribute for the other (Marshall et al. 2009).

It is noteworthy to mention that although various spatial scales of the built environment have been identified by past studies, the exact size and boundaries of the areas falling in each scale category are still ambiguous in literature. For instance, the neighborhood has been arbitrarily defined in past health-related studies as an area with a size ranging from a buffer zone around the residence (see e.g., Frank et al. 2004 and Timperio et al. 2010) to the census tract of the home address (see e.g., Ross 2000). The region can be considered a county as many health studies have conducted their analysis at the county level (see e.g., Samimi et al. 2009; Ewing et al. 2014); however, some researchers argue that in an urban context, the region may be defined as the metropolitan area (National Research Council 2005).

To probe the link between the built environment, health behavior and health outcomes, a three-level built environment hierarchy has been proposed in past research. These three levels include: 1) the micro level (e.g., immediate local area/neighborhood); 2) the meso level (e.g., neighborhood/community); and 3) the macro level (e.g., metropolitan area or county) (King et al. 2002 and Ewing et al 2003b). This hierarchical structure can be used in conceptualization of comprehensive frameworks to examine the role of various spatial scales of the built environment in health as well as in identification of factors that exert the greatest effect on health behavior and health outcomes at each scale.

A.2.6 Why the Macro-level Built Environment Matters in Health Research

A.2.6.1 The Macro-level Built Environment, Health, and Calls in the Literature

Health promotion research is increasingly shifting toward ecological orientations, which provide more comprehensive frameworks by considering influence and interventions at multiple scales and in various contexts (Kent and Thompson 2012). As a basis for research on health behavior, the ecological model of behavior posits that factors from multiple levels of influence including the individual level, the social/sociocultural level, as well as the physical (i.e., built) environment level can affect health behavior. Within these levels, concepts that operate at multiple levels themselves are the sociocultural and the built environment levels (Sallis et al. 2008). The ecological model puts special emphasis on the role of multiple levels of the built environment in health behavior, which can impact health outcomes.

An important type of health behavior is physical activity and its travel-related form, active travel (i.e., walking and bicycling). Research on physical activity suggests that the built environment at many geographic scales—including the micro-level (i.e., neighborhood) as well as the macro-level (i.e., the region)—can influence the propensity of being physically active

(National Research Council 2005). On the other hand, more comprehensive ecological frameworks recognize the role of larger-scale (i.e., macro-level) economic and other factors that shape the factors at the local (i.e., micro-level) context (Kent and Thompson 2012). Therefore, considering the characteristics of the macro-level built and social environments in frameworks of health research is essential.

While the ecological models provide a comprehensive framework to examine the role of multiple levels of the built environment in health behavior, very few empirical studies have included macro-level spatial factors in their analysis. In addition, studies that consider the macro-level spatial factors together with micro-level spatial factors in one model are scarce. The studies that did consider macro-level built environment variables in their analysis found that the macro-level built environment influences physical activity, and may influence health outcomes in the long run (Braun and Malizia 2015). Further, health promotion and health policy research increasingly rely on multilevel interventions to solve health problems such as the obesity epidemic through improving the environment (e.g., built and social) to promote physical activity (Sallis et al. 2008).

Considering the hints in the literature and the limited empirical research regarding the potential role of the macro-level built environment in health behavior and health outcomes, it is crucial to broaden the spatial scope of the analysis to include macro-level spatial factors in the research framework. Such comprehensive framework can help researchers and policymakers determine the role of the overall structure of cities in residents' health behavior and health status.

A.2.6.2 Health Implications of Sprawl, Decentralization, and Commuting

The steady trends in decentralization of metropolitan areas and urban sprawl in the U.S. after World War II has turned most American cities into "automobile cities". The dispersed locations of suburban developments have resulted in increased travel distances to many daily destinations (e.g., school, grocery store, bank, gym) for many Americans. More importantly, increased commute distances and travel times have also made active travel (i.e., walking or bicycling) to many employment sites impractical. Further, other common features of sprawling urban design such as high-speed roads and vast parking lots for commercial sites have made walking and bicycling to destinations unsafe, unpleasant, and unsuitable (McCann and Ewing 2003). As a result, the automobile has become the main mode of travel as it is most often the only practical mode of travel. Long commutes and the dominance of the automobile as the mode of travel has led to a decline in physical activity levels both in the forms of active travel (i.e., walking and bicycling) and leisure-time exercise. This is a problem!

As elaborated previously, physical inactivity and sedentary behavior influence individuals' health both in terms of physical and mental health. Researchers have been long suspecting that sedentary lifestyles associated with automobile dependency can be partially blamed for the declining health trends (Cervero and Duncan 2003; Khattak and Rodriguez 2005). Thus, by increasing commute distances and durations, decentralization and urban sprawl promote physical inactivity and sedentary behavior, which can affect downstream health outcomes for residents.

For instance, the influence of urban sprawl can be considered three-fold as related to physical inactivity and one of its subsequent health outcomes—obesity. These influences include: 1) increased trip distances due to sprawling designs can lower physical activity levels by encouraging automobile use and making active travel impractical; 2) sprawling suburban designs can lead to long commute times and traffic congestion, which divert time from activities such as exercising; and 3) suburban developments do not provide recreational facilities such as parks that allow physical activity (Plantinga and Bernell 2007). Each of these three effects can result in lower physical activity levels and consequently, higher obesity levels.

It is evident from existing research that a movement from compact urban neighborhoods to sprawling suburban communities has meant a reduction in daily levels of physical activity (McCann and Ewing 2003)—an important health behavior with crucial downstream health effects. Urban sprawl has been linked to factors that have a potential to influence health (e.g., long private-vehicle commute distances and times, physical inactivity, poor air quality, and lack of social capital) as well as health outcomes (e.g., obesity, coronary heart disease, and traffic fatalities) (Ewing et al. 2014). In addition, lower regional transit accessibility affects levels of automobile use as well as public transportation ridership and active travel levels— all of which can influence downstream health outcomes. Therefore, consideration of macro-level sprawl measures, regional accessibility, and commute-related characteristics in the analysis of health outcomes is essential.

A.2.6.3 Neighborhood Location in the Context of Metropolitan Area

So far, it has become clear that individuals' health is influenced by their health behavior such as physical activity, which may in turn be influenced by multiple levels of the built environment including the micro-level (e.g., neighborhood-level) and the macro-level (e.g., metropolitan-level) built environments. However, there is a possibility that these levels may not operate separately and can interact to exert joint effects on physical activity levels of residents. Literature suggests that by interacting with the neighborhood-level built environment, the overall built environment of the metropolitan area can impact travel behavior over time (He and Zhang 2012).

Thus, it can be hypothesized that active travel (i.e., physical activity) can be also influenced by interactions between neighborhood-level and metropolitan area-level built environment factors. In addition, the ecological model of behavior specifies that influences on behavior (e.g., physical activity) interact across multiple levels (Sallis et al. 2008) including the various levels of spatial influence (i.e., built environment) such as the micro (i.e., the neighborhood) level and the macro (i.e., the metropolitan area) level. Hence, with regards to health behavior such as physical activity, the location of the neighborhood in the context of the metropolitan area is of importance. Researchers argue that although micro-level built environment factors are associated with physical activity, the prevalence and relevance of micro-level factors depend on the macro-level built environment factors as well as the interaction between built environment factors at the micro and macro levels (Joshu et al. 2008). Others stated that it is unclear which specific macro-level factors may have the strongest influence on physical activity behavior, either by themselves or in combination with other levels (i.e., meso or micro levels) (King et al. 2002).

Therefore, the context of the metropolitan area (i.e., macro-level built environment) within which the neighborhood (i.e., micro-level built environment) is located is an important consideration in the analysis. Such analysis can help in determining the separate effects that each level of the built environment may have on physical activity and health outcomes for residents.

A.2.6.4 People Do Not Stay within Their Neighborhoods

In probing the link between the built environment and health, Braun and Malizia (2015) noted that most of previous studies investigated built environment characteristics within the neighborhood of residence. Nonetheless, people do travel outside of their neighborhoods. Also, built environment attributes exhibit differing spatial patterns, and in any analysis of multiple attributes of the built environment, various areas may trade off one attribute for the other (Marshall et al. 2009). For instance, a specific built environment attribute at the county level can be influential in health of residents, whereas the same attribute at the city level may not have a significant health impact.

As individuals may travel to different places at different distances each day, they may experience a wider range of attributes for some aspects of the built environment than for others. Therefore, various spatial levels may impact health of individuals. Particularly, built environment characteristics beyond the residential neighborhood such as those of the macro level (e.g., county or metropolitan area) may potentially influence health behavior (such as physical activity) and health outcomes. These factors recognize that individuals travel beyond their neighborhood boundaries to conduct various activities (Braun and Malizia 2015). Thus, consideration of the effects of built environment factors at various levels of geography including those beyond the neighborhood boundaries is important in promoting essential health provisions.

A.2.7 Health, Telecommuting, and Teleshopping

As technology rapidly and continuously evolves, it offers more advanced applications, which facilitate communication and electronic access to information. Termed *Information and Communication Technologies* (ICT), these applications can influence travel behavior.

In general, ICT exert their influence on travel through two major effects. These include: 1) the substitution effect; and 2) the complementarity effect (see e.g., Mokhtarian 2002; Banister and Stead 2004; Konrad and Wittowsky 2018). As travel-related applications of ICT, telecommuting and teleshopping may, therefore, impact travel behavior through substitution or complementarity effects. For instance, by substituting commute trips with telecommuting, workers can eliminate actual trips to or from their workplaces.

As a consequence of advances in ICT, a growing number of employers have been offering telecommuting options to their employees in recent years. A 2011 report on the status of telecommuting in the U.S. concluded that telecommuting grew by over 60% between years 2005 and 2009, and over 2% of the non-self-employed workers telecommuted as a primary means of transportation to work (Lister and Harnish 2011). The same study also found that while nearly 3 million individuals telecommute in the U.S., 45% of the U.S. workforce has a job that can be performed—at least part-time—by telecommuting.

But, how does telecommuting affect human health? or does it at all?

Telecommuting has been suggested in prior research to have many psychological benefits. Lower levels of occupational stress, improved job performance, and greater job satisfaction are among the benefits that telecommuting can offer employees (Baruch 2001; Steward 2001; Robertson et al. 2003; Ganendran and Harrison 2007; Henke et al. 2015). These aspects of telecommuting can potentially improve psychological health of employees in the long term.

On the other hand, there are negative aspects to telecommuting. Previous research lists extended work hours and workload, blurriness of work and personal time limits, social isolation, and increased work-related stress among the disadvantages of telecommuting with a potential to impact psychological health of employees (Robertson et al. 2003; Henke et al. 2015).

Moreover, psychological and physical well-being can be interrelated (van Wee and Ettema 2016) as a positive link between psychological and physical health has been confirmed (Gochman 1997). Considering the effects of telecommuting on psychological health, it can therefore be hypothesized that telecommuting has a potential to affect individuals' physical health as well. For instance, telecommuting may pose negative effects on employees' physical health because of psychological pressure and stress levels that it can potentially impose to them.

Stress has, in fact, serious psychological and health consequences (Wener and Evans 2011). Chronic stress is related to lower levels of favorable health outcomes (Lloyd et al. 2005; Hammen 2005; Kiecolt-Glaser et al. 2015; Künn-Nelen 2015), and thereby it is a risk factor for many health problems including obesity, hypertension, coronary heart disease, and cardiovascular disease (McEwen 1998; Henke et al. 2015).

Research suggests that commuting to work is stressful (Evans et al. 2002; Evans and Wener 2006; Ganendran and Harrison 2007). With regards to the mode of commute, although longer commutes by rail have been suggested to be linked to stress (Evans and Wener 2006; Künn-Nelen 2015), commuting by train and bicycle or on foot have been deemed less stressful than commuting by car (Wener and Evans 2011; Rissel et al. 2014).

Driving on congested roads has been suggested to be a major contributor to stress (Stokols et al. 1978; Evans et al. 2002; Jackson 2003; Evans and Wener 2006; van Wee and Ettema 2016). Car commuting stress has been suggested to be related with increased elevated cardiovascular outcomes (Evans and Wener 2006) as well as increased cognitive impairment and illness and lower overall life satisfaction (Rissel et al. 2014).

Aside from stress, many negative health-related outcomes—including elevated pulse and blood pressure as well as lowered frustration tolerance—have been suggested to have a link with commuting (White and Rotton 1998). Also, longer car commuting duration has been found to be associated with higher body mass index (BMI) (Frank et al. 2004; Lindström 2008). Additionally, a recent study found that adverse health effects impacted car drivers more than commuters who used public transit; for car drivers, longer commuting time was related to lower health satisfaction, lower health status and more visits to health providers as well as a higher BMI (Künn-Nelen 2015).

Thus, it is evident that unnecessary commutes—particularly by automobile—can impose health risks to individuals including the risk of elevated: stress, fatigue, and blood pressure levels due to encountering traffic congestion (Evans et al. 2002; Rissel et al. 2014; Künn-Nelen 2015). Other health issues related to car commuting include having poorer health due to inhaling polluted air and an increased possibility of being involved in traffic crashes and sustaining crash-related injuries (or even death). Lack of or unsafe transportation has been postulated to be a "toxic stress", which has adverse health impacts (Corburn 2015). Moreover, chronic exposure to toxic stressors such as long commute times, pollution, and noise contributes to many other health problems including hypertension (Schulz et al. 2012; Corburn 2015).

Telecommuting, on the other hand, eliminates the unnecessary commute to and from the office, and thereby has a potential to lower traffic-related stress levels and health risks for the telecommuter. Existing literature on telecommuting brings these health-related issues to attention, even if not directly focusing on a health context (see e.g., Lister and Harnish 2011; Khan 2015). By eliminating the commute to work, telecommuting can provide employees some extra time during the day. Lister and Harnish (2011) suggest that individuals can regain approximately one week worth of spare time per year by telecommuting. This free time can be spent on physical activity or other health-promoting activities, which can affect the health status of the individual.

Besides having the above-mentioned potentials to influence the health of the telecommuters, telecommuting has a potential to impact the health of other individuals living in the community. The potential role of the telecommuting phenomenon in mitigating traffic congestion and reducing the number of peak-period work trips has been discussed by many researchers in the past (see e.g., Mokhtarian 2003; Balaker 2005; Lister and Harnish 2011; Khan 2015). By alleviating congestion on streets and highways within an area, high rates of telecommuting can lead to lower health risks (such as those of traffic-related stress) for non-telecommuter residents who can enjoy commuting on less-congested networks.

Further, all residents of a high-rate telecommuting community can enjoy the lower levels of transportation-related air pollution within the area, which is a benefit of telecommuting.

Even though telecommuting provides all the advantages above, the effects of telecommuting on physical health can go two ways. On the one hand, and as indicated previously, telecommuters may have more time at hand to spend on physical and exercise activities due to less commute time. This may lead to an improved weight and other favorable health outcomes for them. On the other hand, telecommuting has a potential to encourage a sedentary lifestyle. The telecommuter does not have to leave his home (or even his chair) to go to work, and this may decrease the level of individual's daily physical activity. Excessive participation in computer-related activities has been postulated to decrease physical activity levels (King et al. 2002).

Telecommuting is a perfect example of computer-related activities, which can promote sedentary behavior and physical inactivity. Further, telecommuting may affect the individual's diet. Working from home provides the telecommuter with constant and convenient access to the refrigerator. Over-snacking and overeating may become problems and over time, can affect weight and health status of the telecommuter. Another caveat is that telecommuters may end up working additional hours since there is no specific time to end work activities and return home. This may lead to fatigue and its related adverse physical health effects.

Thus, if telecommuting frequency is high, and the telecommuter does not take a more disciplined approach toward her/his diet, exercise, and work schedule, she/he may not get the basic amounts of physical activity that is necessary to maintain a healthy weight; an issue which can affect her/his physical health. The potential of telecommuting to negatively affect eating and exercise habits has been mentioned in previous research (Henke et al. 2015). These effects may lead to obesity or other related health problems.

Considering the above arguments, it seems that telecommuting can act as a double-edge sword when it comes to its role in health in terms of both physical and phycological health outcomes. Examining the effects of telecommuting on health—particularly physical health—is an interesting area of research which very few empirical studies have so far explored.

Along the same lines of argument is the role of teleshopping in health. The potential of teleshopping to impact health is derived from its potential to influence business-related travel behavior. As a travel-related application of ICT, teleshopping can impact business-related trips through substitution or complementarity effects.

The potential of teleshopping to substitute for business-related trips applies to customer trips to or from stores; teleshopping eliminates the need for customers to make actual trips to different stores to purchase their desired goods. The potential of teleshopping to exert complementarity effects on travel applies to trips made by business associates; teleshopping can lead to generation of an increased number of trips due to deliveries or pick-ups of online orders.

With respect to health impacts, activities related to teleshopping can either promote or discourage physical activity, which in turn, affects the health status of individuals. For instance, by eliminating the need to make actual trips (i.e., substitution effect), teleshopping may save some time during the day, which can be used for exercise. Conversely, elimination of actual trips can also mean that individuals do not have to leave their homes to purchase their needed goods. This latter case may lead to development of sedentary behaviors and lower levels of physical activity—particularly for frequent and regular online shoppers—and thereby, adversely affect their health.

Moreover, the delivery and pick-up activities related to goods purchased through online shopping services may lead to generation of additional automobile or nonmotorized trips by deliverers. Regular deliveries by automobile can limit the time, energy, or willingness for performing physical activity, which may result in adverse health outcomes over time. On the other hand, delivery trips made by bicycle incorporate physical activity into the delivery trip and may lead to health benefits for the deliverer. The same can be said in the case where a deliverer walks to several destinations—located close to each other—to distribute items after parking her/his vehicle. Supporting these arguments are the findings of Frank et al. (2004) who found a higher likelihood of obesity was related to more time spent in a vehicle, whereas a lower likelihood of obesity was associated with higher levels of walking.

In addition to the customers and deliverers themselves, teleshopping can potentially impact the health status of other residents in the community through elimination or generation of vehicular trips. For example, consider the scenario of purchase returns. That is, an online purchase not only requires a delivery trip, but also may require a pick-up trip if the customer is not satisfied with the item. This process can be repeated several times, generating several vehicular trips for the purchase of a single item until the customer is satisfied with the purchase; a task that could have been completed with one vehicular trip to the store by the customer. In such scenarios, the increased number of automobile trips within an area due to activities related to repeated deliveries and return pick-ups may lead to higher levels of air pollution, which can affect the respiratory health of residents.

Other scenarios can also be hypothesized with regards to the role of teleshopping in health. However, the effects of teleshopping on health outcomes have not been previously examined in empirical research and is an open field of hypotheses.

Appendix B

Nonmotorized Travel Behavior, the Built Environment, and Health:

A Comprehensive Review of the Literature

The purpose of this literature review is mainly to synthesize what previous research reveals about the interwoven relationships among nonmotorized travel, the built environment, and health. Specifically, this appendix provides a comprehensive review of the literature on: *i*) pedestrian and bicyclist travel behavior and the role of the built environment in their activities; and *ii*) the health impacts of nonmotorized travel and telecommuting behaviors and the built environment.

The review starts with a general overview of the literature on nonmotorized travel behavior from various fields of research. It continues with a discussion of studies focusing on the relationship between the built environment and nonmotorized travel. This is followed by a detailed review of the effects of various factors that—based on literature—play a key role in walking and bicycling. Next is the literature on the relationship between health and nonmotorized travel, the role of built and social environments in health, and the health impacts of telecommuting behavior.

This comprehensive review of literature provides the foundation of the discussion in Chapter 2 of this dissertation regarding the current state of research on nonmotorized travel behavior and health outcomes, identification of the remaining gaps and limitations in the existing literature, as well as how the present research aims to fill some of those gaps.

B.1 Overview of Nonmotorized Travel Behavior Literature

The topic of nonmotorized (i.e., walking and bicycling) travel behavior and factors affecting it cuts across multiple scientific disciplines and it has been referred to as a “multidisciplinary” issue by some researchers (see e.g., Lee and Moudon 2004; McMillan 2005). As concepts such as active living by design gain more momentum in academic, government and public discourses (Fan 2007), numerous researchers have made endeavors in the walking and bicycling travel behavior subject matter. As a result, the existing literature comes from various academic disciplines including transportation planning, urban design, public health, psychology, sports and preventive medicine.

B.1.1 Transportation Planning/Urban Design Literature

Many studies in the field of transportation planning and urban design have contributed to the discussion on walking and bicycling travel behavior. These modes of transportation are often referred to as *nonmotorized modes of travel* in the transportation planning/urban design literature (see e.g., Frank and Pivo 1994; Cervero 1996; Handy 1996b; Kitamura et al. 1997; Cervero and Kockelman 1997; Porter et al. 1999; Desyllas et al. 2003; Rodríguez and Joo 2004; Targa and Clifton 2005; Schwanen and Mokhtarian 2005; Plaut 2005; Cao et al. 2006; Agrawal and Schimek 2007; Mitra and Buliung 2012; Schneider 2015). The utility-maximization framework—widely used for analysis of travel behavior in transportation planning and urban design studies in the form of discrete choice models (Ben-Akiva and Lerman 1985; Train 2009)—is also applied to model nonmotorized travel choices within these disciplines. The effects of many factors have been tested and several methodologies have been employed in previous research to analyze various travel behavior outcomes including the walking and bicycling mode choice, the frequency of nonmotorized trips, and the proportion of such trips.

Within the transportation planning/urban design community, investigation into the topic of walking and bicycling modes as alternatives to the private automobile mode has intensified during recent years with the emergence of new concepts such as smart growth, new urbanism, transit-oriented development (TOD), complete streets, livable communities, and sustainable transportation. The main principle common to all these concepts is to shift views from traditional land use planning, network design, and travel behavior with the private vehicle being the main mode of travel to planning and designing frameworks that are more conducive to nonmotorized travel modes and sustainable travel behavior (Friedman et al. 1994; Cervero and Radisch 1996; Cervero and Kockelman 1997; King et al. 2002; Rodríguez and Joo 2004; Wood et al. 2010).

B.1.2 Public Health/Preventive Medicine/Psychology Literature

As the interactions between transportation and public health are increasingly recognized (BTS 2016), many studies in non-transportation fields such as public health, preventive medicine, and even psychology have also examined walking and bicycling travel behavior (see e.g., Oja et al. 1991; Lumsdon and Mitchell 1999; Bauman et al. 1999; Andersen et al. 2000; Ross 2000; Troped et al. 2001; Giles-Corti and Donovan 2002, 2003; Cervero and Duncan 2003; Moudon and Lee 2003; Pucher and Dijkstra 2003; Boer et al. 2007; Bassett et al. 2008; Shephard 2008; Gordon-Larsen et al. 2009; Giles-Corti et al. 2009; Rodríguez et al. 2009; Pucher et al. 2010; Merom et al. 2010; Buehler et al. 2011; McDonald et al. 2011; Pucher et al. 2011; Schauder and Foley 2015; Ma and Dill 2015; and Nehme et al. 2016 among many other studies).

Generally, these disciplines examine nonmotorized trip-making activities with an emphasis on the effects of psychological and social factors on such activities, and not on the utility-maximization concept, which is one of the main frameworks used in transportation and planning research (McMillan 2005). Walking and bicycling are often referred to as *active travel*, *active transportation*, or *physical activity* in this literature. Active travel is considered a form of physical activity from the viewpoint of these disciplines.

The health benefits of active travel—for both the individual who participates in such activity as well as the public as a whole—seems to be the incentive that has generated the interest in studying walking and bicycling travel among researchers in these fields of science (see e.g., Ross 2000; Shephard 2008; Bassett et al. 2008; Merom et al. 2010; Nehme et al. 2016).

As a growing number of studies have shown the crucial role of walking and bicycling in human health, health professionals have become more involved in research on these modes of travel. Through these research efforts, the many health benefits of walking and bicycling have been revealed, and the complexity and interdisciplinary nature of the subject has been established.

B.2 Nonmotorized Travel Behavior and Built Environment Literature

The studies mentioned in the previous section constitute the theoretical and empirical foundation based on which the effectiveness of policy and land use planning interventions concerning walking and bicycling travel modes can be evaluated, and future policy decisions can be made. While these studies have significantly contributed to a deeper understanding of walking and bicycling modes, many questions remain unanswered. One reason is that each of these fields examines walking and bicycling based on its own discipline-related perspectives. Therefore, different views have been given and different factors have been tested for their potential impact on walking and bicycling.

Regardless of the field of study, however, the overview of literature (Section B.1) reveals that characteristics of the *built environment* play a crucial role in nonmotorized travel behavior. Thus, a detailed review of the literature focusing on the relationship between the built environment and walking and bicycling is in order. Literature and research findings on the relationship between built environment factors and walking/bicycling travel behavior is abundant, and this research has evolved over several decades (see e.g., Frank and Pivo 1994; Cervero 1996; Cervero and Radisch 1996; Shriver 1997; Cervero and Kockelman 1997; Kitamura et al. 1997; Hess et al. 1999; Black et al. 2001; Greenwald and Boarnet 2001; Handy and Clifton 2001; McMillan 2003; Cervero and Duncan 2003; Kerr et al. 2007; Forsyth et al. 2008; van Loon and Frank 2011; and Schneider 2015). Accumulating evidence provided by these studies supports the existence of a correlation between built environment factors and nonmotorized travel behavior.

This section discusses the supportive theories of the link between the built environment and active travel and provides a review of the existing empirical evidence. Based on the discussion presented in Section B.1, the present section will interchangeably use the terms *nonmotorized travel* and *active travel* when referring to walking and bicycling depending on the context within which these activities are discussed (i.e., transportation or health contexts, respectively).

B.2.1 Theoretical Foundations

The theoretical foundations of the interactions between the environment and human behavior come from a variety of disciplines. The main established theories include the utility-maximization demand theory, which comes from the field of economics, as well as the theory of planned behavior; the social cognitive theory and its extension; the ecological model of behavior, which come from the field of psychology. The utility-maximization framework assumes homogeneity in the decision-making process, while the framework of models in psychology emphasize individual differences and behavior changes (Fan 2007).

As discussed previously, the utility-maximization demand theory assumes that each choice offers a certain value—termed *utility* in this concept—to an individual. It further assumes that given a choice set, a rational individual who is fully informed about all the alternative choices and can compute with perfect accuracy, makes a choice to maximize his/her utility. In travel behavior research this framework conceptualizes behavior as discrete choices (Handy 2005).

Applied to the concept of the role of the built environment in travel behavior in general, the utility-maximization demand theory would mean that any built environment characteristic that influences the utility of a certain mode of travel can have an impact on travel behavior choices. Utility of a travel mode can be quantified as the travel cost, travel time, comfort, convenience, or safety of that certain travel mode. For example, by placing origins and destinations in proximity to each other, pedestrian-friendly neighborhood designs and more mixed-use developments are intended to alter either travel time or travel cost across various modes of travel (Boarnet and Crane 2001). Application of the utility-maximization demand theory to the connection between the built environment and active travel in particular, can mean that individuals would make the choice to make walking or bicycling trips if their utility (e.g., travel cost, travel time, safety, convenience) is somehow maximized by doing so. For example, better sidewalk connectivity can increase the utility of walking and encourage more walking trips.

The theory of planned behavior focuses on psychological attributes that influence behavior such as the influence of beliefs on behavior (National Research Council 2005; Van Acker et al. 2010). More specifically, this theory considers the role of beliefs (i.e., personal attitudes and perceptions), subjective norms (i.e., sociocultural norms or perceived social pressure), and perceived behavioral control (i.e., expected impediments and obstacles) in likelihood of performing a specific behavior (Ajzen 1991; Montano and Kasprzyk 2008). In terms of the built environment, the theory of planned behavior allows personal attitudes and beliefs about the built environment to be incorporated in its framework. It should be noted, however, that attitudes and beliefs are only subjective measures, and therefore, the framework of this theory only allows inclusion of subjective (and not objective) measures of the built environment.

Applied to active travel research, this theory highlights the role of attitudes, perceptions, and beliefs in making the choice to walk or bicycle. In the context of nonmotorized travel behavior, subjective norms can represent perceived social pressure and sociocultural norms that may encourage or discourage walking and bicycling. Also, perceived control in this context can be considered one's perception of how easy or difficult it is to walk or bicycle. As an example, it can be assumed that existence of bicycle lanes and observing other people ride a bicycle can increase an individual's perceived control of bicycling; an effect that may encourage the individual to engage in bicycling. However, inclusion of similar subjective measures is as far as the theory of planned behavior can go with respect of the role of the built environment in behavior. This theory does not consider objective measures of physical environment in its framework to explain behavior (National Research Council 2005) such as nonmotorized travel behavior.

The social cognitive theory considers a role for the social environment in influencing behavior in addition to that of personal characteristics (e.g., attitudes). More specifically, this theory emphasizes the concept of reciprocal determinism in human behavior, which means that individuals and their social environment influence each other. This theory also provides a better understanding of the role of behavioral learning processes in behavior. However, it does not include built environment factors in its framework. Nevertheless, it can be assumed that by considering the reciprocal relations between personal characteristics, the social environment and behavior (Bandura 1986; Van Acker et al. 2010), the social cognitive theory may somewhat allow accounting for attitudes toward the built environment (i.e., subjective measures) in its framework, if applied to the nonmotorized travel behavior concept.

Used in nonmotorized travel behavior (i.e., active travel) research, the social cognitive theory framework would imply that individuals' walking and bicycling travel behavior is influenced by their social environment—mainly, the household—as well as their observed behavior (e.g., sociocultural norms regarding walking and bicycling activities).

While the theory of planned behavior and the social cognitive theory focus on identifying psychological and social attributes that influence behavior such as individuals' attitudes and beliefs (Handy 2005) as well as sociocultural norms, the ecological model of behavior—a variant of the social cognitive theory—emphasizes the influence of the built (i.e., physical) environment and policy on behavior (Sallis et al. 2008). In addition, the ecological model incorporates all the concepts of the theory of planned behavior and the social cognitive theory. Thus, the advantage of this model over the theory of planned behavior and the social cognitive theory is that it allows inclusion of objective built environment factors in its framework.

A signature feature of the ecological model of behavior is that it is conceptualized as a multilevel framework with factors representing multiple interacting levels of various influences on human behavior. These levels include intrapersonal (e.g., biological, psychological), interpersonal (e.g., social factors, sociocultural norms), organizational, community (e.g., physical environment), and policy (Handy 2005; Sallis et al. 2008). In terms of the built environment, the ecological model can include factors representing various geographical levels. Thus, ecological models can provide a more integrated and more comprehensive framework for modeling human behavior as it incorporates all the components of the theory of planned behavior and the social cognitive theory and adds to them the influence of the built environment and policy on behavior.

Applied to nonmotorized travel behavior, the principles of the ecological model suggest that walking and bicycling travel behavior can be influenced by attributes of the physical (i.e., built) environment's at various spatial levels including the micro level (e.g., the neighborhood), the meso level (e.g., the county), and the macro level (e.g., the city, the region or metropolitan area) (Handy 2005; Van Acker et al. 2010).

With regards to the theories from the field of psychology (e.g., theory of planned behavior, the social cognitive theory, and the ecological model theory), it should be kept in mind that they pose some challenges at the operational level. Past research argues that although these theories explain the role of attitudes and social norms in behavior, their implementation by practicing planners and engineers is not without challenges due to difficulties in operationalizing reliable measures of the complex psychological constructs involved (Fan 2007).

Overall, these theories provide the basis for conceptual models that researchers developed in the past to explain nonmotorized travel behavior (i.e., walking and bicycling) and identify the built environment factors that influence walking and bicycling behaviors. Each of these theories suggest that the link between the built environment and nonmotorized travel behavior is guided by a more complex conceptual model than the specific framework that they provide. Thus, it should be noted that although none of these theories can perfectly explain behavior, together, they might add up to a complete framework (Handy 2005), which can be utilized in explaining behavior including nonmotorized travel behavior.

B.2.2 Empirical Studies

To date, a tremendous amount of empirical research on the link between walking and bicycling travel behavior and the built environment has been developed. A detailed review of a few of these studies helps in identifying built environment and non-built environment factors that influence nonmotorized travel behavior as well as areas where further research is needed.

Handy (1996b) found that the number of walking trips was positively correlated with shorter travel distances to destinations and street design factors. The study also found that the average frequency of walking trips to commercial areas and the percentage of pedestrians who walked to commercial areas were higher in neighborhoods with a traditional design compared to those that had a modern design.

Kitamura et al. (1997) found that generation of nonmotorized trips was strongly associated with land use characteristics. In addition, distances to the nearest bus stop and the nearest park were negatively associated with the fraction of nonmotorized trips in that study.

Cervero and Kockelman (1997) examined the relationship between travel demand and three dimensions of the built environment: density, diversity, and design. The study findings supported the idea that compact, mixed-use developments, and pedestrian-oriented designs were associated with higher levels of nonmotorized travel. Hess et al. (1999) investigated the relationship between site design and pedestrian activity in a mixed-use, medium-density context. The researchers found that pedestrian volumes were associated with neighborhood's site design—specifically, with measures of block size and the extent of sidewalk completeness.

Greenwald and Boarnet (2001) found that while neighborhood population density was a strong determinant of number of non-work walking trips, median trip distance was the most important factor in determining number of such trips. Troped et al. (2001) found that steep hills, higher volumes on streets to be crossed, and greater distance were negatively associated with the use of a community bicycle trail. Craig et al. (2002) examined the impact of environmental factors on walking to work. The study employed hierarchical linear modeling and showed that walking to work was significantly associated with the neighborhood environment after controlling for income, university education, poverty, and degree of urbanization. Giles-Corti and Donovan (2003) found that increased access to public open space as well as living on streets with minor traffic, sidewalks, and/or retail shops were associated with higher odds of attaining the recommended amount of walking in terms of health benefits.

McMillan (2003) used urban design factors from school neighborhoods as well as parent survey data on children's travel to school to investigate the role of urban form on children's walking trips to school. The research used data from California's Safe Routes to School program. Results indicated that some urban form factors such as abandoned buildings, street lights and street widths influenced children's walking to school; however, these effects were moderate compared to other factors such as the perceived convenience of driving, perceived distance between home and school, supportive attitudes of family toward walking, neighborhood traffic conditions, and the parent’s country of birth. Cervero and Duncan (2003) examined the relationship between demographic characteristics, the built environment, and nonmotorized travel. The study concluded that built environment factors had weaker influences on walking and bicycling travel behavior compared to demographic characteristics (e.g., race, age, gender), travel impedance factors (e.g., travel time, travel distance), and natural environment factors (e.g., topography, rain, nightfall).

Rodríguez and Joo (2004) examined the association between several measures of the local physical environment and travel behavior. The study results indicated that presence of sidewalks was significantly associated with individual’s propensity to walk to destinations and topography had an effect on the propensity to bicycle. Additionally, the authors suggested that issues related to the role of preferences for travel modes and how these preferences are formed should also be further investigated to address self-selection bias and causality issues.

Plaut (2005) examined the factors that affected the propensity of employed individuals to use the nonmotorized modes of travel for commuting. The study found that living in the central city of the Metropolitan Statistical Area (MSA) was significantly correlated with the probability of walking and bicycling commuting. The author argued that nonmotorized transportation policies should focus on households as well, and not just on individual trip-makers.

McDonald (2005) examined children’s travel behavior (including children’s school trip mode choice and after school activities) as well as the influence of land use on children’s’ walking to school. The author found that travel time and distance played a significant role in children’s walking trips. Population density had a weak but positive correlation with walking to school. This research did not include bicycling travel behavior of children.

As one of the very few studies that analyzed bicycling behavior, Moudon et al. (2005) investigated the relationship between the likelihood of bicycling in neighborhoods and the built environment. The researchers concluded that sociodemographic factors had a more important role in making the decision to bicycle. Also, they concluded that bicycling was moderately associated with the neighborhood built environment and it was more an individual's decision that did not seem to be depending on supportive built environment factors. Cao et al. (2005) found that built environment characteristics had an impact on walking after accounting for preferences toward neighborhoods conducive to walking. Targa and Clifton (2005) investigated the impact of neighborhood-level built environment on walking trip generation rates. The results indicated that variables capturing built environment attributes such as urban density, street connectivity, grid-like streets, and mixed land use were associated with frequency of walking. Also, accessibility to bus transit lines was found to be associated with higher frequency of walking in that study.

Cao et al. (2006) examined the influences of the built environment and self-selection on pedestrian trips. The study found that residential self-selection impacted strolling trips, and it was the most important factor in explaining pedestrian shopping trips. This result also suggested that a preference for walking was a more important factor in frequency of pedestrian trips than the neighborhood built environment factors. The authors also found that after controlling for self-selection, neighborhood attributes were more important in the frequency of strolling trips, whereas characteristics of local commercial areas had an impact on generating pedestrian shopping trips.

Kerr et al. (2007) investigated the relationship between objectively measured urban form variables and walking trips by youths. The study found that urban form was strongly correlated with walking among White youth, but it was not as significantly related to walking for non-White youth. Also, urban form variables were not as significantly associated with walking in low-income groups and youth whose households did not own a car. In addition, living in mixed use-areas and having access to recreational space were associated with walking among youth. Boer et al. (2007) found that higher levels of business diversity and a higher percentage of four-way intersections were associated with higher amounts of walking. The study also suggested that housing density affected walking in an inconsistent pattern and that block length was not correlated with walking.

Frank et al. (2008) found that reductions in highway travel time were associated with less walking and bicycling. Land use variables for this study were calculated for a one-kilometer buffer area around the survey respondent's location of residence or work. The study results confirmed that factors that measured land use mix, residential density, retail density, and street connectivity were statistically significant and associated with the likelihood of walking and bicycling for home-based tours. Forsyth et al. (2008) investigated the impact of design and diversity of destinations on walking. The results indicated that location attributes influenced walking. The study concluded that sidewalk length, traffic calming, smaller blocks, and other measures of connected street patterns were positively associated with walking. However, no positive correlation was found between mixed use factors and amount of walking.

In a meta-analysis of the built environment-travel connection literature, Ewing and Cervero (2010) concluded that walking was most strongly associated with mixed land use, intersection density, and the number of destinations within walking distance. Heinen et al. (2010) conducted a comprehensive review of academic literature on commuting by bicycle and suggested that certain aspects of the built environment including shorter trip distance, land use mix, and access to bicycle storage facilities increased bicycling to work. The study also argued that the effects of denser network layout, block size, and higher densities were still a bit ambiguous. The authors concluded that further research was needed into the relationship between bicycling and the built environment.

Merom et al. (2010) examined changes in walking and bicycling between the years of 1997 and 2007 by population subgroups. The results showed significant increasing trends for all walking indicators in most population subgroups. Bicycling rates were low (less than 1.5%) but had significant increasing trends for all indicators and selected subgroups. The authors stated that the small sample size on bicycling trips did not allow for establishment of significant differences in bicycling among sociodemographic groups. Further research to explore the effect of fuel prices on health-enhancing active travel was also suggested by the authors of that study.

McDonald et al. (2011) found that distance to school exerted the strongest effect on the probability of walking to school by children. Pucher et al. (2011) found that frequency, duration, and distance of walk trips per capita and walk mode share increased between years 2001 and 2009. The study also indicated that walking and bicycling declined for women, children, and older adults but increased among men, the middle-aged, employed, the well-educated as well as among individuals without a private vehicle. Mitra and Buliung (2012) examined the potential impact of the modifiable areal unit problem (MAUP) on the relationship between the built environment and nonmotorized school trips of children. The authors concluded that the statistical significance, size, and the direction of the built environment effects varied across various spatial scales for data aggregation, which confirmed the existence of MAUP and zoning effects. The study results also indicated that travel distance was an important factor in the likelihood of children's walking or bicycling to school as children who lived closer to their school were more likely to walk/bicycle to school. Also, children were more likely to walk or bicycle to school if they lived or went to school in areas where other people also walked to work or school. The authors suggested that future research should study the relationship between children's travel to school and the built environment at various levels of geographical aggregation.

B.3 Influential Factors in Nonmotorized Travel Behavior

The studies reviewed and discussed in Section B.1 and Section B.2 provide evidence of the influence of several factors on walking and bicycling trips. These factors can be categorized into three major groups:

1) built environment factors;

2) psychological factors; and

3) socioeconomic and sociodemographic factors.

Next is a more comprehensive review of literature focusing on factors related to each of these categories and their effects on walking and bicycling as suggested by different research studies in the past.

B.3.1 Built Environment Factors

Using a variety of techniques in a variety of regions, the existing literature on correlations between the built environment and travel demand provides considerable evidence that in general, the built environment influences travel behavior through factors famously known as the *five Ds* of the built environment. These are: *density*, *diversity*, *destination accessibility*, *design*, and *distance to transit* (Cervero and Kockelman 1997; Ewing and Cervero 2010). Almost all of the reviewed studies on the relationship between the built environment and nonmotorized travel behavior included one or more of the *D* factors in their analysis (see e.g., Kitamura et al. 1997; Cervero 2001; Reilly and Landis 2003; Cervero and Duncan 2003; Zhang 2004; Targa and Clifton 2005; Kerr et al. 2007; and Frank et al. 2008 among many more studies).

Findings of a few of these studies on the effects of the micro-level (i.e., neighborhood-level) *D* factors on nonmotorized travel behavior are reviewed below. Existing literature on the macro-level built environment as related to nonmotorized travel behavior is also briefly discussed.

B.3.1.1 Density

With respect to the built environment, density represents the intensity of human activity (Lin and Chang 2010). It is measured as the ratio of the variable of interest (usage level) to the unit of geographical area (Marcus 2008; Ewing and Cervero 2010). Literature suggests that elevated levels of density—typically, resulting from new urbanism designs—can mean increased numbers of people and places, which in turn, can encourage interactions and provide a greater sense of community (Handy 1996a; Forsyth et al. 2008). In addition, high densities can affect travel behavior by reducing distance between origins and destinations; an element that can encourage nonmotorized trips and discourage automobile trips.

For example, researchers such as Boarnet and Sarmiento (1998) argued that new urbanism and neo-traditional community designs feature high neighborhood densities, which encourage walking and discourage automobile travel—at least at the neighborhood level. High densities are also postulated in previous studies to increase parking costs, reduce automobile travel (and thereby reduce congestion levels and improve quality of air), increase transit usage, and encourage nonmotorized travel behavior (Kockelman 1996; Handy 1996a; Cervero and Kockelman 1997; Kitamura et al. 1997; Boarnet and Sarmiento 1998; Krizek 2003b; Zhang 2004; Stinson and Bhat 2004; Forsyth et al. 2008; Chatman 2009; Lin and Chang 2010).

Past empirical evidence has confirmed that high density plays a key role in generating nonmotorized trips. However, these findings are not always consistent, and mixed results have been reported by different studies. Various measures of density have been considered in the past including population density, residential density, housing density, employment density, and activity density (i.e., [population + employment]/unit area) to investigate the relationship between nonmotorized travel behavior and land use.

Some studies found that density measures exert positive and significant effects on nonmotorized travel. Frank and Pivo (1994) found that the proportion of walking trips within a census tract (i.e., neighborhood) was positively and significantly correlated with *population density* at trip origin for work trips, and population density at destination for shopping trips. Kitamura et al. (1997) concluded that higher *residential density* was associated with more person and nonmotorized trips, higher fractions of nonmotorized trips, and lower fractions of automobile trips. Badoe and Miller (2000) concluded that increased *employment density* had a significant, positive effect on walking. From a review of literature, Agrawal and Schimek (2007) found a positive association between walking trips and population density. McDonald et al. (2011) argued that living in urban clusters, which they suggested have higher densities compared to rural area, increased the probability of walking to school by children.

Other studies reported either mixed, negative, or insignificant effects. For instance, Badoe and Miller (2000) concluded that the empirical evidence regarding the role of residential density in determination of walking and bicycling travel was very mixed. Reilly and Landis (2003) found that population density did not affect the likelihood of walking for entertainment trips. Cervero and Duncan (2003) found that although employment density was positively correlated with walking, its effect was not statistically significant. They also found that higher employment density decreased the likelihood of bicycling, but this result was also not statistically significant.

Zhang (2004) found that higher population densities at origins were associated with increased probability of nonmotorized trip-making for work trips but not for non-work trips, whereas higher population density at destinations mattered for both work and non-work trips. This latter study also found that even though higher employment density at trip destinations were associated with a higher probability of choosing nonmotorized modes for work trips, higher employment density at the origin was insignificant for both work and non-work trips.

Rodríguez and Joo (2004) found that population density measured at the block group of each respondent's home location was not consistently related to nonmotorized mode choices. The authors stated that one reason for this may be that block group is not the appropriate unit of analysis for measuring neighborhood density. The other reason they suggested can be that mode choice is more related to employment density at destinations than residential densities at origins.

Scuderi (2005) found that residential density influenced vehicular trips more than walking trips. Kerr et al. (2007) indicated that residential density was significantly associated with higher walking rates. Also, they found that residential density was not significantly linked to walking of youth in the lowest income group, but it was strongly and significantly associated with youth walking behavior in the highest income group. Additionally, Boer et al. (2007) suggested that the effects of *housing density* on walking were inconclusive. Forsyth et al. (2008) reported that residing in high-density areas was positively associated with utilitarian walking but negatively associated with recreational walking. Weinberger and Sweet (2012) suggested that the effect of population density on walk mode share was unclear.

From this review of literature, it is revealed that various measures of density including population density, employment density, and residential density have been tested by researchers for their relationship with nonmotorized travel behavior. Many of the above-mentioned studies as well as many other studies suggested that densities were positively correlated with nonmotorized travel (see e.g., Frank and Pivo 1994; Cervero 1996; Ewing and Cervero 2001; Cervero 2001; Ewing et al. 2003a; Targa and Clifton 2005; Zhang and Kukadia 2005; Salon 2006; Boarnet et al. 2008; Marcus 2008; Rodríguez et al. 2009; Lin and Chang 2010; Wang 2013).

However, in many other studies, densities yielded mixed, negative, and/or insignificant effects (see e.g., Cervero and Duncan 2003; Zhang 2004; Bento et al. 2005; Scuderi 2005; Kerr et al. 2007; Boer et al. 2007). The trip purpose (e.g., work vs. non-work trips) and the focus location of the analysis (e.g., trip origin vs. trip destination) can be among the factors leading to the inconsistent findings. Additionally, as Chen et al. (2008) suggested many studies on the impact of density on travel behavior did not include confounding factors (e.g., residential self-selection, accessibility measures, access to transit stations, and level of mixed use), which can lead to inconsistencies in findings. Another reason can be that even though due to providing shorter distances to destinations, high-density neighborhoods are intuitively expected to lead to fewer automobile trips and more nonmotorized trips (such as walking trips), shorter trips may actually stimulate more automobile trips; in this case, the net result for both automobile and nonmotorized travel is unclear (National Research Council 2005).

Density is the most commonly used *D* factor (and sometimes, the only variable used) in research probing the link between travel behavior and the built environment—likely because it can easily be operationalized (Krizek 2003b). However, since in most cases high-density developments coexist with increased levels of mixed land use, transit service, and pedestrian-friendly designs, many studies suggested that density may act as a proxy or surrogate for other measures such as accessibility, transit service levels, pedestrian-friendly streets, mixed land use, demographics, distance, and car ownership levels (see e.g., Kockelman 1996; Kockelman 1997; Boarnet and Crane 2001; Krizek 2003b; Handy 2005; Forsyth et al. 2008; Cervero and Murakami 2010; Ewing and Cervero 2010). Thus, a few studies have cautioned against using measures of density due to the following reasons: *i*) lack of a sound strategy to integrate population and employment density and capture the effect of both on travel as interrelated (and not separate) factors (Krizek 2003b);

and *ii*) the potential of density to serve as a proxy variable for other built environment factors (Handy 2005; National Research Council 2005). In the latter case, density is correlated with other characteristics of the built environment and its role in travel behavior (including nonmotorized travel behavior) can be considered ambiguous.

B.3.1.2 Diversity (Land Use Mix) and Destination Accessibility

The diversity and destination accessibility dimensions of the built environment overlap (Ewing and Cervero 2010); therefore, they are discussed together in the following paragraphs.

Within the transportation and urban planning context, diversity refers to variety in terms of land use and how mixed various land uses are in a specific geographical area. The extent of mixed land use or the presence of diverse destinations are considered in transportation planning theories as key trip generators (Forsyth et al. 2008). Destinations refer to the commercial, service, and recreational land uses (e.g. stores, restaurants, banks, parks) contained in a geographical area (Giles-Corti et al. 2009). By shortening travel distances between origins and destinations, the proximity of these various land uses to one another allows residents to enjoy opportunities within their community (Dieleman et al. 2002; Krizek 2003b). Shorter travel distances may influence travel mode choice. Literature suggests that the higher the degree of mixed land use, the less likely the people are to drive and the more likely they are to use nonmotorized modes of travel (Friedman et al. 1994; Cervero 1996; Krizek 2003b; Ryan and Frank 2009; Lin and Chang 2010).

Many of the studies reviewed here included measures that represented land use diversity (or lack thereof) and the extent of mixing of land uses in their analysis of the relationship between the neighborhood built environment and nonmotorized travel behavior. Various measures were used for this purpose including existence of mixed-use development, the number or fraction of establishments in each land use classification, and availability of commercial destinations. More often, however, land use diversity is measured in travel behavior studies using the *entropy* index. An entropy index measures how mixed land uses within a given area are. Low values of the entropy index represent non-diverse land uses, whereas high values represent more mixed land uses.

Empirical findings on how the extent of neighborhood's mixed land use affects walking and bicycling of residents are, at best, mixed! This is because on the one hand, there are studies that argue mixed land use and availability of local shopping opportunities encourage nonmotorized travel and, on the other hand, findings of other studies do not support that hypothesis.

Examples of studies in the former group are Cervero and Kockelman (1997), which found that *presence of neighborhood convenience stores* induced nonmotorized trips within the neighborhood. Also, Lund (2003) found that destination-oriented walking trips were significantly higher in neighborhoods with local access to retail shops either by themselves or in combination with local access to parks. Further, Cervero and Duncan (2003) found that *land use diversity at trip origin location* had a positive impact on the likelihood of walking and bicycling, whereas *existence of retail services* around the trip origin location increased the likelihood of walking and bicycling. Moreover, Plaut (2005) concluded that existence of commercial properties nearby had a positive effect on the propensity of workers to walk to work. Kerr et al. (2007) indicated that youth who lived in areas with more than one *commercial land use* were twice as likely to walk than their counterparts who lived in areas with no or just one commercial land use.

Among studies that reported mixed or no effects on the role of land mix use in nonmotorized travel is Frank and Pivo (1994), which concluded that even though local land use mix had a significant effect on walking for work trips, it was not significantly correlated with walking for shopping trips. Hess et al. (1999) concluded that pedestrian volumes were not associated with the *size of commercial centers* (measured in that study by the number of businesses and types of retail facilities provided within a 0.5-mile pedestrian catchment area). Additionally, Rodríguez et al. (2009) found that having a higher level of mixed land use was associated with walking for exercise for more than 90 minutes/week, and that self-reported ease of access to destinations was related to higher levels of exercise walking for a sample of older adults. However, the study also found that even though *availability of retail* was positively associated with utilitarian walking, *entropy* was not correlated with utilitarian walking trips.

Further, Handy and Clifton (2001) suggested that local shopping did not prove to induce travel by walking. The study concluded that existence of local shops was not a significant factor in reducing vehicular travel and encouraging walking. Reilly and Landis (2003) found that for shopping trips, the proportion of commercial land uses within the neighborhood did not have a significant impact on walking, whereas for entertainment trips, neighborhoods with a higher mix land use encouraged walking. McMillan (2003) found that increased mixed land use was associated with decreased likelihood of children walking/bicycling to school. Moudon et al. (2005) concluded that even though presence of a mix of offices, clinics/hospitals, and fast food restaurants was a significant built environment factor that contributed to increased likelihood of bicycling, presence of convenience stores had a negative impact on bicycling. Moreover, presence of parks was found to be an insignificant factor in this study. Forsyth et al. (2008) reported that no positive correlation was found between walking and mixed land use factors.

Other studies examined the role of destination accessibility in nonmotorized travel behavior. Destination accessibility refers to factors that measure ease of access to destinations. As mentioned previously, accessibility can be regional or local (Handy 1993). Regional accessibility is the number of destinations reachable within a given travel time and is usually measured by the gravity model of trip attraction, whereas local accessibility is often quantified as the distance from the origin (typically, place of residence) to the closest destination (such as a shopping center) (Ewing and Cervero 2010). An increase in the trip's distance results in an increase in the time and effort needed for traveling (Heinen et al. 2010); thus, the assumption is that proximity to local destinations such as stores can induce more nonmotorized trips or allow them to substitute for motorized trips (Cervero 1996).

Many papers reviewed for this literature review included distance to local stores as a measure of accessibility to local commercial destinations in their examination of the role of neighborhood built environment factors in nonmotorized travel behavior. Compared to the role of land use diversity, research findings are more consistent with regards to the role of distance to local destinations—mainly commercial establishments—in nonmotorized travel behavior.

Although Reilly and Landis (2003) found that for home-based shopping trips, distance to the nearest commercial land use did not have a significant impact on walking, several other studies found that shorter distance to commercial opportunities within the neighborhood promoted walking and bicycling. For instance, Handy (1996a, 1996b) found that having commercial areas within walking distance encouraged walking. Additionally, Handy and Clifton (2001) found that the tendency to walk to local stores was strongly correlated with distance; in neighborhoods where there was a greater distance between the location of stores and the residents, fewer residents indicated tendency to walk to stores. The study also suggested that each additional quarter mile of distance decreased the number of an individual's walking trips by one per month.

Also, Cervero and Duncan (2003) found that the likelihood of walking and bicycling decreased with an increase in distance to retail activity destinations. Further, the presence of destinations within walking distance from places of residence was found to be the strongest correlate of home-based walking trips in the Hoehner et al. (2005) study. Handy et al. (2006)

concluded that destination accessibility in terms of having shops and services (e.g., banks) nearby was the most important factor in increasing walking activity. Further, Lee and Moudon (2006) found that shorter distances from homes to routine local destinations (e.g., grocery stores, eating and drinking places, banks) were positively associated with walking. Cao et al. (2006) reported that distance to the nearest store was highly significant in explaining frequency of pedestrian trips to the store. Later, Cao et al. (2010) found that distance to the nearest grocery store was negatively associated with frequency of walking to stores. In addition, Schneider (2015) found that walking was associated with shorter trip distances (in terms of travel times) to local shopping opportunities.

Regarding bicycling, Heinen et al. (2010) interestingly related the importance of distance to the spatial scale of city and its bicycling mode share as they suggested that the highest bicycle shares in small and medium-sized cities in the Netherlands were a result of the proximity of destinations in these cities. The authors suggested that in the choice of commuting by bicycle, distance to destinations was the most important built environment factor. Later, Ma and Dill (2015) found that the number of retail jobs within 1/2-mile circular buffers around home was negatively associated with bicycling. The authors argued that this result was because individuals who lived near retail stores (1/2-mile) probably preferred walking over bicycling to these destinations.

Based on research findings similar to the above, some studies consider distance to local destinations (e.g., commercial establishments) the most important local built environment factor to influence nonmotorized trips, particularly walking trips (Pivo and Fisher 2011).

Distance also plays a key role in nonmotorized travel to non-commercial destinations. Among non-commercial destinations, schools have received tremendous scholarly attention—likely because as some researchers argued travel to schools and shopping stores provide the highest potential for walking trips (Demetsky and Perfater 1975).

Based on a review of literature on children’s school trips, McMillan (2005) suggested that distance from home to school may be the biggest barrier to children’s walking or bicycling to school. This finding was confirmed by Schlossberg et al. (2006) who found that distance to school was highly associated with walking and bicycling to and from school, and by Yarlagadda and Srinivasan (2008) who found that the distance between home and school was strongly and negatively associated with the choice of walking to and from school. Also, in a review of literature, Giles-Corti et al. (2009) suggested that distance was one of the key factors that affected children’s walking or bicycling to school. Later, Mitra and Buliung (2012) also concluded that distance was an influential factor in determining the likelihood of children’s walking and bicycling to school.

Work locations are the other destinations that have been examined in past research. Studies have found that distance to work destinations impacts nonmotorized travel behavior. One example is a study by Stinson and Bhat, who found that distance to the employment location had a very strong influence on the propensity to commute by bicycle (Stinson and Bhat 2004).

B.3.1.3 Design (Neighborhood Design and Transportation Infrastructure)

Design represents the conditions of the neighborhood’s physical environment and transportation network (Lin and Chang 2010). The role of neighborhood and transportation network design in nonmotorized travel has been considered and explored by many research studies in the past. For example, Cervero and Gorham (1995) concluded that neighborhood design influences the degree to which people walk or bicycle, and Handy and Clifton (2001) suggested that whether or not people feel safe and comfortable walking around neighborhood stores is an important element, which emphasizes the role of design and pedestrian-oriented infrastructure in the choice to walk.

Various aspects of design have been represented by different measures in previous studies to capture the differences between automobile-oriented environments and pedestrian- as well as bicycle-friendly environments. These measures include, but are not limited to, variables representing: *i*) street patterns (e.g., block length, block size and density of intersections); *ii*) vehicular network and facility conditions and vehicular traffic (e.g., width and number of traffic lanes, traffic volume and speeds, parking availability); and *iii*) pedestrian and bicyclist amenities and facility conditions (e.g., presence and extent of connectivity of sidewalks and bicycle lanes).

Literature related to each of these categories are discussed below.

Street Patterns

Past research has often quantified the extent of grid-like street patterns by using variables that measure the size of the blocks in the study area. These variables generally include those that either measure the size of the block directly (e.g., block size/area/perimeter, block length) or indirectly (e.g., density of intersection). It is notable that although smaller blocks found in grid-like designs are postulated to encourage nonmotorized trips in theory, the empirical findings on the relationship between street pattern-related variables and nonmotorized travel have not reached consensus.

For example, pedestrian volumes were found to be associated with neighborhood site design and street patterns—specifically, with *block size*—in Hess et al. (1999). This is while Cervero and Duncan (2003) argued that pedestrian- and bicycle-friendly designs represented by variables such as block size and *intersection configuration* did not affect the likelihood of walking. Further, Moudon et al. (2005) found that when objectively measured, street block size was not a significant factor in predicting the likelihood of bicycling. Also, Boer et al. (2007) suggested that *block lengths* did not seem to be correlated with walking.

In addition, block size is also considered to capture the degree to which streets are interconnected. For example, suburban cul-de-sac designs with superblocks although may appear short-blocked but are actually large in total area (Ewing et al. 2003a); therefore, controlling for street connectivity is essential in nonmotorized travel behavior research. In a general sense, connectivity has been defined as "the directness of travel to destinations" in past studies (National Research Council 2005).

Street and network connectivity have been controlled for in many empirical studies including Zhang (2004) who found that although marginally significant, increased *network connectivity* at trip origins promoted nonmotorized travel. Also, Targa and Clifton (2005) found that among built environment factors, street network connectivity (measured as the perimeter of the census block in that study) had the largest elasticity with respect to frequency of walking. Cao et al. (2006) showed that providing connections for pedestrians between the street and stores encouraged pedestrian shopping trips. Dill and Voros (2007) found that a higher level of street connectivity was correlated with more utilitarian bicycling trips.

Another variable used in past research to represent street patterns and connectivity is *intersection density*. Kerr et al. (2007) indicated that for youth whose households owned more than two cars and for those who came from households with higher income, intersection density was significantly related to higher youth walking rates regardless of gender. Additionally, existence and *density of four-way intersections* have been suggested to influence nonmotorized travel. Cervero and Kockelman (1997) argued that existence of numerous four-way intersections promoted nonmotorized trips—particularly walking trips—by providing controlled street crossings and additional access points. Boer et al. (2007) suggested that increasing the number of intersections shortens the distance between destinations and may promote walking. They found that higher *percentages of four-way intersections* were positively correlated with walking.

Intersection density was also a strong determinant of children's walking trips to and from school in other research (Schlossberg et al. 2006). Further, Lin and Chang (2010) reported that increased number of intersections dissuaded children from walking to school. From computing elasticity in a meta-analysis of past empirical studies, Ewing and Cervero (2010) concluded that intersection density (i.e., a proxy for block size) was a more important variable in walking behavior than street connectivity. The authors stated that this finding was intuitive because even with well-connected street networks, walkability may be limited when blocks are long. Later, Mitra and Buliung (2012) found that higher density of four-way intersections was associated with lower likelihood of active travel to school by children. Among other street pattern measures used in previous research is *density of major roads* near school or home, which did not show association with active travel of children to school in the latter study (Mitra and Buliung 2012).

Vehicular Traffic, Network and Facility Conditions

Past research findings reveal that vehicular traffic (e.g., traffic volumes and speeds) as well as conditions of the vehicular network (e.g., width and number of lanes, signalized vs. unsignalized intersections, grades) and vehicular facilities (e.g., parking availability) can influence nonmotorized travel behavior.

For instance, Appleyard (1981) and Gehl (1987) found that greater *traffic volumes* decreased the amount of walking activity. Harkey et al. (1998) found that variables representing *traffic speed* and volumes had the greatest impact on the perceived comfort levels of potential bicyclists. However, Moudon et al. (2005) found that when objectively measured, traffic speed and volume were insignificant factors in predicting the likelihood of bicycling. Also, Cao et al. (2006) showed that a higher traffic volume in commercial streets was associated with a reduction in the number of pedestrian trips. Nehme et al. (2016) concluded that recreational walking was associated with percentage of street length with *speed limits* less than 25 miles per hour (mph).

Regarding vehicular network conditions, Harkey et al. (1998) showed that *lane width* was an important variable in modeling the perceived comfort levels of potential bicyclists, whereas Moudon et al. (2005) found that objectively measured *number of traffic lanes* and *slope* were insignificant variables in predicting the likelihood of bicycling. Additionally, from a comprehensive review of literature on commuting by bicycle, Heinen et al. (2010) concluded that *traffic lights* and *stop signs* negatively affected the perception of bicyclist; however, the study indicated that the effects of these perceptions on frequency of bicycle use or on bicycle mode choice were not clear. Finally, Mitra and Buliung (2012) found that children who lived and went to school in an area where a larger proportion of intersections were signalized (within a 250-meter buffer distance of home or the TAZ of the school) were more likely to walk or bicycle to school.

Vehicular facilities—most importantly—availability of parking, have also been linked to nonmotorized travel behavior. For instance, Cervero and Kockelman (1997) found that *paid parking* encouraged nonmotorized trips to shops and other non-work destinations within the neighborhood and Harkey et al. (1998) found that *on-street parking* had an impact on the perceived comfort levels of potential bicyclists.

Pedestrian and Bicyclist Amenities and Facility Conditions

Pedestrian and bicyclist friendliness of the neighborhood and its transportation facilities is also another design element suggested by past research to influence nonmotorized travel behavior. Kitamura et al. (1997) found that *presence of sidewalks* was positively associated with the number of nonmotorized trips, and Hess et al. (1999) found that pedestrian volumes were associated with the extent of *sidewalk completeness* in the neighborhood. Additionally, Rodríguez and Joo (2004) showed that a higher *percentage of sidewalk* available in the shortest route to a destination was correlated with a higher propensity to choose to walk to work or school.

Ewing et al. (2004) found that the proportion of arterials and collectors with sidewalks along them had the most significant influence on children's walking to school. Targa and Clifton (2005) reported that people who perceived the *condition of sidewalks* as being "a little and somewhat of a problem" (as opposed to "a big problem") were more likely to walk more frequently. Also, Nehme et al. (2016) concluded that recreational walking was associated with *presence of walking trails*.

Regarding bicycling, Harkey et al. (1998) found that the *presence or absence of a bicycle lane or paved shoulder* had the largest effect on the Bicycle Compatibility Index—an index which captured individuals' comfort level ratings to ride a bicycle on specific roadway segments or through intersections with right-turning traffic. Additionally, Dill and Carr (2003) found that each additional mile of *bicycle lane* per square mile was associated with an increase of approximately one percentage point in the bicycle commute mode share.

However, Rodríguez and Joo (2004) showed that the *presence of walking and bicycling paths* was not consistently related to mode choice as related to nonmotorized trips. Confirming the latter finding were Ewing et al. (2004) who did not find associations between the proportion of arterials and collectors with bicycle lanes and bicycling, as well as Hoehner et al. (2005) who found that utilitarian bicycling was significantly associated with *perceived presence of bicycle lanes* but was not associated with the corresponding objective measure.

Moudon et al. (2005) also found that although perceived presence of bicycle lanes was positively associated with the likelihood of bicycling, when objectively measured, presence of bicycle lanes was an insignificant factor in predicting the likelihood of bicycling. Finally, Dill and Voros (2007) found that residing in a neighborhood with a higher density of bicycle lanes was not associated with utilitarian bicycling.

B.3.1.4 Distance to Transit

Access to transit has been quantified in previous studies using various measures including distance to transit, number of transit stations within a unit area, or number of transit stations per unit area (i.e., transit station density). Literature suggests that as a measure of access to mass transit service, distance to transit station is an important attribute of the built environment (Chen et al. 2008). This factor has a potential to influence nonmotorized trips.

Access to transit may induce walking and bicycling trips by eliminating the necessity to drive. According to a previous study, 90% of all public transit trips involve walking at both ends of the trip for access and egress, and bicycling can also be a potentially important mode of access to public transportation (Pucher et al. 2011). Residents may be encouraged to walk or bicycle to bus stops or metro stations if these facilities are nearby.

The impact of distance to local transit and other measures of access to transit on nonmotorized travel have been investigated by researchers in the past, although perhaps not to the extent of the impact of the other *Ds* of the built environment.

In an investigation of the effects of local transit accessibility, Kitamura et al. (1997) concluded that access to the Bay Area Rapid Transit (BART) system was associated with a tendency to make more nonmotorized trips. Also, bus accessibility (distance to nearest bus stop) was negatively correlated with fraction of nonmotorized trips in that study.

Cervero (2001) found that reasonable proximity to a rail transit station (measured in that study as time from residence to nearest rail station in highway network minutes) increased the likelihood of walking to the station (walking access trips). The same study found that distance from rail station to destination (measured in highway network miles) increased the likelihood of egress walking trips.

Later, Reilly and Landis (2003) showed that availability of local transit did not affect the likelihood of walking to entertainment destinations. De Bourdeaudhuij et al. (2003) found that perceived convenience of walking to a transit stop was associated with more walking.

Targa and Clifton (2005) concluded that accessibility to bus transit was associated with higher frequency of walking. Also, Ryan and Frank (2009) suggested that having transit stops nearby may encourage walking. Further, Durand et al. (2016) found that longer distances were associated with lower probabilities of walking to transit stops.

B.3.1.5 The Macro-level Built Environment

The previous discussions indicate that the relationship between micro-level (i.e., neighborhood level) built environment attributes and walking and bicycling travel behavior has been extensively examined. On the other hand, literature also suggests that to exert effects on travel, micro-level environmental factors may interact with macro-level factors (Joshu et al. 2008).

Macro-level built environment attributes, however, have not been tested in previous studies for their potential role in nonmotorized travel behavior. The most likely reason for this is that nonmotorized trips have been considered short trips occurring within the neighborhood boundaries. Nonetheless, there have been small hints in the literature for considering the effects of macro-level built environment factors on nonmotorized travel.

For example, one study that reviewed the existing literature on the relationship between physical activity such as nonmotorized travel and the built environment suggested that accessibility (at both micro level and macro level) emerges from the literature as a key factor that impacts physical activity (e.g., walking and bicycling); thus, the impact of larger geographical-scale factors such as *regional accessibility* on such activities should be examined in the future (National Research Council 2005).

As previously mentioned, different studies measure neighborhood (micro-level) accessibility in different ways (e.g., distance or travel time to transit or destinations, number of transit stations or stores in the area). Nevertheless, all of these methods quantify either destination or transit accessibility.

In a metropolitan area (macro-level) context, Hansen (1959) defined accessibility as the total number of activities (e.g., employment, residential, commercial) around a zone, adjusted for some measure of travel impedance (e.g., time, distance, cost). The paper formulated a relatively simple method for calculating accessibility within metropolitan areas, which can be used to compute macro-level accessibility measures and examine their effects on nonmotorized travel within the metropolitan area.

The literature also discusses the potential role of urban sprawl, automobile-oriented urban designs, and the associated sedentary lifestyles in walking and bicycling travel behavior. For example, King et al. (2002) suggested that automobile-oriented urban designs restrict utilitarian walking or bicycling to work or stores.

Plantinga and Bernell (2007) suggested that urban sprawl increases trip distances, which makes active travel impractical.

Also, Braun and Malizia (2015) argued that macro-level built environment factors such as urban sprawl at the regional or metropolitan level can potentially influence health behavior (e.g., walking and bicycling).

A very limited number of studies tested the effects of macro-level built environment attributes on nonmotorized travel behavior. In an attempt to examine the impact of regional-level land use on walking behavior, Greenwald and Boarnet (2001) included zipcode-level population density and retail employment density in their analysis. The study concluded that regional densities were not important factors in determining walking. The authors suggested that the effects of regional density attributes as well as other regional-level built environment measures (such as pedestrian environment and percentage of street grid orientation) should be examined in the future to allow inferences about the impact of the built environment beyond the local level.

Other studies found that the extent of urban sprawl impacted walking travel behavior. These studies used metropolitan area-level sprawl index by combining many built environment variables representing density, land use diversity, degree of centralization, and street accessibility. The studies suggested that metropolitan area-level compactness promoted walking (Ewing et al. 2003b; Ewing et al. 2008).

Also, Dill and Carr (2003) analyzed city-level data from 42 U.S. cities to examine the relationship between city-level built environment and the percentage of workers in the city that commuted by bicycle. The study found that higher levels of bicycle infrastructure in the cities were positively correlated with higher percentages of commuting by bicycle.

Leslie et al. (2007) hypothesized that the built environment characteristics of different urban regions were not homogenous. They found significant sub-regional differences in walking behavior. Particularly, living in the city inner region positively affected the likelihood of walking to a store. The study also suggested that the sprawling design of suburban areas encouraged sedentary behavior by discouraging active living choices including active travel choices.

Later, Weinberger and Sweet (2012) concluded that the influence of Walk Score (i.e., a measure for walkability of an area) on walking mode share functions at two levels: 1) the local level; and 2) the regional level. The study further concluded that potentially important differences may exist in the effects of regional built environment characteristics versus those of local built environment characteristics between trips with different purposes.

B.3.2 Psychological Factors

B.3.2.1 Attitudes, Perceptions, and Preferences

An attitude has been defined by Heinen et al. (2010) as the "expectation of all the outcomes of an activity, and the personal value of these outcomes". Others described attitudes as a reflection of "an individual's specific opinions, intentions, affections, and beliefs about something" (Handy and Xing 2011). The differences between perceptions, attitudes, and preferences have been described by Van Acker et al. (2010) who stated that *perceptions* are the way a person perceives different aspects of the built environment, activities, and travel and develops *attitudes* as an evaluation and ranking of these characteristics and formulates *preferences* based on these attitudes and perceptions.

The influence of the built environment as well as that of the health and travel-related attitudes (including those toward walking and bicycling) on travel behavior have been recognized and discussed in many research studies (see e.g., Kitamura et al. 1997; Handy and Clifton 2001; Bagely and Mokhtarian 2002; Lund 2003; Rodríguez and Joo 2004; Handy et al. 2005; Targa and Clifton 2005; Næss 2005; Agrawal and Schimek 2007; Cao et al. 2010; Handy and Xing 2011; Ma and Dill 2015).

These studies argue that pro-walking, pro-bicycling, pro-health, and pro-environment individuals are more likely to choose nonmotorized modes of travel, even if built environment attributes do not provide much support for these modes. Conversely, individuals who have pro-car and pro-driving attitudes will choose the automobile mode, even if the built environment provides relatively adequate support for alternative modes including for walking and bicycling.

Findings and arguments of a few studies related to the effects of attitudes, perceptions, and preferences on nonmotorized travel are summarized below.

Handy (1996a) found that in the decision to walk, individual motivations and limitations were more important than perceptions on neighborhood built environment characteristics. Further, Kitamura et al. (1997) found that factors related to individual's attitudes had a stronger influence on travel behavior (including nonmotorized travel behavior) than land use and socioeconomic factors. The study also found that pro-environment and pro-transit attitudes both had positive and significant effects on nonmotorized travel behavior. Porter et al. (1999) suggested that by interacting strongly with built environment and policy factors, personal attitudes affected travel behavior and mode choice, particularly for bicycling.

Later, Handy and Clifton (2001) suggested that attitudes and preferences played a role in the choice of walking to grocery stores more frequently. Bagely and Mokhtarian (2002) found that residential location type (i.e., neighborhood type) had little independent influence on nonmotorized travel behavior once attitudinal and lifestyle factors were controlled for. Lund (2003) suggested that factors representing personal attitudes were the most significant factors in determining the number of walking trips, even after controlling for built environment variables.

Stinson and Bhat (2004) indicated that pro-health and pro-environment attitudes affected bicycling in a positive direction. Targa and Clifton (2005) used attitudinal and perceptual data as proxies for psychological characteristics and found that both attitudinal and built environment attributes helped to better explain walking travel behavior. Moudon et al. (2005) found that an attitude toward physical activity benefits (i.e., a pro-health attitude) was positively associated with bicycling, and Shay et al. (2006) found that pro-walking attitudes were associated with increased numbers of walking trips. Also, Handy et al. (2006) found that pro-walking/bicycling attitudes were positively associated with walking trips for shopping as well as for strolling trips. Cao et al. (2006) concluded that a preference for walking—rather than the neighborhood built environment—explained residents' walking frequencies to shops. Goddard et al. (2006) found that pro-walk/bicycle/transit attitudes were associated with more walking for shopping. Agrawal and Schimek (2007) suggested that cultural attitudes toward walking may contribute to differences in the amount of individuals' walking for both utilitarian and recreational trips.

Additionally, Dill and Voros (2007) showed that negative attitudes toward driving as well as pro-bicycling and pro-environment attitudes increased the likelihood of commuting by bicycle. Gatersleben and Appleton (2007) also suggested that pro-bicycling attitudes were related to bicycling to work. From conducting a meta-analysis of the literature on the link between the built environment and travel behavior, Ewing and Cervero (2010) concluded that while the built environment seemed to play a more significant role in travel behavior, attitudes and preferences were also influential in making travel choices. Cao et al. (2010) found that pro-walking/bicycling attitudes were positively associated with both frequency of walking trips to store and strolling trips.

Handy and Xing (2011) found that attitudinal factors including higher scores on bicycling comfort, liking of bicycle riding, and willingness to limit driving were associated with increased likelihood of bicycle commuting. Ma and Dill (2015) found that pro-walking/bicycling/transit and pro-environment attitudes were significantly associated with utilitarian bicycling propensity, and pro-bicycling/pro-transit attitudes were significantly associated with the frequency of utilitarian bicycling trips. This study also suggested the objective built environment attributes may influence bicycling through affecting individuals' perceptions of the environment.

Finally, Schneider (2015) found that enjoyment of walking did not have a statistically significant association with walking to shopping districts, whereas Aditjandra et al. (2016) found that changes in walking were determined mostly by built environment characteristics rather than travel attitudes.

B.3.2.2 Self-selection

An important stream of nonmotorized travel behavior research—particularly as related to the built environment—addresses the issue of correlation or causality. Here, the argument is that existence of a correlation between built environment characteristics and nonmotorized travel behavior does not guarantee existence of a causal link between the two. This research specifically investigates the role of *residential self-selection* in explaining nonmotorized travel behavior. As Handy et al. (2005) suggested "understanding the role of self-selection is the key to understanding the causal relationship between the built environment and travel behavior".

Theoretical Foundations

Theoretically, self-selection confounds the analysis of the link between nonmotorized travel and the built environment due to ambiguity in the spurious or causal nature of the link. Thus, research on self-selection aims to determine whether a causal relationship exists between built environment factors and nonmotorized travel, or if the correlation observed between the two is the effect of a spurious relationship. In the latter case, the spuriousness can be due to the concurrent influence of attitudes on both the travel choices and the residential location choice (and thereby the resulting built environment) (Handy 2005; Cao et al. 2009). Figure B illustrates such spurious relationship.

The policy implications are crucial: while existence of correlations does not imply that a change in the built environment would necessarily lead to a change in nonmotorized travel behavior, causal effects will help policy arguments for interventions aiming at promoting nonmotorized travel behavior through changing the built environment. In other words, while a simple correlation cannot confirm a causal link or provide sufficient and robust evidence for policy development (Fan 2007), causal relations can provide supportive evidence for developing policies that promote pedestrian- and bicycle-friendly designs.

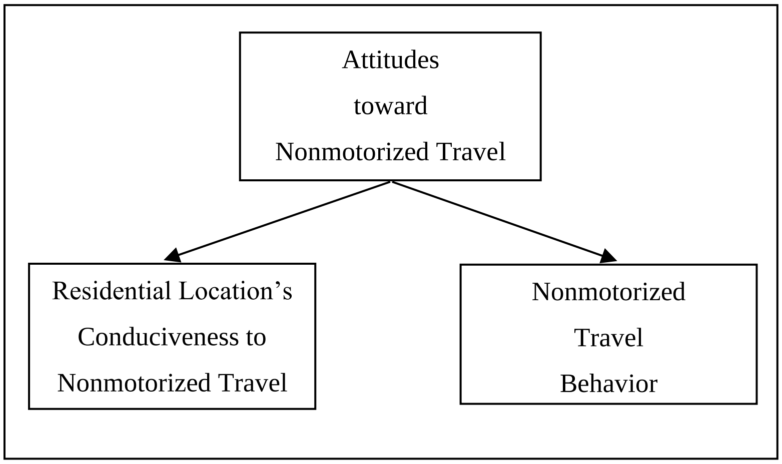

Figure B. Spurious Relationship between Residential Location and Nonmotorized Travel Behavior

In theory, residential self-selection can result from socioeconomic characteristics and/or personal attitudes (Næss 2005; Cao et al. 2009). For example, individuals with a low income or no private vehicles may choose to locate in more walkable or bikeable neighborhoods. In this case, it is not the pedestrian- or bicyclist-friendly facilities and designs but individuals' socioeconomic constraints that influence their choice of walking and bicycling modes. Further, from the preceding discussion, it is logical to think that individuals' attitudes toward travel, environment, or health are tightly interwoven with their choices of residential location, and given the chance, individuals may choose to reside in locations that satisfy their travel preferences and personal attitudes.

In other words, the theoretical idea behind the issue of self-selection mechanism as related to attitudes toward nonmotorized travel is that individuals who prefer to walk or bicycle may self-select themselves into walkable and bikeable residential locations. In this case, individuals' residential location choices—and not the effect of built environment attributes—can be considered as a possible explanation for nonmotorized travel occurring at those locations.

Therefore, observing a correlation between nonmotorized travel and the built environment does not necessarily mean that changing the built environment would lead to changes in people's nonmotorized travel behavior as individuals who prefer nonmotorized modes may select to live in neighborhoods that support that preference (Handy et al. 2006). In a sense, the self-selection argument takes into consideration individual preferences and attitudes when making residential location and travel choices. This indicates that self-selection is closely tied to attitudes and preferences, and by accounting for attitudinal predispositions, many studies have in fact been attempting to address the issue of self-selection (Handy et al. 2005).

These arguments establish that self-selection plays a key role in travel behavior, and omitting it from the analysis of the link between the built environment and travel behavior may have consequences in terms of accuracy of results and magnitude of built environment effects. Cao et al. (2009) formulated the relationship between the built environment and travel behavior as:

$$TB = f\,(BE, X) + \varepsilon \qquad \text{Equation B-1}$$

where,

TB = observed travel behavior outcome (i.e., the dependent variable);

BE = observed built environment variable;

X = other observed variables (e.g., socioeconomic factors); and

ε = the error term (i.e., unobserved variables such as attitudes and self-selection).

The standard Ordinary Least Squares (OLS) estimation of such models requires that the observed independent variables (BE and X) be nonrandom and uncorrelated with the unobserved independent variables (i.e., ε). If these requirements are violated—that is, if an observed independent variable in Equation B-1 is a random function of other independent variables in the model or is correlated with the error term—the model will become subject to the *endogeneity bias*, which produces biased and inconsistent estimations for standard errors and coefficients (National Research Council 2005; Cao et al. 2009).

For instance, if the choice of residential location (and thereby the built environment near the residence) is influenced by unobserved attitudes toward nonmotorized modes of travel (i.e., self-selection), then variables representing the built environment attributes of the residence (i.e., BE) can be correlated with the error term (i.e., ε —which may contain the effects of attitudes). In this case, the endogeneity bias manifests itself as the self-selection bias (National Research Council 2005). The self-selection of individuals into residential locations will produce biased parameter estimates if the OLS regression is used to model the travel behavior outcome (i.e., TB). This is because existence of a correlation between BE and ε will turn BE into an endogenous variable in the model (hence, the phrase endogeneity bias). An endogenous variable is one that is jointly determined with the outcome variable or is otherwise correlated with variables that influence the outcome variable despite not being included in the model (Schauder and Foley 2015).

Thus, the endogeneity bias may occur if travel attitudes and residential self-selection are not accounted for in the analysis of the link between the built environment and travel behavior. Supporting this argument are arguments by Chen et al. (2008), National Research Council (2005), and van Wee and Ettema (2016). The referenced studies suggested that in probing the role of the built environment in travel behavior or transportation-related physical activity (e.g., walking and bicycling), a study should control for residential self-selection, or it may run the risk of producing biased results by overestimating the effect of the built environment on travel choices. Other scholars agree that biased results can be produced if self-selection is not statistically controlled for (see e.g., Pinjari et al. 2007; Chatman 2009; Cao 2010; Schneider 2015).

Self-selection Studies and Empirical Findings

The role of self-selection in travel behavior has been discussed in many studies and its effects have been investigated in many empirical analyses including those focusing on the topic of nonmotorized travel behavior (see e.g., Handy 1996a; Boarnet and Sarmiento 1998; Greenwald and Boarnet 2001; Handy and Clifton 2001; Ewing and Cervero 2001; Lund 2003; National Research Council 2005; Khattak and Rodriguez 2005; Handy et al. 2005, 2006; Salon 2006; Cao et al. 2006, 2007, 2009; Frank et al. 2008; Burbidge and Goulias 2008; Chatman 2009; Cao 2010; Handy and Xing 2011; Wang 2013; Schneider 2015; van Wee and Ettema 2016).

The available empirical evidence confirms the existence of a correlation between the built environment and nonmotorized travel behavior. However, the existence of a causal link between the two requires further research as only a limited number of studies have provided formal evidence of causality. Moreover, within the existing empirical studies, ambiguity remains about the issues of causality and residential self-selection as the results from different studies are mixed.

A summary of the literature and empirical findings with respect to residential self-selection is provided below.

Handy and Clifton (2001) found that individuals with a preference to walk to stores selected to live in neighborhoods that supported this predilection. Thus, they concluded that self-selection of these residents into walk-supportive neighborhoods was a key factor in the correlation observed between walking and the neighborhood stores.

Also, Ewing and Cervero (2001) suggested that the prevalence of walking and bicycling in more traditional urban neighborhoods may be due to the self-selection effects of residents with preferences toward nonmotorized modes who chose to live in the neighborhood that supported their travel preferences (i.e., traditional neighborhood).

Further, Greenwald and Boarnet (2001) concluded that after considering the possibility of self-selection, certain characteristics of the neighborhood built environment remained significant determinants of non-work walking frequency.

Later, Lund (2003) suggested that traces of self-selection bias existed in the analysis due to residents with walking preferences self-selecting into neighborhoods with local access to retail stores.

Additionally, Rodríguez and Joo (2004) suggested that the role of preferences for travel modes and how these preferences are formed and reinforced should further be investigated in nonmotorized travel behavior research to address self-selection and causality issues. As they suggested, this should examine more integrated frameworks of residential location decisions and travel behavior that explicitly address the role of residential location characteristics that attract or repel individuals with particular travel preferences.

Cao et al. (2006b) examined the influences of built environment and self-selection factors on pedestrian strolling and shopping trips. The study found that residential self-selection impacted both types of trips, and it was the most important factor in explaining destination-oriented walking (i.e., walking for shopping purposes). Also, they inferred that after controlling for the self-selection effect, perceived characteristics of the neighborhood and local commercial areas influenced frequency of strolling and pedestrian shopping trips, respectively. Consistent with those findings, Handy et al. (2006) showed that the effects of neighborhood characteristics on walking behavior were significant, even after controlling for self-selection factors. The authors stated that this result suggested a direct causal effect by the built environment on walking behavior.

Chatman (2009) found the residential self-selection bias to be modest and not rendering the influence of the built environment insignificant. Cao et al. (2009) reviewed 38 self-selection studies and concluded that the nature and extent of the causality between the built environment and travel behavior were not clear. Also, in their meta-analysis of past studies, Ewing and Cervero (2010) concluded that including residential self-selection measures in the analysis increased the absolute magnitude of elasticities for influential built environment effects. Further, Cao (2010) found that neighborhood type played a more important role in influencing walking than did the self-selection effect. Lastly, Handy and Xing (2011) found that self-selection influenced bicycle commuting significantly as people who chose to live in locations with bicycling-friendly environment were more likely to use their bicycles to commute.

Methodologies to Circumvent Self-selection (i.e., Endogeneity) Bias

As the literature review above reveals, different researchers have tried to control for self-selection bias in different ways. The main methodologies used to address self-selection include: direct survey-based questioning, statistical control, sample selection, instrumental variables analysis, propensity score, structural equations modeling techniques, and longitudinal designs among others (Cao et al. 2009). For brevity, the discussion below will focus on a few of the most important of these methodologies—namely—instrumental variables analysis, structural equations modeling techniques, and longitudinal designs.

Many researchers have used *instrumental variable* techniques to account for the potential effect of self-selection bias. As indicated before, if the observed independent variable representing the residential location choice in Equation B-1 (i.e., BE) is correlated with the error term (i.e., ε), the parameter estimates produced by the OLS regression model can be biased and inconsistent due to the endogeneity bias.

Using instrumental variables to cleanse BE of its correlation with the error term (ε) is a common solution to remedy the endogeneity problem in the analysis. To achieve this, one must use instrumental variables that are highly correlated with the built environment variable (i.e., BE—reflecting the residential choice) but not significantly correlated with the error term (i.e., ε—reflecting preferences and attitudes) in the model (Greenwald and Boarnet 2001; Cao et al. 2009).

Thus, this technique is basically, regression analysis with multiple endogenous variables. This is because in the case of self-selection, both BE (i.e., the residential choice) and TB (i.e., the travel choice) become endogenous variables.

Using the same notations in Equation B-1 (Cao et al. 2009), and based on Wooldridge (2010), the instrumental variable analysis can be formulated by the two following equations:

$BE = f(Z, X) + \mu$ Equation B-2

$TB = f(\widehat{BE}, X) + \upsilon$ Equation B-3

where,

TB = the endogenous observed travel behavior outcome;

BE = the endogenous observed built environment variable (representing the residential location choice);

X = other exogenous observed variables (e.g., socioeconomic variables);

Z = instrumental variables representing residential location attributes that influence the choice to live in a certain location but not travel choices;

μ = the error term (i.e., unobserved variables influencing residential location choice); and

υ = the error term (i.e., unobserved variables such as travel-related attitudes influencing travel behavior).

The instrumental variable analysis consists of two stages: in the first stage, BE is modeled as a function of instruments Z, which are strongly correlated with the endogenous independent variable (i.e., BE) but are uncorrelated with the error term of the Equation B-1 (i.e., ε). In the second stage, the observed BE in Equation B-1 is replaced with its estimated value from the first stage of analysis ($\widehat{BE}$, estimated from Equation B-2).

In other words, the first stage of the instrumental variable analysis is a regression of the endogenous independent variable (BE) on the instrumental variables (Z) and the control variables (X), whereas the second stage is a regression of travel behavior outcome (TB) on estimated values of BE from the first stage ($\widehat{\mathrm{BE}}$) and the control variables (X).

By assumption, the error term in Equation B-3 (i.e., υ) is uncorrelated with ($\widehat{\mathrm{BE}}$) and the control variables (X), so the OLS can now consistently estimate the parameters in Equation B-3. Thus, the endogeneity bias in Equation B-1 due to BE being correlated with ε is corrected by using the instrumental variables analysis as formulated in Equations B-2 and B-3.

In should be noted that the instrumental variable analysis assumptions require that the Z variables (i.e., instruments) be variables that influence the residential location choice (BE) but do not also influence the travel behavior outcome of interest (TB). Because many socioeconomic and sociodemographic characteristics that influence residential location choices may also influence individuals' travel choices, caution must be taken in specifying the instrumental variables and regression models (National Research Council 2005).

Variables such as quality of neighborhood schools, tax levels, having a large backyard, and median age of the housing stock in surrounding neighborhoods have been proposed by Greenwald and Boarnet (2001) and Khattak and Rodriguez (2005) as potential instruments for the residential location choice. These two studies used instrumental variable techniques to control for the choice of residential location in examining how built environment characteristics of neo-traditional neighborhoods influenced walking trips as well as other travel behavior outcomes.

Another method to deal with self-selection bias is employment of *Structural Equations Modeling* (SEM) techniques. The SEM method allows for estimation of coefficients for multiple interrelated regression equations, simultaneously. Each equation represents a hypothesized direction of causality; thus, the SEM approach accounts for multiple directions of causality (National Research Council 2005) between multiple endogenous variables in the model.

In addition, the SEM techniques can estimate both direct and indirect effects of one endogenous variable on another. As indicated formerly, in presence of self-selection bias, both the travel behavior variable (i.e., TB) and the residential location choice variable (i.e., BE) are assumed to be endogenous variables in the model.

Applied to the concept of residential self-selection, the SEM techniques can account for multiple causal links such as the bidirectional relationships between the travel behavior and residential location choice endogenous variables, influence of attitudes on both travel and residential location, and the influence of residential location on travel behavior after controlling for attitudes. The direct and indirect effects of the residential location choice endogenous variable on the travel behavior outcome variable can be estimated by SEM as well. Literature suggests that allowing multiple directions of causality is a conceptual improvement that SEM techniques offer over the single-equation regression methodology (Cao et al. 2009).

Several past studies applied the SEM techniques to address self-selection and examine the causality of the links between travel behavior (including nonmotorized travel behavior) and the built environment.

For instance, Bagley and Mokhtarian (2002) used SEM to concurrently account for multiple directions of causality in examining the link between travel behavior and the neighborhood built environment. Their models took into consideration the effects of attitudes on travel and residential location, and the effect of residential location on travel behavior once attitudes were controlled for. Also, Cao et al. (2007) employed SEM to investigate the relationships between changes in the built environment and changes in travel behavior including walking.

The SEM has also been used in examining the link between nonmotorized travel behavior and the built environment in other countries (see Scheiner and Holz-Rau 2007).

Finally, *longitudinal designs* can be employed in the analysis of self-selection bias to avoid reliance on cross-sectional designs, which are used in many studies due to available sources of travel data. One example of application of longitudinal designs is conducting *intervention* studies, which allow for comparisons of behavior before and after an intervention (i.e., change) is applied. In the context of the role of built environment in nonmotorized travel behavior, an intervention can be defined as changes (i.e., improvements) to the existing built environment of the current residence (or workplace) (Burbidge and Goulias 2008).

Boarnet et al. (2005) is one such study, which considered travel behavior changes as a result of changes to the current built environment. The study provided an assessment of the impact of improvements in the built environment on walking and bicycling of children to school. The changes in the built environment were due to implementation of the Safe Routes to School (SR2S) program in California. The study concluded that built environment interventions related to the SR2S program increased children's walking and bicycling to school.

Another example of a built environment intervention is a move to a new location with a different built environment. In this case, employment of the longitudinal design allows the researcher to observe the longitudinal changes in the travel behavior of an individual who moves to a new residential location. The goal is to investigate the link between changes in the built environment around the new residence (in relation with the old one) and changes in travel behavior of the individual. Handy et al. (2005) used travel survey and preferences data from 688 movers in California to examine the influence of changes in the built environment on changes in travel behavior including walking, as well as to control self-selection and establish causality.

Wasfi et al. (2016) studied approximately 3,000 individuals who lived in Canada and found that moving to a neighborhood with better walkability increased the odds of moderate and high utilitarian walking by nearly 60% compared with other types of residential moves.

Also, Hirsch et al. (2014) conducted a longitudinal study to estimate the impact of neighborhood walkability on utilitarian walking of 701 older adults (45 to 84 years old) who moved to a new residential location. The study found that moving to a more walkable neighborhood (a 10-point higher Walk Score) was associated with an increase in utilitarian walking and meeting a goal of “walking more than 150 min/week”. The authors concluded that their study provided longitudinal evidence that utilitarian walking shifted in response to relocation to a residential neighborhood with higher walkability.

Causal relationships can be validly established by before-after research designs (Handy et al. 2005); thus, performing an intervention (i.e., before-after) study is a more direct way of testing for causality and self-selection. Longitudinal designs are favored over cross-sectional designs due to substantial improvements and more robust causal inferences that they provide on the link between the built environment and travel behavior (Cao et al. 2009).

Although all the different methodologies mentioned above deal with the issue of endogeneity bias (i.e., self-selection bias in this context), the strength or weakness of the specific methodology to correct for the bias depends on the data used and the complexity of the model framework. After reviewing 38 studies that controlled for self-selection bias, Cao et al. (2009) recommended the use of longitudinal structural equations modeling with control groups; a design which they argued “is strong with respect to all causality requisites.”

Table B lists all the self-selection papers reviewed for this literature review along with the methodology they used to address self-selection and a summary of their findings.

Table B. Overview of Self-selection Studies

Study	Sample	Nonmotorized Travel Behavior Measure(s)	Built Environment Measures	Attitudinal Measures	Methodology	Conclusions
Review of Self-selection Studies						
Cao et al., 2009	38 studies	Various	Various	Various	Review of past studies	Nine methodologies exist for controlling self-selection: direct questioning (survey-based), statistical control, instrumental variable analysis, sample selection, propensity score, joint discrete choice models, structural equations models, mutually dependent discrete choice models and longitudinal designs. The study recommended usage of longitudinal structural equations modeling with control groups.
Survey-based/Statistical Control						
Handy, 1996d	250 respondents from six neighborhoods in Austin, TX	Frequency of walking to the store; and frequency of strolling trips	Perceptions on attributes of the neighborhood built environment including distance to store; parking; sidewalks and trees	Several variables on individual attitudes toward walking	Simple correlations	BE and SS. In the decision to stroll, individual attitudes are more important than the urban form. Distance from home to store is the most important urban form factor in the decision to walk to store. Self-selection has an effect in walking frequency of residents in traditional neighborhoods.
Shriver, 1997	214 pedestrians from four neighborhoods in Austin, Texas	Walking trip purpose; distance; and duration	Perceptions on: continuous sidewalks or trails; canopy of trees/shades; good lighting; destinations within walking distance; traffic	Several attitudinal variables on the importance of conditions for walking and importance of walking as an opportunity to maintain health and be around people	Descriptive analysis; Spearman's correlations	BE and SS. In traditional neighborhoods, walkable distances to stores, work, entertainment and transit are more important factors as well as the attitudes toward being outdoors. In modern neighborhoods, walkway continuity and trees are more important built environment factors, and as are the attitudes toward maintaining health and fitness.
Kitamura et al., 1997	963 households in the San Francisco Bay Area, California, 1993	Number of nonmotorized trips; fraction of nonmotorized trips	Residential density; land use mix; and rail transit accessibility	Several attitudinal factors	Linear regression	BE < SS. Attitudes have more explanatory power in explaining the variation in travel behavior, but residential environment also exerts influence on travel behavior. Making walking and bicycling trips is strongly associated with attitudes toward the environment and public transit.

Handy and Clifton, 2001	1,368 individuals and 75 interview participants in Austin, TX, 1995	Frequency of walking to store	Distance to store; neighborhood dummy; perceived store characteristics	Several attitudinal factors representing perceptions on walking safety and comfort	Descriptive analysis; and linear regression	BE and SS. Distance to local stores and the characteristics of stores influence the frequency of walking; however, the authors also suggested that "having the option to walk to the store is to some extent an effect of the desire to walk to the store".
Shay et al., 2005	348 adult residents of Southern Village in Chapel Hill, North Carolina	Number of internal utilitarian walking trips; and walk mode choice	Distance from home to commercial center	Personal attitudinal factors on: enjoying walking; considering environment important; and valuing stores and services nearby	Negative binomial regression	BE and SS. Positive attitudes toward walking are associated with more walking trips. Distance is negatively related to walking.
Næss, 2005	1,406 residents of Copenhagen, Denmark	Trip distance by walk/bicycle mode on weekday	Local area density; location of the residence relative to downtown; distance from the residence to closest second-order center; distance from the residence to the closest urban rail station	Additive indices for attitudes toward transport and environmental issues	OLS	BE < SS. Having car-oriented attitudes is related to lower proportions of walk/bike travel. The influences of the built environment variables are considerably lower than the effects of travel-related attitudes.
Handy et al., 2006b	1,480 (walking to store) and 1,534 (strolling) respondents in Northern California, 2003	Frequency of walking to store; and frequency of strolling	Objective measures of "Neighborhood Type" (neighborhood selection based on neighborhood type, size of the metro area, and region of the state); and neighborhood destination accessibility	Various measures for residential preferences and travel attitudes	Negative binomial regression	BE and SS. Pro-bike/pro-walk and pro-transit attitudes as well as preferences for physical activity options and having stores within walking are positively associated with both utilitarian walking and strolling frequency. Neighborhood built environment characteristics are significant in the analysis, even after accounting for attitudes and preferences; thus, the built environment has a causal influence on walking.

Cao et al., 2006	1,368 individuals in Austin, TX, 1995	Frequency of strolling; and frequency of walking to store	Objective and perceived neighborhood characteristics (safety, traffic, shade, etc.); and perceived store factors (pedestrian connections, traffic, walk comfort, etc.)	Residential preference based on stores being within walking distance	Negative binomial regression	BE and SS. Residential preference is the most important factor explaining the frequency of walking to store. Among built environment factors: a) neighborhood characteristics (particularly, perceptions of these characteristics) influence strolling frequency; and b) characteristics of local commercial area influence walking trips to stores.
Salon, 2006	4,382 respondents to the Regional Travel-Household Interview Survey in New York City	Walking level (none, some, a lot)	Population density		Multinomial logit model	BE > SS. Residential self-selection accounts for between one-third and one-half of the total effect of the built environment (population density in this study) on walking level.
Fan, 2007	7,422 respondents in Orange, Durham, and Wake Counties in North Carolina	Walking trip duration; and bicycling trip duration	Population density; employment density; % of retail uses; % of industrial uses; land parcel count; retail count; industrial count; connected node ratio; and sidewalk coverage	Household location choice factors (length of commute and access to transit) to represent attitudes toward travel time; travel distance; alternative mode choice; and self-selection	OLS	BE and SS. Positive attitudes toward transit are associated with more time allocated to walk and bike trips. Built environment attributes of residence location also influence walk/bike trip time allocation.
Chatman, 2009	999 adults in San Francisco and San Diego metro areas, California, 2003 and 2004	Number of non-work walk/bicycle trips	Objective measures: number of retail workers; residents per road mile; four-way street intersections; presence of a heavy-rail station; presence of a light-rail station; distance to the nearest major CBD. Subjective measure: whether there is a sidewalk on both sides of the street	Preferences for neighborhood characteristics and travel modes (auto, transit, walk/bicycle)	Negative binomial regression	BE > SS. Mode preferences affect nonwork walk/bicycle travel; and The built environment independently affects nonwork walk/bicycle travel after controlling for preferences.

Ma and Dill, 2015	616 adults in Portland, Oregon	Propensity of utilitarian bicycling in the past month; number of days of utilitarian bicycling in the past month	Objective measures (for 1/2-mile circular buffers around home) including miles of off-street bike path; miles of bike lanes; miles of minor streets; number of retail jobs; terrain (% area with a slope greater than 25 percent)	Factor scores on attitudes: pro-walk, pro-bike, pro-transit, safety, pro-environment, anti-car	Two-step modeling: first, binary logistic model; second, multivariate linear model	BE and SS. Miles of bicycle path and bicycle lanes, miles of minor streets, and number of retail jobs within the neighborhood influence the utilitarian bicycling propensity. Pro-bike/pro-walk/pro-transit and pro-environment attitudes are significantly associated with utilitarian bicycling propensity. Pro-bike/pro-transit attitudes are significantly associated with utilitarian bicycling trip frequency. Perceived and objective measures of destinations within bicycling distance as well as perceptions on quiet streets are positively associated with bicycling frequency.
Quasi-longitudinal Analysis and Longitudinal Designs						
Handy et al., 2005	688 movers in Northern California, 2003	Change in walking	Objective measures of "Neighborhood Type" (neighborhood selection based on neighborhood type, size of the metro. area, and region of the state); and neighborhood destination accessibility	Various measures for residential preferences and travel attitudes	Simple bivariate analysis	BE > SS. Neighborhood characteristics have the strongest association with changes in walking. Perceptions on higher neighborhood accessibility, physical activity options, safety, socializing, and attractiveness promote walking.
Boarnet et al., 2005	862 respondents to the SR2S program across 10 schools in California, 2002	Walking/bicycling to school	SR2S project improvements including sidewalk, crossing and traffic control improvements		Two-sample t-test (for a pre-test and post-test research design)	BE. All built environment improvements supported by the SR2S program appear to increase children's walking/bicycling to school.
Handy et al., 2006b	1,505 movers in Northern California, 2003	Change in walking (including walking to the store and strolling as well as other walking in the neighborhood); and change in bicycling	Objective measures of: "Neighborhood Type" (neighborhood selection based on neighborhood type, size of the metro. area, and region of the state); and neighborhood destination accessibility	Various measures for residential preferences and travel attitudes	Ordered probit model	BE and SS. An increase in perceptive neighborhood attractiveness and higher levels of the pro-bike/walk attitudes has a positive impact on changes in walking and bicycling. Changes in measures of the built environment and destination accessibility measures also have a positive impact on changes in walking and bicycling, even after controlling for residential preferences and attitudes.

Hirsch et al., 2014	701 movers in Baltimore, MD; Chicago, IL; Forsyth County, NC; Los Angeles, CA; New York, NY; and St. Paul, MN, 2000–2002	Minutes of transport walking/week; minutes of leisure walking/week; meet the goal of "walking minutes ≥ 150/week"; BMI	Walk Score		Chi-squared test; t-test; and analysis of variance (ANOVA)	BE. Moving to a location with higher walkability is associated with an increase in transport walking and a decrease in BMI.
Wasfi et al., 2016	2,976 individuals in Canada	Four levels of utilitarian walking from none to high (≥ 6 hours per week)	Walk Score		Binary logistic regression model	BE. Moving to more walkable neighborhoods is associated with increases in utilitarian walking.
Aditjandra et al., 2016	192 movers from 10 communities in the metropolitan area of Tyne and Wear, in northeast England	Changes in walking	Subjective neighborhood measures (factor scores) based on safety, accessibility, residential spaciousness and attractiveness	Various measures on residential preferences and travel attitudes	Ordered logit model	BE > SS. Changes in walking are determined by built environment attributes such as accessibility. Pro-walk attitudes promote walking.
Propensity Score Analysis						
Boer et al., 2007	10 metropolitan areas in the 1995 NPTS	Choice of walking	Land use mix; housing density; housing age; block length; parking pressure; share of four-way intersections		Propensity Score Matching	BE and SS. Built environment factors have a limited (and sometimes insignificant) effect on walking after propensity score matching analysis.
Cao, 2010	1,553 residents from Northern California, 2003	Frequency of strolling; frequency of walking to the store	Neighborhood Type: Traditional vs. suburban neighborhoods	Various measures for residential preferences and travel attitudes	Propensity score stratification and binary logistics regression	BE > SS. Neighborhood type plays a more important role in influencing walking than does self-selection. However, not controlling for self-selection may lead to overestimation of the causal effects of neighborhood type for both utilitarian and recreational walking frequency.

Instrumental Variable Analysis						
Greenwald and Boarnet, 2001	1,091 individuals from the 1994 Household Activity and Travel Behavior Survey in Portland, Oregon	Frequency of non-work walking trips per person over two days	Population density; retail employment density; street grid pattern; and pedestrian environment factor at census block group, census tract and zip code levels		Instrumental variable regression	BE. Built environment attributes influence the frequency of non-work walking at the neighborhood level, even after controlling for the residential self-selection effects.
Khattak and Rodriguez, 2005	Survey of 453 households in Chapel Hill and Carrboro, North Carolina	Frequencies of walking trips; trip distance; and trip duration	Neo-traditional and suburban neighborhoods	Eight attitudinal factors (attitudes toward residential spaces and the environment)	Instrumental variable regression	BE. The built environment influences most measures of travel behavior, even after controlling for attitudes toward residential location. Neo-traditional neighborhood households substitute alternative modes (e.g., walking) for driving trips.
Structural Equation Modeling (SEM)						
Bagley and Mokhtarian, 2002	515 individuals in the San Francisco Bay Area, California, 1993	Average daily miles traveled by walking/bicycling	Neighborhood type (traditional vs. suburban neighborhoods) factor scores based on various measures such as residential density and land use mix	Various lifestyle and attitude factor scores	Structural equations model	BE < SS. Residential location (neighborhood) type does not influence nonmotorized travel behavior. Attitudinal and lifestyle factors have a more important impact on nonmotorized travel behavior.
Cao et al., 2007	547 mover respondents from Northern California, 2003	Respective changes in walking (and driving)	Number of different types of businesses within specified distances; distance to the nearest locations of each business type. Subjective neighborhood characteristics and their changes	Various measures for residential preferences and travel attitudes	Structural equations model (with a quasi-longitudinal analysis)	BE and SS. Attitudes and residential self-selection influence walking travel behavior; and The built environment also has a separate (i.e., independent) effect on walking.
Scheiner and Holz-Rau, 2007	Survey of 2,691 residents in Cologne, Germany, 2002–2003	Nonmotorized mode use	Quality of transit; density of supply (sum of retail, services and leisure opportunities per km squared); and mixed use	Lifestyle and life situation factors and attitudes toward residential choice	Structural equations model	BE and SS. Lifestyle factors and attitudes influence both the choice of residential location and nonmotorized travel behavior; and Built environment factors are also associated with nonmotorized trips.

NOTES: also, see Table 1 in Cao et al. (2009) for more information on studies addressing self-selection; BE = Built environment; SS = Self-selection

B.3.2.3 The Social Environment: Social and Cultural Norms, Crime, and Perceptions of Crime

Research suggests that factors related to the social environment such as social and cultural differences influence nonmotorized travel. Many studies suggest that factors representing social norms, social values, public image, and prestige appear to impact nonmotorized travel (Pucher et al. 1999; McMillan 2005; Plaut 2005; McDonald 2005; Agrawal and Schimek 2007; Boer et al. 2007; Yarlagadda and Srinivasan 2008; Giles-Corti et al. 2009; Heinen et al. 2010; Handy and Xing 2011; Harms et al. 2014; Musselwhite et al. 2015; Gowdin and Price 2016).

Social norms have been defined by Heinen et al. (2010) as values and "norms held by a society, or by smaller groups, which influence and regulate individual behavior by functioning as informal social controls". It is assumed that to better fit a society or group, individuals may adapt their behavior in line with the norms of that society or group (Heinen et al. 2010). Others simply described social norms as the perceived need to comply with the perceived beliefs of the society (van Loon and Frank 2011), or perceived social pressure to perform or not perform a certain behavior (Montano and Kasprzyk 2008; Van Acker et al. 2010).

Literature postulates that social norms can influence travel behavior by socializing the residents of a certain area into a travel culture, which may be influenced by the structural characteristics of an urban area (Næss 2005). In this context, social norms can play an important role in the choice of alternatives to driving such as walking and bicycling as well as riding the public transit (Handy 2005). For example, Ross (2000) argued that due to walking being an outdoor and visible activity, individuals may see others walking for various purposes and adopt that behavior themselves. Also, based on a thorough literature review, Heinen et al. (2010) suggested that social norms and values have a significant effect on commuting by bicycle; if the individual lives or works where social norms and values accept bicycling to business or work, then there is a higher chance that the individual will bicycle to work.

The effects of social norms and *culture* on nonmotorized travel can come from a variety of sources including the geographic context of current or prior residence (i.e., country, region, metropolitan area, and city). In line with this argument, Handy (1996c) suggested that in travel behavior research, geographical context is important due to the role of culture, and Bauman et al. (1999) suggested that cultural norms regarding physical activity (including walking) can be interrelated with geographical location and can subsequently influence human behavior.

Two empirical studies lend support to this hypothesis as they found that the likelihood of children walking and bicycling to school decreased if they had a parent who was born in the U.S. (McMillan 2003), and that neighborhoods with higher percentages of immigrants had higher levels of walking to school by children (McDonald 2005). The former study concluded that these findings confirmed that cultural and societal differences may exist when it comes to “accepted/preferred modes of travel”—which in this case, validates the “popular image of the U.S. car-dominated culture” (McMillan 2003). The latter study suggested that further research into the role of neighborhood’s social environment on children’s school and non-school travel was needed.

Moreover, literature suggests that differences in nonmotorized travel behavior exists among different metropolitan areas. In examining data from the Baltimore metropolitan region, Targa and Clifton (2005) mentioned some concern regarding the potential transferability of the results to other geographical locations (presumably, other metropolitan areas or cities).

Other research suggested that the culture and nature of nonmotorized travel vary among different countries. Pucher et al. (1999) stated that in some European countries such as the Netherlands and Denmark, bicycling for all purposes by all people in considered a “normal thing” regardless of age, social status, or income levels, whereas in the U.S., bicycling is mainly recreational and performed by men. The authors suggested that culture and custom (social norms) are key factors in affecting bicycling levels in a country.

In her review of the literature, McMillan (2005) briefly discussed the differences in modal splits—particularly walking and bicycling modes—between the U.S. and many other countries. The author suggested that although these differences in modal distributions may be partially due to the more pedestrian- and bicycle-friendly urban form in other countries, "cultural" differences may also play a role, and research is needed to determine if these cultural differences would still hold if an individual moved to the U.S. (McMillan 2005).

Giles-Corti et al. (2009) suggested that cross-cultural differences may exist for families in children's walking activities with more supportive societal attitudes in European countries compared with Australia and the U.S. The authors suggested that these cross-cultural differences merited further investigation. Several other studies have discussed differences in levels of nonmotorized travel among different countries (see e.g., De Bourdeaudhuij et al. 2003; Heinen et al. 2010; Pucher et al. 2010; Buehler et al. 2011).

Social norms and sociocultural values have a potential to influence nonmotorized travel behavior in both positive and negative directions. With regards to a positive influence, the concept of *observational learning*—defined within the social cognitive theory—and the concept of *contagion perspective* can be applied to nonmotorized travel behavior. Observational learning influences human behavior in the direction of performing the behavior. The contagion perspective concept posits that behavior can be spread within the community because individuals are influenced by others around them and may copy their behavior (Ross 2000).

Based on both the notions of observational learning and contagion perspective, it can be assumed that individuals who see others walk and bicycle are encouraged to engage in such activities. Literature suggests that social and cultural support including frequently observing others engage in physical activity increases the levels of such activity (Trost et al. 2002), which can include walking and bicycling. Others argued that in cities where more workers engage in commuting by means of walking or bicycling, these alternatives to driving may be culturally more acceptable or even admired (Godwin and Price 2016). Other research suggested that seeing others walk, may lead to adopting that behavior (Ross 2000).

Empirical research by Dill and Voros (2007) confirms these arguments as they found adults who stated they observed others bicycle on their street once a week or more were more likely to be regular bicyclists themselves. Further, although not explicitly stated in their paper, Mitra and builing (2012) operationalized the concept of observational learning by using a “walking density” variable (defined as total work and school-related walking trips produced by residents of a TAZ divided by the area of the TAZ) in modeling children’s active travel mode choice to school. They found that the walking density near both the place of residence and school was associated with active travel to school, which showed that a child was more likely to walk or bicycle to school in locations where others also walked.

Another empirical study also found that propensity for utilitarian bicycling was associated with a supportive social environment such as having family members, friends, or colleagues who rode a bicycle for utilitarian purposes (Ma and Dill 2015). In addition, Nehme et al. (2016) found that neighborhood recreational walking was associated with perceptions about others being physically active (engage in walking and bicycling among other activities).

On the other hand, the social environment and sociocultural norms can negatively influence nonmotorized travel behavior through concepts such as *public prestige* and *social stigma*. Researchers have suggested that existence of societal barriers such as the social stigma attached to utilitarian walking or bicycling may discourage these activities (Lumsdon and Mitchell 1999).

Moreover, it is likely that other factors such as *crime* rates, which are related to the social environment, play an integral role in the decision to walk or bicycle (Demetsky and Perfater 1975; Boer et al. 2007; Agrawal and Schimek 2007). Past research found higher levels of crime to be associated with lower levels of walking to school (McDonald 2005). Nonetheless, in a review of the literature that examined the link between neighborhood crime and physical activity such as walking, Foster and Giles-Corti (2008) stated that studies probing this link have reached inconsistent findings. Thus, they concluded that there is insufficient evidence on the link between crime-related safety and physical activity (inclusive of walking). The authors also suggested that perceptions of crime may have a stronger influence on behavior than objective crime measures.

Empirical findings by Nehme et al. (2016) showed that neighborhood recreational walking was inversely associated with concerns about crime. The findings confirmed that perceptions of crime were more strongly linked with walking than objective measures of crime as walking and the number of violent crimes within the neighborhood were not significantly associated.

Joh et al. (2009) found that violent crime rates had a negative effect on walking, even after controlling for built environment variables. The study suggested that crime and perceptions of crime may have a stronger effect on walking than built environment factors. Other empirical research also found that perceptions of crime were negatively associated with nonmotorized travel—particularly with walking (Ross 2000). Other researchers did not find any relation between walking and perceived safety from crime (De Bourdeaudhuij et al. 2003).

B.3.3 Socioeconomic and Sociodemographic Factors

Many empirical studies have included socioeconomic and sociodemographic attributes such as age, gender, income, status of driver’s license, and car ownership status in their analyses to investigate how these factors affect nonmotorized travel behavior by individuals.

Age and *gender* did not enter as significant factors in the non-work trip model in Cervero and Kockelman’s study (1997); however, their personal business and work trip models indicated that the probability of making a nonmotorized trip was lower for males. The authors suggested that individuals with limited access to personal vehicles, without a driver’s license, of younger age, and from poorer households were more likely to walk or ride bicycles. Also, Kitamura et al. (1997) found that age was an insignificant determinant of nonmotorized trip generation. *Vehicle ownership* and having a *driver’s license* were both found to be negatively associated with the use of nonmotorized modes of travel in that study.

Hess et al. (1999) found that in suburban areas a substantial share of pedestrian trips was made by young individuals (under age 18). Considering the *race* of walkers, this study also found that a disproportionately high number of non-White individuals walked in both urban and suburban areas. Ross (2000) concluded that residents of *low-income* (i.e., poor) neighborhoods as well as residents of neighborhoods where a high percentage of residents had a college *education* were more likely to walk. Troped et al. (2001) found that age and gender were associated with bicycling as males and younger individuals used the bicycle trail under investigation more. They also found that higher education was positively related to the use of the bicycle trail.

Cervero and Duncan (2003) found that *physical disability* and household’s car ownership were negatively associated with the likelihood of walking. Additionally, they found that compared with Whites and Asian Americans, African Americans were more likely to walk or bicycle. Study findings further indicated that males were more likely to walk and bicycle than females. The results of this study also suggested that living in a low-income neighborhood had a negative correlation with walking and bicycling, although this correlation was not statistically significant.

Targa and Clifton (2005) found that individuals who were younger, male, non-licensed driver, full-time worker, healthy as well as individuals with higher educational levels, with a lower number of vehicles and with a higher number of bicycles in the household, and individuals from lower-income households walked more frequently. Plaut (2005) found that age was correlated with a higher propensity of walking to work and that higher income was associated with a lower likelihood of nonmotorized commuting. The study also reported that non-White workers and females were less likely to walk or bicycle to work and car ownership was strongly correlated with lower probabilities of choosing the walking or bicycling modes.

McDonald (2005) found that a child's age had a strong effect on the likelihood of walking to school. Being female decreased the probability of walking to school only by a slight amount according to the results of this study, so the author suggested that gender may not have an effect on walking to school. Further, race was not an important factor in predicting the probability of walking trips to school. The study also found that high-poverty neighborhoods had higher levels of walking. Moudon et al. (2005) found that the likelihood of bicycling increased for White, middle-aged, and male individuals as well as for individuals who owned a bicycle. Based on the results of this study, household income did not indicate a significant relationship with the likelihood of bicycling. On the other hand, the number of cars in the household was positively associated with the likelihood of bicycling. This study argued that in the case of bicycling, socioeconomic characteristics play a more important role than built environment factors.

Cao et al. (2006) found that older individuals were more likely to stroll around the neighborhood, and *presence of children* in the household induced more strolling trips but fewer shopping trips. Kerr et al. (2007) found that in general, the lowest income group was significantly more likely to walk than the highest income group in their sample. Further, the study found that more urban form variables were related to youths' walking in households with more cars. Agrawal and Schimek (2007) showed that higher income was correlated with more recreational pedestrian trips but fewer utilitarian trips. The study found that race and ethnicity had an impact on walking and suggested that cultural attitudes toward walking and physical activity could contribute to the differences between the likelihood of walking by individuals with different races.

Merom et al. (2010) found that significantly lower levels of health-enhancing walking were reported by men, middle-aged adults and people with more cars in their household. Also, higher levels of health-enhancing bicycling were reported by men, younger individuals, full-time workers, and high-income earners. Further, Heinen et al. (2010) concluded that the relationship between bicycling and age, income, and gender was unclear. However, car ownership had a negative effect on bicycling, whereas bicycle ownership had a positive effect on bicycling.

McDonald et al. (2011) found that being male was positively associated with walking to school by children. The study also concluded that children who lived in households that did not own a vehicle had a higher probability of walking or bicycling to school. Mitra and Buliung (2012) argued that a household's car ownership was negatively associated with walking/bicycling to school and that the male students were more likely to walk and/or ride their bicycle to school.

Further evidence for the effects of socioeconomic and sociodemographic factors on nonmotorized travel behavior has been provided by many previous studies on walking and bicycling travel.

B.4 Health Literature

The reason for the interest of public health researchers in the topic of walking and bicycling is twofold: 1) concerns about the deterioration of the public health; 2) concerns about the costs of these health problems. According to Khattak and Rodriguez (2005), in 2000, approximately 65% of the U.S. population was overweight and approximately 30% was obese and these health problems cost tens of billions annually. The authors suggested that automobile dependency (less nonmotorized travel) was partially to blame for these health issues; therefore, the health impacts of transportation activities were crucial and needed to be examined (Khattak and Rodriguez 2005).

A more detailed review of the studies that examined the association between health, nonmotorized travel behavior, and built environment characteristics is presented in this section. Additionally, the role of other travel-related behavior such as that of telecommuting in health will be reviewed per the limited literature that exists in this area of research.

B.4.1 Health and Nonmotorized Travel Behavior Literature

The impact of nonmotorized travel or *active travel*—as more typically called in the health-disciplined literature—on health has been studied by many researchers in the past. Active travel has been defined by Ciles-Corti et al. (2009) as travel by means of walking, bicycle, and other nonmotorized vehicles. Walking and bicycling are considered common and popular types of physical activity (Boarnet 2004; Lee and Moudon 2004; DHHS 2008); therefore, some health studies refer to these activities simply as *physical activity*.

Previous research also deems walking and bicycling as important, more affordable, more effective, and more sustainable means of staying physically active, and therefore, means to benefit the public health (Lee and Moudon 2004; Moudon et al 2005; Frosyth et al. 2008).

Active travel has been suggested to lower risks of an array of health problems and diseases including mortality, overweight, obesity, and other chronic diseases (Andersen et al. 2000; Lindström 2008; Buehler et al. 2011; Nehme et al. 2016; Liao et al. 2016).

The health benefits of even a small amount of walking and bicycling are well documented (Pollock et al. 1978; DHHS 1996; Oja et al. 1998; National Research Council 2005; Oja et al. 2011). To attain health benefits, the U.S. Department of Health and Human Services (DHHS) and the Centers for Disease Control and Prevention (CDC) recommend 150 minutes of moderate-intensity physical activity (e.g., brisk walking or bicycling) per week for adults, which can translate into 30 minutes of physical activity each day for five days a week (DHHS 2008, 2018; CDC 2019). Although many types of physical activity can satisfy these recommendations, literature suggests that walking and bicycling (i.e., unstructured physical activity) are more cost effective than structured exercises (Moudon and Lee 2003; Moudon et al. 2005; Burbidge and Goulias 2008).

Empirical evidence for health benefits of walking and bicycling is abundant. For instance, Andersen et al. (2000) found that bicycling to work destinations lowered the risk of mortality by approximately 40%, after adjusting for other factors including leisure time physical activity.

Frank et al. (2004) found a reduction in the likelihood of obesity by approximately 5% for each additional kilometer walked per day. In contrast, the study results also showed an increase of 6% in the likelihood of obesity for each additional hour spent in a car per day. The study concluded that travel behavior patterns (including walking behavior) are important predictors of obesity and policy interventions aimed at distance walked can be supportive of health.

Further, Smith et al. (2008) concluded that higher levels of walking among neighborhood residents helped lowering individuals' risk of obesity as higher proportions of residents who walked to work were associated with lower BMI and lower risk of overweight and obesity.

Samimi and Mohammadian (2009) and Samimi et al. (2009) examined the effects of travel behavior on health outcomes including obesity. Although nonmotorized travel behavior was not controlled for in these studies, their findings did show that increased automobile use was correlated with higher rates of obesity and lower rates of general health. Increased transit use was associated with lower rates of obesity, improved general health, but also with higher levels of asthma.

Schauder and Foley (2015) used individual-level survey data to examine the effects of number of minutes of walking and bicycling on ten health outcomes including BMI, obesity, cholesterol, and general health. The study found that after accounting for endogeneity, active travel was negatively correlated with weight variables (BMI and obesity) and cholesterol levels.

Tajalli and Hajbabaie (2017) showed that walking was associated with lower probabilities of obesity, hypertension, diabetes, and mental disorders.

B.4.2 Health and Built Environment Literature

Researchers argue that increasing daily levels of active travel through interventions that improve the pedestrian friendliness and bikeability of the built environment can be more effective than encouraging people to participate in structured physical activities such as exercise classes (Samimi et al. 2009; Samimi and Mohammadian 2009). Therefore, examination of the effects of active travel on health has more often been conducted in a framework that included built environment factors as well.

The relationship between the built environment and health is rather a complex one. That is in part due to the potential of the built environment to influence health both directly through availability/absence of services and qualities that can improve/worsen health (e.g., level of access to healthy food outlets, ambient air quality), and indirectly through promoting health-behavior (e.g., active travel choices).

Kent and Thompson (2012) identified three key domains through which the built environment can influence human health: 1) physical activity; 2) social interaction; and 3) access to healthy food. The authors suggested that these three domains address three major health risk factors for chronic diseases—namely—physical inactivity, social isolation, and obesity.

Other literature also suggests that built (i.e., physical) environment attributes can play important roles in physical (in)activity (see e.g., Trost et al. 2002) by facilitating or constraining physical activity (King et al. 2002; National Research Council 2005).

Moreover, McCann and Ewing (2003) argued that the design of communities (i.e., the built environment) can influence weight by encouraging or discouraging physical activity. For example, a built environment supportive of active travel (with pedestrian and bicyclist facilities and infrastructure) can promote a healthy weight by promoting walking and bicycling, which are important types of physical activity.

A comprehensive study of the effects of the built environment on physical activity (National Research Council 2005) provided a conceptual framework, proposing that the built environment of both the neighborhood and the region may play important roles in the amount of physical activity (e.g., walking and bicycling) performed by residents.

Further, a built environment that is supportive of physical activity—especially in the form of walking—can create opportunities for social interaction (Boniface et al. 2015), which can in turn, have a positive health impact. Social interaction can also be influenced by the built environment in various other ways. For instance, existence of public spaces (e.g., parks, playing fields, outdoor food courts) as well as mixed-use developments can encourage individuals to spend time outside, engage in social activities, and interact with other community members—all of which can contribute to their psychological health.

In addition, the built environment can impact health by facilitating or constraining access to healthy food. An example of facilitated access to healthy food through the built environment is existence of farmers markets within communities, which facilitates access to fresh produce including farm-produced fruits, vegetables and herbs. Literature has postulated that sprawling metropolitan areas can impact health of residents through restricting access to healthy food (see e.g., Ewing et al. 2014).

The role of the built environment in health as discussed in past research is reviewed in the next subsections with respect to applicable theoretical foundations as well as the findings of empirical studies.

B.4.2.1 Theoretical Foundations

As mentioned previously, the influence of the built environment on health is mainly viewed through the lens of indirect effects of the built environment on health outcomes by promoting or restricting health behavior such as physical activity. Therefore, the behavioral theories discussed in Subsection B.2.1 can provide the basis for physical activity behavior (e.g., active travel behavior) in health-related research.

Specifically, the theory of planned behavior (Ajzen 1991) enables researchers to account for the influence of subjective measures of the built environment (i.e., attitudes and beliefs about the surrounding built environment) on health behavior such as physical activity.

The social cognitive theory (Bandura 1986) would allow focusing on reciprocal relationships between personal characteristics (e.g., attitudes about the built environment features), the social environment (e.g., social and cultural attributes of the surrounding environment) and health behavior (e.g., physical activity levels).

Evolved from the social cognitive theory, the ecological models of behavior can also be used to model health behavior such as physical activity and active travel. Ecological models of behavior incorporate objective measures of the built environment in their frameworks; therefore, they offer a more comprehensive approach to examine the link between the built environment and health behavior (Sallis et al. 2008) such as physical activity and active travel.

Although not explicitly a theory, the theory on the direct influence of the built environment on health consists of an assembly of ideas about certain qualities or characteristics of the built environment that may influence health directly (e.g., ambient air quality, access to healthy or unhealthy food outlets).

B.4.2.2 Empirical Studies

Various aspects of the built environment have been found in prior research to affect various aspects of health. The health indicators under investigation in these studies range from obesity and other weight-related indicators to respiratory diseases including asthma (see e.g., Ewing et al. 2003b; Kelly-Schwartz et al. 2004; Frank et al. 2004, 2005; Smith et al. 2008; Samimi et al. 2009; Samimi and Mohammadian 2009; Timperio et al. 2010; Marshall et al. 2014; Schauder and Foley 2015). Most of the attention, however, seems to be concentrated on obesity.

The CDC defines *obesity* as having a body mass index (BMI) of 30 or higher, and *overweight* as a BMI between 25 and 30 (CDC 2018). The main cause of overweight and obesity have been noted as an imbalance between calories consumed through food and beverages and calories expended through physical activity as well as other activities (DHHS 2008; Ewing et al. 2014). Obesity is the condition at which health problems are likely to develop (Gochman 1997).

The association of obesity with several health conditions and diseases including hypertension, diabetes, asthma, cancer, and heart disease is well established (Mokdad et al. 2001; McCann and Ewing 2003; Kelly-Schwartz et al. 2004; Maddock 2004; Frank et al. 2004; Smith et al. 2008; Ewing et al. 2014; Meehan 2015). Due to being a contributing factor to having these chronic health issues, obesity is considered a risk factor and the culprit behind many health problems.

Empirical finding provide evidence that built environment factors can affect health outcomes including obesity. A summary of a few of studies probing the link between the built environment and health outcomes is provided below.

Empirical Findings on the Link between Physical Health and the Built Environment

Frank et al. (2004) examined the relationship between obesity, BMI, the built environment of the immediate neighborhood, and travel behavior including walking. The built environment factors were objectively measured within a one-kilometer network distance of the survey participants' home. The results showed a reduction in the likelihood of obesity by approximately 12% for a 1-quartile increase in land-use mixing. The study concluded that measures of built environment are among the essential predictors of obesity, and that policy interventions aimed at increasing land use mix can promote health. Street connectivity (i.e., intersection density) and residential density showed insignificant effects in the obesity model in this study.

Frank et al. (2005) concluded that mixed land use, residential density, and intersection density were correlated with minutes of moderate physical activity per day (representing a health outcome). Smith et al. (2008) concluded that the risk of obesity was lower among persons living in older and in more pedestrian-friendly neighborhoods. Also, a difference in body weight was observed between individuals living in most and least walkable neighborhoods. The study also found that pedestrian-friendly street network designs lowered the risks of being overweight or obese. Also, the authors suggested that future studies examining the link between weight-related measures and the built environment would benefit from including measures of the food environment as an environmental factor that supports healthy behavior.

Samimi et al. (2009) showed that larger block sizes had positive effects on general health. County-level road density, intersection density, and population density did not show significant impacts on general health. Block size showed a positive correlation with obesity, whereas road density, intersection density, and population density exhibited negative effects in the obesity model. The authors suggested that people living in urban areas were less likely to be obese.

Samimi and Mohammadian (2009) found that larger average block sizes were associated with higher obesity rates but also with improved general health. Average block size was negatively related to asthma rates in this study. Population density did not show any significant impact on general health, asthma, or obesity. Timperio et al. (2010) found that children's BMI z-score was inversely associated with the number of sport/recreation public open spaces and the length of local roads, whereas the BMI of mothers was associated with the length of walking/bicycling tracks. Their other results showed that the proportion of four-way intersections within the neighborhood was negatively associated with a change in the BMI z-score among children.

Further, literature suggests that residents of more compact counties have lower BMIs (Ewing et al. 2003b, 2008; Ewing et al. 2014), and lower probabilities of obesity, diabetes, high blood pressure, and heart disease (Ewing et al. 2014). In the latter study, however, moderate physical activity was negatively related to county compactness. Compactness was measured based on a sprawl index, which combined factors representing density, land use mix, centering of jobs and population, and street network design.

The possibility of bidirectional causality between physical health indicators and the built environment has also been examined in past research. Using samples of recent movers whose county of residence changed between 1998 and 2000, Plantinga and Bernell (2007) found that BMI influenced residential self-selection of individuals into low- and high-sprawl areas; and therefore, suggested that sprawl is an endogenous determinant of BMI. The authors concluded that moving to denser counties resulted in weight loss and such areas were unlikely to be chosen by individuals with a high BMI. Also, in their analysis of the relationship between neighborhood walkability and BMI, Zick et al. (2013) found that while no significant association between neighborhood walkability and BMI was revealed when using standard cross-sectional estimation, once residential self-selection was controlled for, neighborhood walkability had statistically significant effects on BMI. The authors, therefore, concluded that residential self-selection understates of the causal effects of neighborhood walkability features on BMI.

Empirical Findings on the Link between Psychological Health and the Built Environment

While studies examining the influence of the built environment on physical health are abundant, the role of the built environment in mental and psychological health has not been thoroughly examined. Literature hints that the built environment has the potential to not only influence physical health but also mental health (Giles-Corti et al. 2009). The built environment seems to exert its effects on mental health through factors such as sense of community, interaction with neighbors, social inclusion (or exclusion), and cohesion among community members (Foster and Giles-Corti 2008; Mackett and Thoreau 2015; Corburn 2015). For instance, it can be argued that pedestrian-oriented (as opposed to car-oriented) street environments can provide more social encounter, more effective civic engagement, and more interaction opportunities for individuals, and thereby can impact community sentiments and residents' mental health state over time (Lund 2002, 2003; Leyden 2003; Ryan and Frank 2009; Wood et al. 2010).

Past studies provide some insights on the potential of the built environment in affecting mental health of individuals. Handy (1996a) found that seeing neighbors when walking had the highest correlation with strolling frequency. As indicated previously, more walking has a potential to increase *social interaction*, which may lead to a better state of mental health; therefore, this finding is noteworthy. A more direct link between social interaction and the built environment was drawn by Leyden (2003) who found that pedestrian-friendly neighborhoods with mixed-use developments affect *social capital* (e.g., feeling connected to the community, knowing neighbors, trust others), and thereby may influence physical and mental health. In addition, Lund (2003) found that frequency of unplanned social interactions and neighboring behaviors were significantly higher in neighborhoods with local access to parks, whether by themselves or in combination with local access to retail stores.

Examining the link between the built environment and *sense of community*, Lund (2002) found that walkable neighborhoods were associated with a greater overall psychological sense of community score, which was a tool developed to measure sense of community at the individual level. Others found that sense of community was positively associated with recreational walking, but it was negatively associated with presence of mixed-use development (Wood et al. 2010).

Health, the Macro-level Built Environment Literature, and Empirical Findings

As evident from preceding discussions, the built environment can influence health in many ways including through affecting health-related behavior. The influence of multiple levels of the physical (i.e., built) environment on health has been emphasized in studies that discuss and/or suggest incorporation of the ecological models of behavior in health-related research (see e.g., King et al. 2002; Trost et al. 2002; De Bourdeaudhuij et al. 2003; Handy 2005; Sallis et al. 2008).

In explaining health behavior such as physical activity, the ecological model framework allows incorporation of the influence of built environment attributes at various levels including the micro level (e.g., the individual or household), the meso level (e.g., the neighborhood or perhaps the county), and the macro level (e.g., the city, the region, or the metropolitan area) (King et al. 2002; Handy 2005; Van Acker et al. 2010). Some researchers argue that the influence of built environment attributes on physical activity (e.g., active travel) as well as health promotion theories and interventions should be considered at all of these spatial levels, ranging from micro to meso to macro levels (King et al. 2002). In addition, it has been postulated that in excreting their effects, micro-level environmental factors may interact with macro-level factors; however, these potential interactions have not been considered in past empirical research (Joshu et al. 2008).

Many studies have shown that micro-level (i.e., neighborhood-level) built environment factors can influence health outcomes (see e.g., Frank et al. 2004; Smith et al. 2008; Marshall et al. 2009; Timperio et al. 2010 among others). These studies found that built environment attributes at the micro level including pedestrian friendliness of designs, extent of land use mix, and accessibility to parks and other recreational facilities were associated with health behavior such as physical activity as well as health outcomes such as obesity. Further, many other studies examined the connection between health and the meso-level (i.e., county-level) built environment (see e.g., Ewing et al. 2003b; Samimi et al. 2009; Samimi and Mohammadian 2009). These studies showed that built environment attributes at the meso level such as county-level compactness and the average size of blocks can impact health outcomes such as obesity, BMI, and general health.

Moving one level higher in the spatial hierarchy, the macro-level (e.g., city- or metropolitan area-level) built environment will be next. Literature suggests that urban structural (i.e., macro-level built environment) characteristics and city designs play a role in health behavior (e.g., physical activity) of residents. According to King et al. (2002), while most cities are composed of both automobile-oriented and pedestrian-oriented designs, the latter provides residents with opportunities for physical activity associated with daily life, whereas the former does not. The referenced study also argued that automobile-oriented urban designs particularly restrict utilitarian active travel (e.g., walking or bicycling to workplace or stores), and thereby can influence health outcomes down the line. Other researchers also argued that the macro-level built environment can play a role in residents' health. Specifically, urban sprawl and its consequential automobile dependency and sedentary lifestyle have been blamed for escalating health problems of Americans including their high levels of obesity (Cervero and Duncan 2003; Khattak and Rodriguez 2005).

A more specific argument in linking obesity and urban sprawl came from Plantinga and Bernell (2007) who suggested that urban sprawl may lead to obesity by discouraging physical activity and encouraging sedentary behavior. The authors provided three reasons for their arguments: first, sprawling designs increase trip distances, which makes active travel impractical; second, sprawling designs discourage public transit use and encourage automobile use, which may lead to traffic congestion and consequently, diversion of time from activities such as physical activity; third, suburban development—a feature of urban sprawl—does not adequately provide recreational facilities such as parks that promote physical activity (Plantinga and Bernell 2007). All of the above suggests that macro-level built environment factors such as urban sprawl can influence health outcomes such as obesity by influencing physical activity and active travel levels. Another study agreeing with this argument is Leslie et al. (2007) who suggested that the sprawling design of suburban areas promotes sedentary behavior by discouraging active living choices including active travel choices.

Other studies highlight the role of sprawling designs in reduced levels of social interaction, which can influence mental health outcomes. For instance, (Næss 2005) argued that urban sprawl negatively affects people's participation in community activities. Other literature on the role of macro-level environment on health suggests that communities vary in built as well as social environments—depending on the level of urbanization—as the extent of urbanization can influence the extent of walkability and mixed development in an area (Joshu et al. 2008).

Also, Schauder and Foley (2015) concluded that building cities that are supportive of active travel can be an effective policy intervention toward the betterment of residents' health and lowering healthcare costs. Braun and Malizia (2015) suggested that macro-level built environment characteristics beyond the residential neighborhood—such as urban sprawl at the regional or metropolitan area level—have a potential to influence health behavior (e.g., active travel) as well as health outcomes.

Empirical studies on the role of macro-level built environment in health are, however, scarce and their findings are sparse. A summary of the studies that considered the built environment attributes of larger scale (i.e., macro-level) geographical areas—including those of metropolitan areas—in their analysis is provided below.

Ewing et al. (2003b) analyzed health data from individuals living in approximately 450 different U.S. counties (over 80 metropolitan areas) to investigate the relationship between urban sprawl and health outcomes. The study found that increased county-level sprawl was associated with reduced walking levels and increased BMI, obesity, and hypertension levels. The results also showed that people in more sprawling counties weigh more regardless of how much they walk for exercise. At the metropolitan area level, higher sprawl was associated with lower walking levels but not with health indicators.

Kelly-Schwartz et al. (2004) integrated data on individuals' health from 29 Primary Metropolitan Statistical Areas (PMSAs) with data on sprawl from Ewing et al. (2002) to examine health outcomes. The study found that residents of areas with more street network connectivity had higher health ratings, whereas those living in more densely populated urban areas had lower health ratings. Results showed that living in less-sprawling counties was correlated with walking more and having lower BMIs. However, measures of sprawl did not show a significant relationship with frequency of walking, BMI, or chronic diseases when PMSAs were the unit of analysis. Additionally, the authors suggested that "various dimensions of sprawl affected health in different and contradictory ways". They further concluded that the influence of sprawl on health was both positive and negative; higher street connectivity correlated with better health ratings, but higher density was associated with poorer overall health ratings.

Joshu et al. (2008) evaluated environmental correlates of obesity at both the micro and macro geographical levels using a sample of adults in the U.S. The goal of the study was to determine whether personal and neighborhood barriers differed by the level of urbanization and as related to BMI of residents. Findings showed that associations between perceived neighborhood and personal barriers and obesity differed by urbanization level, and that differences also existed in micro-level (neighborhood) barriers across levels of urbanization. The macro-level analysis indicated that living in a more compact county was inversely associated with BMI.

Marshall et al. (2014) used data from 24 cities in the state of California to examine the effects of three measures of street network design including street connectivity, street network density, and street configuration on various health outcomes. The study analyzed the effects of street design at two different spatial levels: neighborhood level and city level. The results showed that increased intersection density was significantly correlated with reduced rates of obesity at the neighborhood level, and reduced rates of obesity, diabetes, high blood pressure, and heart disease at the city level. The study also suggested that in terms of health, citywide intersection density (a proxy for compactness) was more important than the neighborhood-level intersection density. The authors concluded that with respect to public health outcomes, "the overall character of the city makes a bigger difference" than the character of each individual neighborhood (Marshall et al. 2014). The referenced study also found that increased street connectivity at the neighborhood level was associated with lower rates of obesity and heart disease. Street connectivity factors at the city level were not found to be associated with health outcomes. A higher percentage of major streets with bicycle lanes at the city level was associated with lower diabetes rates. Also, in terms of food environments, the study found that having more fast food restaurants was associated with lower high blood pressure rates at the neighborhood level, and higher diabetes rates at the city level.

Braun and Malizia (2015) developed a composite downtown vibrancy index for 48 cities in the U.S. to examine the association of this index with public health outcomes (e.g., obesity, diabetes). The downtown vibrancy index incorporated several built environment characteristics at both the local and metropolitan area levels. The index also captured the cultural aspect of vibrancy (% of the downtown population whose primary language was not English) as a proxy for social and cultural diversity. The analysis was conducted at the county level.

The results indicated that the vibrancy index was significantly associated with physical inactivity but not with diabetes, premature death, and obesity. This study also disaggregated the vibrancy index into four components: compactness/density, destination accessibility, local connectivity (i.e. street design), and mixed land use and examined their association with physical inactivity. The results showed that limited destination accessibility and street connectivity were associated with higher physical inactivity levels. The authors also reported that greater street connectivity was correlated with higher prevalence of obesity.

B.4.3 Health and Social Environment Literature

The social environment can impede or support human behavior (Bandura 1986). Based on social cognitive theory and the ecological model, one can assume that the social environment plays a role in health behavior such as active travel (i.e., walking and bicycling) as well as other types of physical activity. Through influencing health behavior, the social environment has a potential to influence health outcomes. In addition, the social levels of influence on behavior proposed by the ecological model framework (i.e., social groups such as families, organizations, and institutions) reflect the culture in which they exist (Gochman 1997). Thus, the role of culture in health behavior and health outcomes should not be overlooked.

Past research argues that modern society is becoming more aware that culture is an important factor of the environment and human health is associated with the surrounding environment (Jackson 2003). Literature suggests that social support (e.g., supporting social and cultural norms) promotes health behavior such as physical activity, meaning observing others engage in physical activity has positive, encouraging effects for individuals to do the same (see e.g., Trost et al 2002). Others suggest that the effects of macro-level built and social environments on physical activity and health outcomes are interwoven. Thus, changes in the macro-level built environment can potentially override individuals' attitudes by changing social norms (Joshu et al. 2008) and culture. Therefore, together, the built and social environments can encourage health behavior such as physical activity, and consequently influence health outcomes such as BMI.

Further, concerns about safety may be a barrier to physical activity (CDC 1999). Chronic exposure to community violence and crime have been named as examples of social environment factors that can influence levels of physical activity (King et al. 2002).

Many studies in the past have found a relationship between social environment factors such as social and cultural norms as well as crime on levels of active travel and physical activity. This literature has been elaborately discussed in Subsection B.3.2[54].

Regarding the role of crime in physical activity, two points should be noted: 1) a study by the CDC reported that individuals who perceived their neighborhood to be unsafe were more likely to be physically inactive (CDC 1999); and 2) it is also worth highlighting the findings of a study by Foster and Giles-Corti (2008) who concluded that research findings on this topic are inconsistent and future research is needed to determine the link between physical activity and real and perceived crime-related safety.

B.4.4 Health and Telecommuting Literature

The role of telecommuting in health has been examined and discussed in the past (see e.g., Baruch 2001; Steward 2001; Spinks 2002; Ganendran and Harrison 2007; De Croon et al. 2010; and Henke et al. 2015). However, a review of the available literature reveals that many studies that discussed the health effects of telecommuting did so within a psychological and mental health context.

Existing literature suggests that telecommuting can offer employees a number of psychological benefits. These can range from lower levels of occupational stress to improved job performance and greater job satisfaction (see e.g., Baruch 2001; Steward 2001; Robertson et al. 2003; Ganendran and Harrison 2007).

[54] See Subsection "*B.3.2.3 The Social Environment: Social and Cultural Norms, Crime, and Perceptions of Crime*".

On the other hand, negative aspects of telecommuting have also been discussed in past studies. These can include longer work hours, the blurriness of work and personal times (as work time encroaches into personal time), social isolation (as a result of less face-to-face time and less interaction with colleagues and the society), and increased work-related stress (as a result of colleague jealousy or employer pressure) (see e.g., Robertson et al. 2003; Henke et al. 2015).

To provide a snapshot of the state of knowledge, findings of a few studies on the influence of telecommuting in health are summarized below.

Using a system approach for the teleworking process, Baruch (2001) recognized quality of life and lower levels of stress (i.e., individual-level outcomes) as well as environment and community improvements (i.e., society-level outcomes) as positive impacts of telecommuting. Potential isolation from human interactions (at both individual and society levels) was listed in this study as a negative impact of telecommuting. The study also suggested that health impacts of telecommuting can be a beneficial topic for future studies.

Robertson et al. (2003) proposed a work system design approach for telecommuting programs to explain the impact of workplace factors including the psychosocial factors on telecommuters' health and safety.

De Croon et al. (2010) conduced a systematic review of the literature on how concepts related to place of work such as office location (conventional vs. telework from home), office lay out (open vs. cellular), and office use (fixed vs. shared work stations) affected employee work conditions (e.g., autonomy or interpersonal relations at work), short-term reactions (e.g., physiological or psychological reactions or job satisfaction), as well as long-term reactions (e.g., performance and health). The study argued that there was insufficient evidence to conclude about the effects of telecommuting on either employee short-terms reactions or long-term reactions. The study suggested that further research is needed to examine the health effects of telecommuting as this practice gains popularity and stress-related health problems gain higher prevalence. The authors stated that considering the issues above “this gap in knowledge is remarkable.”

Research on physical health impacts of telecommuting is limited, if not scarce. There have been few hints in the literature that telecommuting can affect physical health. For example, Steward (2001) investigated health experiences of telecommuters by collecting and analyzing longitudinal survey data on work and health of these individuals over a six-month period. The survey results indicated that telecommuters—especially if female—experienced a high level of stress-related illnesses. However, the data on illness were self-reported by survey-takers; therefore, the results of the study were not based on an empirical analysis of the relationship between telecommuting and objective measures of a health outcome (i.e., illness).

Other researchers postulated that excessive participation in sedentary behavior, computer-related activities and high levels of informational overload have a potential to reduce physical activity levels (King et al. 2002), and thereby can lead to adverse physical health outcomes. Telecommuting is a perfect example of computer-related activities, which can be accompanied by an overload of information and work, leading to lower levels of physical activity and as a result, affecting the health status of the telecommuter. Regarding other physical health effects of telecommuting, Lister and Harnish (2011) suggested that telecommuters may benefit from fewer illnesses. However, there are not many empirical studies to support this hypothesis.

By the time the proposal for this dissertation research was presented to the Dissertation Advisory Committee, the author had been able to find only one empirical study that examined the effects of telecommuting on physical health: Henke et al. (2015). Confirming the lack of empirical evidence on the role of telecommuting in physical health outcomes, the referenced study investigated the effects of telecommuting intensity on health of employees. The researchers included measures of telecommuting status and intensity as well as eight measures on health risk status (e.g., obesity, depression, stress, and physical inactivity) in their analysis.

The results of the above-mentioned study indicated that health status varied by telecommuting intensity. Employees who did not telecommute were at greater risk for being obese and physically inactive. The results also showed that workers who telecommuted 8 or fewer hours per month during regular work hours had a reduced risk for depression over time compared to workers who did not telecommute. The authors indicated that their study did not find any association between telecommuting and stress (Henke et al. 2015).

More recently and after the proposal for the present dissertation was written and presented to the Committee), Tajalli and Hajbabaie (2017) also investigated the effects of telecommuting on physical health outcomes. They found that telecommuting was associated with mental health disorders but not with indicators of physical health (i.e., obesity, blood pressure, and diabetes).

B.5 Conclusions of the Literature Review and Discussion of Research Gaps/Limitations

This review of literature on the factors that impact nonmotorized travel behavior and human health provides insights into the theoretical bases as well as empirical research findings on these topics.

Based on this comprehensive literature review, Chapter 2 of this dissertation summarizes the main conclusions reached with respect to the existing research and empirical findings on the relationships between nonmotorized travel behavior, the built environment, and health.

Chapter 2 also identifies the gaps in existing research and discusses opportunities for further research as well as how the present dissertation aims to take advantages of those research opportunities to fill some of the gaps in knowledge in this research areas.

Appendix C

Nonmotorized Travel Behavior: A Baltimore, Maryland and Washington, D.C. Case Study

C.1 The Baltimore-Washington, D.C. Case Study

In this case study, statistical models are developed to examine the relationship between built environment factors of the place of residence and the extent of nonmotorized travel by residents. The case study focuses on the Baltimore, Maryland and Washington, D.C., metropolitan areas. These two metropolitan areas were chosen for this analysis because their travel surveys and land use data collection were conducted concurrently, resulting in consistent datasets.

The two metropolitan areas locate close to each other, which facilitates mapping and comparison efforts. Even though the two metropolitan areas are similar in many ways such as their highway systems, they are adequately different in terms of income levels, built environment, and regional accessibility characteristics as well as public transit systems to allow a statistical model to capture the most significant effects of the built and social environments on travel behavior.

C.1.1 Baltimore-Washington, D.C. Data

The final database for the Baltimore-Washington, D.C. nonmotorized travel behavior statistical models consists of the following individual datasets: *i)* metropolitan household travel survey data; *ii)* metropolitan land use data; *iii)* metropolitan highway and transit skimming matrices; *iv)* Walk and Bike Score data; and *v)* spatial data (GIS shapefiles). These datasets are described below.

C.1.1.1 Metropolitan Household Travel Survey

The metropolitan household travel survey data come from Baltimore, Maryland and Washington, D.C., metropolitan areas in the U.S. These data were obtained from the Baltimore Metropolitan Council (BMC) and the Metropolitan Washington Council of Governments (MWCOG). The most recent travel surveys within these areas were conducted in 2007 and included 11,000 households in Washington, D.C. and 4,650 households in the Baltimore metropolitan area.

These travel survey data provide information on each surveyed household's Transportation Analysis Zone (TAZ), household socioeconomic/demographic attributes (e.g., household size, income, number of vehicles, number of licensed drivers) as well as detailed information on trips made by individuals within each household during a particular day. The trip information includes the mode of travel, travel time, and distance traveled for each trip made. Figure C-1 shows mode shares for trips in the study area based on the 2007 BMC- MWCOG household travel survey data.

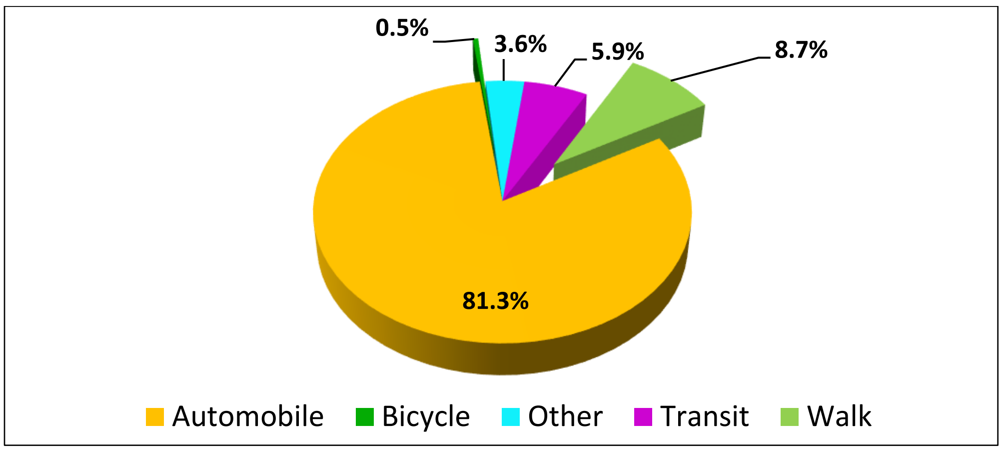

Figure C-1. Baltimore-Washington, D.C. Trip Mode Share (2007)

The travel survey data also indicate that of the 9,969 pedestrian and bicycle trips:

- 2,760 trips (i.e., approximately 28%) listed "Home" as trip destination;
- 837 trips (i.e., over 8%) went beyond 1.5 miles in trip distance;
- 791 trips (i.e., approximately 8%) lasted longer than 30 minutes in trip duration; and
- 5,270 trips (i.e., approximately 53%) did not stay within the TAZ they originated in.

These statistics show that a sizable proportion of the Baltimore-Washington D.C. pedestrian and bicyclist trips did not originate at the home location and did not stay within the neighborhood boundaries.

C.1.1.2 Metropolitan Land Use

The most recent land use data for Baltimore and Washington, D.C. metropolitan areas were obtained from the BMC and the MWCOG.

The land use data were collected in 2005 and provide detailed information on land use in the two metropolitan areas including the total number of establishments in each land use type class (e.g., retail, office, industry) in addition to housing, population, and employment information for each TAZ within the two metropolitan areas.

C.1.1.3 Highway and Transit Skimming Matrices

BMC and MWCOG zone to zone highway and transit skimming matrices have also been used in the analysis of nonmotorized travel behavior within the Baltimore-Washington, D.C. study areas.

These matrices provide information on highway and transit travel times between various origin-destination (OD) pairs in the two metropolitan areas as well as terminal times in the case of transit travel. The OD zones considered in the skimming matrices are TAZs.

For the transit matrix, the information includes in-vehicle times, wait times, transfer times between stations, as well as walk access times.

C.1.1.4 Walk/Bike Score Data, and Spatial Data

Detailed information about Walk Score and Bike Score data is provided in Section 3.2 of this dissertation (see Subsection 3.2.10). Also, Walk/Bike Score categories are listed in Appendix D.

With regards to spatial data, TAZ-level shapefiles come from BMC and MWCOG. Further, U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line shapefiles have been used to obtain census block-level and county-level spatial data within the Baltimore-Washington, D.C. study area. Additional information on TIGER/Line Shapefiles spatial data can be found in Section 3.2 of this dissertation (see Subsection 3.2.7).

C.1.1.5 Final Database

The travel survey data provided information on the residential location of each household at the TAZ level, the household TAZ code was used to spatially link the built environment attributes of each household's residential location to the walking/bicycling trips of the household members by utilizing GIS tools. Through these data manipulations, the final integrated database for the models was obtained, which combines information from all the independent datasets described previously.

C.1.2 Baltimore-Washington, D.C. Models: Dependent Variables

The nonmotorized trips of the households within the study area have been considered for statistical modeling. Four separate models are developed based on the following four dependent variables:

1) household's number of daily per capita walking trips;

2) household's number of daily per capita bicycling trips;

3) household's total number of daily walking trips; and

4) household's total number of daily bicycling trips.

The total numbers of household's daily walking and bicycling trips were computed by aggregating the number of walking (or bicycling) trips recorded in the travel survey during the travel day for all of the members of that particular household.

To obtain the household's number of daily per capita walking trips, the total number of household's walking trips was divided by the total number of household members.

Similarly, the household's number of daily per capita bicycling trips was computed by dividing the total number of household bicycling trips by the total number of household members.

Table C-1 provides information on the frequency and percentage of the Baltimore-D.C. household's total number of daily walking and bicycling trips.

Table C-1. Number and Proportion of Baltimore-D.C. Household Nonmotorized Trips

Number of Trips	Frequency		Percent	
	Walking	Bicycling	Walking	Bicycling
0	6,448	9,281	68.01	97.89
1	568	17	5.99	0.18
2	1,266	110	13.35	1.16
3	273	26	2.88	0.27
4	396	24	4.18	0.25
5	139	9	1.47	0.09
6	147	8	1.55	0.08
7	64	1	0.68	0.01
8	70	3	0.74	0.03
9	24	—	0.25	—
10	28	1	0.30	0.01
11	10	1	0.11	0.01
12	17	—	0.18	—
13	2	—	0.02	—
14	5	—	0.05	—
15	5	—	0.05	—
16	4	—	0.04	—
17	3	—	0.03	—
18	6	—	0.06	—
19	2	—	0.02	—
20	3	—	0.03	—
21	1	—	0.01	—
Total	9,481	9,481	100.00	100.00

NOTES: — = Not applicable; Source of data: 2007 MWCOG-BMC metropolitan household travel survey.

The table indicates that the maximum number of trips was 21 and 11 for walking and bicycling trips, respectively.

Also, as it can be seen from Table C-1, a considerable percentage (68%) of households did not report any walking trips. This percentage is even higher in the case of bicycling trips as almost 98% of households did not report any bicycling trips during the day of travel survey.

The average number of daily household walking and bicycling trips were 0.99 trips and 0.06 trips, respectively. These low figures are consistent with previous studies that suggested trips using the nonmotorized modes of travel occur at very low rates compared to trips using other modes of travel (see e.g., Friedman et al. 1994; Agrawal and Schimek 2007; Marcus 2008; Kuzmyak et al. 2014).

Figures C-2 and C-3 map the average daily number of household's per capita walking and bicycling trips for each TAZ within the Baltimore-Washington D.C. study area. The figures show that the average daily number of household's per capita walking and the average daily number of household's per capita bicycling trips are generally higher in TAZs closer to the central business district (CBD) of the two metropolitan areas (i.e., the Baltimore and the Washington, D.C. metropolitan areas).

The figures also show that the average daily number of household's per capita walking and bicycling trips in some suburban communities within the study area are relatively high, especially in the Baltimore metropolitan area. This may be reflecting leisure walking and bicycling trips by residents of those suburban communities.

In addition, Figures C-2 and C-3 reveal that compared to households located in the Baltimore metropolitan area, household in the Washington, D.C. metropolitan area are located within TAZs farther from the CBD.

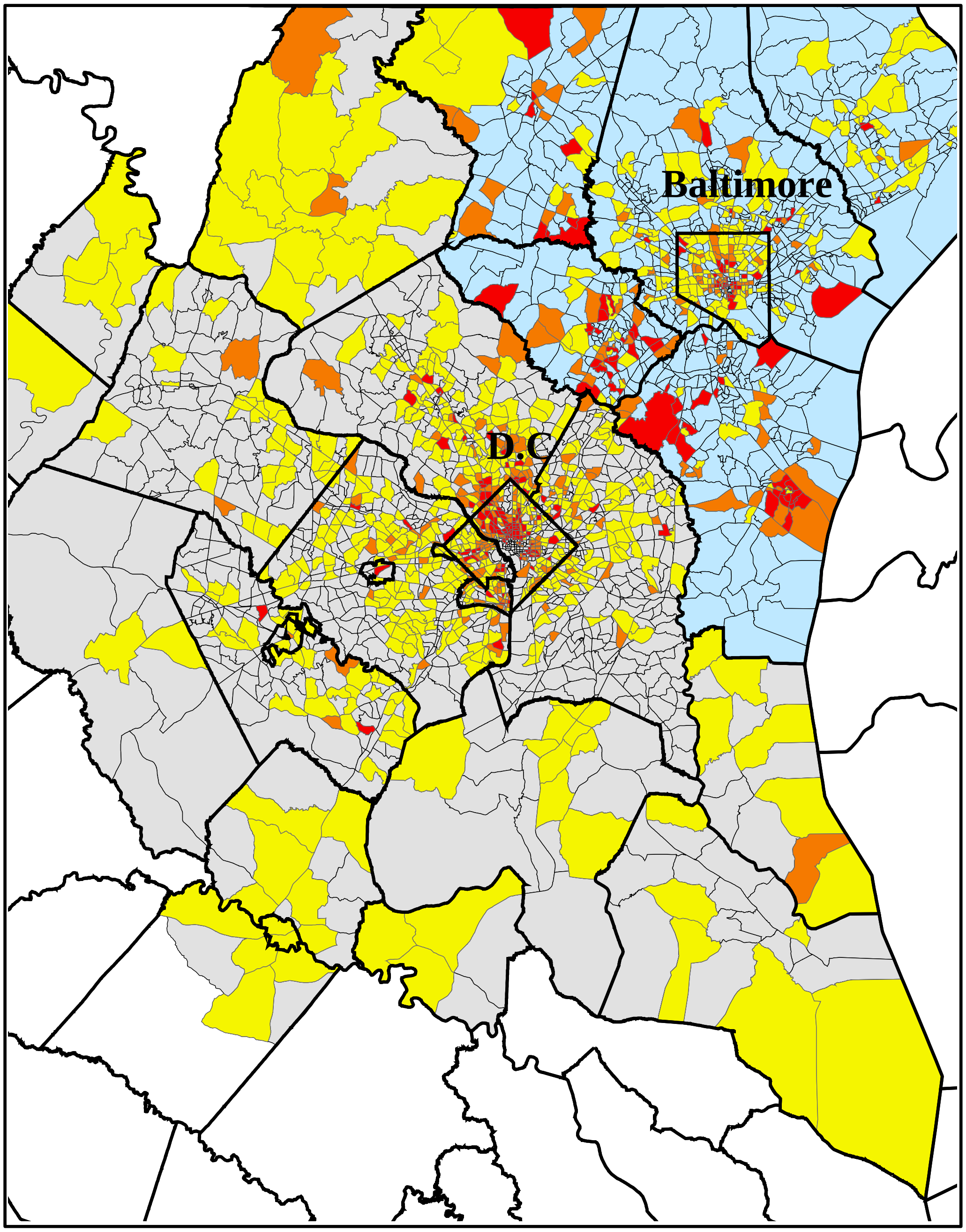

Figure C-2. Average Daily Number of Household Per Capita Walking Trips by TAZ

TAZ Areas

D.C. TAZs

Baltimore TAZs

County Boundaries

Average Number of Per Cap. Walking Trips

0.01 – 0.49

0.50 – 0.99

≥ 1.00

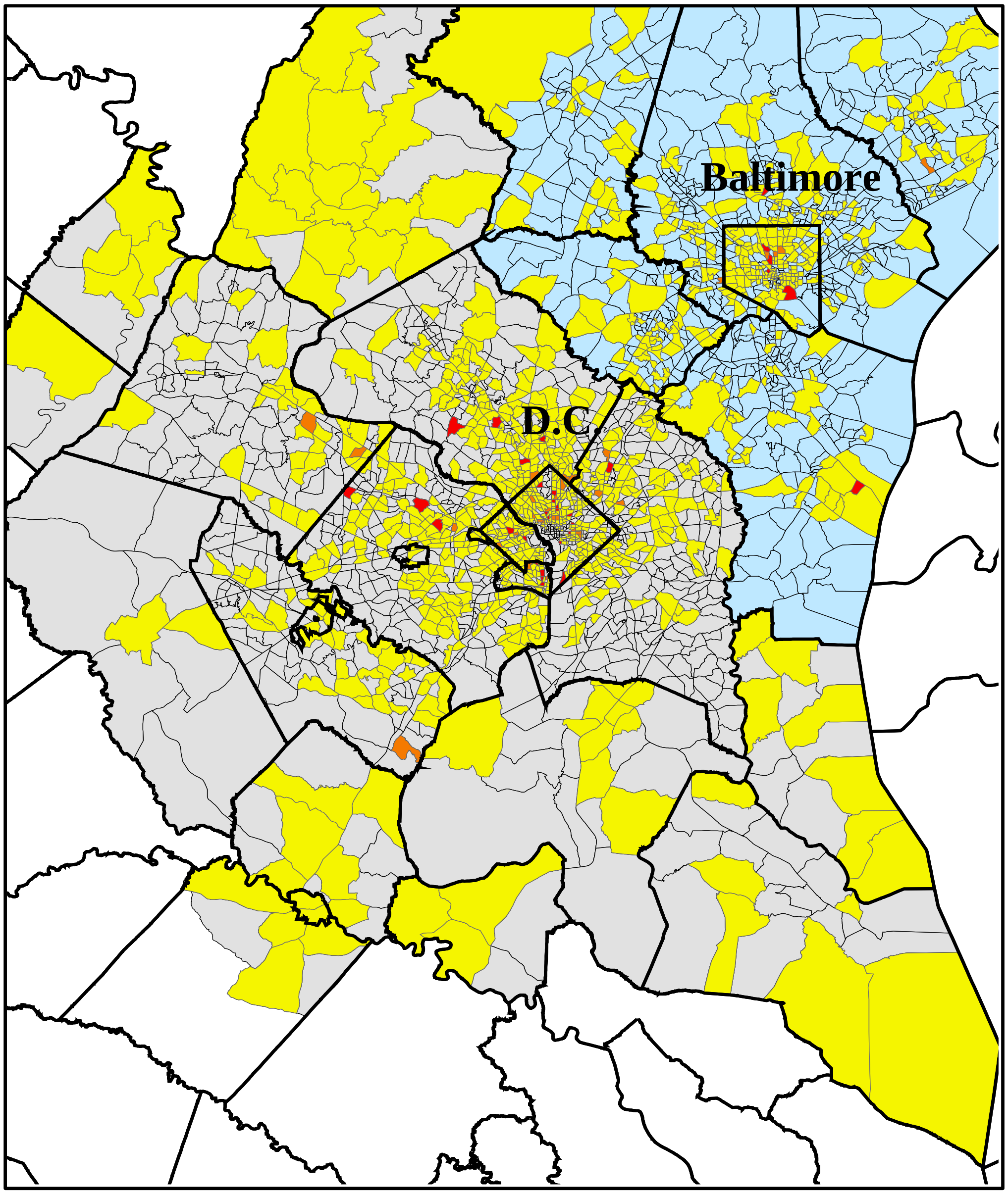

Figure C-3. Average Daily Number of Household Per Capita Bicycling Trips by TAZ

TAZ Areas		Average Number of Per Cap. Bicycling Trips	
	D.C. TAZs		0.01 – 0.15
	Baltimore TAZs		0.15 – 0.30
	County Boundaries		≥ 0.30

NOTES:

Study area: the Baltimore, Maryland and Washington, D.C. metropolitan areas;

Source of data for figures: 2007 MWCOG-BMC metropolitan household travel survey.

C.1.3 Baltimore-Washington, D.C. Models: Independent Variables

The independent variables for the statistical models have been chosen based on the principles of the ecological model of behavior as well as findings of previous research (see Chapter 2 and Appendix B). The independent variables are categorized into four sets representing four potential ecological levels of influence on walking and/or bicycling behavior: 1) household control variables, which provide information on socioeconomic attributes of households; 2) neighborhood-level built environment variables; 3) county-level built environment variables; and 4) regional accessibility variables.

Household has been selected as the unit of analysis in this study. This choice was made in part because the social cognitive theory considers the household as the most important setting among the social environment levels of influence that determine an individual's behavior (Gochman 1997; Van Acker et al. 2010). Moreover, a previous study argued that households (as opposed to individuals) are the appropriate unit of analysis in travel research (Ewing 1995). Households have been used as units of analysis in many past travel behavior studies including in research on nonmotorized travel behavior (see e.g., Friedman et al. 1994).

The built environment factors have been included in the model based on the ecological model of behavior, which emphasizes the role of the physical (i.e., built) environment on behavior. As previously mentioned over half (53%) of the nonmotorized trips in this sample crossed the boundaries of the neighborhood (i.e., did not start and end in the same TAZ). Also, because many of the nonmotorized trips had a long travel distance (>1.5 miles) or travel time (>30 minutes), it is possible that the built environment patterns of geographical areas larger than the neighborhood influenced these trips.

Thus, the built environment characteristics have been measured utilizing two geographical scales (i.e., neighborhood and county) to capture the impact of two levels of built environmental influence on nonmotorized travel behavior: the micro-level and the meso-level.

Further, variables representing regional accessibility have been included in the models to capture the potential influence of regional accessibility characteristics on nonmotorized travel behavior of residents.

The independent variables are categorized and computed as described below.

C.1.3.1 Household Control Variables

Examples of the measures of household ties that can influence behavior such as walking and bicycling are household size and working status of adults (Gochman 1997). Such variables along with many other household-level variables, have been used in previous research on nonmotorized travel behavior (see Chapter 2 and Appendix B).

For the present study, household-level variables provide information on the socioeconomic attributes of each household including the household's:

- size (i.e., number of household members);
- annual income;
- number of students;
- number of workers;
- number of vehicles owned;
- number of licensed drivers; and
- number of bicycles owned.

The values for these variables are taken directly from the relevant metropolitan area (i.e., Washington, D.C. or Baltimore) travel survey data.

C.1.3.2 Micro-level (i.e., Neighborhood-level) Built Environment Variables

These variables provide information on neighborhood-level built environment and land use for each household location. In this case study, the neighborhood-level built environment variables are represented by the attributes of the TAZ where the household is located. Past research suggests that many walking and bicycling trips occur within a TAZ (National Research Council 2005), and TAZ-level built environment factors have been used to represent neighborhood built environment characteristics in previous nonmotorized travel behavior research (Ewing and Schroeer 2004; Zhang 2004; Zhang and Kukadia 2005; Boarnet et al. 2008; Mitra and Builing 2012; Weinberger and Sweet 2012). A relatively recent report, which assessed the factors influencing walking and bicycling, suggested that a spatial scale finer than TAZ should be used in future studies (Kuzmyak et al. 2014). In the present study, however, TAZ was selected as the geographical area to represent neighborhood because geocoded data for household locations were not available (which made using smaller geographical areas such as block group or buffer distances infeasible). Thus, TAZ was the smallest geographical area for which travel survey and land use information was available.

The neighborhood-level variables include:

- population density;
- employment density;
- average block size;
- local transit accessibility;
- Walk Score;
- Bike Score;
- Transit Oriented Development (TOD) status; and
- entropy.

Some of these variables—including the population and employment density variables, average block size, local transit accessibility, and the entropy variables—have been chosen based on past research (see Chapter 2 and Appendix B).

Walk Score and Bike Score variables have been included in the model due to previous research showing Walk Score as a better predictor of walking mode choice across various trip purposes compared with population density (Weinberger and Sweet 2012) as well as other research conclusions, which found Walk Score to be a reliable measure for walkability and destination accessibility (See Subsection 3.2.10 in this dissertation).

Population and employment density variables have been calculated for each TAZ by dividing the corresponding total population or employment numbers by the area of the TAZ (acres). Block size (measured in area or length) has been postulated in previous studies to capture the extent to which street networks are interconnected (see e.g., Ewing et al. 2003a; National Research Council 2005). Thus, the average block size has been selected in the present study to represent the extent of street network connectivity. This variable has been computed by averaging the areas of all blocks within the TAZ where the household locates in.

Moreover, the number of rail transit stations and bus stops in each TAZ have been added together and the sum is used to represent the value of the local transit accessibility variable. The rail transit stations include rail stations that are served by the Washington Metropolitan Area Transit Authority (WMATA), MARC Train, Maryland Transit Administration's Light Rail and Metro Subway, as well as the AMTRAK railroad services. The bus stops include stops served by WMATA and the Maryland Transit Administration's bus transit services.

In addition, a variable indicating the status of Transit Oriented Development (TOD) has been included in the model. Past research defines TODs as "projects that involve mixed-use development (i.e., residential and commercial) near public transit stations" (National Research Council 2005). TODs have been suggested to create a friendly environment for nonmotorized travel, particularly for walking trips (Roshan Zamir et al. 2014); therefore, controlling their effects in nonmotorized travel behavior models is reasonable. TOD data for the Baltimore and D.C. metropolitan areas came directly from Roshan Zamir et al. (2014). These data are dichotomous in format, indicating whether or not a TAZ in the study area is identified as a TOD.

The entropy variable captures the extent of mixed-use development in the neighborhood (TAZ). The values for this variable have been computed using the following well-established formula used in previous research (see e.g., Frank and Pivo 1994; Cervero and Kockelman 1997; Cervero 2001; and Cervero and Duncan 2003):

$$\text{Entropy} = -\sum_j \frac{P_j * ln(P_j)}{ln(J)}$$

where,

$J =$ number of land use classes in the household TAZ; and $P_j =$ proportion of land use in the *j*th class. Five land-use classes have been considered for this case: residential, retail, office, industry and other (i.e., $J = 5$). The value of the entropy variable ranges from 0 to 1, representing non-diverse (one-class-only) land use to most diverse (well- mixed) land use, respectively.

The Walk Score variable—measured as the Walk Score for the centroid of each TAZ—has been included in the walking model as a proxy for neighborhood destination accessibility. As mentioned in Chapter 3 (see Subsection 3.2.10), this objectively measured score provides information on walkability of locations based on a destination-accessibility approach.

Similarly, the Bike Score for the centroid of each TAZ has been included in the bicycling model as a proxy for neighborhood bikeability.

An interaction variable of the two scores has also been considered for inclusion in the bicycling model to account for the tendency of bicyclists to ride their bicycle in a neighborhood with walking-supportive characteristics but not much bicycling-supportive features. For instance, if the neighborhood has sidewalks but not bicycle lanes, it may still encourage bicycling as individuals may ride their bicycles on the sidewalks around the neighborhood.

In urban settings, bicycling on sidewalks is usually prohibited by law and bicycling is typically restricted to shared-use roadways or bicycle lanes that share the right-of-way with vehicular traffic (National Research Council 2005). Nonetheless, the tendency of bicyclists to use sidewalks has been noted in previous studies (Rodríguez and Joo 2004), and this behavior can be observed in various occasions and places (see Figure C-4).

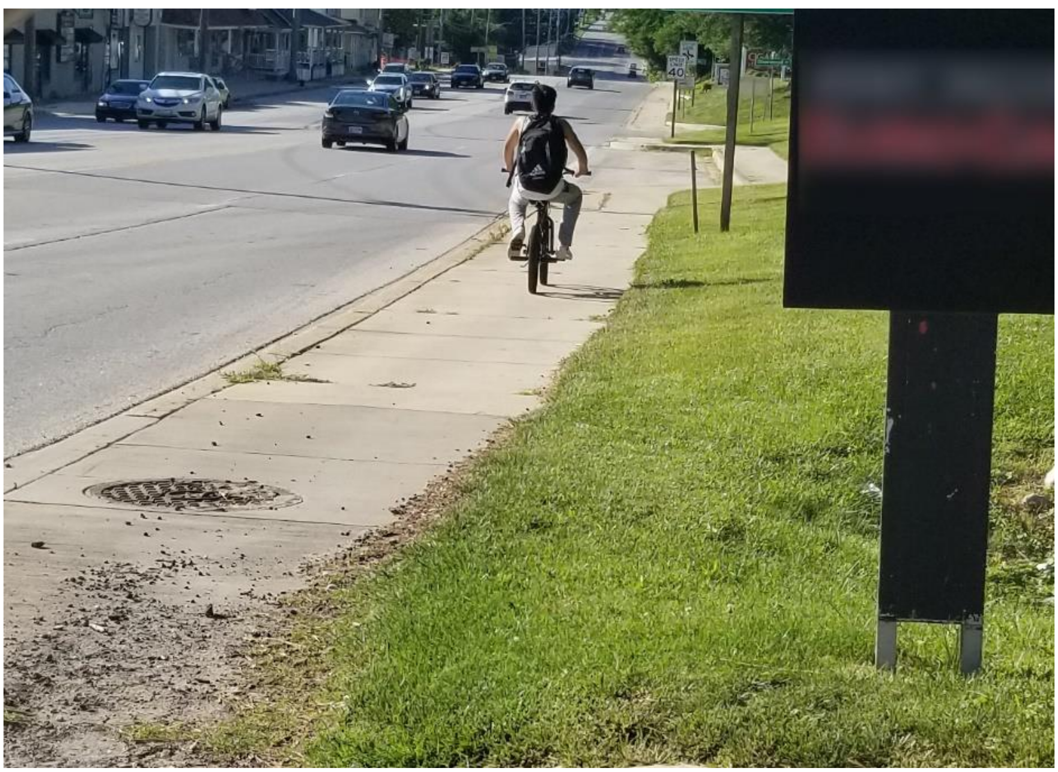

Figure C-4. Bicycling on Sidewalk

C.1.3.3 Meso-level (County-level) Built Environment Variables

These variables capture the connectivity and accessibility of the street network, the extent of mixed-use development, as well as population and employment densities of the household's county. To obtain the county-level measures, the TAZ-level measures were aggregated for each household's county and the mean of each measure was obtained at the county-level.

Aggregation of data at smaller scales to obtain the mean of the explanatory variables at larger scales provides a meaningful contextual variable (i.e., the group mean) for inclusion in the multilevel mixed-effects models (Snijders and Bosker 2012). This method of calculation of the built environment for larger scales has been suggested to prevent measurement biases (Nasri and Zhang 2014). The county-level variables included in the models are:

- average total population density;
- average employment density;
- average block size; and
- average entropy.

C.1.3.4 Regional Accessibility Variables

Literature suggests that the effects of regional-level accessibility on nonmotorized travel behavior should be examined in future research (Handy 2005). Thus, measures of regional accessibility have been included in the models to capture the effects of regional accessibility on a household's walking and bicycling travel behavior.

Regional accessibility can be measured in various ways. Ewing and Cervero (2010) stated that some studies calculate regional accessibility as simply the distance to the central business district (CBD), whereas others calculate regional accessibility as the number of employment opportunities or other attractions reachable within a given travel time. In the latter case, the gravity model of trip attraction can be used to measure destination accessibility.

The regional accessibility variables in the present study have been measured in such way to provide information on household's location relative to the regional urban centers as well as the number of employment opportunities and working population within a certain travel time.

First, a variable representing the distance from the residential location to the center of the city has been included in models as a proxy for regional accessibility. This variable is computed as the measure of a straight line connecting the centroid of the household's TAZ to the CBD of the metropolitan area where the household resided (i.e., MWCOG or BMC area). Downtown areas (i.e., CBDs) are often the geographical point of gravity of the employment offices and service facilities (Næss 2005); hence, distance to CBD has been used in previous research as a proxy for accessibility to regional jobs and other destinations (see e.g., Miller and Ibrahim 1998; Renne et al. 2015).

Distance to CBD can influence nonmotorized travel behavior in many ways. For example, the closer the household locates to the CBD, the shorter the distances to work and other destinations may be, which can encourage nonmotorized mode choices. Conversely, the farther the residence from the CBD, the longer the distances to destinations may become, which may encourage more driving trips and discourage nonmotorized trips. Moreover, since the CBD is usually the major node for public transit lines, transit trips from a household in one suburb to a destination in another suburb can be longer the farther from the CBD the household is located (Næss 2005). This may adversely influence the transit mode choice and since transit trips are often associated with walking or bicycling trips, any decline in the number of transit trips may mean a decline in the nonmotorized trips associated with those transit trips.

Second, measures of zone-to-zone accessibility have also been included in the models to capture the effects of interzonal (regional) accessibility on household's walking and bicycling trips. Interzonal accessibility has been computed based on Hansen's formula, which provides a relatively simple method for calculating accessibility for regions (see Hansen 1959):

$$A_{ij} = \sum_j \frac{S_j}{{T_{(ij)}}^e}$$

where,

A_{ij} = relative accessibility measure at zone i to an activity that is located within zone j;

S_j = size of the activity in zone j (i.e., the number of jobs in zone j for employment accessibility, or the number of people in zone j for population accessibility);

$T_{(ij)}$ = travel time or distance between zones i and j; and

e = exponent capturing the effects of travel time between zones i and j.

The value of exponent e differs for various types of trips depending on the trip purpose. The more important the trip purpose is, the smaller the exponent e will be. A smaller e indicates individuals' willingness to travel farther for activities that they consider more important (e.g., work trips). The total accessibility index for each zone i to some activity (i.e., employment, shopping, population, etc.) in zone j is the sum of the accessibilities to each of the individual zones j neighboring zone i. The accessibility index of zone i increases as this sum increases.

It is noteworthy to mention that Hansen's accessibility is one of the earliest forms of what later was termed *potential accessibility*. Reminiscent of Newton's gravity model, potential accessibility includes in its formula an inverse power function and is measured based on the assumption that the attraction of a destination increases with its size and decreases with some indicator of impedance such as travel distance, travel time, or travel cost (Schürmann et al. 1997).

Two types of activities have been considered in the regional (interzonal) accessibility computations in the present case study: employment and population activities. The exponent *e* for these activities was found previously to be equal to 2.20 for employment, and 2.35 for population accessibility when travel time between zones was expressed in terms of travel time plus terminal times (Hansen 1959). This case applies to the present case study.

In constructing accessibility indicators, Cervero and Kockelman (1997) used travel times between zones estimated for regional highway networks and numbers of jobs as measures of destination attraction. Thus, for the present case study, MWCOG and BMC off-peak zone-to-zone highway and transit skimming matrices have been used to calculate travel times and terminal times between TAZs in the study area. Further, the employment and population accessibilities for each TAZ have been added together to obtain one accessibility measure for each TAZ.

Through these computations, three variables are obtained capturing the interzonal accessibility. These include:

- highway accessibility index;
- transit-drive accessibility index; and
- transit-walk accessibility index.

These accessibility indices measure accessibility (by mode) of each TAZ to all other TAZs in the region. Thus, they are referred to as regional accessibility (or interzonal accessibility) in the present case study.

Table C-2 summarizes all the independent variables used in the Baltimore-Washington, D.C. nonmotorized travel behavior models along with brief descriptions, method of computation, and data sources.

Together, the micro-level (neighborhood) and the meso-level (county) built environment variables and the regional (macro-level) accessibility variables represent the built environment at multiple levels of influence as conceptualized within the ecological model framework.

Table C-3 presents the descriptive statistics for the dependent and independent variables. The table indicates that the average number of household's total and per capita daily walking trips are higher in the Baltimore metropolitan area, whereas the average number of household's total and per capita daily bicycling trips are higher in the Washington, D.C. metropolitan area.

Table C-2. Variable Descriptions and Data Sources for Baltimore-D.C. Models

Variable	Method of Computation	Data Source
Household Socioeconomics: The Household		
Number of Members (Size)	Data provided	MWCOG/BMC Travel Survey
Number of Students	Data provided	MWCOG/BMC Travel Survey
Number of Workers	Data provided	MWCOG/BMC Travel Survey
Number of Vehicles Owned	Data provided	MWCOG/BMC Travel Survey
Number of Bicycles Owned	Data provided	MWCOG/BMC Travel Survey
Number of Licensed Drivers	Data provided	MWCOG/BMC Travel Survey
Annual Income (1,000s of $)	Data provided	MWCOG/BMC Travel Survey
Micro-Level Built Environment (TAZ Level): The Neighborhood		
Population Density	Total population/acre	MWCOG/BMC Land Use Data
Employment Density	Jobs/acre	MWCOG/BMC Land Use Data
Average Block Size	Average block size (acres) for the TAZ	Census TIGER Block Shapefiles
Transit Accessibility	Number of (transit stations + bus stops)	MWCOG/BMC Land Use Data
Transit Oriented Development	TAZ is a TOD? 1 = yes, 0 = no	Roshan Zamir et al. (2014)
Walk Score	Data provided	Walk Score®
Bike Score	Data provided	Walk Score®
Entropy	Entropy formula	MWCOG/BMC Land Use Data
Meso-Level Built Environment (County Level): The County		
Mean Population Density	TAZ densities averaged for the county	MWCOG/BMC Land Use Data
Mean Employment Density	TAZ densities averaged for the county	MWCOG/BMC Land Use Data
Mean Block Size	Average block size (acres) for the	Census TIGER Block Shapefiles
Mean Entropy	TAZ entropies averaged for the county	MWCOG/BMC Land Use Data
Regional Accessibility: The Region		
Distance to CBD (miles)	Straight line from zone centroid to CBD	MWCOG/BMC Land Use Data
Highway Accessibility Index	Accessibility formula (Hansen 1959)	MWCOG/BMC Skim Matrices
Transit-Drive Accessibility Index	Accessibility formula (Hansen 1959)	MWCOG/BMC Skim Matrices
Transit-Walk Accessibility Index	Accessibility formula (Hansen 1959)	MWCOG/BMC Skim Matrices

Table C-3. Descriptive Statistics for Baltimore-D.C. Nonmotorized Travel Behavior Models

Variable	Metropolitan Planning Organization Area			
	Washington, D.C. (within MWCOG area)		Baltimore, MD (within BMC area)	
	Mean	SD	Mean	SD
Dependent Variables				
Household's Number of Daily per Capita Walking Trips	0.51	1.09	0.58	1.07
Household's Number of Daily per Capita Bicycling Trips	0.03	0.24	0.02	0.24
Household's Total Number of Daily Walking Trips	0.96	1.99	1.14	2.08
Household's Total Number of Daily Bicycling Trips	0.06	0.47	0.05	0.41
Independent Variables				
Household-level Socioeconomic Attributes: The Household				
Number of Members (Size)	2.20	1.22	2.17	1.25
Number of Students	0.53	0.91	0.57	0.94
Number of Workers	1.25	0.81	1.13	0.86
Number of Vehicles	1.68	0.99	1.51	1.01
Number of Bicycles	1.12	1.48	0.96	1.47
Number of Licensed Drivers	1.65	0.73	1.49	0.77
Annual Income (1,000s of dollars)	75 - 100	—	50 - 60	—
Micro-level Built Environment (TAZ Level): The Neighborhood				
Population Density (total population/acre)	22.35	36.42	23.14	36.44
Employment Density (jobs/acre)	8.72	26.52	9.69	32.65
Average Block Size (acres)	17.84	26.11	12.77	22.07
Transit Accessibility (number of transit stations + bus stops)	23.94	18.95	15.35	19.36
Walk Score[a]	40.94	31.05	49.52	28.35
Bike Score[a]	22.61	34.13	21.47	30.44
Entropy[a]	0.43	0.22	0.49	0.22
Meso-level Built Environment (County Level): The County				
Mean Residential Population Density (residential population/acre)	8.18	5.97	11.59	6.47
Mean Employment Density (jobs/acre)	14.94	18.87	18.25	13.92
Mean Block Size (acres)	27.33	23.86	20.05	19.71
Mean Entropy[a]	0.44	0.07	0.53	0.02
Regional Accessibility: The Region				
Distance to CBD (miles)	14.34	13.21	8.54	7.80
Highway Accessibility Index[a]	2,920	4,490	6,362	5,399
Transit-Drive Accessibility Index[a]	2,828	2,686	3,772	2,017
Transit-Walk Accessibility Index[a]	1,603	1,401	4,688	4,892
Number of Observations (Households)	7,547		1,934	
Number of TAZs	867		413	
Number of Counties	13		12	

NOTES: SD = Standard deviation; — = Not applicable; a = Dimensionless.

Also, some variation exists in the household socioeconomic characteristics between the two metropolitan areas. The average numbers of household members (household size) is slightly higher for households within the Washington, D.C. metropolitan area, whereas the average number of household students is higher in Baltimore. Households within the Washington, D.C. metropolitan area have a higher average number of workers and on average, earn a higher annual income than households in Baltimore.

Additionally, D.C. households have more licensed drivers and own more vehicles and bicycles compared to Baltimore households. These statistics are consistent with what a previous study of the two metropolitan areas reported (Roshan Zamir et al. 2014). The lower household average annual income in Baltimore likely explains many of the observed differences in the household socioeconomic characteristics between the two metropolitan areas.

Variations also exist between built environment attributes of household locations for the two different metropolitan areas. At the micro level (i.e., neighborhood/TAZ level), Table C-3 indicates that Baltimore households have higher population and employment densities. Baltimore households are also located in neighborhoods with smaller average block sizes and a higher level of mixed-use development (i.e., entropy). The entropy and block size statistics variation are consistent with descriptive statistics on entropy and block size reported in previous studies of the two metropolitan areas (Nasri and Zhang 2012; Roshan Zamir et al. 2014).

The average Walk Score for household neighborhood is higher within the Baltimore metropolitan area, whereas the average neighborhood Bike Score is slightly higher for households within the Washington, D.C. area. Also, Washington, D.C. households have access to a larger number of transit stations and bus stops within their neighborhood.

In terms of meso-level (i.e., county-level) built environment variables, average population and employment densities are higher for counties in the Baltimore study area. Baltimore has a smaller average block size and a higher entropy at the county level. These statistics indicate that

Baltimore households are located within counties with better street network connectivity and a higher extent of mixed-use development.

The descriptive statistics for the regional (interzonal) accessibility variables also indicate differences between Washington, D.C. and Baltimore households. On average, Baltimore households have a higher accessibility to highways and transit (by both driving and walking means). These statistics may be explained by the descriptive statistics on the *Distance to CBD* variable. Looking at this variable, it can be seen from Table C-3 as well as from the maps presented in Figures C-2 and C-3 that compared to the Baltimore households, the Washington D.C. households locate at a greater distance from the CBD. This indicates that D.C. neighborhoods (i.e., TAZs) in this sample locate farther from the core city where the core of activities (population and employment) locates. This may be the reason for lower average statistics on regional highway and transit accessibility indices as well as those of the population and employment densities, Walk Score, and entropy variables for households located within the Washington D.C. study area.

C.1.4 Baltimore-Washington, D.C. Nonmotorized Travel Behavior Models

The analysis of nonmotorized travel behavior has been performed using linear mixed-effects (i.e., multilevel) models as well as ordered probit models.

First, mixed-effects models have been developed to relate the number of household's daily per capita walking and bicycling trips to household's socioeconomic characteristics (i.e., social environment), neighborhood- and county-level built environment characteristics, as well as regional accessibility measures. Then, ordered probit models have been developed to predict the total number of household's daily walking or bicycling trips based on the same factors above.

The results of the two types of models are used for comparison purposes.

C.1.4.1 Linear Mixed-effects Models (i.e., Multilevel Models)

Specification of Models: Baltimore-DC Mixed-effects Nonmotorized Travel Models

Mixed-effects (multilevel) models have been employed in this analysis to examine the association between nonmotorized travel behavior and social as well as built environment characteristics at two geographical scales: the micro-level (i.e., neighborhood) and the meso-level (i.e., county).

The reason for selecting the linear mixed-effects model to analyze the household nonmotorized travel behavior is the capability of this type of model to deal with clustered data where correlations may exist between observations from the same cluster. These correlations violate the iid assumption of the ordinary regression modeling techniques, whereas the mixed-effects model enables the analyst to relax this assumption. Therefore, the mixed-effects modeling technique is a more appropriate statistical technique when treating clustered data as elaborated in Subsection 3.3.1. Also, research in the past suggests that application of mixed-effects models to travel behavior analysis is a suitable choice due to capabilities of these models to parameterize interrelationships of clustered data (Reilly and Landis 2003).

Data for the current case study are assumed to be clustered as groups of surveyed households locate within similar geographical areas (e.g., neighborhoods) and there may be correlations between households that locate in the same area. Thus, the clustered nature of observations warrants the use of mixed-effects models for this case study. As previously mentioned, clustered datasets such as the one at hand contain two types of observations:

i) *observations within a particular cluster*: these observations are likely to have similar characteristics. For example, travel behavior of households within the same neighborhood may be correlated because of the common neighborhood built environment characteristics;

ii) *observations from different clusters*: these observations have independent characteristics from each other. For instance, the travel behavior choices of households that locate in different neighborhoods are made independently of each other and each other's neighborhood built environment.

Considering the two types of observations above, two sources of variation are assumed for clustered datasets:

i) *variations within clusters (i.e., intraclass variance)*: for example, differences in travel behavior of households within the same neighborhood;

ii) *variation between clusters (i.e., interclass variance)*: for example, differences in travel behavior of households that locate in two different neighborhoods.

The between-cluster variations can be assumed across different levels due to households being nested within aggregated levels (e.g., neighborhood, county) of the sample dataset.

With their multilevel structure, mixed-effects models allow for capturing the effects of the two sources of variation among clustered data as well as the effects of the various levels of data clustering. In the latter case, the model introduces random effects for each level of the data.

Applying the mixed-effects model concepts to the Baltimore-D.C. case study, TAZs (i.e., neighborhoods) have been considered as clusters. This case study specifies random effects at the TAZ-level (i.e., neighborhood-level) in the mixed-effects models due to the importance of effects of neighborhood-level built environment. This model design introduces two levels: the first level is the household, and the second level is the TAZ. The use of the mixed-effects (multilevel) model is appropriate for the data used in this analysis because there are households that live in the same TAZ (cluster), but the individual household's characteristics differ from each other. This introduces two sources of variation in the model: the variation between different TAZs (i.e., interclass variance), and the variation within each TAZ (i.e., intraclass variance). These variations are also estimated by the model.

Based on the general formulas for the linear mixed-effects model (Equations 1 and 2), the Baltimore-D.C. nonmotorized travel behavior mixed-effects models are specified as follows:

$$\mathrm{Y} = \beta_0 + \beta_1' \mathrm{SE}_{\mathrm{HH}} + \beta_2' \mathrm{BE}_{\mathrm{TAZ}} + \beta_3' \mathrm{BE}_{\mathrm{County}} + \beta_4' \mathrm{RA} + u_{\mathrm{TAZ}} \mathbf{RE}_{\mathrm{TAZ}} + \varepsilon \qquad \text{Equ. C-1}$$

where,

β_0 = model intercept;

$\beta_1' - \beta_4'$ = column vectors of model parameters;

u_{TAZ} = vector of iid TAZ-level random effects;

ε = vector of model error terms;

SE_{HH} = column vector of household social environment (i.e., household socioeconomics);

BE_{TAZ} = column vector of micro-level (i.e., neighborhood) built environment attributes;

BE_{County} = column vector of meso-level (i.e., county) built environment attributes;

RA = column vector of regional accessibility attributes;

$\mathbf{RE}_{TAZ}$ = matrix of neighborhood-level covariates for TAZ-level random effects; and

Y = vector of observations (household's number of per capita walking or bicycling trips).

It is assumed that the slope of similar covariates contained within the random portion of the model (i.e., $\mathbf{RE}_{TAZ}$) is constant across TAZs. Therefore, the TAZ random effects are simplified to a TAZ-specific effect, which captures an effect that is common to all households within the same TAZ ($u_{0\mathrm{TAZ}}$). In other words, the model specified in Equation C-1 becomes a random intercept model (Equation C-2), which assumes that TAZs add a random offset to households' nonmotorized travel behavior (i.e., household's number of daily per capita walking or bicycling trips) due to TAZ-level random (unexplained) processes.

The simplified (i.e., random intercept) model formula is:

$$\mathrm{Y} = \beta_0 + \beta_1'\mathrm{SE}_{\mathrm{HH}} + \beta_2'\mathrm{BE}_{\mathrm{TAZ}} + \beta_3'\mathrm{BE}_{\mathrm{County}} + \beta_4'\mathrm{RA} + u_{0\mathrm{TAZ}} + \varepsilon \qquad \text{Equation C-2}$$

Since TAZs represent the neighborhoods in this study, the variance estimates (random effects) computed by the mixed-effects model provide information as to how random differences between neighborhoods affect the walking and bicycling travel behavior of residents. The model estimates also provide information on the existence and the extent of any effects exerted by meso-level (county) built environment factors on the levels of walking or bicycling of the households.

The walking and bicycling mixed-effect models relate the dependent variables (household's number of daily per capita walking and household's number of daily per capita bicycling trips) to the independent variables summarized in Table C-3.

The dependent variables are extremely skewed toward zero, meaning that a majority of households reported no walking or bicycling trips. This introduces the potential that the data may need zero-inflated treatment due to over-dispersion. However, as Kim and Susilo (2013) suggested over-dispersed data should not be used as an ultimate criterion for rejecting models; the appropriateness of different modeling techniques needs to be determined based on empirical analysis. Therefore, this study proceeds with testing the mixed-effects models for examination of the factors that are associated with nonmotorized travel behavior.

Pearson pairwise correlation coefficients have been calculated to examine the correlations between all original independent variables. The issue of high correlations between built environment factors is a concern mentioned in many past studies (see e.g., Cervero and Radisch 1996; Cervero and Kockelman 1997; Greenwald and Boarnet 2001; Krizek 2003b; Ewing et al. 2003a; Cervero and Duncan 2003; Frank et al. 2004; Næss 2005; Lee and Moudon 2006; Frank et al. 2008; Wood et al. 2010). This is in part due to the fact that denser urban designs often coexist with other features that are friendly to pedestrians and bicyclists. For example, Cervero and Kockelman (1997) stated that factors such as neighborhood densities, extent of mixed land use, and sidewalk provisions can be highly collinear due to the tendency of dense neighborhoods to have higher levels of land use mix, shorter blocks, and better sidewalk networks. Also, Rodríguez and Joo (2004) suggested that population density can act as a surrogate for mixed land use and improved street connectivity. Moreover, high correlations between population and housing densities were observed by Langerudi et al. (2015).

According to Franke (2010), correlation coefficients higher than 0.8 or 0.9 between independent variables are considered as excessively collinear and are indicators of multicollinearity. Two basic remedies have been proposed to deal with extreme collinearity between variables: 1) elimination of variables with extreme collinearity; and 2) replacement of highly correlated variables with a composite variable obtained from some kind of combination function (e.g., summing or averaging the values) (Kline 2011).

Therefore, one way to remedy the issue of high correlations between built environment variables is the usage of techniques such as factor analysis to combine the highly correlated variables into a composite factor. However, it should be borne in mind that a high correlation between built environment variables does not mean that these variables represent the same thing. Ewing et al. (2003a) suggested that while density and mixed land use are often correlated, they are very different constructs. As discussed in Subsection 2.5.3.[55], composite variables lack specificity and do not allow the contributions of individual independent variables to the outcome variable to become apparent.

[55] See the "*Health and Macro-level Built Environment*" part under Subsection "2.5.3 Health and Environmental Factors: Gaps and Limitations in Research".

Although many past studies used composite indices in their analysis to deal with highly correlated built environment variables (see e.g., Cervero and Kockelman 1997; Ewing et al. 2002; Ewing et al. 2003b; Braun and Malizia 2015), many other researchers voiced concerns regarding the use of composite indices and challenges it presents in interpreting the results, inferring conclusions, and making policy decisions (see e.g., Cervero and Radisch 1996; Humpel et al. 2002; Kelly-Schwartz et al. 2004; Rodríguez and Joo 2004; Lee and Moudon 2006; Fan 2007; Foster and Giles-Corti 2008). Distinct built environment factors—while sometimes highly correlated—have been suggested to represent distinct characteristics of the built environment and have been included in the past studies regardless of high correlations observed (see e.g., Ewing et al. 2003a; Ewing et al. 2014; Kelly-Schwartz et al. 2004). Therefore, to gain a better understanding of the effects of each of the built environment variables on nonmotorized travel, the use of composite indices has been avoided—to the extent possible—in this dissertation.

The alternative to using composite indices is to include highly correlated variables, which theory suggests can influence nonmotorized travel behavior, but select a reasonable threshold for high correlation tolerance. Previous research can assist in selection of an appropriate high correlation threshold. A few examples from past studies are discussed below.

The measures of density and street connectivity were highly correlated in Kelly-Schwartz and co-authors' study (r = 0.788) and the researchers indicated that this high correlation suggested the fact that many highly gridded urban streets also tend to be relatively dense (Kelly-Schwartz et al. 2004). Further, Bento et al. (2005) indicated that the correlation of their measures of population density and bus supply measure was 0.73. Fan (2007) eliminated a variable representing bus stop density due to being highly correlated with the sidewalk coverage variable. That study considered a Pearson correlation index greater than 0.8 as an indication of a high correlation between the two variables (Fan 2007). The correlations between density, land use mix, employment and population centering, and street accessibility factors fell in a range of 0.399 to 0.647 in the Ewing et al. (2014) study. The researchers suggested that these correlations were expected; however, the built environment factors "seem to represent distinct constructs based on their bivariate correlations". Finally, Marshall et al. (2014) stated that none of the independent variables used in their analysis had a Pearson correlation coefficient higher than 0.5 with another independent variable.

Table C-4 provides the Pearson correlation matrix for the independent variables used for the present case study. As expected, a few of the built environment variables show high correlations with each other, which is consistent with what researchers in the past suggested. This introduces the risk of multicollinearity, which can cause the models developed based on such data to drop potential key variables from the analysis.

The final independent variables were selected based on the Pearson correlations between them. Based on the above guidelines from the literature regarding dealing with highly correlated variables, efforts were made to reduce the risk of multicollinearity in the models. For example, due to a high correlation between variables representing the number of household vehicles and licensed drivers (r = 0.79), the latter was excluded from the models.

Also, the interacted variable of Walk Score and Bike Score, which was initially considered for inclusion in the bicycling model, was removed due to a high correlation with the *Bike Score* variable (r = 0.94).

Further, since the variables representing population and employment densities at the county level were highly correlated (r = 0.89), these variables were replaced with an activity density variable (i.e., the *Average Activity Density* variable) that quantifies the density of total population plus employment opportunities within each county.

Table C-4. Pearson Correlation Matrix for Independent Variables

Household-level Socioeconomic Attributes

Variable	Number of Members	Number of Students	Number of Workers	Number of Vehicles	Number of Bicycles	Number of Licensed Drivers	Annual Income
Household Size	1.0000						
Number of Students	0.7622	1.0000					
Number of Workers	0.4931	0.3027	1.0000				
Number of Vehicles	0.4616	0.2362	0.4674	1.0000			
Number of Bicycles	0.5341	0.5102	0.3315	0.3351	1.0000		
Number of Licensed Drivers	0.6246	0.3023	0.5936	0.7961	0.3341	1.0000	
Annual Income	0.2716	0.1155	0.4449	0.4517	0.3155	0.4715	1.0000

Micro-level (Neighborhood) Built Environment

Variable	Population Density	Employment Density	Average Block Size	Transit Accessibility	TOD	Walk Score	Bike Score
Population Density	1.0000						
Employment Density	0.4061	1.0000					
Average Block Size	-0.3261	-0.1441	1.0000				
Transit Accessibility	-0.0455	0.0762	-0.1219	1.0000			
TOD	0.3401	0.3176	-0.1598	0.0120	1.0000		
Walk Score	0.6344	0.3971	-0.5001	0.0881	0.4050	1.0000	
Bike Score	0.6372	0.3416	-0.2970	0.3742	0.3742	0.6977	1.0000
Entropy	0.0404	0.3277	-0.0202	0.0782	0.4101	0.2589	0.1979

Meso-level (County) Built Environment and Regional Accessibility

Variable	Mean Population Density	Mean Employment Density	Mean Block Size	Distance to CBD	Highway Acc. Index	Transit-Drive Acc. Index	Transit-Walk Acc. Index
Mean Population Density	1.0000						
Mean Emp. Density	0.8997	1.0000					
Mean Block Size	-0.6715	-0.6109	1.0000				
Mean Entropy	0.4540	0.3697	-0.2161	-0.1141			
Distance to CBD	-0.6368	-0.5797	0.6899	1.0000			
Highway Acc. Index	0.6701	0.6444	-0.5394	-0.5841	1.0000		
Transit-Drive Acc. Index	0.6774	0.5847	-0.5906	-0.6688	0.6354	1.0000	
Transit-Walk Acc. Index	0.6980	0.6847	-0.5741	-0.6614	0.7256	0.8194	1.0000

NOTE: Acc. = Accessibility

In the real world, however, the effects of many built environment factors are correlated and there is not an easy way to separate these correlations (Reilly and Landis 2003). Therefore, a correlation threshold of $|p| > 0.7$ has been used to eliminate highly correlated independent variables, as suggested by previous research (Kim and Susilo 2013)[56].

Any continuous variable with a correctable skewed distribution was normalized by transformation into its naturally logged form before inclusion in the model. Logarithmic transformation is a convenient means of transforming a highly skewed variable into one that is more approximately normal (Benoit 2011). Many previous studies also used the log transformation method to treat variables with skewed distributions (see e.g., De Bourdeaudhuij et al. 2003; Handy et al. 2005; Evans and Wener 2006; Fan 2007; Gordon-Larsen 2009; Cao et al. 2010; Renne et al. 2015). Log-linear transformations are advantageous, since they enable interpretation of the coefficients as elasticities—reflecting the sensitivity (i.e., percentage change) in the dependent variable to a 1% change in each of the independent variables, holding all other variables constant (Cervero and Murakami 2010). Also, log-log transformations enable interpretation of the coefficients as arc elasticities (Renne et al. 2015).

Many variables in the present analysis, however, either showed a normal (or nearly normal distribution) or did not show improvement in their distribution curve by transformation to naturally logged form (including the dependent variables). In the latter case, the variable was included in the model in its original form.

Moreover, since the natural log of zero is undefined, if the value of an independent variable was equal to zero, it was changed to 0.25 before the variable was log-transformed—a practice also used in previous research (see e.g., Schauder and Foley 2015).

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[56] Variables with correlation coefficients slightly ≥ 0.70 were retained in the models if they reached a significance level of 0.05 or if there was a theoretical reason for retaining the variable; for example, if the variable was deemed to play a key role in generation of nonmotorized trips based on previous studies.

Discussion of Results: Baltimore-DC Linear Mixed-effects Nonmotorized Travel Models

Table C-5 summarizes the estimation results of the mixed-effects walking and bicycling models for the two metropolitan areas. The results show strong associations between household nonmotorized travel behavior—especially walking—and the built environment attributes at both micro-level (neighborhood) and meso-level (county). The results also indicate that regional accessibility measures have a statistically significant association with nonmotorized travel.

Household Control Variables Findings: The effects of the socioeconomic status of households were estimated by controlling for households' number of members (household size), number of students and number of workers as well as household vehicle and bicycle ownership.

The results show that household size has a negative correlation with walking and bicycling trips; being a member of a larger household may mean making fewer nonmotorized trips. Although Plaut (2005) found that household size had positive effects on the likelihood of choosing nonmotorized modes, the household size was defined in that study in terms of square foot floor space of the housing unit, and not the number of household members as in the present study.

The coefficient of the variable for the number of household students in both the walking and bicycling models has a negative sign, which is expected; households with a larger number of students are more likely to choose driving (and not walking or bicycling) as their mode of travel to and from school and perhaps other destinations.

Past literature lends support to these statements suggesting that automobile has become the predominant mode for school trips in the U.S., even for short-distance trips, while rates of walking and bicycling to school have declined (CDC 2002; Ewing and Greene 2003; McMillan 2003, 2005; National Research Council 2005; McDonald 2005; Schlossberg et al. 2006; McDonald et al. 2011).

Table C-5. Results:Baltimore-D.C. Multilevel (Mixed-effects) Nonmotorized Travel Models

Dependent Variable: Number of Household's Daily Per Capita Walking/Bicycling Trips				
	Walking Model		**Bicycling Model**	
Independent Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Household-level Socioeconomic Attributes (SE_{HH}): The Household				
Number of Members (Size)	-.0424058***	0.006	-.0089737**	0.013
Number of Students	-.0323689*	0.076	-.0071362*	0.099
Number of Workers	.0422162***	0.008	.0099524***	0.008
Number of Vehicles	-.1732062***	0.000	-.0116361***	0.000
Number of Bicycles	.0358879***	0.000	.0267977***	0.000
Annual Income (1,000s of dollars)	.0089051*	0.052	-.0001983	0.853
Micro-level Built Environment (BE_{TAZ}): The Neighborhood				
Population Density (total population/acre)	.0030982***	0.009	.0001035	0.676
Employment Density (jobs/acre)	.0023263***	0.000	-.0002976**	0.014
Average Block Size (acres) - logged	-.0609581***	0.013	.0004346	0.926
Transit Accessibility	.0007898*	0.080	.0001584*	0.091
Transit Oriented Development	.0546366*	0.097	.0051992	0.592
Walk Score[a]	.0022659***	0.005	—	—
Bike Score[a]	—	—	.0005874***	0.000
Entropy[a]	.2339221***	0.001	.0208084*	0.054
Meso-level Built Environment (BE_{County}): The County				
Average Activity Density [(population + employment)/acre]	.0057054***	0.000	-.0002024*	0.078
Average Block Size (acres) - logged	-.2166408***	0.000	.0020607	0.789
Average Entropy[a]	-.0326816	0.870	-.0496237*	0.082
Regional Accessibility (RA): The Region				
Distance to CBD (miles) - logged	-.1383853***	0.000	.0047567	0.518
Highway Accessibility Index[a] - standardized	-.0600699***	0.000	-.0048065*	0.060
Transit-Drive Accessibility Index[a] - standardized	-.0474197***	0.000	.0007805	0.748
Transit-Walk Accessibility Index[a] - standardized	.0448405***	0.001	.0026444	0.343
Variance Estimates (Random Effects)				
TAZ (i.e., The Neighborhood)	.0315613***	0.000	.0004021*	0.085
Residuals	.9668831***	0.000	.05538***	0.000
Model Goodness Parameters				
Likelihood Ratio Test vs. Linear Regression:	χ^2 = 43.54***	0.000	χ^2 = 2.13*	0.073
R^2 Marginal	0.1463989		0.0297893	
R^2 Conditional	0.1752696		0.0367733	
Observations; Clusters	9,481; 1,280		9,481; 1,280	

NOTES:

*, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;

[a] Dimensionless.

For example, McDonald et al. (2011) used data from the 2009 NHTS to provide a summary of children's trips to school and find trends in such trips by comparing the results of analysis of the 2009 data with those obtained from analyzing similar national data from 1969, 1995, and 2001. The analysis showed that walking trips to school decreased between 1969 and 2009 as more students were making automobile trips to school in 2009 compared to 1969.

With respect to non-school trips of households with students, McMillan (2003) suggested that all of children's trips (and not just school trips) were greatly dependent on automobile travel, while Dieleman et al. (2002) found that households with children were more likely than others to use the private vehicle mode instead of other modes of travel. In addition, from analyzing the 2001 NHTS data, McDonald (2005) found that automobile accounted as the travel mode for most of children's trips for all trip purposes (i.e., school, shopping, sports, socializing).

However, it is noteworthy that a few past studies found correlations between being a student and nonmotorized travel behavior. For example, Rodríguez and Joo (2004) found that being a university student was associated with higher propensity to walk and bicycle. Being a high school student was also found to be associated with prevalence of health-enhancing walking and bicycling levels in Merom et al. (2010).

Therefore, it would be helpful to have more details in travel surveys on the level of school that is being attended by the student(s) instead of just collecting data on the "number of students in the household". Nonetheless, this variable shows a significant correlation (at the 10% significance level) in both the walking model and the bicycling model in the present study.

The number of household workers is positively and significantly correlated with household walking and bicycling travel. The correlation between household income and walking is positive and significant, even though Plaut (2005) found that higher income was associated with a lower likelihood of nonmotorized commuting.

The positive impact of income on walking in the present study is probably reflecting recreational walking of individuals within wealthier households as suggested by previous studies (Kockelman 1997; Leslie et al. 2007; Agrawal and Schimek 2007; Roshan Zamir et al. 2014). The negative effect of income on bicycling can mean that to reach destinations, wealthier individuals use their private vehicles more instead of bicycling. However, the coefficient of income variable in the bicycling model does not reach a statistical significance threshold; a result which is consistent with that of Moudon et al. (2005) who found household income did not indicate a significant link with the likelihood of bicycling.

Dill and Carr (2003) also concluded that income had no significant effect in bicycling travel. In the latter study, income was included at the aggregate level (i.e., city level) and the authors suggested that in analysis of bicycling trips, socioeconomic variables such as income might be significant at the disaggregate level (Dill and Carr 2003). The results of the present case study, however, do not support that statement as the coefficient of the variable representing the household income is insignificant in the bicycling model.

The number of household vehicles is significantly and negatively correlated with household's number of daily per capita walking and bicycling trips. These results confirm previous findings (see e.g., Cervero 1996; Cervero and Radisch 1996; Kitamura et al. 1997; Stinson and Bhat 2004; Plaut 2005; Mitra and Buliung 2012) and are intuitive; one can expect that members of households with more vehicles be encouraged to drive more and walk or bicycle less. By contrast, the number of household bicycles is significantly and positively correlated with households' walking and bicycling. This is expected and consistent with previous findings (Cervero and Duncan 2003; Targa and Clifton 2005; Moudon et al. 2005; Heinen et al. 2010).

Although owning a bicycle is a natural prerequisite for bicycling (Moudon et al. 2005), this variable is potentially capturing general preferences toward nonmotorized travel in a household; the more bicycles a household owns, the more nonmotorized trips—including walking trips—is expected from members of that household.

Micro-level (Neighborhood-level) Built Environment Variables Findings: A few micro-level built environment variables are significantly correlated with household nonmotorized travel behavior. Population and employment densities seem to have significant and positive correlations with household's number of daily per capita walking trips. However, population density does not have a significant correlation with the number of daily per capita bicycling trips, whereas employment density seems to have a significantly negative correlation with bicycling. These results mean that increased levels of residents' walking are associated with increased neighborhood population and employment densities. However, higher levels of employment opportunities within a neighborhood are associated with lower levels of bicycling—a finding that was also reported in previous research (Cervero and Duncan 2003). The referenced study suggested that denser urban employment settings create many roadway conflict points, which may deter bicyclists due to safety concerns. Overall, the results on the role of neighborhood-level density measures in nonmotorized travel confirm the findings of previous studies that reported densities at the local level were associated with nonmotorized travel behavior (Frank and Pivo 1994; Cervero and Duncan 2003; Næss 2005; Targa and Clifton 2005; Boarnet et al. 2008).

The *Average Block Size* variable exhibits a significant and negative association with walking, but its coefficient is not significant in the bicycling model. This variable is considered a proxy for street network connectivity and pedestrian friendliness in this study and has the expected direction in the walking model; smaller block sizes indicate more connected and walkable streets within the neighborhood with shorter distances to destinations, which thereby can encourage more pedestrian trips. When measured objectively, block size has been found in past research to be an insignificant factor in bicycling travel behavior (Moudon et al. 2005) and the results of the present study confirms that finding.

Table C-5 also indicates that higher accessibility to local transit (i.e., higher number of transit stations and bus stops within the neighborhood) is significantly and positively associated with nonmotorized trips, which is consistent with findings of previous studies (see e.g., Kitamura et al. 1997; Targa and Clifton 2005; Ewing and Cervero 2010). The results also show that proximity to transit has a significant correlation with walking; living in transit-oriented neighborhoods is estimated by the model to be correlated with walking more—a finding suggested in previous research (Roshan Zamir et al. 2014). However, transit-oriented development does not seem to play a role in generating bicycling trips.

The *Walk Score* and *Bike Score* variables exhibit significant and positive correlations with households' walking and bicycling, respectively. In part, this outcome corroborates past findings of a strong positive relationship between Walk Score and walking (Weinberger and Sweet 2012). Together, the coefficients of the *Average Block Size* and *Walk Score* variables confirm past findings that suggested neighborhood walkability influenced walking (see e.g., Giles-Corti et al. 2009). The coefficients of the *Walk Score* and *Bike Score* variables also confirm findings of previous studies that neighborhood destination accessibility—particularly distance to desired local destinations such as stores and schools—is an influential factor in estimating nonmotorized trips (Cervero and Kockelman 1997; Handy and Clifton 2001; Schlossberg et al. 2006).

Neighborhood-level entropy (a variable representing the extent of mixed-use development) shows positive correlations with walking and bicycling trips. This indicates that as expected, higher levels of neighborhood mixed land use are associated with more nonmotorized trips. These findings parallel those of previous research (see e.g., Cervero and Kockelman 1997; Cervero and Duncan 2003; Moudon et al. 2005; Kerr et al. 2007; Lin and Chang 2010).

Together, these outcomes confirm that neighborhood-level built environment factors are influential elements in the nonmotorized travel behavior of residents.

Meso-level (County-level) Built Environment Variables Findings: At the county level, the *Average Activity Density* variable exhibits significant correlations with both walking and bicycling; however, the directions of impact are opposite of one another. Average activity density is positively associated with the household's number of daily per capita walking trips, but it is negatively associated with the household's number of daily per capita bicycling trips. This indicates that higher levels of walking by residents of a county are associated with higher population and employment densities within the county.

Conversely, living in highly populated counties with more employment opportunities is associated with fewer bicycling trips. Pucher et al. (1999) suggested that high-density environments attract utilitarian bicycling due to existence of more destinations within a short bicycling distance. On the other hand, Cervero and Duncan (2003) argued that denser urban employment settings may deter bicyclists due to safety concerns related to the many roadway conflict points created by these environments. The results of the present study are consistent with the latter argument. These results confirm the hypothesis of this study that densities at the county level can be significantly associated with household's nonmotorized travel behavior. The results also show that built environment characteristics can affect walking and bicycling differently.

The direction of the coefficient of the statistically significant *Average Block Size* variable at the county level further supports the hypothesis that a smaller average block size (i.e., better street network connectivity) within the county is associated with more walking. This means that as street network connectivity improves within the county, there may be more walking trips generated by residents. The coefficient of this variable is not significant in the bicycling model.

The sign of the coefficient of the *Average Entropy* variable at the county level is negative in both the walking and bicycling models. It should be noted, however, that the coefficient of the average county-level entropy variable is only significant in the bicycling model. This means that a higher extent of mix land use within the county is associated with fewer bicycling trips. This result is unexpected. Improved mixed-use development throughout the region is expected to lower the extent of driving by residents because they can reach various destinations in their own locality. Previous studies confirmed this hypothesis by reporting a negative association between average county-level entropy and household Vehicle Miles Traveled (VMT) (Nasri and Zhang 2012). This finding intuitively gives rise to expectations of having more nonmotorized trips associated with higher levels of county-level entropy variable. However, as it can be seen from Table C-5, the findings of the present analysis do not support that hypothesis.

Together, these results confirm that county-level built environment factors can play a role in the nonmotorized travel behavior of residents.

Regional Accessibility Variables Findings: The *Distance to CBD* variable exhibits a significantly negative correlation with walking. This implies that living in suburban areas with greater distances from households to the city's business district is negatively associated with walking trips of the household members. This finding stands in agreement with findings of Boarnet et al. (2008) as well as arguments by other researchers (see e.g., Næss 2005; Leslie et al. 2007;

Cao et al. 2007; Cao et al. 2009). The consistency in these findings lends some degree of confidence to the results. Intuitively, this result is expected; due to greater distances from suburban residences to various destinations, driving is probably the preferred and practical mode of travel for members of these households. This statement is supported by previous studies that suggested residents of suburban areas drive more (Cao et al. 2007), as well as those that suggested decentralization and urban sprawl contribute to automobile dependency (see e.g., Cao et al. 2010; Siu et al. 2012; Ewing et al. 2014). On the other hand, distance to CBD does not seem to play a significant role in generating bicycling trips according to the results of the present study, although Dill and Voros (2007) found that individuals who lived in neighborhoods closer to downtown were more likely to make a utilitarian bicycle trip.

The coefficients of the *Highway Accessibility* and *Transit-Drive Accessibility* indices are both significant in the walking model. As expected, these variables are negatively associated with walking, which confirms the hypothesis that increased regional accessibility by means of driving on the roads and/or driving to transit stations may discourage walking. The *Transit-Walk Accessibility Index* exhibits a positive correlation with household's number of daily per capita walking trips. This implies that higher access to transit by means of walking throughout the region is associated with making additional walking trips. This result is expected because as walking access to transit increases, it is more likely that residents are encouraged to walk to and from transit stations. However, except for the *Highway Accessibility Index*, which shows a negative sign, none of the other regional accessibility variables are statistically significant in the bicycling model. This result can mean that as regional accessibility by means of driving on roads increases, households may generate fewer numbers of daily per capita bicycling trips.

Together, these findings provide evidence that accessibility at the regional level—especially in terms of highway accessibility—can be significantly associated with nonmotorized travel behavior, just as it is at the local (i.e., neighborhood) level.

Interpretation of Results: Baltimore-DC Mixed-effects Nonmotorized Travel Models

The results presented in Table C-5 can be interpreted using standard interpretation methods for regression coefficients. For brevity, only a few examples are provided here for interpretation of the model coefficients. The coefficient estimated for the household vehicle ownership in the walking model (-0.1732062), for instance, indicates that each additional private automobile that is available to the household is associated with a decline of approximately 0.17 in the number of daily walking trips for each household member (0.17 fewer daily walking trips/person for each additional household vehicle). Also, the coefficient of the variable representing the TOD status of the neighborhood in the walking model (0.0546366) indicates that approximately 0.06 additional daily walking trips per household member are generated if the household is located within a TOD neighborhood rather than in a non-TOD neighborhood. The entropy index is in a proportion form, meaning its value ranges between 0 and 1. Therefore, the coefficient of the county-level entropy variable in the bicycling model (-0.0496237) indicates that all else being equal, an increase of one unit (i.e., 0.01) in the entropy index within the county of residence is associated with 0.049 fewer bicycling trips generated by each household member for households located in that specific county.

A few of the built environment variables in the models are log-transformed variables which should be considered in the interpretation of the coefficient estimates. For example, the coefficient of the county-level *Average Block Size* variable in the walking model (-0.2166408) means that all else being equal, if the average block size within the county of residence doubles (an increase of %100 in the value of the county-level *Average Block Size* variable), the number of daily walking trips per household member drops by nearly 0.22 trips (walking trips/person). Also, the coefficient estimate of the *Distance to CBD* variable in the walking model (-0.1383853) indicates that if the distance (in miles) of a particular household to the center of the city doubles, the number of daily walking trips generated by each household member drops by nearly 0.14 trips (walking trips/person). For standardized variables (i.e., regional accessibility indices), the coefficient estimates can be interpreted in terms of the standard deviation. For example, the coefficient estimate on the *Highway Accessibility Index* in the walking model (-0.0600699) can be interpreted as: all else being equal, a one standard deviation increase in the value of *Highway Accessibility Index* is associated with a decrease of (0.06 × standard deviation) in the number of daily walking trips for each household member.

The above interpretations serve as examples for quantifications of the correlations between a household's nonmotorized trips and neighborhood-level, county-level, and regional built environment characteristics as estimated by the models.

As mentioned previously, the random effects of TAZs have been considered in the above mixed-effects models to assess how differences between neighborhoods affect nonmotorized travel behavior of residents. The between-TAZ (level two) component of variance (i.e., the variance component corresponding to the random intercept) is σ_u^2= 0.0315613 in the walking model and σ_u^2= 0.0004021 in the bicycling model. These estimates are statistically significant, which indicates that after controlling for the various variables in the models, there remains some TAZ-level variance unaccounted for. Thus, there appears to be significant variation in the means of the number of households' per capita walking/bicycling trips across TAZs.

With respect to the walking model, the between-TAZ (level two) component of variance (σ_u^2= 0.0315613) is much smaller that the within-TAZ (level one) component of variance (σ_e^2=

0.9668831). This result is probably because the number of households in each TAZ (number of observations per cluster) is relatively small (an average of 8 observations per cluster), whereas the number of TAZs (clusters) that are compared to each other is large (1,280 TAZs)[57]. This finding (i.e., $\sigma_e^2 > \sigma_u^2$) also indicates the considerable variability of the number of households' per capita walking trips from household to household within a TAZ. The two variance components can be used to partition the variance across the two levels in the model. The total variance for the walking model is $\sigma_u^2 + \sigma_e^2$= 0.0315613 + 0.9668831= 0.9984444. The degree of resemblance between level-one units (i.e., households) belonging to the same level-two cluster (i.e., TAZs) can be expressed by the intraclass correlation coefficient (see Snijders and Bosker 2012). The intraclass correlation coefficient (i.e., variance partition coefficient) is equal to 0.0315613/0.9984444 = 0.0316, which indicates that 3.16% of the variance in the number of households' daily per capita walking trips is attributable to TAZ-level random (unexplained) processes that affect the number of households' daily per capita walking trips[58] (i.e., TAZ random intercept effects).

Considering the bicycling model, it can be seen from Table C-5 that the between-TAZ component of variance (σ_u^2= 0.0004021) is much smaller that the within-TAZ component of variance (σ_e^2= 0.05538). This difference is also attributable to the fact that the number of households in each TAZ (number of observations per cluster) is relatively small (an average of 8 observations per cluster), but a large number of TAZs (clusters) are being compared to each other

[57] The small number of households in each TAZ (i.e., number of observations per cluster) further justifies employment of mixed-effects modeling techniques and computing random effects in this analysis. Per Demidenko (2004), a small number of clusters with a large number of observations per cluster constitutes the treatment of the cluster-specific coefficients (i.e., random effects containing the effects of clustering of the observations under various levels) as fixed effects, whereas having a large number of clusters with a small number of observations per cluster, necessitates the treatment of the cluster-specific coefficients as random effects.
[58] Computations based on examples in Leckie (2010), Albright and Marinova (2010), and Rabe-Hesketh and Skrondal (2012).

(1,280 TAZs). The total variance for the bicycling model is $\sigma_u^2 + \sigma_e^2$= 0.0004021 + 0.05538 = 0.0557821. Thus, the intraclass correlation coefficient (i.e., variance partition coefficient) is equal to 0.0004021/0.0557821 = 0.0072, which indicates that approximately 0.7% of the variance in the number of households' daily per capita bicycling trips is attributable to differences between TAZs (TAZ random intercept effects).

The p-values of the TAZ random effects are significant in both walking and bicycling models. These results suggest that random differences between neighborhoods (i.e., TAZ random effects) play a small but statistically significant role in nonmotorized travel behavior of residents.

Thus, it can be inferred that contextual effects such as those of the neighborhood structure can play an autonomous role in nonmotorized travel choices. Literature agrees that neighborhood differences such as impediments or stimulants to walking and bicycling are likely to vary greatly among different types of neighborhoods such as inner-city neighborhoods, suburban developments, and rural communities (National Research Council 2005).

Further, the results of the Likelihood Ratio tests in both models are statistically significant as evidenced by the value of chi-squared (χ^2) and the corresponding p-values. These results mean that in both models, the multilevel (i.e., mixed-effects) modeling technique offers improvements over an ordinary linear regression model with fixed effects only. These results justify taking into consideration the random effects of individual TAZs on walking and bicycling behavior and using the multilevel models instead of ordinary linear regression models. It should be noted that although statistically significant at 10% significance level, the improvements offered by the multilevel model in the bicycling model are not very robust (p-value = 0.073).

The marginal R-squared values provide information on variance explained by fixed factors, whereas the conditional R-squared is for variance explained by both fixed and random factors;

thus, differences between values of the two reflect how much variability exists in random effects (Nakagawa and Schielzeth 2013). The referenced paper recommended that both marginal and conditional R-squared be reported in publications because they convey unique information.

Elasticities: Table C-6 shows the elasticities computed for the multilevel mixed-effects models with all the independent variables set to their mean values. Elasticities measure the percentage change in the dependent variable due to a 1% change in the independent variable. Basically, an elasticity is the ratio (dimensionless measure) of the percentage change in one variable (i.e., dependent variable) associated with the percentage change in another variable (i.e., independent variable) (Ewing and Cervero 2010).

Among the household socioeconomic attributes, the elasticity of the number of household's daily per capita walking trips is highest with respect to the number of vehicles owned by the household (-0.528005). The elasticity indicates that an increase by 100% in the number of vehicles (i.e., if number of household vehicle doubles) is associated with a decrease of approximately 53% in the number of household's daily per capita walking trips. Among the micro-level built environment characteristics, the *Walk Score* variable has the highest statistically significant elasticity (0.1793713), meaning an increase in the neighborhood Walk Score by 100% (i.e., if the Walk Score doubles) is associated with an increase by approximately 18% in the number of household's daily per capita walking trips. At the meso level (i.e., county), *Average Block Size* with an elasticity of -0.40173, and among the regional accessibility variables, *Distance to CBD* with an elasticity of -0.2566162 have the highest elasticities in the walking model.

These results further emphasize the role of vehicle ownership, neighborhood destination accessibility, street connectivity at the county level, and distance to the center of the city in generating walking trips.

Table C-6. Elasticities: Baltimore-D.C. Multilevel Nonmotorized Travel Models

Dependent Variable: Number of Household's Daily Per Capita Walking/Bicycling Trips				
	Walking Model		**Bicycling Model**	
Independent Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Household-level Socioeconomic Attributes (SE_{HH}): The Household				
Number of Members (Size)	-.172466***	0.006	-.7316617**	0.016
Number of Students	-.0325094*	0.077	-.1436839	0.103
Number of Workers	.0960777***	0.008	.4540818***	0.010
Number of Vehicles	-.528005***	0.000	-.7111199***	0.001
Number of Bicycles	.0726418***	0.000	1.087422***	0.000
Annual Income (1,000s of dollars)	.1226014*	0.052	-.0547232	0.853
Micro-level Built Environment (BE_{TAZ}): The Neighborhood				
Population Density (total population/acre)	.0769952***	0.009	.051561	0.676
Employment Density (jobs/acre)	.0364353***	0.000	-.0934592**	0.016
Average Block Size (acres) - logged	-.1130383**	0.013	.0161547	0.926
Transit Accessibility (number of transit stations + bus stops)	.0144692*	0.084	.0581854*	0.095
Transit Oriented Development	.0121823*	0.099	.0232404	0.593
Walk Score[a]	.1793713***	0.005	—	—
Bike Score[a]	—	—	.4885906***	0.000
Entropy[a]	.1917095	0.001	.3418802*	0.055
Meso-level Built Environment (BE_{County}): The County				
Average Activity Density [(population + employment)/acre]	.2590538***	0.000	-.1842209*	0.082
Average Block Size (acres) - logged	-.40173***	0.000	.0766082	0.789
Average Entropy[a]	-.0278555	0.870	-.8479248*	0.084
Regional Accessibility (RA): The Region				
Distance to CBD (miles) - logged	-.2566162***	0.000	.1768309	0.518
Highway Accessibility Index[a] - standardized	-.045429***	0.000	-.0728727*	0.064
Transit-Drive Accessibility Index[a] - standardized	-.0532558***	0.000	.0175724	0.748
Transit-Walk Accessibility Index[a] - standardized	.050781	0.001	.0600361	0.345
Observations; Clusters	9,481; 1,280		9,481; 1,280	

NOTES:
*, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;
[a] Dimensionless.

Similarly, the elasticities of the independent variables in the bicycling model indicate the important role of vehicle and bicycle ownership, neighborhood bicycle-friendliness, and extent of neighborhood and county mixed land use among other factors in bicycling trip generation. While the bicycle ownership variable (i.e., *Number of Bicycles*) has the largest elasticity in the bicycling model, the entropy variables at both the neighborhood and county level also exhibit large elasticities in the bicycling model. These variables were included in the model to represent land use mix; thus, a better mix of residential, retail, office and other uses within the neighborhood and county are among the most important built environment attributes in determining bicycling, which is in line with previous findings (Moudon et al. 2005).

Multicollinearity Check: To further check for multicollinearity in the models, Variance Inflation Factors (VIFs) are estimated and listed for all the independent variables in Table C-7.

Table C-7. Variance Inflation Factors (VIFs) for Independent Variables

Models / ***Independent Variables***	***Walking Model***		***Bicycling Model***	
	VIF	***1/VIF***	***VIF***	***1/VIF***
Household-level Socioeconomic Attributes: The Household				
Number of Members (Size)	3.37	0.2969	3.37	0.2970
Number of Students	2.67	0.3752	2.67	0.3752
Number of Workers	1.63	0.6132	1.63	0.6132
Number of Vehicles	1.90	0.5271	1.90	0.5277
Number of Bicycles	1.56	0.6402	1.56	0.6398
Annual Income (1,000s of dollars)	1.53	0.6540	1.54	0.6513
Micro (Neighborhood)-Level Built Environment (TAZ Level)				
Population Density (total population/acre)	2.29	0.4358	2.33	0.4293
Employment Density (jobs/acre)	1.51	0.6635	1.50	0.6653
Average Block Size (acres) -logged	3.69	0.2708	2.95	0.3392
Transit Accessibility (number of transit stations + bus stops)	1.19	0.8407	1.22	0.8168
Transit Oriented Development	1.59	0.6288	1.59	0.6271
Walk Score	3.93	0.2547	—	—
Bike Score	—	—	4.44	0.2249
Entropy	1.69	0.5918	1.63	0.6135
Meso-level Built Environment (County Level)				
Average Activity Density [(population + employment)/acre]	5.56	0.1799	6.40	0.1562
Mean Block Size (acres) - logged	7.77	0.1287	7.71	0.1297
Mean Entropy	1.64	0.6096	1.74	0.5755
Regional Accessibility				
Distance to CBD (miles) - logged	8.05	0.1242	8.14	0.1228
Highway Accessibility Index - standardized	3.37	0.297	3.36	0.2978
Transit-Drive Accessibility Index - standardized	3.59	0.2789	3.66	0.2732
Transit-Walk Accessibility Index - standardized	5.45	0.1834	5.46	0.1829
Mean	**3.20**	**0.4297**	**3.24**	**0.4279**

All the estimated VIFs are less than 10, which is considered the threshold for redundancy of variables (Kline 2011) and significant and potentially harmful collinearity (Franke 2010). The latter reference also states that “collinearity creates fewer problems when sample sizes are large, predictors have high variances relative to that of the criterion variable"—as is the case in the sample for the present case study. Thus, it can be concluded that multicollinearity is not a problem in the Baltimore-DC mixed-effects (i.e., multilevel) nonmotorized travel models.

Summary of Findings: Baltimore-DC Linear Mixed-effects Nonmotorized Travel Models

Taken together, the results of the multilevel (i.e., mixed-effects) models confirm previous findings that walking and bicycling are associated with household socioeconomic characteristics including vehicle ownership as well as the micro-level (i.e., neighborhood-level) built environment attributes of the place of residence. The results of the present study show that living in more compact and pedestrian- and bicycle-friendly neighborhoods with improved street connectivity, higher levels of mixed land use, and increased transit accessibility is associated with a higher number of daily nonmotorized trips. The results also suggest that random differences between neighborhoods may play a role, albeit humble, in walking and bicycling of people.

The analysis adds to the body of knowledge that meso-level (i.e., county-level) built environment characteristics as well as regional accessibility attributes may also play important roles in nonmotorized travel behavior. Particularly, living in highly populated counties with more employment opportunities is associated with more walking trips but fewer bicycling trips. Moreover, living in counties with better street connectivity throughout is associated with more walking trips. Higher levels of mixed-use development throughout the county is associated with fewer bicycling trips. Also, increased highway accessibility as well as increased accessibility to transit by means of driving throughout the entire county are associated with fewer walking and bicycling trips, whereas higher regional accessibility to transit by means of walking is associated with more walking trips. Additionally, walking trips are negatively associated with residing in locations farther away from the city center.

C.1.4.2 Ordered Probit Models

Specification of Models: Baltimore-DC Ordered Probit Nonmotorized Travel Models

Similar to the multilevel models, ordered probit models have been employed to examine the association between nonmotorized trips and built environment attributes at micro-level (i.e., neighborhood) and meso-level (i.e., county) geographical scales. This allows comparison of the model results and confirmation of the findings.

Ordered probit models allow modeling of discrete choices and enable the analyst to deal with ordinal dependent variables. These models can be applied to ordinal dependent variables that are coded as consecutive integers. The total number of household's daily walking or bicycling trips represent discrete choices; therefore, the ordered probit model is an appropriate technique to be employed in modeling them.

Applying the ordered probit modeling concepts to the Baltimore-D.C. case study, the total number of household's daily walking (or bicycling) trips can be defined as the observed ordinal dependent variable (y). This observed variable is assumed to take on a series of values—from zero to the maximum number of trips in the dataset (21 for walking trips and 11 for bicycling trips, based on Table C-1)—depending on the value of the unobserved latent variable y^*.

Based on Equation 10 (see Subsection 3.3.2 in this dissertation), the equation for the ordered probit model for the total number of nonmotorized trips can be formulated as:

$$y^* = \beta_1' \mathrm{SE}_{\mathrm{HH}} + \beta_2' \mathrm{BE}_{\mathrm{TAZ}} + \beta_3' \mathrm{BE}_{\mathrm{County}} + \beta_4' \mathrm{RA} + \varepsilon \qquad \text{Equation C-3}$$

where,

$\beta_1' - \beta_4'$ = column vectors of model parameters;

ε = an iid error term with a normal distribution ($\varepsilon \sim N\ (0, 1)$);

$\mathrm{SE}_{\mathrm{HH}}$ = column vector of household social environment attributes (i.e., socioeconomics);

BE_{TAZ} = column vector of micro-level (i.e., neighborhood) built environment attributes;

BE_{County} = column vector of meso-level (i.e., county-level) built environment attributes;

RA = column vector of regional accessibility attributes; and

y^* = value of the unobserved latent variable.

The probability of a certain number of walking (or bicycling) trips having been generated from a certain household, *i*, is computed by the ordered probit model through relating the observed number of household trips, y, to the unobserved latent variable y^*. That probability is given by:

Probability $(y_i = y_n) = \Phi(\alpha_n - x_i\beta) - \Phi(\alpha_{n-1} - x_i\beta)$

where,

y_n = an integral number of walking (or bicycling) trips;

Φ = the cumulative normal distribution function;

α_n = the upper threshold for the range of y^* which corresponds to *n* trips;

α_{n-1} = the lower threshold for the range of y^* which corresponds to *n* trips;

x_i = vector of independent variables containing SE_{HH}, BE_{TAZ}, BE_{County} and RA; and

β = column vector of the parameters β'_{1-4} (in Equation C-3).

Given the representation above, ordered probit models can be estimated for the household's daily number of walking (or bicycling) trips based on household's socioeconomic characteristics, neighborhood- and county-level built environment characteristics, as well as regional accessibility characteristics. The model also estimates the thresholds (cut points) as y^* crosses them.

Discussion of Results: Baltimore-DC Ordered Probit Nonmotorized Travel Models

Table C-8 summarizes the estimation results of the ordered probit model for the two metropolitan areas (i.e., Washington, D.C. and Baltimore). The results of the ordered probit models generally agree with those of the mixed-effects models in terms of the sign of the coefficient estimates.

Household Control Variables Findings: Similar to the results of the mixed-effect models, household size shows a significant and negative association with household's walking and bicycling travel in the ordered probit models.

Table C-8. Results: Baltimore-D.C. Ordered Probit Nonmotorized Travel Behavior Models

Dependent Variable: Number of Household's Daily Walking/Bicycling Trips				
	Walking Model		**Bicycling Model**	
Independent Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Household Socioeconomics (SE_{HH}): The Household				
Number of Members (Size)	-.1946126***	0.000	-.0200455**	0.016
Number of Students	-.0269893	0.224	.0011314	0.983
Number of Workers	.1064911***	0.000	.1687302***	0.002
Number of Vehicles	-.2685013***	0.000	-.2077118***	0.000
Number of Bicycles	.0660427***	0.000	.2896479***	0.000
Annual Income (1,000s of dollars)	.020404***	0.000	.0204818	0.172
Micro-level Built Environment (BE_{TAZ}): The Neighborhood				
Population Density (total population/acre)	.0017949*	0.091	-1.54e-06	1.000
Employment Density (jobs/acre)	.0010783**	0.049	-.0034208*	0.076
Average Block Size (acres) - logged	-.0380194*	0.073	-.0235782	0.721
Transit Accessibility (number of transit stations + bus stops)	.0000921	0.153	.0028038*	0.087
Transit Oriented Development	.0199667*	0.084	-.048641	0.651
Walk Score	.0021871***	0.010	—	—
Bike Score	—	—	.0057826***	0.004
Entropy	.2626597***	0.001	.4403056**	0.025
Meso-level Built Environment (BE_{County}): The County				
Average Activity Density [(population + employment)/acre]	.0043551***	0.000	-.0015022*	0.080
Average Block Size (acres) - logged	-.1468318***	0.000	.0536983	0.616
Average Entropy	-.3166882**	0.017	-1.374268**	0.040
Regional Accessibility (RA): The Region				
Distance to CBD (miles) - logged	-.2372252***	0.000	-.1001062	0.303
Highway Accessibility - standardized	-.0025195**	0.027	-.0098194	0.724
Transit-Drive Accessibility - standardized	-.0360983***	0.003	.0307451	0.310
Transit-Walk Accessibility - standardized	.0587439***	0.000	.0025355	0.939
Model Goodness Parameters				
Likelihood Ratio Test	1425.38 (DF=20)		374.77 (DF=20)	
Pseudo R^2	0.0623		0.1483	
Log likelihood	-10734.719		-1075.9936	
Observations (households)	9,481		9,481	

NOTES:
DF=Degrees of freedom;
*, **, *** = Coefficient is significant at the 10%, 5% and 1% significance level, respectively;
For brevity, the cut point estimates are not reported in the table.

Also similar to what is estimated by the mixed-effects models (see Table C-5), the ordered probit models show that the number of household workers positively and significantly correlates with household's number of walking and bicycling trips. In addition, household's annual income has a positive association with walking and bicycling trips, although its coefficient is not significant in the bicycling model. The number of vehicles owned by the household shows a significant and negative correlation with household's daily number of walking and bicycling trips, whereas the number of household's bicycles owned exhibits a significant and positive correlation with walking and bicycling. These results are also consistent with results from the mixed models.

Micro-level (Neighborhood-level) Built Environment Variables Findings: Considering the neighborhood built environment variables, the ordered probit models indicate that population and employment density significantly and positively correlate with the number of household's daily walking trips. Population density does not have a significant correlation with the number of bicycling trips, whereas employment density seems to have a significantly negative correlation with those trips. The *Average Block Size* variable shows a significant and negative correlation with household walking. This variable does not reach a significance threshold in the bicycling model.

Higher proximity to transit is significantly and positively correlated with walking as indicated by the coefficient estimate on the *Transit Oriented Development* variable in the walking model. The *Walk Score* and *Bike Score* variables are significantly and positively associated with household's number of daily walking and bicycling trips, respectively. The neighborhood-level *Entropy* variable shows a positive correlation with walking and bicycling trips. Together, these outcomes confirm the results of the mixed-effects models (Table C-5) regarding the correlations of neighborhood-level built environment factors with the number of nonmotorized trips.

Meso-level (County-level) Built Environment Variables Findings: At the county level, the *Average Activity Density* variable is positively and significantly associated with the household's number of walking trips but negatively associated with the household's number of bicycling trips (as it was in the mixed-effects models). County-level *Average Block Size* and *Average Entropy* variables show negative and significant associations with the number of walking trips. County-level entropy also shows a negatively significant correlation with the number of bicycling trips.

Regional Accessibility Variables Findings: The *Distance to CBD* variable in the ordered probit walking model exhibits the same direction and extent of significance as it did in the mixed-effects walking model. Moreover, for both the walking and bicycling models, the direction and extent of significance of the other regional accessibility variables are consistent in the ordered probit models and the mixed-effects models. A small difference is that the coefficient of the *Highway Accessibility Index* becomes insignificant in the bicycling ordered probit model, whereas it showed a significant effect in the mixed-effects bicycling model.

Interpretation of Results: Baltimore-DC Ordered Probit Nonmotorized Travel Models

Although Table C-8 provides initial insights into the direction and significance of the coefficients of different independent variables on the number of household's nonmotorized trips, a more precise interpretation of the results of ordinal regression models is possible by computing the marginal effects. Marginal effects are a popular method that can be used to make the effects of variables in nonlinear models more intuitive and meaningful (Williams 2012). The marginal effect is the partial derivative of the dependent variable with respect to a specific independent variable. For nonlinear models, the value of the marginal depends on the specific values of all of the independent variables (Long and Freese 2006). More specifically, marginal effects measure the change in the probability of a certain category of the ordinal dependent variable occurring when the independent variable changes by one unit. Marginal effects can be interpreted as changes in percentage points. Since the "unit" may be very small (infinitesimal), a change in the unit represents the instantaneous change for continuous independent variables (Wasfi et al. 2016). Therefore, the marginal is the instantaneous rate of change (Long and Freese 2006) for continuous variables. For binary independent variables, the meaning of "one unit" is clearer as the change represents moving from 0 to 1. For binary variables, the discrete change is computed instead of the marginal effect as the variable changes from 0 to 1 (Long and Freese 2006).

In this case study, the ordinal categories of the dependent variable consist of various values of household's "total number of daily walking or bicycling trips". Consequently, marginal effects can be computed for each specific total number of trips to obtain the probability of a household generating that exact number of walking or bicycling trips. Since the "total number of daily walking or bicycling trips" consist of too many ordinal categories (0-21 for walking trips; 0-11 for bicycling trips), reporting marginal effects for all categories is cumbersome and interpretation of results may become ambiguous.

To facilitate interpretations, the average marginal effects have been computed for the case of a household that did not report any walking/bicycling trips during the travel survey day. This means that average marginal effects are computed for a total number of waking (or bicycling) trips equal to zero. The marginal effects in this case represent the expected change in the probability of the household reporting no walking/bicycling trips during the travel survey day, associated with a one-unit change in a certain independent variable. Since ordered probit model is a nonlinear model, that effect varies from household to household. The average marginal effect computes the effect for each observation (i.e., household) and then computes the average for all observations.

Table C-9 summarizes the average marginal effects along with the p-values estimated after the ordered probit models for a total number of "zero" daily walking and bicycling trips generated from a household. The average marginal effects are interpreted as the average probability of the household generating exactly "zero" walking/bicycling trips during a day.

Table C-9. Average Marginal Effects: Baltimore-D.C. Ordered Probit Models

Average Marginal Effects for Number of Household's Daily Nonmotorized Trips = 0				
	Walking Model		**Bicycling Model**	
Independent Variable	**Average Marginal Effects**	**p-value**	**Average Marginal Effects**	**p-value**
Household Socioeconomics (SE_{HH}): The Household				
Number of Members (Size)	.0622333***	0.000	.0008346**	0.016
Number of Students	.0086306	0.224	.0000471	0.983
Number of Workers	-.0340538***	0.000	-.0070254***	0.002
Number of Vehicles	.0858614***	0.000	.0086485***	0.000
Number of Bicycles	-.0211191***	0.000	-.0120601***	0.000
Annual Income (1,000s of dollars)	-.0065248***	0.000	.0008528	0.173
Micro-Level Built Environment (BE_{TAZ}): The Neighborhood				
Population Density (total population/acre)	-.000574	0.091	6.39e-08	1.000
Employment Density (jobs/acre)	-.0003448**	0.049	.0001424*	0.077
Average Block Size (acres) - logged	.0121579	0.073	-.0009817	0.721
Transit Accessibility (number of transit stations + bus stops)	-.0000294	0.153	-.0001167*	0.088
Transit Oriented Development	-.0064121*	0.085	-.0019725	0.642
Walk Score	-.0006994***	0.010	—	—
Bike Score	—	—	-.0002408***	0.004
Entropy	-.0839934***	0.001	-.018333**	0.025
Meso-Level Built Environment (BE_{County}): The County				
Average Activity Density [(population + employment)/acre]	-.0013927***	0.000	.0000625*	0.080
Average Block Size (acres) - logged	.0469539***	0.000	-.0022358	0.616
Average Entropy	.1012706**	0.017	.0572203**	0.041
Regional Accessibility (RA): The Region				
Distance to CBD (miles) - logged	.0758599***	0.000	.0041681	0.304
Highway Accessibility - standardized	.0008057**	0.027	.0004088	0.724
Transit-Drive Accessibility - standardized	.0115435***	0.003	-.0012801	0.311
Transit-Walk Accessibility - standardized	-.018785***	0.000	-.0001056	0.939
Observations (households)	9,481		9,481	
Model Prediction for Total Number of Household's Trips = 0 (all variable set to their mean values)	.69588***		.99044***	

Due to the ordered probit model being a nonlinear model, for interpretation purposes here, it is assumed that the average marginal effects of a unit change in a certain independent variable on the probability of the household generating exactly "zero" walking (or bicycling) trips during a day is conditional on the distribution of all the model variables being as they are in the dataset. The average marginal effect can be interpreted for a certain independent variable as if it represents the response to a unit change[59].

For instance, the average marginal effect on the household vehicle ownership in the walking model (0.0858614) indicates that each additional private vehicle that is available to the household is associated with an increase of approximately 8.6 percentage points in the average probability of the household generating no walking trips (i.e., households are less likely to generate walking trips if they own more vehicles).

Furthermore, the average marginal effects on the household bicycle ownership in the bicycling model (-0.0120601) indicates that owning an additional bicycle is associated with a decrease of approximately 1.2 percentage points in the average probability of the household generating zero bicycling trips (i.e., households are more likely to generate bicycling trips if they own more bicycles).

As another example, the sign and magnitude of the average marginal effect for the neighborhood employment density variable in the walking model (-0.0003448) suggests that for each additional 100 employees per acre of the TAZ, the average probability of a household within that TAZ generating no walking trips decreases by approximately 3.4 percentage points (i.e.,

[59] See Stata 13 Manual "margins — Marginal means, predictive margins, and marginal effects": https://www.stata.com/manuals13/rmargins.pdf

households are more likely to generate walking trips if employment density within the neighborhood is higher).

The average marginal effect of the variable for distance (in miles) to city center in the walking model is 0.0758599. Since this variable is log-transformed, this result implies that an increase of 1 in the value of the natural logarithm of distance of the household to the center of the city[60] is associated with an increased average probability (by nearly 7.6 percentage points) of households generating no walking trips (i.e., households are less likely to generate walking trips if they locate farther from the CBD).

Also, the average marginal effects of the *Transit-Walk Accessibility Index* in the walking model (-0.018785) indicates that as the value of this variable increases by one standard deviation, the average probability of households generating no walking trips decreases by approximately 1.9 percentage points (i.e., higher accessibility to transit by means of walking is associated with a higher probability of generation of walking trips from households).

The probability of a household generating no walking trips if the independent variables are set at their mean values is 70% (model prediction is 0.69588). The probability of a household generating no bicycling trips if independent the variables are set at their means is 99% (model prediction is 0.99044), which is another indication of the low levels of bicycling.

These results are in line with results obtained from the mixed-effects model estimation in both the direction and significance of estimates and further emphasize the role of socioeconomic characteristics, neighborhood- and county-level built environment factors, as well as regional accessibility characteristics in in generating or eliminating nonmotorized travel.

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[60] An increase of 1 in the value of the natural log (x) means that x is multiplied by e=2.718. Therefore, the absolute increase in x will be equal to 2.718x – x=1.718x, which means a 171.8% increase in x.

Summary of Findings: Baltimore-DC Ordered Probit Nonmotorized Travel Models

Tables C-8 and C-9 provide evidence that the results of the ordered probit models are consistent with those of the mixed-effects models in terms of the association of micro-level (i.e., neighborhood) and meso-level (i.e., county) built environment factors as well as that of the regional accessibility characteristics with nonmotorized trips. The ordered probit model estimations confirm that members of households located in compact, pedestrian- and bicyclist-friendly neighborhoods with improved street connectivity, and higher levels of mixed-use development are more likely to walk or bicycle.

Furthermore, findings show that county-level built environment characteristics and regional accessibility play key roles in nonmotorized travel behavior, especially walking. Densely populated counties with more employment opportunities are associated with more walking trips but fewer bicycling trips. More walking trips are also associated with living in counties with better street connectivity. High extents of mixed-use developments throughout the county are associated with fewer number of nonmotorized trips, in both walking and bicycling cases.

Also, higher accessibility to highways as well as higher accessibility to transit (by means of driving) throughout the entire county are correlated with fewer walking trips by residents. By contrast, increased numbers of walking trips are associated with better regional accessibility to transit by means of walking. Residing in locations farther away from the CBD has a negative association with household's number of walking trips.

C.2 Conclusions of the Baltimore-Washington, D.C. Case Study and Next Steps

Findings from the Baltimore-D.C. case study corroborate research findings in the past that nonmotorized travel behavior is associated with household socioeconomic characteristics as well as the micro-level (i.e., neighborhood) built environment attributes of the place of residence. Moreover, the results shed light on the potential role of the meso-level (i.e., county-level) built environment attributes and regional accessibility in nonmotorized travel behavior. The findings provide insights into the long-overlooked relationship between built environment characteristics of locations beyond the neighborhood and walking as well as bicycling trips of residents.

Nevertheless, to develop a better understanding of the potential link between the built environment of geographical areas larger than the neighborhood and nonmotorized travel behavior, an analysis of additional case studies will be helpful. Further, the role of the social environment in nonmotorized travel behavior needs to be more thoroughly tested since the direct influence of travel emerges by exposure of travelers to both the built and social environments (van Wee and Ettema 2016). Thus, inclusion of social environment factors beyond the household level in the analysis can contribute to improvement of the models and enhancement of the findings. The Florida case study (Section 4.1) addresses these limitations in the Baltimore-D.C. case study.

As mentioned previously, a few studies discussed consideration of a three-level ecological hierarchy for the influence of the built environment on physical activity such as nonmotorized travel. These include: the micro level (e.g., neighborhood), the meso level (e.g., county), and the macro level (e.g., metropolitan area) (see e.g., King et al. 2002; Ewing et al. 2003b). For instance, King et al. (2002) suggested that the influence of built environment attributes on physical activity (e.g., nonmotorized travel) should be considered at the micro, meso, and macro levels.

This three-level hierarchical structure has been adopted in the Florida case study to develop models that link walking and bicycling trips to household characteristics as well as environmental attributes in terms of both the built and social environments (see Section 4.1 of this dissertation).

Appendix D

Walk and Bike Score Categories

Score	Label	Description
Walk Score		
90 - 100	Walker's Paradise	Daily errands do not require a car
70 - 89	Very Walkable	Most errands can be accomplished on foot
50 - 69	Somewhat Walkable	Some errands can be accomplished on foot
25 - 49	Car-Dependent	Most errands require a car
0 - 24	Car-Dependent	Almost all errands require a car
Bike Score		
90 - 100	Biker's Paradise	Daily errands can be accomplished on a bike
70 - 89	Very Bikeable	Biking is convenient for most trips
50 - 69	Bikeable	Some bike infrastructure exists
0 - 49	Somewhat Bikeable	Minimal bike infrastructure exists

Source: www.walkscore.com (https://www.walkscore.com/methodology.shtml)

Appendix E

Pearson Correlation Matrix for Independent Variables

(Florida Household-level Nonmotorized Travel Behavior Models)

Household-level Variables

Variable	Number of Adults	Number of Vehicles	Number of Workers	Annual Income			
Number of Adults	1.0000						
Number of Vehicles	0.5347	1.0000					
Number of Workers	0.4598	0.4667	1.0000				
Annual Income	0.2797	0.4193	0.4070	1.0000			

Neighborhood-level Variables

Variable	Activity Density	Entropy	Intersection Density	Pedestrian-friendly Network Density	Local Transit Service	Local Transit Accessibility	Percentage of HHs with No Cars
Activity Density	1.0000						
Entropy	-0.0437	1.0000					
Intersection Density	0.1136	0.0842	1.0000				
Ped-friendly Network Density	0.3184	-0.1718	0.0697	1.0000			
Local Transit Service	0.6021	0.0035	0.0507	0.2167	1.0000		
Local Transit Accessibility	-0.1257	0.0127	0.0132	-0.0424	-0.1493	1.0000	
Percentage of HHs with No Cars	0.2957	-0.0344	0.1345	0.1881	0.3007	-0.0758	1.0000

County-level Variables

Variable	Mean Activity Density	Mean Entropy	Mean Intersection Density	Mean Regional Diversity	Mean Ped-friendly Network Density	Mean Transit Service	Mean Automobile Accessibility
Mean Activity Density	1.0000						
Mean Entropy	-0.3259	1.0000					
Intersection Density	0.6992	-0.0793	1.0000				
Mean Regional Diversity	0.1264	0.5975	0.4019	1.0000			
Mean Ped-friendly Network Density	0.8487	-0.2897	0.6561	0.1804	1.0000		
Mean Transit Service	0.6578	-0.4609	0.7067	-0.0268	0.6200	1.0000	
Mean Automobile Accessibility	0.6735	-0.1518	0.6985	0.2436	0.6369	0.6407	1.0000
Mean Transit Accessibility	0.7069	-0.4471	0.6454	0.0204	0.6333	0.7847	0.8453

Metropolitan-level Variables

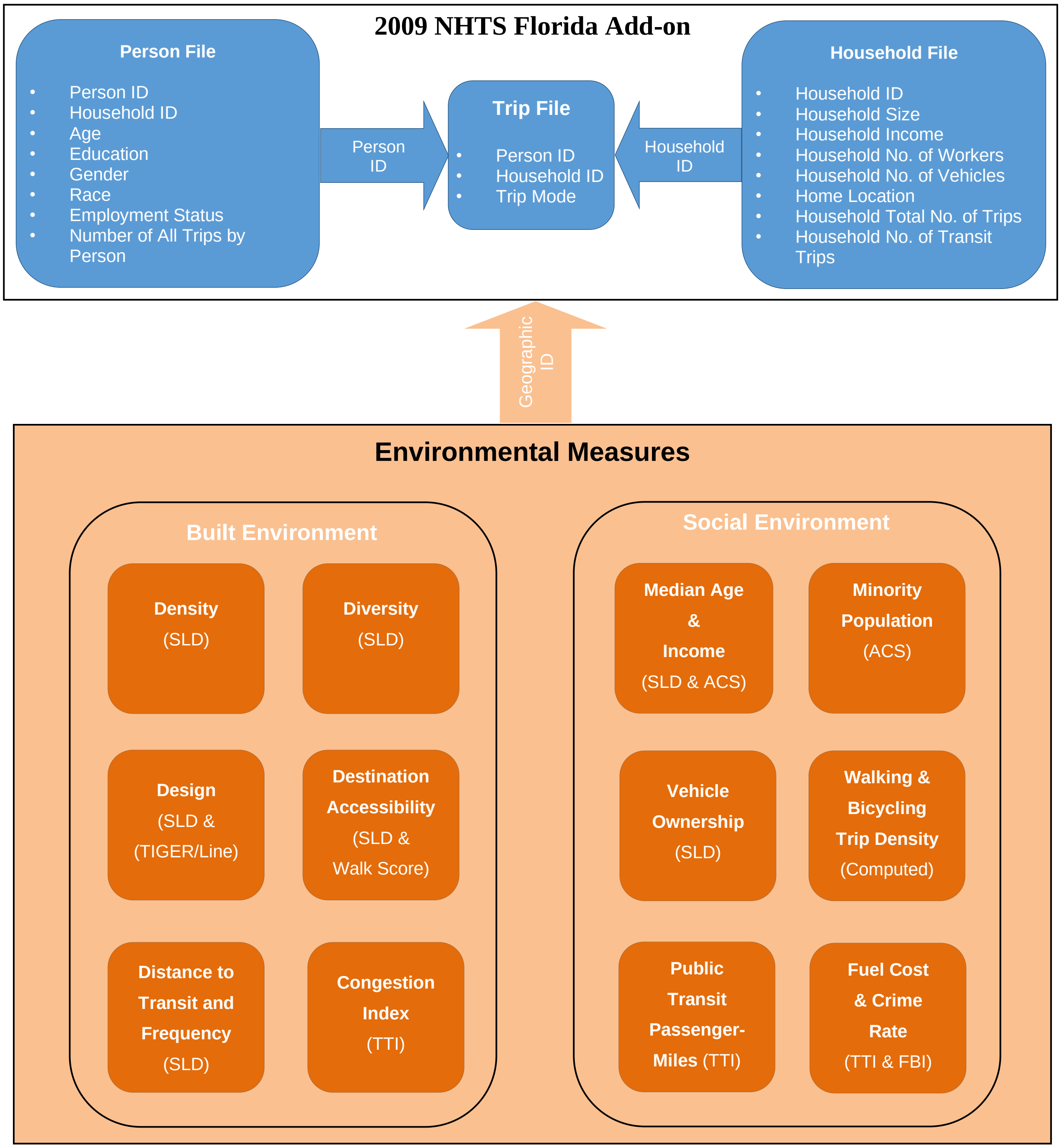
Variable	Mean Activity Density	Mean Entropy	Mean Total Road Network Density	Percentage of 0.01 Blocks	Mean Automobile Accessibility	Mean Transit Accessibility	Average Percentage of 2^+ Car HHs
Mean Activity Density	1.0000						
Mean Entropy	-0.3706	1.0000					
Mean Total Road Network Density	0.2789	0.1538	1.0000				
Percentage of 0.01 Blocks	0.6925	-0.3289	0.2754	1.0000			
Mean Automobile Accessibility	0.7301	-0.2883	0.3798	0.6257	1.0000		
Mean Transit Accessibility	0.7549	-0.6309	0.1886	0.6686	0.7991	1.0000	
Average Percentage of 2^+ Car HHs	-0.3091	0.7038	0.0890	-0.4675	-0.2603	-0.4397	1.0000

Correlations not shown in the table are all below the |p| > 0.7 threshold adopted in this study.

Appendix F

Data Structure

(Florida Person-level Nonmotorized Travel Behavior Models)



Appendix G

Attitudinal Data Fields in the Florida 2009 NHTS Add-on Person File

Variable	Description	Observations	Missing Observations	Total Observations	Percentage of Missing Data
DTACDT [a]	Safety concerns	4,125	26,827	30,952	87%
DTCONJ [a]	Highway congestion	4,223	26,729	30,952	86%
DTCOST [a]	Price of travel (fees, tolls and gas)	6,831	24,121	30,952	78%
DTRAGE [a]	Aggressive/distracted drivers	4,527	26,425	30,952	85%
DTRAN [a]	Access or availability of public transit	1,632	29,320	30,952	95%
DTWALK [a]	Lack of walkways or sidewalk	738	30,214	30,952	98%
SCHSPD [b]	Walk/Bike issue: speed of traffic along route	1,744	29,208	30,952	94%
SCHTRAF [b]	Walk/Bike issue: amount of traffic along route	1,747	29,205	30,952	94%
SCHCRIM [b]	Walk/Bike issue: violence/crime along route	1,738	29,214	30,952	94%

NOTES:

[a] Response categories included: Appropriate skip, Refused, Don't know, Not ascertained, Not a problem, A little problem, Somewhat of a problem;

[b] Response categories included: Appropriate skip, Refused, Don't know, Not ascertained, Not an issue, A little bit of an issue, Somewhat of an issue, Very much an issue, A serious issue.

Appendix H

Variable Labels for Multilevel SEM Structure

(Florida Person-level Nonmotorized Mode Share Models—Figure 7)

Independent Variable	Label
Person Level: The Individual	
Age (person's age in years)	age
Race (person's race: 1 = White, 0 = otherwise)	racewhite
Gender (person's gender: 1 = male, 0 = female)	gendermale
Employment Status (employed? 1 = yes, 0 = no)	worker
College Education (college degree? 1 = yes, 0 = no)	college
Social Environment	
Micro Level: The Household	
Number of Members	hhsize
Number of Vehicles	hhveh
Number of Workers	hhworkers
Annual Income (1,000s of dollars)	hhincmedian
Number of Daily Transit Trips (count of daily transit trips by all members of the household)	hhtransittripcount
Number of Daily Nonmotorized Trips (count of daily nonmotorized trips by all hh members)	hhpbtrips
Micro Level (Census Block Group): The Neighborhood	
Percentage of Households with No Cars	pa0_cbg
Meso Level (County): The County	
Average Walking Density [average (number of walking trips in CBG/CBG area in acres)]	ave_wd_co
Average Bicycling Density [average (number of bicycling trips in CBG/CBG area in acres)]	ave_bd_co
Macro Level (Core Based Statistical Area): The Metropolitan Area	
Average Percentage of Households with 2+ Cars (%)	ave_pa2_cbsa
Average Percentage of Low-Wage Workers (workers earning ≤ $1250/month) (%)	ave_plw_cbsa
Average Walking Density [average (number of walking trips in CBG/CBG area in acres)]	ave_wd_cbsa
Average Bicycling Density [average (number of bicycling trips in CBG/CBG area in acres)]	ave_bd_cbsa
Annual Public Transportation Passenger-Miles (millions)	ave_ptm_cbsa
Average State Gasoline Cost (dollars/gallons)	ave_gp_cbsa
Average Median Age (years)	ave_ma_cbsa
Average Percentage of Foreign-Born Population (%)	ave_fb_cbsa
Average Crime Rate (annual crimes/100,000 population)	ave_cr_cbsa
Built Environment	
Micro Level (Census Block Group): The Neighborhood	
Activity Density [(employment + housing units)/acres)]	ad_cbg
Entropy (dimensionless)	en_cbg
Intersection Density (auto-oriented intersections/mi^2)	id_cbg
Pedestrian-friendly Network Density (facility miles of pedestrian-oriented links/mi^2)	pf_cbg
Local Transit Service (aggregate frequency of transit service/mi^2)	tf_cbg
Local Transit Accessibility (distance from centroid to the nearest transit stop in meters)	dt_cbg

Meso Level: The County	
Mean Activity Density [average (employment + housing units)/acres)]	ave_ad_co
Mean Entropy (dimensionless)	ave_en_co
Mean Intersection Density [ave. (auto-oriented intersections/mi^2)]	ave_id_co
Mean Pedestrian-friendly Network Density [ave. (facility miles of pedestrian-oriented links/mi^2)]	ave_pf_co
Mean Transit Service [ave. (aggregate frequency of transit service per mi^2)]	ave_tf_co
Mean Local Transit Accessibility [ave. (distance to the nearest transit stop in meters)]	ave_dt_co
Mean Temporal Automobile Accessibility (ave. number of jobs within a 45-minute auto commute)	ave_aa_co
Mean Temporal Transit Accessibility (ave. number of jobs within a 45-minute transit commute)	ave_ta_co
Mean Walk Score (dimensionless)	ws_co
Macro Level (Core Based Statistical Area): The Metropolitan Area	
Mean Activity Density [average (employment + housing units)/acres)]	ave_ad_cbsa
Mean Entropy (dimensionless)	ave_en_cbsa
Mean Total Road Network Density [ave. (total road network miles/mi^2)]	ave_rd_cbsa
Percentage of 0.01 Blocks (% blocks with an area smaller than 0.01mi^2)	pb01_cbsa
Mean Temporal Automobile Accessibility (ave. number of jobs within a 45-minute auto commute)	ave_aa_cbsa
Mean Temporal Transit Accessibility (ave. number of jobs within a 45-minute transit commute)	ave_ta_cbsa
Mean Walk Score (dimensionless)	ws_cbsa
Mean Roadway Congestion Index (dimensionless)	ave_rci_cbsa
Random Intercepts	
Household-level Random Intercept	$HHID_1$
Neighborhood-level Random Intercept	$CBGID_1$

NOTES:

ave. = Average;

hh/HH = Household.

Appendix I

Health Impacts of Active Travel and the Built Environment: A County-level Analysis

I.1 County-level Health Outcome Models

Most sources that provide health data rely on the Behavioral Risk Factor Surveillance System (BRFSS) data—the world's largest health dataset available to the public[61]. However, due to the confidential nature of health data, the BRFSS data are only available at the county level. This means that the smallest geographical scale for which nonproprietary health data can be obtained is the county. Consequently, many analyses of the health impacts of the built environment are conducted at aggregate levels of geography as only aggregate-level health data are publicly available (Langerudi et al. 2015). For a similar reason, county has been selected as the unit of analysis for the health models in the present study. Past research suggested that county may be an appropriate scale for health research in auto-oriented societies such as the U.S. (Ewing et al. 2014).

The county-level health models have been developed using county-level data from various states in the U.S. including Florida, Maryland, Virginia, Washington, D.C., and West Virginia[62]. For the most part, the study area for the county-level health models is the same as the study areas from which data were utilized in the analysis of nonmotorized travel behavior (Chapter 4).

Past findings emphasize consideration of multiple levels of the environment within an ecological framework when investigating the role of environmental factors in health (Joshu et al. 2008). Thus, the models developed in this section examine the link between county-level health indicators and the built and social environment attributes at two levels of geography: the county level (i.e., meso level), and the CBSA within which the county locates (i.e., macro level).

[61] Centers for Disease Control and Prevention "Behavioral Risk Factor Surveillance System": https://www.cdc.gov/brfss/index.html
[62] A full list of the counties included in the county-level models is provided at the end of this Appendix (Table I-4).

I.1.1 County-level Health Outcome Models: Data

The database for the county-level health outcome models consists of the following datasets:

- Smart Location Database (SLD);
- Community Health Status Indicators (CHSI);
- County Health Rankings & Roadmaps (CHR&R);
- American Community Survey (ACS);
- Walk Score data;
- Woods & Poole Complete Economic and Demographic Data Source (CEDDS); and
- Census Bureau's TIGER/Line Shapefiles.

The SLD database provided information on land use and built environment characteristics (i.e., the *D*s of the built environment) of counties. These data include population and employment densities, extent of mix land use development, network design factors, and transit accessibility.

The CHSI and the CHR & R datasets provided information on population health behavior and other health factors that influence population health status and health outcomes. Health outcomes provided in these datasets are based on measures of mortality (e.g., premature death) and morbidity (e.g., self-reported fair or poor health, number of poor physical or mental health days). Health factors are represented in these datasets by health behavior measures, clinical care measures, socioeconomic measures, and the physical environment measures. Basically, health outcomes measured by CHSI and the CHR & R datasets represent how healthy the population of a county is, while health factors are factors that can influence the public health within a county.

County-level travel behavior and telecommuting measures were obtained from the American Community Survey (ACS). These measures include the county-level mode shares for: nonmotorized, private vehicle, and transit travel modes as well as telecommuting. ACS also provided information about other social environment factors of counties (i.e., socioeconomic/demographic attributes such as average median age, median household income and percentage of minorities within the county). The Woods and Poole's CEDDS provided information about county-level total employment and employment by each industry. Also, county-level shapefiles were obtained from the U.S. Census Bureau's TIGER/Line database. GIS tools were used to spatially link travel behavior, telecommuting behavior, and socioeconomic/demographic data to built environment and health data and obtain the final integrated database for statistical modeling of health outcomes. Chapter 3 provides more information on all of the datasets used.

I.1.2 County-level Health Outcome Models: Dependent Variables

The dependent (i.e., endogenous) variables for the county-level health models have been selected based on county-level health outcomes provided in the CHSI and the CHR & R datasets[63]. The health outcomes provided in these datasets are based on measures of mortality and morbidity. Six separate models have been developed for the following six county-level health outcomes:

1) prevalence of adult obesity[64];
2) prevalence of adult diabetes;
3) prevalence of fair or poor health;
4) poor physical health days;
5) poor mental health days; and
6) premature death.

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[63] The 2012 data have been used in this study. It should be noted that CHSI and CHR & R data provide information on health profiles and health rankings for each county, which are often produced based on multiyear estimates. Therefore, the 2012 data provide information based on several previous years.

[64] Many past studies have treated obesity as a health outcome alongside other health outcomes (e.g., Mokdad et al. 2003; Samimi and Mohammadian 2009). Therefore, obesity is considered a health outcome in the present study, albeit listed as a health factor in CHR & R. Nonetheless, obesity is a risk factor for many chronic diseases (e.g., Mokdad et al. 2001; Kelly-Schwartz et al. 2004; Maddock 2004; Smith et al. 2008; Ewing et al. 2014; and Meehan 2015).

Maps presented in Figures I-1 to I-6 show the prevalence of each of the above indicators for counties within the study area based on the data available from the 2012 CHR & R datasets.

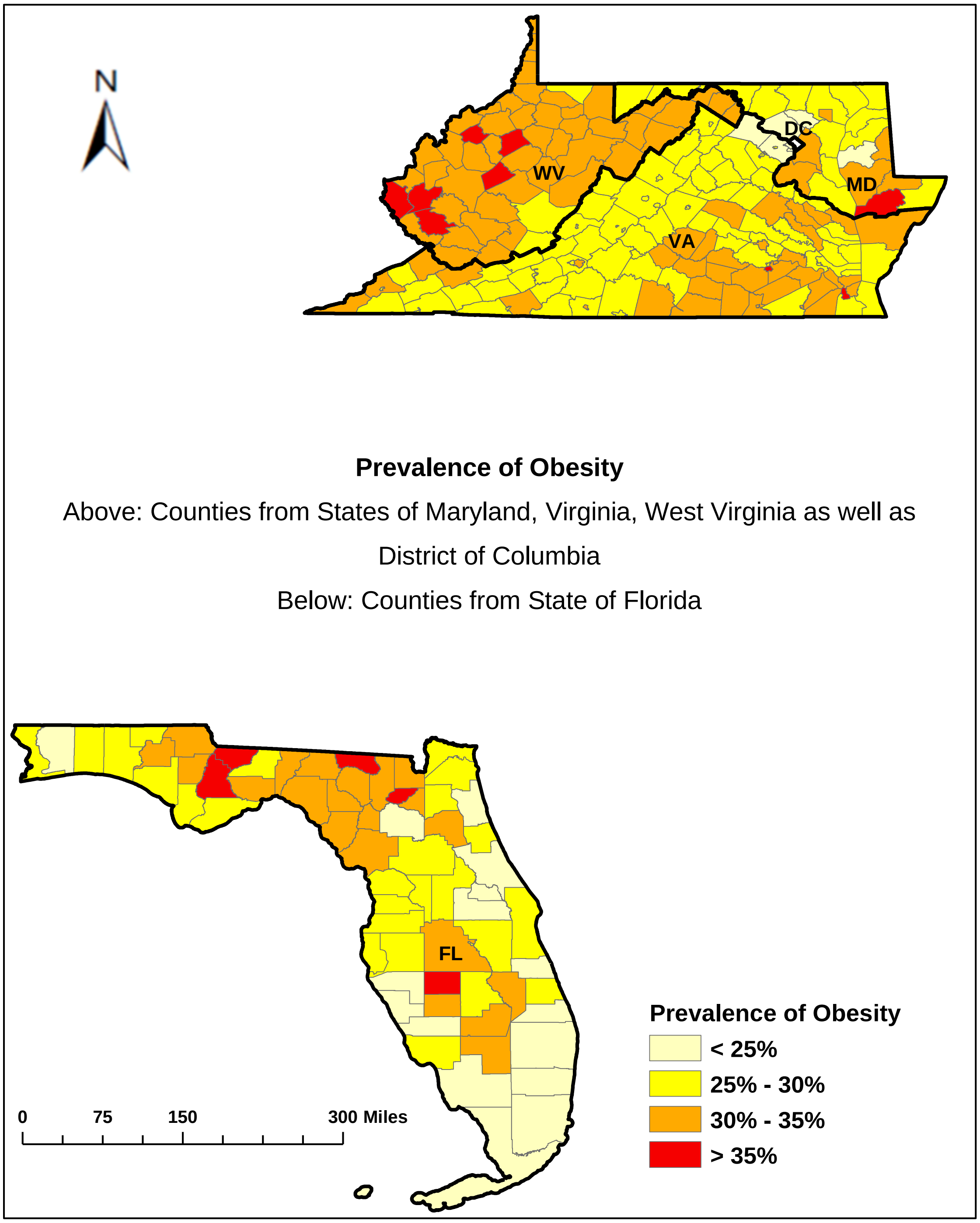

Figure I-1. Prevalence of Obesity for Counties within the Study Area

(Average of Years 2006 – 2009 Based on 2012 CHR & R Data)

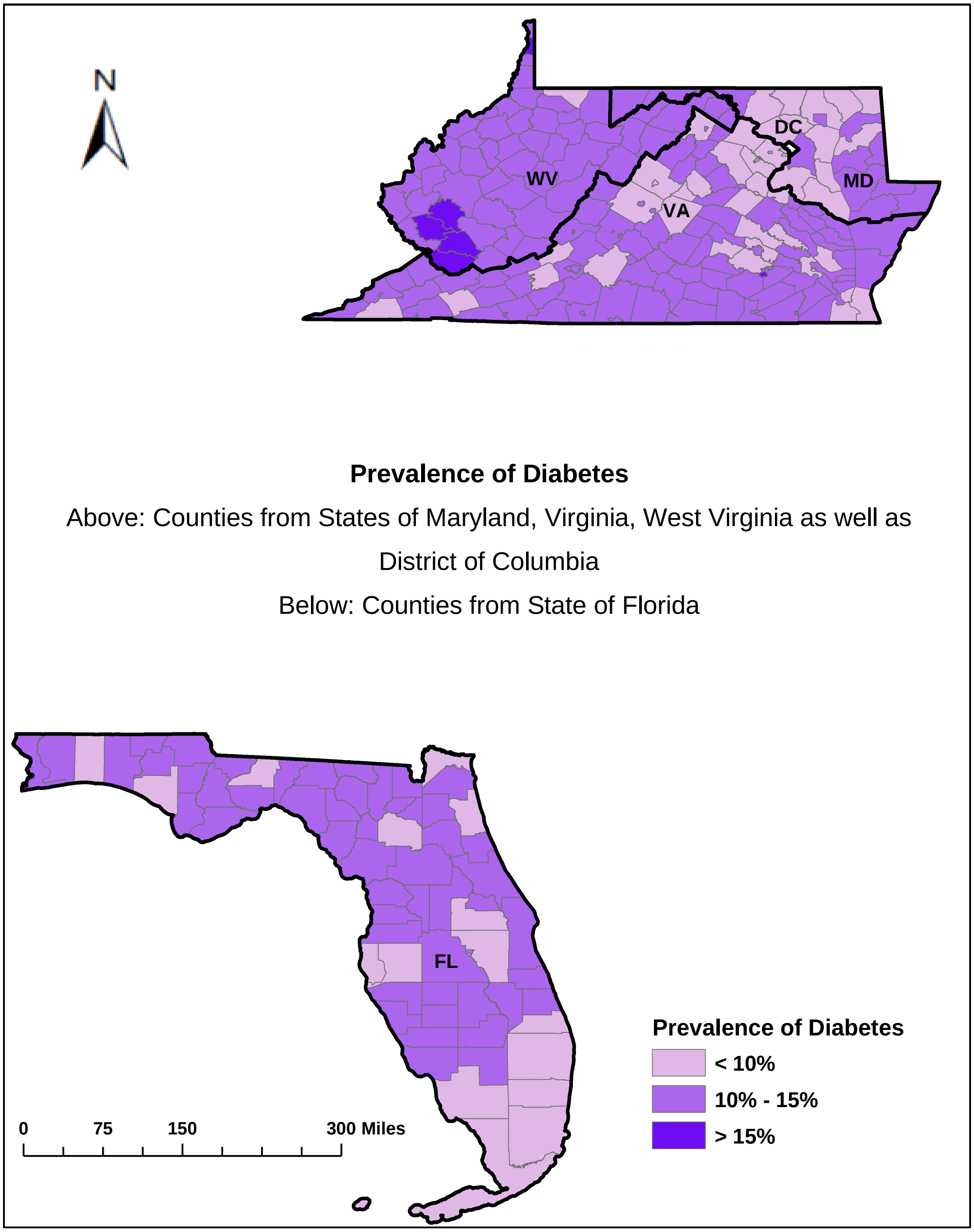

Figure I-2. Prevalence of Diabetes for Counties within the Study Area

(CHR & R Data Available for Year 2009)

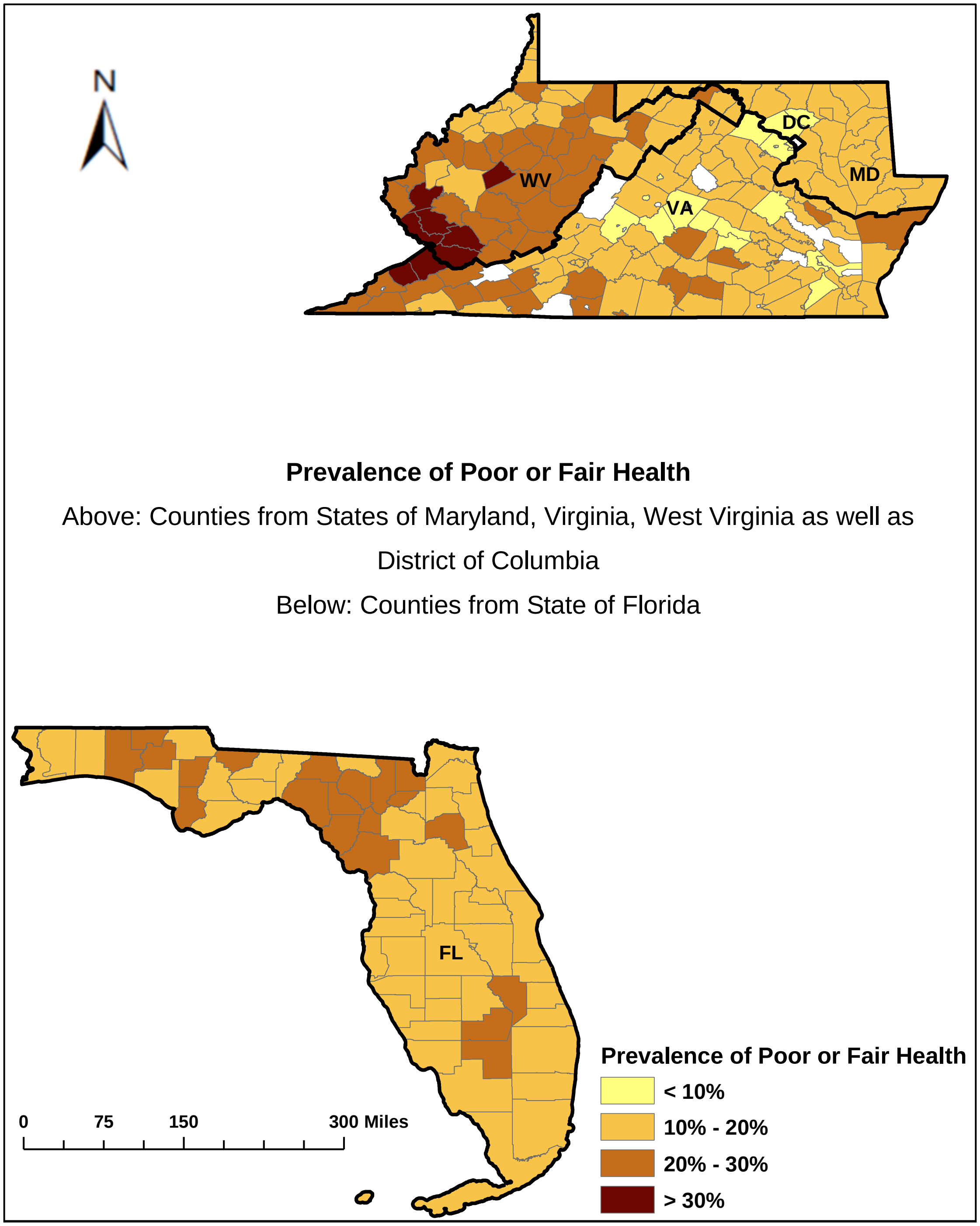

Figure I-3. Prevalence of Poor or Fair Health for Residents of Counties in the Study Area

(Average of Years 2002 – 2010 Based on 2012 CHR & R Data)

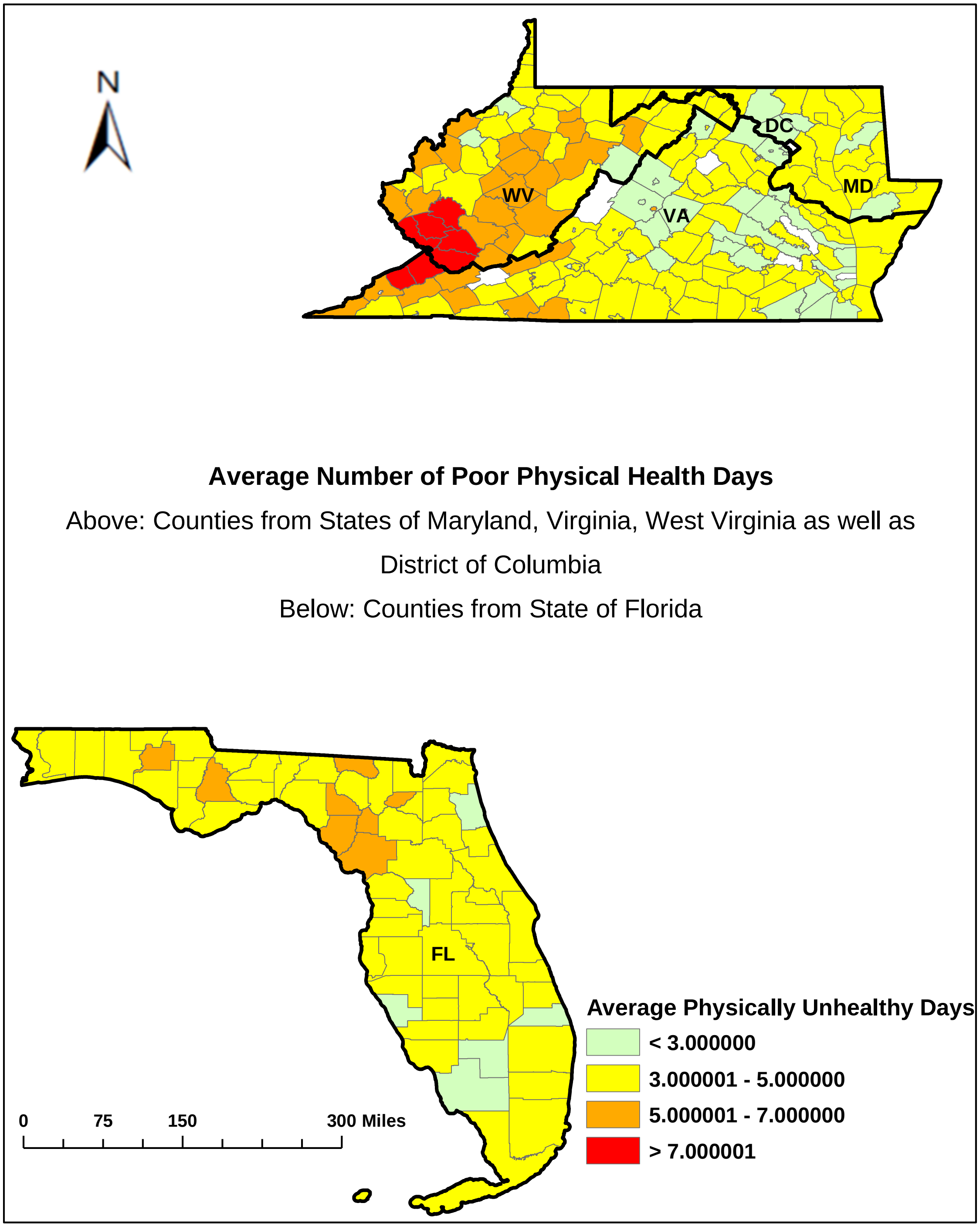

Figure I-4. Average Number of Poor Physical Health Days for County Residents

(Average of Years 2002 – 2010 Based on 2012 CHR & R Data)

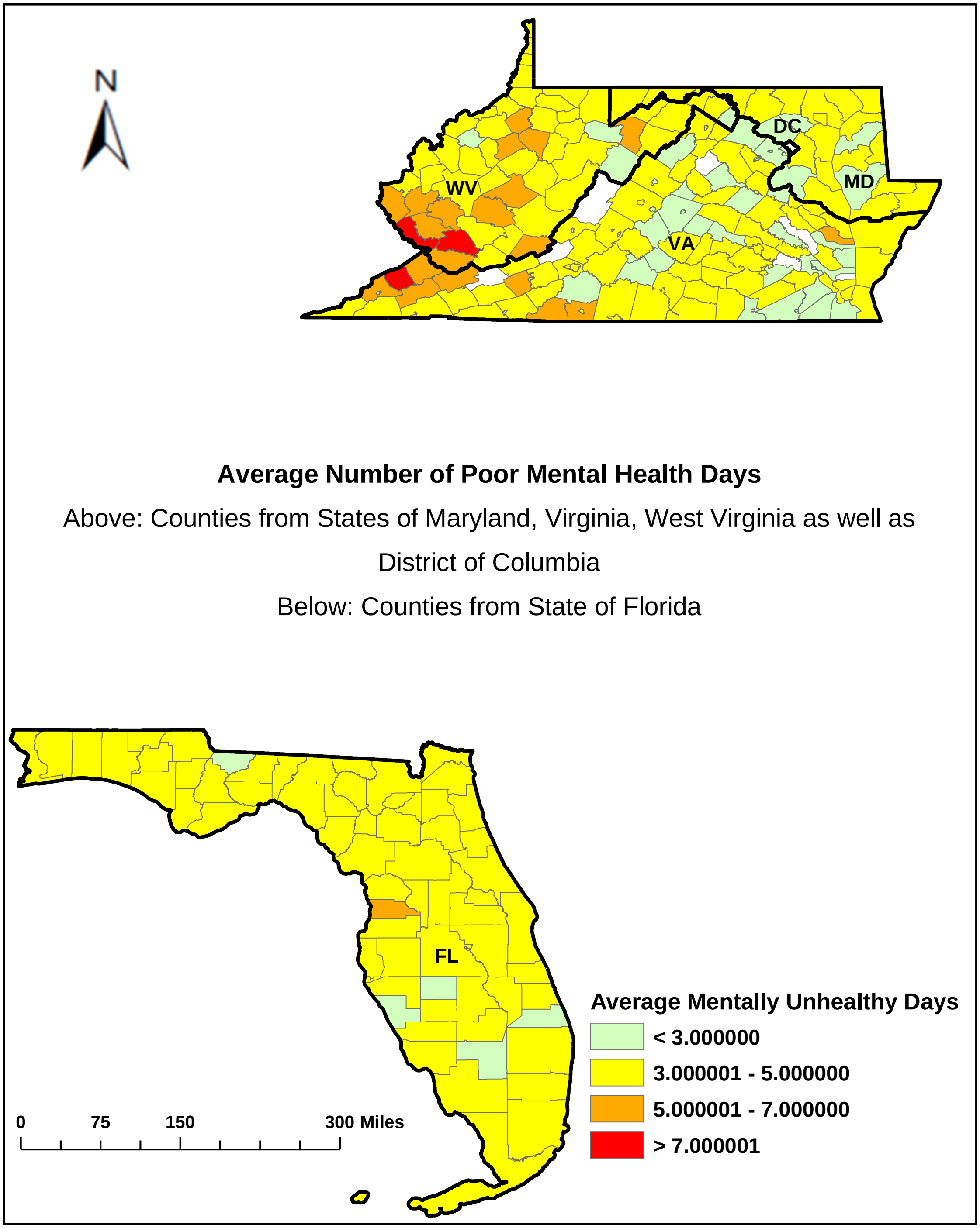

Figure I-5. Average Number of Poor Mental Health Days for County Residents

(Average of Years 2002 – 2010 Based on 2012 CHR & R Data)

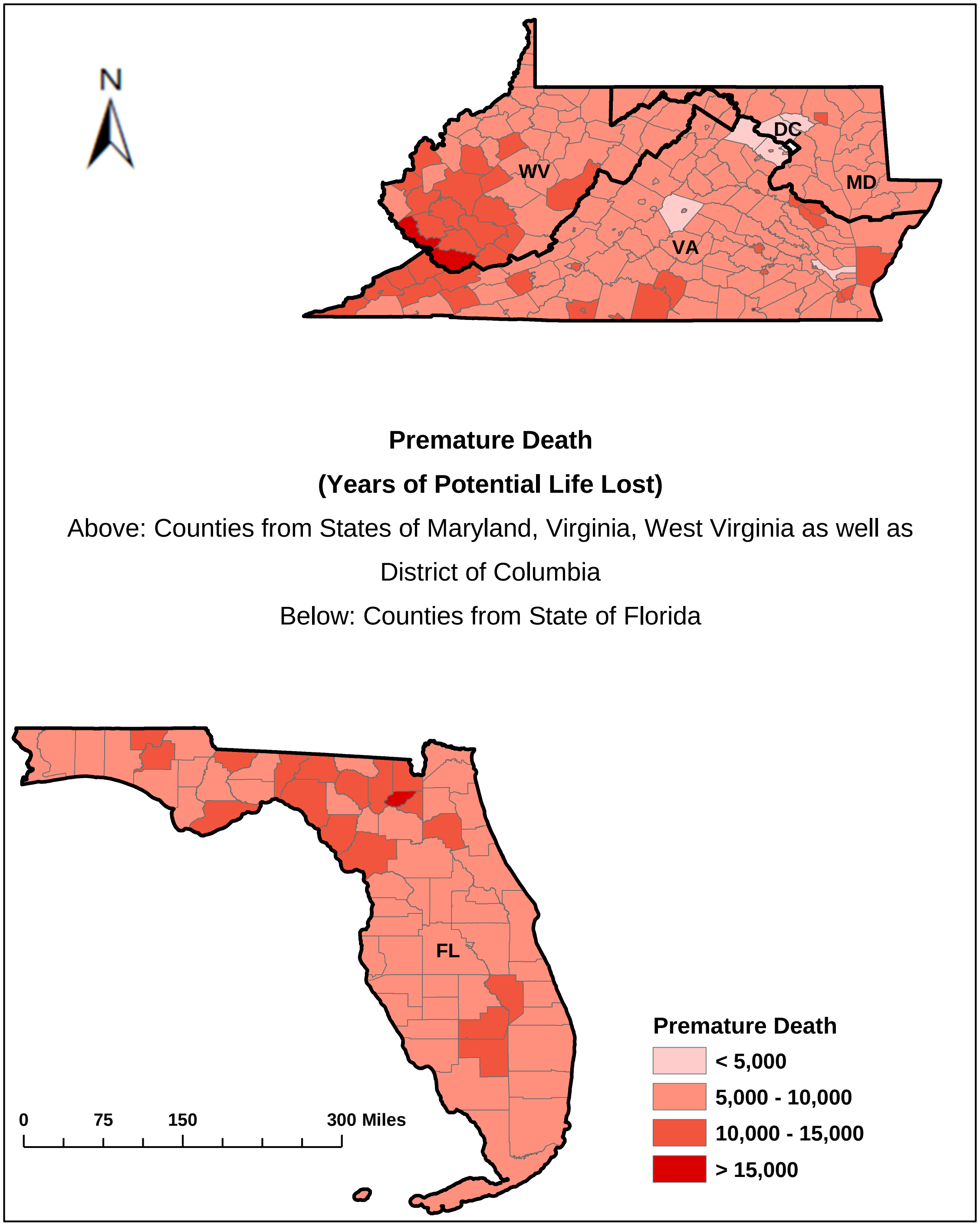

Figure I-6. Years of Potential Life Lost (Premature Death) for County Residents

(Average of Years 2004 – 2008 Based on 2012 CHR & R Data)

As seen from the above figures, obesity is prevalent within most West Virginia counties. This is consistent with findings of a previous study, which reported that West Virginia had the highest obesity prevalence in the U.S. (Maddock 2004). West Virginia counties also show some of the highest rates of diabetes, fair or poor health as well as the highest average number of poor physical or mental health days compared to other counties within the study area. Premature death shows the highest prevalence within some West Virginia and Florida counties.

I.1.3 County-level Health Outcome Models: Independent Variables

To avoid misleading results, a key element of modeling health impacts is to include the recognized causes of unhealthiness (Samimi et al. 2009). Therefore, the independent (i.e., exogenous variables) for the statistical models in the present study have been considered based on previous research as well as the proposed conceptual framework presented in Figure 1. The values for the health-related independent (i.e., exogenous) variables come from the health factors' data provided in CHSI and the CHR & R datasets. The independent variables are categorized as follows:

I.1.3.1 Built Environment Variables

Built environment variables have been included in the health models to account for the most important built environment factors that, based on the literature, can influence the health status of individuals. These factors include those with a potential to directly affect people's health through access to services and qualities that can impact health (e.g., level of access to healthy/unhealthy food outlets, level of access to parks and other recreational facilities, ambient air quality) and those that can affect people's health indirectly through promoting health behavior such as active travel (e.g., compactness of neighborhood and urban designs, pedestrian friendliness of streets).

These factors basically highlight the three domains identified by Kent and Thompson (2012) through which the built environment can influence human health. These three domains are: physical activity, social interaction, and access to healthy food.

Within the context of the built environment, Joshu et al. (2008) defined micro-level environmental factors as neighborhood and/or street-level characteristics, and macro-level environmental factors as large-area characteristics such as the level of urbanization and land-use patterns. However, due to confidentiality issues, the health data utilized for the present study did not provide information on the neighborhood of residence. This means that data on micro-level built environment were unavailable and county was the smallest spatial scale at which this analysis could be conducted. Therefore, built environment attributes have been included in the county-level health outcome models at two levels of geography: the meso level (i.e., the county level) and the macro level (i.e., the CBSA level).

Meso-level (County-level) Built Environment Variables

Census block group-level built environment and land use measures provided by SLD were aggregated to obtain the average county-level built environment measures. Other built environment variables at the county level are related to health factors and come from the CHSI and the CHR&R datasets. These variables include data on the level of access to clinical healthcare, unhealthy food, and recreational facilities for the population residing within a county as well as the air quality within the county. Walk Score data have also been used. The meso-level (i.e., county-level) built environment variables included in the county-level health models are:

- average activity density;
- average entropy (i.e., mixed land use);
- average network density in terms of pedestrian-friendly links;

- Walk Score;
- prevalence of fast food restaurants;
- prevalence of liquor stores;
- access to recreational facilities;
- access to primary care physicians; and
- ambient air pollution.

Together, these variables represent important built environment factors at the county level that, based on the literature, may play a role in the health of the population. For instance, the fast food restaurant variable has been included in the models because literature suggests that in examining weight-related health outcomes, measures of the food environment should be incorporated in the analysis (see e.g., Smith et al. 2008), and that the prevalence and unequal distribution of fast food restaurants throughout the U.S. can impact obesity rates (Maddock 2004; Plantinga and Bernell 2007). Also, Ewing et al. (2008) suggested that future research should relate the density of fast food restaurants to obesity rates.

Macro-level (CBSA-level) Built Environment Variables

To capture the effects of various levels of geography on health outcomes, this study includes measures representing the macro-level built and social environments in the analysis. The macro-level variables have been defined based on the Core Based Statistical Area (CBSA) of residence. For county-level health models, CBSAs include both metropolitan areas and micropolitan areas[65]. Counties for which CBSA information was not available were excluded from the analysis.

[65] According to the United States Census Bureau web site, “the general concept of a metropolitan or micropolitan statistical area is that of a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core.”; and “Each metropolitan statistical area must have at least one urbanized area of 50,000 or more inhabitants. Each micropolitan statistical area must have at least one urban cluster of at least 10,000 but less than 50,000 population.” (see “Delineating Metropolitan and Micropolitan Statistical Areas”: https://www.census.gov/programs-surveys/metro-micro/about.html).

Census block group-level built environment measures were aggregated to obtain the average CBSA-level built environment measures for each county. The macro-level built environment variables are:

- average activity density;
- average entropy;
- average total road network density; and
- average transit accessibility (i.e., average distance to local transit).

These variables capture a good picture of the overall physical environment (i.e., built environment and land use characteristics) of the CBSAs in the study area including the extent of compactness, mixed land use, road network, and access to transit within those urbanized areas.

I.1.3.2 Social Environment Variables

Social environment factors have been included in the county-level health models at two spatial levels: the county (i.e., the meso level) and the CBSA (i.e., the macro level).

*Meso-level (County-level) Social Environment Variable*s

County-level socioeconomic/sociodemographic attributes have been included in the county-level health models to represent the meso-level social environment. These variables are:

- median age;
- median household income;
- percentage of population of the White race;
- percentage of industry employment that can be performed by telecommuting.

These variables provide information on key socioeconomic and sociodemographic characteristics of a county that, based on the literature, can play a role in health outcomes of the residents.

Macro-level (CBSA-level) Social Environment Variables

CBSA-level socioeconomic and sociodemographic characteristics have been included in the county-level health models to represent the macro-level social environment. The CBSA-level social environment variables are:

- average percentage of low-wage workers; and
- average percentage of the minority population.

These variables control for the effects of macro-level sociodemographic and socioeconomic factors on county population health outcomes.

I.1.3.3 Travel Behavior and Telecommuting Behavior Variables

Consistent with many past studies, measures of travel behavior have been included in health models developed in the present study to examine county-level health outcomes. The travel behavior measures were obtained from ACS and provide consistent information about the extent of travel by each travel mode within each county in the study area.

The county-level travel behavior measures include:

- nonmotorized travel mode share;
- private vehicle mode share; and
- transit mode share.

Additionally, this study includes a variable in the health models to capture the effects of telecommuting on population health. Telecommuting behavior has been represented by the percentage of the county workers who, according to the ACS, reported working at home (i.e., telecommuting) as their means of transportation to work. In a sense, this variable reflects the telecommute mode share within the county. The travel behavior and telecommuting behavior variables potentially represent another aspect of the social environment of the county.

This is because, cumulatively, these measures characterize each county in terms of its "travel culture", and thereby can be considered measures of the sociocultural characteristics of the county—or in other words, measures of the county's social environment. Several other county-level social environment variables including unemployment and poverty levels, percentage of the uninsured population, crime rates, as well as various additional built environment at both county and CBSA levels were considered for inclusion in the statistical models. The final variables were selected in such way to obtain parsimonious models with a reduced risk of multicollinearity.

The final database included in the county-level health models is presented in Table I-1. Table I-2 provides descriptive statistics for the exogenous and endogenous variables included in the county-level health models by state.

Table I-1. County-level Health Model Variable Descriptions and Data Sources

Independent Variable	Represented Effect	Variable Description/Units	Data Source	Data Field (Computation)
Social Environment				
Meso Level (County): The County				
Median Age	Sociodemographics	Median age within county (years)	2006-2010 ACS 5-year estimates	HC01_EST_VC35
Median Annual Household Income	Socioeconomics	Median household annual income within county (dollars)	2008-2010 ACS 3-year estimates	HC01_EST_VC13
Percent White	Sociodemographics	Percentage of population of the county that is of the White race	2006-2010 ACS 5-year estimates	HD01_VD02
Percent of Telecommutable[66] Jobs	Extent of Telecommutability[66] of Employment/ Socioeconomics	Percentage of jobs in the county that fall into the "Information", "FIRE" (Finance, Insurance, Real Estate), "Services" and "Government" sectors	Woods and Poole[67]	(sum of jobs in "Information" "FIRE", "Services" and "Government" sectors)/(total jobs)
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area				
Average Percentage of Low-Wage Workers	Socioeconomics	Average percentage of workers earning $1250/month or less	SLD	R_PctLowWage (Averaged)[a]
Average Percentage of Minority Population	Sociodemographics	Percentage of population of the CBSA that is of non-White (minority) races	2006-2010 ACS 5-year estimates	HD01_VD03 to HD01_VD08

[66] Although not found in official English language dictionaries, the words *telecommutable* and *telecommutability* have previously been used in scholarly papers (see e.g., Buckinger 1994; Handy and Mokhtarian 1996; Mariani 2000).

[67] Source: Woods & Poole Economics, Inc. Washington, D.C. Copyright 2018.
Woods & Poole does not guarantee the accuracy of this data. The use of this data and the conclusion drawn from it are solely the responsibility of the author of this dissertation.

Travel Behavior				
Meso Level (County): The County				
Nonmotorized Travel Mode Share	Travel Behavior/ Sociocultural	Walking and bicycling mode share within county	2010 ACS 5-year estimates	HC01_EST_VC11 & HC01_EST_VC12
Private Vehicle Travel Mode Share	Travel Behavior/ Sociocultural	Private vehicle (car, truck, or van) mode share within county	2010 ACS 5-year estimates	HC01_EST_VC03
Public Transit Travel Mode Share	Travel Behavior/ Sociocultural	Public transit (excluding taxicab) mode share within county	2010 ACS 5-year estimates	HC01_EST_VC03
Telecommuting Mode Share	Travel Behavior/ Sociocultural	Telecommuting (working at home) mode share within county	2010 ACS 5-year estimates	HC01_EST_VC14
Built Environment				
Meso Level (County): The County				
Mean Activity Density	Density	(Employment + Housing units) on unprotected land in county	SLD	D1d (Averaged)[a]
Mean Entropy	Land use Diversity	5-tier employment entropy for county	SLD	D2b_E5Mix (Averaged)[a]
Mean Ped-friendly Network Density	Urban Design	Average facility miles of pedestrian- oriented links/mi^2	SLD	D3apo (Averaged)[a]
Walk Score	Destination Accessibility	Walk Score of the centroid of the county (dimensionless)	Walk Score®	Data provided
Primary Care Physician	Access to Health Care	Primary care provider rate per 100,000 population	CHR&R	PCP Rate
Percentage of Fast Food Restaurants	Access to Unhealthy Food	Percent of all restaurants that are fast food establishments [b]	CHR&R	Fast Food Restaurants
Liquor Store Density	Access to Unhealthy Food	Number of liquor stores per 10,000 population	CHR&R	Liquor Store Density
Recreational Facilities Density	Access to Recreational Facilities	Number of recreational facilities[c] per 100,000 population	CHR&R	Access to Recreational Facilities
Ambient Air Pollution	Air Pollution	Number of unhealthy air quality days	CHR&R	Air Pollution Days
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area				
Mean Activity Density	Density	(Employment + Housing units) on unprotected land in CBSA	SLD	D1d (Averaged)[a]
Mean Entropy	Land use Diversity	5-tier employment entropy for CBSA	SLD	D2b_E5Mix (Averaged)[a]
Mean Total Road Network Density	Urban Design	Average (total road network miles/mi^2) in CBSA	SLD	D3a (Averaged)[a]
Mean Distance to Transit (Transit Accessibility)	Mean Distance to Transit	Average distance to nearest transit stop (meters) for CBSA	SLD	D4a (Averaged)[a]

NOTES:

a Measure was computed by averaging values of the referenced field provided in data source over the relevant geographical area (i.e, county or CBSA);

b Data on fast food restaurants considered in CHR&R come from the County Business Patterns (CBP) economic data;

c CHR&R defines recreational facilities as “establishments primarily engaged in operating fitness and recreational sports facilities, featuring exercise and other active physical fitness conditioning or recreational sports activities such as swimming, skating, or racquet sports.”

Table I-2. Descriptive Statistics for County-level Health Outcome Models' Variables (by State)

Variable (Units)	*District of Columbia*[a]	*Maryland*		*Virginia*		*West Virginia*		*Florida*	
	Mean	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Dependent (i.e., endogenous) Variables: County Level									
Prevalence of Adult Obesity (% of adults that report a BMI $\geq$ 30)	21.50	29.55	4.27	29.35	3.32	33.51	2.44	29.21	4.73
Prevalence of Adult Diabetes (% of adults aged 20 and above with diabetes)	8.20	10.07	1.69	10.41	1.69	12.73	1.43	11.19	1.64
Prevalence of Fair or Poor Health (% of adults reporting fair or poor health)	12.70	13.12	2.74	13.68	4.81	20.61	5.09	17.54	3.69
Number of Poor Physical Health Days (average number in past 30 days)	2.90	3.27	0.46	3.31	0.98	4.66	1.10	3.93	0.79
Number of Poor Mental Health Days (average number in past 30 days)	2.94	3.41	0.63	3.30	0.89	4.40	0.93	3.62	0.69
Premature Death (years of potential life lost before age 75 per 100,000 population)	11660.7	7455.1	2211.9	7810.5	2170.9	9103.2	1512.3	8888.5	1566.6
Independent (i.e., exogenous) Variables: County Level									
Social Environment									
Meso Level: The County									
Median Age (years)	33.8	39.77	3.73	39.16	5.62	41.64	3.00	41.46	5.91
Median Annual Household Income (dollars)	59822	67863	19164	56509	19414	38653	7122	43565	7217
Percent White (%)	38.50	70.91	19.29	73.49	16.61	95.11	3.56	76.64	8.23
Percent of Telecommutable Jobs (%)	84.65	55.98	7.11	55.40	9.50	48.08	6.27	54.33	8.08
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area									
Average Percentage of Low-Wage Workers (workers earning $\leq$ \$1250/month) (%)	18.59	22.82	3.18	25.25	3.54	26.79	2.71	27.78	1.89
Average Percentage of Minority Population (%)	30.05	26.37	8.24	27.15	12.03	5.44	5.27	23.36	8.23

Travel Behavior									
Meso Level: The County									
Nonmotorized Travel Mode Share (%)	14.10	3.01	2.43	2.79	3.18	2.70	1.31	2.25	1.68
Private Vehicle Travel Mode Share (%)	42.40	87.68	6.54	89.82	6.44	92.56	2.36	90.67	3.80
Public Transit Travel Mode Share (%)	37.60	4.11	5.44	2.22	4.37	0.67	0.84	1.33	2.50
Telecommuting Mode Share (%)	4.70	4.20	1.72	4.11	1.58	2.94	0.82	3.93	1.43
Built Environment									
Meso Level: The County									
Mean Activity Density [average (employment + housing units)/acres)]	34.09	3.57	4.00	3.11	4.98	2.42	4.43	2.58	2.64
Mean Entropy (dimensionless)	0.38	0.53	0.15	0.54	0.10	0.46	0.11	0.54	0.08
Mean Pedestrian-friendly Network Density [average (facility miles of ped.-oriented links/mi^2)]	18.91	6.91	4.39	6.99	5.14	5.76	3.25	8.57	4.23
Walk Score (dimensionless)	74.64	17.25	18.69	21.20	25.41	4.05	7.83	8.21	16.28
Primary Care Physician Rate (primary care provider rate per 100,000 population)	223.99	100.07	54.09	101.97	85.46	81.77	64.77	66.69	37.15
Percentage of Fast Food Restaurants (percent of all restaurants that are fast food establishments)	51.91	53.06	9.46	46.60	12.29	49.17	14.90	45.64	9.66
Liquor Store Density (number of liquor stores per 10,000 population)	3.04	2.04	0.83	.69	0.73	0.24	0.37	0.84	0.62
Recreational Facilities Density (number of recreational facilities per 100,000 population)	10.84	12.55	4.72	10.53	7.47	6.93	5.90	7.65	5.23
Ambient Air Pollution (number of unhealthy air quality days due to Ozone & Fine PM)	13.00	7.19	4.46	1.81	2.75	2.67	2.88	2.42	1.97
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area									
Mean Activity Density [average (employment + housing units)/acres)]	12.15	6.87	4.21	4.70	3.61	3.87	3.71	3.82	2.16
Mean Entropy (dimensionless)	0.47	0.52	0.06	0.52	0.04	0.50	0.06	0.56	0.06
Mean Total Road Network Density [average (total road network miles/mi^2)]	16.05	13.56	5.39	11.64	3.72	9.73	2.43	15.34	9.68
Mean Local Transit Accessibility [average (distance to the nearest transit stop in meters)]	372.71	415.99	128.60	452.61	52.65	854.82	111.67	677.12	63.86
Number of Counties: 201; Number of CBSAs: 65									

NOTE: [a] District of Columbia is considered one county and one CBSA; therefore, no standard deviation is included in the table for District of Columbia data.

I.1.4 County-level Health Outcome Models: Methodology and Results

County-level health models have been developed based on variables included in Table I-2. As previously mentioned, many other built and social environment variables were considered for inclusion in the county-level health models and several different model specifications were considered. However, inclusion of these additional variables did not contribute to an improvement in the models. At the end, the most parsimonious model specifications representing logical cause-effect relationships were selected with consideration of reducing the risk of multicollinearity.

Since the nature of the data is cross-sectional and reverse causality may exist between health outcomes and nonmotorized travel behavior and/or the built environment, the analysis is susceptible to endogeneity bias. Addressing this issue requires the use of an advanced methodology to analyze the link between health outcomes, travel behavior factors, and built environment attributes, while controlling for any potential endogeneity bias.

Therefore, the health impacts of county-level measures characterizing the travel and telecommuting behavior of a county's residents as well as the meso-level (i.e., county level) and macro-level (i.e., CBSA level) social and built environment factors have been estimated by using multilevel Structural Equation Modeling (i.e., multilevel SEM) techniques.

The employment of multilevel SEM allows examination of the complex relationships and causal links among health outcomes, active travel, and built as well as social environment factors, while accounting for endogeneity bias.

In addition, the capabilities of the multilevel SEM make it a suitable model to deal with any potential multicollinearity problems in the models and can also help in statistical treatments of any spatial autocorrelation issues, which may exist due to interdependencies among clustered data (i.e., counties clustered in CBSAs).

I.1.4.1 Specification of Models: County-level Health Outcome Models

The first step in estimating a SEM is to postulate causal relationships, which are typically expressed as a path diagram (Kelloway 1998; Cervero and Murakami 2010). Figure I-7 shows the multilevel SEM model structure (i.e., path diagram) describing the causal links among endogenous variables as well as between exogenous and endogenous variables for the county-level health models as hypothesized in this study. Table I-5 at the end of this Appendix lists variable labels as depicted in Figure I-7.

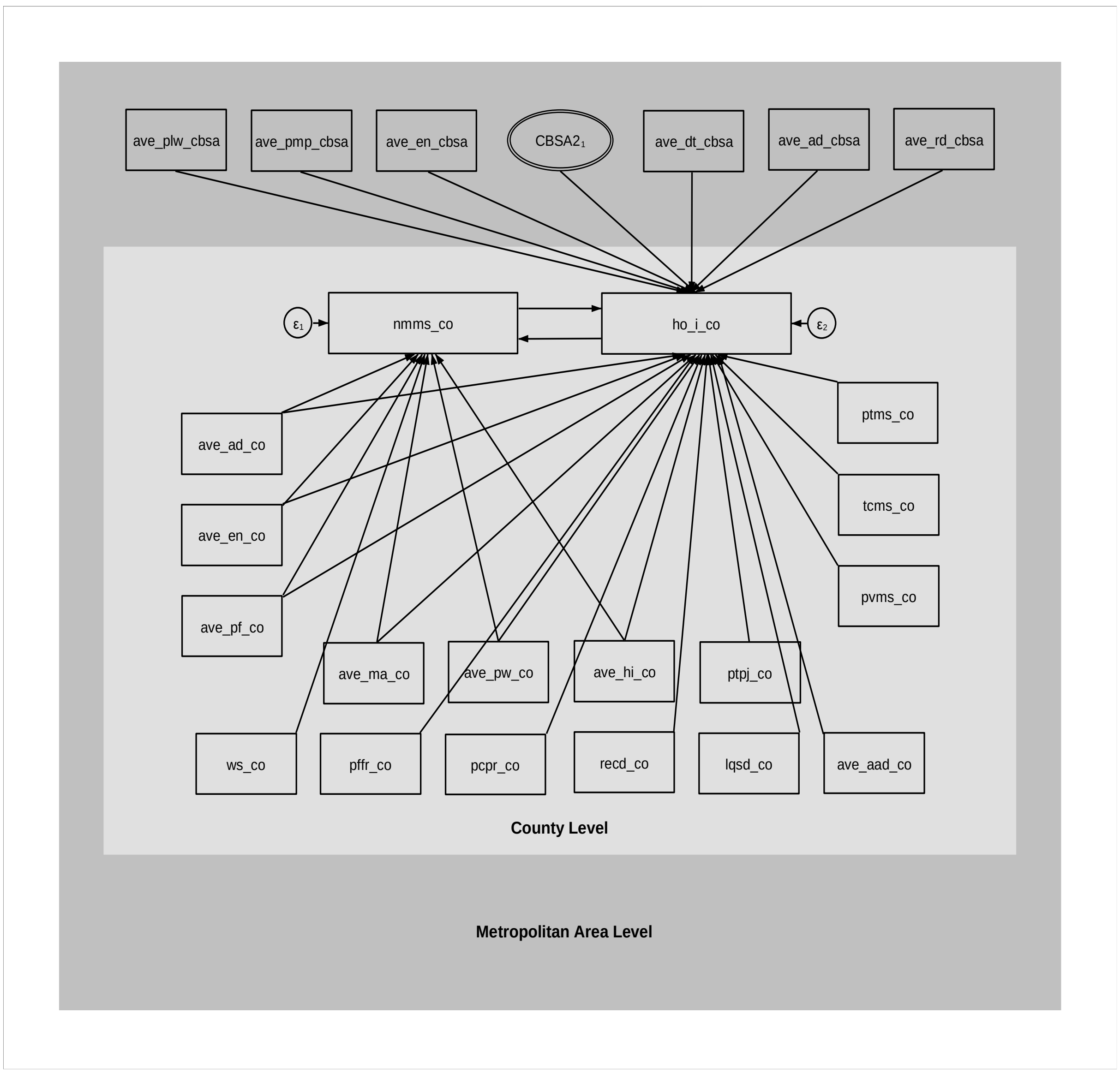

Figure I-7. Multilevel SEM Structure — County-level Health Models

Per SEM conventions, latent (i.e., unobserved) variables are represented in ovals or ellipses, whereas observed variables are represented in squares or rectangles (Kelloway 1998; Kline 2011). Therefore, the path diagram used in the multilevel SEM is shown with rectangles representing observed variables, and ovals representing latent variables. Endogenous and exogenous variables are connected by arrows indicating the direction of influence coming from the exogenous variables and heading toward the endogenous variables. The path diagram includes bidirectional arrows to incorporate the reciprocal causation, which may potentially exist between nonmotorized travel and health outcomes. Although requiring the assumption of equilibrium[68]—which is difficult to directly evaluate when data are cross-sectional—the estimation of reciprocal causation between variables measured concurrently in cross-sectional designs is the only viable alternative to longitudinal designs (Kline 2011).

Since in this sample counties reside within CBSAs, CBSAs are considered as clusters in the models and their random effects can be estimated by the multilevel SEMs. The double-ringed oval variable in Figure I-7 indicates the random intercept latent variable at the CBSA level. This variable stays constant within the same CBSA but varies across different CBSAs; thus, this variable represents the random effects at the CBSA level in the model.

As mentioned previously, six models have been developed for six county-level health outcome endogenous variables including prevalence of adult obesity, prevalence of adult diabetes, prevalence of fair or poor health, number of poor physical health days, number of poor mental health days, and premature death.

[68] The assumption of equilibrium implies that any changes in the system with a presumed reciprocal relation have already exerted their effects and the system is in an equilibrium state (Kline 2011).

The path diagram shown in Figure I-7 can be represented by the following two simplified regression equations for the county-level health outcomes and the nonmotorized travel mode share (Equations I-1 and I-2):

$$\text{County} - \text{level health outcome}_{i\ (Observed\ Endogenous\ Variable)} = \beta_i + \beta_1'\text{SE}_{\text{County}} + \beta_2'\text{SE}_{\text{CBSA}} + \beta_3'\text{TB}_{\text{County}} + \beta_4'\text{BE}_{\text{County}} + \beta_5'\text{BE}_{\text{CBSA}} + u_{0\text{CBSA}} + \varepsilon_2 \quad \text{Equation I-1}$$

$$\text{County} - \text{level nonmotorized travel mode share}_{(Observed\ Endogenous\ Variable)} = \alpha_i + \beta_7'\text{HO}_{i\ (\text{County})} + \beta_8'\text{SSE}_{\text{County}} + \beta_9'\text{SBE}_{\text{County}} + \varepsilon_1 \quad \text{Equation I-2}$$

where,

α_i, β_i = model intercepts;

$\beta_1' - \beta_9'$ = column vectors of model path coefficients;

$\text{SE}_{\text{County}}$ = a column vector of meso-level (county) social environment attributes;

SE_{CBSA} = a column vector of macro-level (CBSA) social environment attributes;

$\text{TB}_{\text{County}}$ = a column vector of meso-level (county) travel behavior attributes;

$\text{BE}_{\text{County}}$ = a column vector of meso-level (county) built environment attributes;

BE_{CBSA} = a column vector of macro-level (CBSA) built environment attributes;

$u_{0\text{CBSA}}$ = the CBSA-level random intercept (random effects);

$\text{HO}i_{\ (\text{County})}$ = the county-level health outcome *i*;

$\text{SSE}_{\text{County}}$ = a subset column vector of meso-level (county) social environment attributes;

$\text{SBE}_{\text{County}}$ = a subset column vector of meso-level (county) built environment attributes;

$\varepsilon_1, \varepsilon_2$ = model error terms.

To simplify interpretation of the results a few of the continuous variables with skewed distributions were normalized by transformation into their naturally logged form before inclusion in the models. Nonetheless, the distribution of two of the observed variables—namely, the

Nonmotorized Travel Mode Share variable and the *Public Transit Travel Mode Share* variable—remained non-normal in the analysis as these variables were not normalized by log-transformation. This was because the mode share variables are in the form of a percentage and log-transformation will make interpretation of the results difficult. However, it is assumed that by using the maximum likelihood estimation (MLE) method—commonly used in practice (Cao et al. 2007)—in estimation of the multilevel SEMs, the non-normality of the two above-mentioned variables did not pose a problem to the model results. This is due to the usage of the Generalized Structural Equation Modeling (GSEM) mode of the Stata software for model estimation.

In standard linear SEMs, the validity of MLE depends on the SEM meeting the assumption of multivariate (i.e., joint) normality of all model variables, observed and latent. However, the MLE method used in GSEM is applied to a different likelihood function, which assumes only conditional normality (i.e., for latent variables only), and does not require the full joint-normality assumption for the observed variables as in the standard linear SEMs (StataCorp 2013)[69]. Applying the MLE method has the bonus of dealing with endogeneity bias in the county-level models since in estimating bidirectional relationships, potential endogeneity bias can be statistically corrected by using MLE (Cervero and Murakami 2010).

The Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were used for model evaluation and to select the best model for each of the six health outcomes. AIC and BIC are usually used for model comparison and selection. The AIC and/or BIC for several

[69] See Stata Structural Equation Modeling Reference Manual Release 13, Pages 43-45 "Differences in assumptions between sem and gsem": https://www.stata.com/manuals13/sem.pdf

models can be calculated and compared, and the "best" model is the candidate model with the smallest value for these criteria (Kelloway 1998; Kline 2011; Fabozzi, et al. 2014)[70].

I.1.4.2 Discussion of Results: County-level Health Outcome Models

Table I-3 summarizes the estimation results of the multilevel SEM models for the six county-level health indicators of interest. The table provides side-by-side comparison of the estimates for the models that—in a comprehensive framework—link physical and psychological health indicators of a community (i.e., county) to its active travel, motorized travel, and telecommuting behavior as well as built and social environment factors at different spatial levels. The direction of arrows in a SEM path diagram represents the effect priority as hypothesized (i.e., $X \rightarrow Y$ implies that X affects Y) (Kline 2011). Therefore, the results of the multilevel SEMs are discussed considering such links as causal relations. The results show that county-level health outcomes are linked with built and social environment characteristics at the meso level (i.e., county) and the macro level (i.e., CBSA). The results also show statistically significant paths between county-level travel behavior characteristics (including telecommuting behavior) and county-level health indicators.

<u>The Health Outcome Equation Findings</u>

Social Environment Variables Findings

Social environment factors have been included in the county-level health models at two spatial levels: the county (i.e., the meso level) and the CBSA (i.e., the macro level). At both levels of geographical scale, sociodemographic and/or socioeconomic factors prove to play important roles in a community's (i.e., county) health profile.

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[70] The values of the minimum AIC and BIC for each health outcome model are not reported in the model results. This is because the process of model selection is not discussed in this dissertation, and as literature argues the AIC/BIC for just one model in isolation are meaningless (Fabozzi, et al. 2014).

Meso-level (County-level) Social Environment Variables Findings: The effects of sociodemographic and socioeconomic factors on a community's health outcomes have been controlled for by including county-level: median age and median annual household income as well as the percent of the county population that is of the White race and the percent of total telecommutable jobs available within the county. The variable representing the median age of the county shows a positive link with all health outcomes (prevalence of obesity, prevalence of diabetes, prevalence of fair/poor health, number of poor physical health days, number of poor mental health days, and premature death). This means that older age is linked to adverse health outcomes, which is a reasonable finding and corroborates past findings (see e.g., Lindström 2008; Joshu et al. 2008; Langerudi et al. 2015).

From the results, it appears that the racial composition of the county plays a role in county-level health outcomes as higher percentages of White residents within the county are linked with lower rates of obesity, diabetes, and premature death. With respect to obesity, these results are consistent with those of Joshu et al. (2008) who found that BMI was positively associated with being of the "non-Hispanic black" or "other" race compared to being of the "non-Hispanic white" as well as findings by Ewing et al. (2008) and Ewing et al. (2014) that BMI was higher for Blacks and Hispanics compared to Whites. Also, the results of the county-level health models developed in the present study indicate that higher median household incomes are related to lower prevalence of obesity, lower prevalence of diabetes, lower prevalence of fair or poor health, and lower levels of premature death. These results corroborate past findings that higher income levels are associated with lower rates of obesity (see e.g., Samimi and Mohammadian 2009; Marshall et al. 2014) as well as better general health (see e.g., Samimi and Mohammadian 2009; Langerudi et al. 2015) and lower rates of premature death (see e.g., Braun and Malizia 2015).

Table I-3. Results: County-level Health Outcome Models (Multilevel SEMs)

Endogenous Response Variables / *Exogenous and Endogenous Predictor Variables*	*Prevalence of Adult Obesity*		*Prevalence of Adult Diabetes*		*Prevalence of Fair or Poor Health*		*Number of Poor Physical Health Days*		*Number of Poor Mental Health Days*		*Premature Death*[a, c]	
	Path Coefficient	***p-value***	***Path Coefficient***	***p-value***	***Path Coefficient***	***p-value***	***Path Coefficient***	***p-value***	***Path Coefficient***	***p-value***	***Path Coefficient***	***p-value***
The Health Outcome Equation												
Social Environment												
Meso Level: The County												
Median Age	1.021887*	0.075	1.218937*	0.076	2.934992*	0.100	.2019078**	0.016	.2544379***	0.007	.0060282**	0.023
Median Annual Household Income[a]	-6.000631**	0.047	-2.207459*	0.068	-13.40427*	0.056	NS	NS	NS	NS	-.626315***	0.000
Percent of White Population	-.4513066**	0.020	-.2183968***	0.000	NS	NS	NS	NS	NS	NS	-.002959**	0.013
Percent of Telecommutable Jobs	.3856962*	0.057	NS	NS	NS	NS	.0578596*	0.063	.0698131*	0.100	NS	NS
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area												
Ave. Percent of Low-Wage Workers	.9473392*	0.093	.431751*	0.078	NS	NS	NS	NS	NS	NS	.012174**	0.017
Ave. Percent of Minority Population	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Travel Behavior												
Meso Level: The County												
Nonmotorized Travel Mode Share[b]	-1.920880**	0.023	-1.587329***	0.000	-4.37055*	0.087	-.388474***	0.001	-.431648***	0.002	-.0088538*	0.097
Private Vehicle Travel Mode Share	1.536219**	0.022	NS	NS	3.526575*	0.085	.2891368***	0.001	.3214949***	0.002	NS	NS
Public Transit Travel Mode Share	-1.452743**	0.024	-1.224258*	0.095	3.454486*	0.084	.2760268***	0.001	.3064172***	0.002	NS	NS
Telecommuting Mode Share	1.480438**	0.025	NS	NS	3.368343*	0.091	.258565***	0.002	.2871268***	0.003	NS	NS
Built Environment												
Meso Level: The County												
Mean Activity Density[a]	NS	NS	NS	NS	8.33899*	0.070	.7550993*	0.056	1.032327**	0.034	-.0265743*	0.056
Mean Entropy	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Mean Ped-friendly Network Density[a]	-4.655807*	0.076	NS	NS	-9.833479*	0.067	-.9612095**	0.037	-1.2561**	0.046	-.0354871*	0.083
Primary Care Physician Rate	-.0435531*	0.079	-.0569483*	0.099	-.183371**	0.048	-.017753***	0.005	-.0170922**	0.016	-.0003359*	0.096
Percent of Fast Food Restaurants	.1444621**	0.048	NS	NS	NS	NS	NS	NS	NS	NS	. 0014469**	0.042
Liquor Store Density	—	—	0.0212266**	0.027	—	—	—	—	—	—	.0066186***	0.000
Access to Recreational Facilities	NS	NS	NS	NS	-.6751073**	0.047	-.0318808*	0.067	-.0146593**	0.049	NS	NS
Ambient Air Pollution	—	—	—	—	NS	NS	NS	NS	NS	NS	.0074849*	0.081
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area												
Mean Activity Density[a]	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	-.071602***	0.009
Mean Entropy	.05482797*	0.098	.06697445**	0.016	.200335*	0.097	.122036**	0.035	.128634**	0.047	NS	NS
Mean Total Road Network Density[a]	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	.0124712***	0.002
Mean Distance to Local Transit	.0120661*	0.080	.0149588*	0.085	.0403235*	0.064	.0041299**	0.041	.0038276*	0.080	NS	NS

The Nonmotorized Mode Share Equation												
Health Outcome												
Meso Level: The County												
Prevalence of Adult Obesity[b] (%)	-2.906638***	0.000	—	—	—	—	—	—	—	—	—	—
Prevalence of Adult Diabetes[b] (%)	—	—	-1.083103**	0.015	—	—	—	—	—	—	—	—
Prevalence of Fair or Poor Health[b] (%)	—	—	—	—	-1.741682***	0.000	—	—	—	—	—	—
Number of Poor Physical Health Days[b]	—	—	—	—	—	—	-.744672***	0.000	—	—	—	—
Number of Poor Mental Health Days[b]	—	—	—	—	—	—	—	—	-1.60396**	0.035	—	—
Premature Death[b]	—	—	—	—	—	—	—	—	—	—	—	— [c]
Social Environment												
Meso Level: The County												
Median Age	-.685114***	0.000	-1.200585**	0.048	-.1592093*	0.069	-.3398***	0.000	NS	NS	-.180648***	0.000
Median Annual Household Income[a]	-1.580434***	0.000	-3.547685**	0.014	-1.899436***	0.000	-1.30980***	0.000	-1.987423**	0.035	-1.256101**	0.032
Percent of White Population	.094803**	0.017	.1818724*	0.066	.0643224**	0.039	.1269255***	0.002	.2362414*	0.061	NS	NS
Built Environment												
Meso Level: The County												
Mean Activity Density[a]	4.644115***	0.000	5.723195**	0.046	NS	NS	NS	NS	NS	NS	.534013**	0.012
Mean Entropy	.1247384**	0.024	.2615506**	0.047	.130786***	0.005	.0932844**	0.037	.214506*	0.084	.2043407*	0.093
Mean Ped-friendly Network Density[a]	3.811178***	0.003	7.437143**	0.045	NS	NS	1.471607*	0.069	2.38445*	0.070	-.5882365*	0.052
Walk Score	.0965907*	0.059	NS	NS	NS	NS	NS	NS	NS	NS	.0281987***	0.001
Other Model Factors												
CBSA Variance Estimates (i.e., CBSA Random Effects)	NS		NS		NS		NS		NS		NS	
Log likelihood	-713.8606		-524.00906		-703.36816		-405.36923		-410.3505		-330.1273	
Observations (Counties) [71] ; CBSAs	201; 65		201; 65		192; 65		192; 65		194; 65		201; 65	

NOTES:

[a] Variable was log-transformed;

[b] Endogenous variable;

[c] This model does not include bidirectional links (no link was considered from the *Premature Death* variable to the *Nonmotorized Travel Mode Share* variable);

NS = Not statistically significant;

— = Not included in the model;

*, **, *** = Path coefficient is significant at the 10%, 5% and 1% significance level, respectively.

[71] SEM is a large sample technique; a sample of approximately 200 observations has been deemed as an appropriate sample size for models of moderate complexity (Kelloway 1998; Kline 2011). Therefore, the sample size for county-level models developed here are assumed to be adequate for model estimations.

This is an expected result since higher incomes mean higher levels of affordability for better quality goods and services including those that can affect health. For instance, high-income individuals can afford organic and healthy food, better healthcare services, as well as gym and sports facilities memberships—all of which may favorably influence their health status.

Most notably, the results of the multilevel SEMs indicate that the level of "telecommutability" of employment opportunities within counties can affect residents' health status. Higher percentages of telecommutable jobs within the county are linked with adverse health outcomes including higher levels of obesity as well as higher numbers of poor physical and mental health days. These findings imply that the extent of telecommutability of employment within a county can influence its residents' physical and psychological health status. The direction of these effects, however, indicate that higher levels of telecommutability of jobs within a county may lead to unfavorable health outcomes for county residents.

Macro-level (CBSA-level) Social Environment Variables Findings: The results of the models suggest that macro-level socioeconomic factors can also be influential in the health status of communities (i.e., counties) as evidenced by the effects of the CBSA-level *Average Percent of Low-Wage Workers* variable on levels of obesity, diabetes, and premature death. Higher rates of obesity, diabetes, and premature death are linked to higher average percentages of low-income workers within the CBSA. These results are consistent with the direction of effects of the meso-level (i.e., county-level) income variable and suggest that higher income levels within the CBSA (i.e., metropolitan/micropolitan area) of residence are related to better community health outcomes. On the other hand, percentage of minority population within the CBSA does not seem to exert any effects on community health status as the path coefficient for this variable does not reach a statistical significance threshold in any of the health outcome models.

Travel Behavior and Telecommuting Behavior Variables Findings

Meso-level (County-level) Travel Behavior Variables Findings: The multilevel SEM results indicate that travel behavior (i.e., extent of usage of each travel mode) of residents of a county influences the health outcomes within the county. Most importantly, the path coefficients of the nonmotorized travel mode share variable are negatively linked to all health outcomes including prevalence of obesity and prevalence of diabetes as well as the number of poor physical and mental health days. These findings are in line with those of Lindström (2008) who found that the odds ratios of being overweight and obese among individuals who walked or bicycled were significantly lower (compared to the driving base category in that study) as well as findings by Tajalli and Hajbabaie (2017) who found that compared to using private vehicles, walking was associated with a lower probability of obesity, diabetes, and mental disorders. In the case of obesity, the results are also consistent with other previous research (Frank et al. 2004; Gordon-Larsen 2009; Schauder and Foley 2015).

Also, in terms of mental health, the results indicate that the higher the extent of active travel within the county, the fewer the average number of mentally unhealthy days for the residents. This means that an improved mental health status for residents of the county is more likely to occur if residents engage in more walking and bicycling activities. These results are expected and consistent with past research (Leyden 2003). Thus, according to the results, higher levels of walking and bicycling within the county can lead to better physical and psychological health status for residents of a community (i.e., county).

Equally important is the model estimations on the effects of telecommuting behavior. The results indicate that higher levels of the telecommuting mode share within the county are linked to higher prevalence of obesity, higher prevalence of poor/fair health, as well as higher numbers of poor physical and mental health days. These results confirm the direction of effects of the variable capturing the extent of telecommutability of employment within the county.

Research in the past has postulated that excessive participation in computer-related activities has a potential to reduce physical activity levels (King et al. 2002). Therefore, one possible explanation for these findings can be that more working from home can lead to less physical activity, which in turn, can lead to obesity and other adverse physical and mental health outcomes. In the case of obesity, it is also possible that easy access to food—as provided by working from the convenience of one's home—can lead to an increase in the individual's overall food consumption. If telecommuting is a frequent event, the additional food intake—while staying at home—may lead to obesity. However, Henke et al. (2015) found that individuals who did not telecommute were at greater risk for being obese, while Tajalli and Hajbabaie (2017) did not find a statistically significant association between telecommuting and obesity.

These past findings are not consistent with the results obtained in the current study. It should be noted, however, that both Henke et al. (2015) and Tajalli and Hajbabaie (2017) conducted their study at the individual level, whereas the present study investigates the effects of telecommuting at the county level. Nevertheless, the inconsistency in results suggests a need for further investigation into the relationship between obesity and telecommuting.

In addition, telecommuting has been found in previous studies to be negatively linked with psychological health. Past research suggests that telecommuting may lead to social isolation and mental exhaustion (see e.g., Baruch 2001; Tajalli and Hajbabaie 2017). The latter study found that compared with using private vehicles, telecommuting was associated with a higher probability of having mental disorders (Tajalli and Hajbabaie 2017). The results from the present study corroborate those findings as the model estimations indicate that a higher telecommuting mode share within the county is related to a higher average number of poor mental health days for residents. On the other hand, Henke et al. (2015) found that that employees who telecommuted during regular work hours had a reduced risk for depression over time compared to workers who did not telecommute. Considering the inconsistencies in the findings, further research may be required to clarify the role of telecommuting in psychological health outcomes, particularly with regards to the direction of effects. Further, similar to what Tajalli and Hajbabaie (2017) reported, this study does not find a statistically significant link between telecommuting and diabetes. Nonetheless, these findings provide evidence that telecommuting affects health outcomes in terms of both physical and psychological health.

Also, the results indicate that more traveling by means of private vehicle is linked with adverse health outcomes. Specifically, higher private vehicle mode shares are related to higher prevalence of obesity and poor/fair general health as well as higher numbers of poor physical and mental health days. In terms of general health, these results can be a manifestation of the effects of increased exposure to other people, higher disease diffusion rates and its negative impact on health status, as Widener and Hatzopoulou (2016) suggested. The referenced study argued that the level of exposure to other people increases via increased levels of mobility offered by private vehicles; the more interactions between people, the more opportunities for diseases to spread, which can negatively affect personal health (Widener and Hatzopoulou 2016).

The results can also be indicative of the health impacts of being exposed to chronic stress related to operating an automobile as well as other factors associated with automobile use such as congestion levels, long commute duration, pollution, noise, and other stressors such as road rage. Commuting by automobile has been suggested to be associated with higher levels of stress and a negative mood (Galovski and Blanchard 2004; Wener and Evans 2011). Further, car commuting stress has been suggested to be linked with adverse physical and psychological health outcomes such as lower levels of subjective well-being (van Wee and Ettema 2016), increased elevated cardiovascular outcomes (Evans and Wener 2006), increased cognitive impairment and lower overall life satisfaction (Rissel et al. 2014), and higher body mass index (BMI) (Frank et al. 2004; Lindström 2008). For car drivers, a longer commuting time was also found to be related to lower health satisfaction, lower levels of general health status, more visits to health providers, and a higher BMI (Künn-Nelen 2015). In addition, Leyden (2003) suggested that long commutes—resulted from suburbanization—are among the factors contributing to the decline in social capital, which is a measure for mental health. Social capital was defined in that study as social interactions that inspire trust and community connections among individuals. Past research also found that increased automobile use within a county was associated with higher levels of obesity as well as lower levels of good general health for residents (Samimi and Mohammadian 2009; Samimi et al. 2009). The findings of the present study corroborate these past findings.

According to the results of the multilevel SEMs, higher levels of public transit mode share within the county are related to lower levels of obesity and diabetes but higher levels of fair/poor health as well as higher numbers of poor physical and mental health days. These findings indicate that traveling by public transportation influences physical and psychological health outcomes. Literature argues that a positive association exists between public transit use and active travel, particularly walking, as using public transportation involves walking (and/or bicycling) to, from, and within the transit stations (Cervero 2001; Lindström 2008; Liao et al. 2016; Barr et al. 2016; Sener et al. 2016). Therefore, the negative link between public transportation mode share and prevalence of obesity and diabetes can be a result of the active travel involved in transit trips at each end, as also suggested by past research (Langerudi et al. 2015). Although, the direction of effects in the multilevel SEM models developed in the present study is favorable in the case of obesity and diabetes, the effects of public transit use on other physical and psychological health outcomes is not desirable.

In terms of physical health, Tajalli and Hajbabaie (2017) found that compared to use of automobiles, use of subway for commuting was associated with lower probability of obesity and diabetes, whereas using the city bus was linked with a higher probability of obesity. Other studies reported that using public transportation was associated with better weight-based health outcomes such as a lower odds ratio of overweight and obesity among men (Lindström 2008), a lower risk of overweight (Liao et al. 2016), and improved BMI and obesity (Sener et al. 2016). Other empirical research found that higher transit use within a county was associated with lower levels of obesity (Samimi et al. 2009), and better general health status for residents (Samimi and Mohammadian 2009; Samimi et al. 2009).

Overall, the results of the current study are consistent with the literature suggesting that public transit use is associated with improved weight-based health outcomes such as obesity. However, the results reveal that increased public transit use may adversely affect general health as evidence by the positive direction of effects of public transit mode share on other physical health outcomes such as the prevalence of fair/poor health and number of physically unhealthy days per month in the models. The findings can be indicative of the adverse health effects of conditions typically associated with public transit use such as long wait times; higher stress levels due to unpredictability of vehicle arrival; exposure to inclement weather conditions; exposure to crowded stations; exposure to higher levels of air pollution due to transit vehicle operations, congestion delays, and vehicle idle times behind traffic signals; as well as interaction with other users who may be ill. Past studies suggest that rail transit commuters experience higher levels of perceived stress, particularly due to factors such as long duration of commute and unpredictability (e.g., Evans et al. 2002; Evans and Wener 2006). The higher levels of stress experienced by public transit riders can lead to adverse physical and mental health outcomes.

Looking from a different angle, the adverse effects of transit use on general health can be a result of inhaling harmful pollutants produced by transit vehicles. Past research suggests that walkers and bicyclists may disproportionally be affected by vehicle emissions (Sener et al. 2016), and that air pollution from traffic negatively impacts health (Mackett and Thoreau 2015). Empirical findings have shown that more walkable, near-transit areas have higher concentrations of Nitric Oxide (NO)—an indicator of air pollution due to direct vehicle emissions (Marshall et al. 2009). Therefore, it can be assumed that walking, bicycling, or waiting related to public transit use can negatively affect health due to inhaling polluted air. Empirical research found that more county-level transit use was correlated with higher rates of asthma infection, and suggested that this effect was due to transit riders being more exposed to polluted air because of the additional walking trips associated with transit use (Samimi and Mohammadian 2009).

On the other hand, the adverse effects of transit use on general health can also be indicative of the effects of increased exposure to other riders and disease diffusion rates among transit users. The more interactions between individuals, the more opportunities for diseases to spread, which can have a negative effect on personal health (Widener and Hatzopoulou 2016). All considered, the findings warrant additional examination of the role of public transit in general health outcomes.

Concerning mental health, van Wee and Ettema (2016) suggested that using public transit may lead to lower levels of subjective well-being due to exposure to incidents such as undesired interactions with personnel or other travelers, which may evoke negative emotions. Therefore, in the case of recurrent travel such as commuting by public transit, these negative emotions may lead to an increased number of mentally unhealthy days for the traveler.

Overall, the findings of the present study on the effects of different travel modes on health outcomes are consistent with past findings. It should be noted that the effects of travel and telecommuting mode share variables on county-level health outcomes potentially entail the role of a county's "travel culture" in the health status of its residents. In that sense, the travel behavior measures partially characterize each county in terms of its sociocultural characteristics, and thereby they can be considered another aspect of the county's social environment.

Built Environment Variables Findings

The effects of built environment on health outcomes have been controlled for at two levels of geography: the meso (i.e., county) level and the macro (i.e., CBSA) level. Several built environment factors show statistically significant effects in the health outcome models.

Meso-level (County-level) Built Environment Variables Findings: County-level built environment variables have been included in the health models to control for the most important built environment factors that can influence the health status of residents of a county. These variables characterize each county based on levels of compactness (i.e., activity density), mixed land use (i.e., entropy), pedestrian friendliness of street network design, access to clinical healthcare, access to recreational facilities, access to unhealthy food outlets, as well as ambient air pollution. The model estimates provide evidence that the built environment factors of the county of residence play an important role in the collective health profile of the community.

The model estimates show that the county-level *Mean Activity Density* variable, which represents population and employment densities combined, has a positive link with prevalence of fair/poor health as well as the number of poor physical and mental health days. This indicates that the higher the densities (i.e., higher compactness) within a county, the more unfavorable the physical and mental health effects. These results line up neatly with arguments of a previous study which suggested that even though high-density developments may foster nonmotorized travel (and thereby promote health), dense urban areas can also lead to negative mental and physical health effects due to their potentially stressful environments (Samimi and Mohammadian 2009).

Other research also found that neo-traditional developments with higher population densities (i.e., compact designs) were less consistent with people's general health condition (Langerudi et al. 2015). Based on such findings, past studies suggested that the highly stressful, polluted, and crowded conditions in dense urban areas may be detrimental to residents' health status despite their potential pedestrian- and bicyclist-friendly designs (Langerudi et al. 2015), and that denser urban environments may be less inviting and more stressful, and thereby may adversely affect health of individuals (Kelly-Schwartz et al. 2004). The consistency in these past findings and the findings of the present study lends some degree of confidence to the results obtained.

The *Mean Activity Density* variable at the county level does not exhibit a statistically significant path coefficient with obesity and diabetes in the present study. These findings are consistent with the findings of a few past studies including those of the Samimi and Mohammadian (2009) who reported a statistically insignificant association between county-level population density and obesity. Further, Smith et al. (2008) suggested that population density at the census block group was not consistently related to weight measures, and Frank et al. (2004) reported that residential density at one-kilometer buffer around the household was insignificant in the obesity model. Population density, however, was found to be correlated with lower rates of obesity in another study, suggesting that people living in dense urbanized areas were less likely to be obese (Samimi et al. 2009). Also, Ewing et al. (2003b) found that residents of counties with higher levels of sprawl (i.e., an index obtained by combining residential density and street accessibility variables in that study) had a higher BMI and were more likely to be obese. However, no statistically significant link between county-level sprawl and diabetes was found in that study. Other studies also suggested that residents of more compact counties had lower BMIs (Joshu et al. 2008; Ewing et al. 2014), and lower probabilities of obesity and diabetes (Ewing et al. 2014).

Therefore, the findings of the present study, which imply that county-level activity density does not impact the obesity and diabetes rates within the county, are in line with a few previous research efforts but inconsistent with a few others. It should be noted that the latter studies measured compactness based on a sprawl index, which combined factors representing different dimensions of the built environment—namely—density, land use mix, centering of jobs and population, and street network design. Thus, the different methods of operationalization of activity density and compactness may have contributed to the inconsistent results. Further research may be needed to clarify the role of compactness (i.e., population and/or employment density) in obesity and diabetes. Moreover, the path coefficient of the county-level *Mean Activity Density* variable shows a negative sign in the premature death model, indicating that increased compactness within the county of residence may lead to lower rates of premature death (i.e., fewer years of potential life lost before age 75 per 100,000 county population).

The *Mean Entropy* variable at the county level does not show a statistically significant path coefficient in any of the health outcome models. Langerudi et al. (2015) suggested that mixed-use and presence of recreational facilities in a neighborhood along with retail stores and malls can lead to improved general health. However, that study might not have completely captured the effects of land-use mixing. The reason is that even though the study controlled for presence of specific land uses including recreational centers, retail stores, and medical centers, it did not control for the level of mixing of these land uses. For instance, it is not clear from that study how the effect of the presence of retail stores on general health of residents would change if retail stores were the only type of land use present (i.e., an entropy of zero, indicating non-diverse land use); or, if retail stores were present in conjunction with the other land uses (i.e., an entropy of more than zero, indicating diverse land use). Further research may be needed to shed light on the role of county-level mixed land use in health outcomes for residents.

The results also indicate that increased pedestrian friendliness of the network design within the county is linked with lower prevalence of obesity, lower prevalence of poor/fair health, fewer numbers of poor physical and mental health days, as well as lower rates of premature death. These findings highlight the importance of a network design that is conducive to active travel in promoting both physical and mental health.

Many studies in the past included measures of street network connectivity and pedestrian friendliness of the network in their health impact analysis. General findings suggest that street designs that foster walking and bicycling are associated with better physical and psychological health outcomes. For instance, Leyden (2003) found that pedestrian-friendly neighborhoods may affect social capital, and thereby may influence physical as well as mental health. In terms of mental health, past research provided evidence for a positive link between walkable and pedestrian-friendly designs and a greater psychological sense of community score, which is a proxy for mental health state (Lund 2002).

Regarding obesity, the results of the present study are consistent with those of Smith et al. (2008) who found that pedestrian-friendly street network designs lowered the risk of being overweight or obese for residents as well as findings by Samimi et al. (2009) who found that higher levels of intersection density (a proxy for connectivity and pedestrian friendliness of the street network) were correlated with lower rates of obesity. Also, Samimi and Mohammadian (2009) reported that a smaller average block size (another proxy for connectivity and pedestrian friendliness of the street network) was associated with lower rates of obesity. Nonetheless, Frank et al. (2004) found that intersection density within one-kilometer buffer around the household was insignificant in the obesity model. These findings may be indicative that neighborhood may not be a suitable geographical area to capture the effects of street connectivity and pedestrian friendliness on obesity and these effects are exerted at larger spatial levels such as counties. Together, the results of the present study corroborate findings in the past that indicate that a pedestrian-friendly network design within the county is linked with better health outcomes.

Other built environment factors included in the models capture the effects of access to clinical healthcare, access to unhealthy food, and access to healthy natural environments on county-level health outcomes.

Not surprisingly, access to clinical care shows a positive impact on health outcomes. This is evidenced by the direction of the estimated effects (i.e., path coefficients) for the *Primary Care Physician Rate* variable in the health models. The models' estimates mean that as the number of primary care physicians per 100,000 county population increases, the prevalence of obesity, diabetes, and fair/poor health within the county declines. The models' path coefficients also imply that increased access to clinical care within the county leads to fewer number of physically and mentally unhealthy days, and lower rates of premature death for county residents. These results are intuitive and consistent with research in the past that suggested living in an area where access to physicians and pharmacies is facilitated encourages healthcare-seeking behaviors (Widener and Hatzopoulou 2016), and thereby can lead to better health outcomes. These findings highlight the importance of access to healthcare in the health profile of the community.

Also, as it is essential for any research that examines the relationship between the built environment and health to account for food environments (Marshall et al. 2014), this study included variables representing access to unhealthy food (i.e., fast food restaurants and liquor stores) in the analysis. The significance of access to fast food outlets in health outcomes has been discussed in previous research. For instance, Joshu et al. (2008) suggested that by encouraging unhealthy food choices and discouraging physical activity, “obesogenic” environments promote obesity in the population, and Plantinga and Bernell (2007) pointed to prevalence of fast food restaurants as one of the factors that may explain the rise in obesity rates in the U.S.

The results of the models developed in the present study confirm the existence of a positive link between prevalence of fast food restaurants and prevalence of obesity within the county. This finding also corroborates past empirical findings suggesting that prevalence of fast food restaurants is positively related to obesity (Maddock 2004). In addition, the results indicate that prevalence of fast food restaurants contributes to premature deaths of the county residents. However, prevalence of fast food restaurants within the county does not show statistically significant path coefficients with other county-level health outcomes.

The direction of the effect of the *Liquor Store Density* variable in the diabetes model suggests that having more liquor stores per population of the county can lead to higher rates of diabetes for residents. This variable was included in the diabetes model as a proxy for alcohol consumption levels of county residents. Literature suggests that diabetes may be related to the levels of alcohol consumption. However, studies on the link between alcohol consumption and diabetes have produced inconsistent results in terms of the direction of the effect—a conclusion also reached by Wannamethee et al. (2003). Nonetheless, the general finding of previous research is that although light to moderate alcohol intake may be associated with a reduced risk of diabetes, high levels of liquor intake is associated with increased risk of diabetes (Rimm et al. 1995; Wannamethee et al. 2003; Howard et al. 2004). Further, the density of liquor stores within the county shows a positive link with premature death of residents. This finding is in line with that of Zhao et al. (2013) who reported that increases in the density of private liquor stores were associated with increases in alcohol-attributable mortality rates. The present study's finding on the adverse effect of higher access to liquor stores on premature death is also in line with findings of a more recent international study that concluded "alcohol use is a leading risk factor for disease burden worldwide, accounting for approximately 10% of global deaths among populations aged 15–49 years" (Griswold et al. 2018).

The variable representing access to recreational facilities is negatively linked with prevalence of fair or poor health as well as the numbers of physically and mentally unhealthy days. This implies that having recreational facilities within the county can influence residents' physical and psychological health status in a positive direction. Recreational and outdoor fitness facilities can be frequently used for physical activity (Lee and Moudon 2004); thus, these results are reasonable as having access to fitness and recreational facilities can encourage people to exercise more and be physically more active leading to lower likelihood of having physical health problems.

On the other hand, more exercise has been linked to higher levels of mental well-being and improved life satisfaction (Zayed et al. 2018); therefore, having access to recreational facilities to perform physical activities can boost life satisfaction, and thereby lead to a better mental health status. Further, these facilities also foster human interaction and social inclusion, which can promote mental health.

The *Ambient Air Pollution* variable represents the number of ambient air pollution days for each county and has been obtained by combining the annual number of unhealthy air quality days due to Ozone and Fine Particulate Matter. These air pollutants have been included in the analysis since both pollutants have been associated with adverse health effects (WHO 2006). The results indicate that higher numbers of ambient air pollution days within counties are positively linked to premature death of residents. This finding is in line with that of Tainio (2015) who found that most of all disability-adjusted life-years (i.e., years of life lost due to premature mortality or fatality or years lived disabled or injured) due to air pollution were attributable to natural mortality caused by Fine Particulate Matter (PM 2.5). It is also noteworthy to mention the findings of the 2015 WHO European Region document, which provided estimates of the economic costs of air pollution with respect to premature death. Based on that report, as of 2010, the annual economic costs of premature deaths from air pollution across the countries on the WHO European region stood at U.S. $1.431 trillion, and the overall annual economic cost of health impacts and mortality from air pollution stood at U.S. $1.575 trillion (WHO 2015).

Macro-level (CBSA-level) Built Environment Variables Findings: CBSA-level built environment variables have been included in the health models to control for the most important macro-level built environment factors that can influence the health status of residents of a metropolitan/micropolitan area (i.e., urbanized areas). These variables characterize each CBSA based on levels of compactness (i.e., activity density), mixed land use (i.e., entropy), road network density, and access to transit within the CBSAs. The results of the multilevel SEM models reveal that the built environment attributes of the CBSA play a role in health status of residents.

The CBSA-level *Mean Activity Density* variable (representing combined population and employment densities) exhibits a negative link with premature death indicating that higher levels of compactness within CBSAs may lead to lower rates of premature death for residents. The direction of the effect is consistent with that of the county-level *Mean Activity Density,* which implies that residents of more compact counties and urban areas may have a lower risk of premature death. Compactness within the CBSA (within which the county of residence locates) does not seem to affect any other county-level health outcome.

The *Mean Entropy* variable at the CBSA level shows a positive link with prevalence of obesity, prevalence of diabetes, prevalence of fair/poor health, as well as the number of physically and mentally unhealthy days for residents. These effects claim that higher mixed-use development within metropolitan/micropolitan areas may lead to adverse physical and psychological health outcomes within communities (i.e. counties). In terms of physical health, these results are somewhat unexpected. Considering the case for obesity, Frank et al. (2004) reported that higher mixed land use at one-kilometer buffer from the place of residence was associated with lower odds of obesity. Although this can be the case at the neighborhood level, the results of the current study suggest that higher mixed land use throughout the entire CBSA area (i.e., higher macro-level entropy) can lead to the opposite effects (i.e., higher rates of obesity).

One possible explanation is that higher mixed land use within macro-scale geographies such as metropolitan/micropolitan areas can mean additional destinations at farther distances. Additional remotely located destinations can lead to more driving and less walking/bicycling travel (i.e., active travel), which in turn, can lead to obesity. Similarly, other health outcomes can be influenced through the potential increased levels of driving to additional destination options offered by higher extent of mixed-use development within the CBSA. With regards to psychological health, the findings of the present study are in line with those of Wood et al. (2010) who found an inverse relationship between sense of community (a proxy for mental health state) and mixed land use. Nevertheless, further research with additional data may be required to confirm these results and to investigate the effects of macro-level mixed land use on physical and psychological health of residents.

The extent of transit accessibility within the entire urban area (i.e., mean distance to transit stops at the CBSA level) also influences community health outcomes. This is evidenced by the statistically significant path coefficients of the *Mean Distance to Local Transit* variable in all of the health models developed (except the premature death model). The path coefficients of this variable indicate that an increased average distance to the nearest transit stop within the entire CBSA of residence is linked to higher prevalence of obesity, higher prevalence of diabetes, higher prevalence of fair/poor health, as well as increased numbers of physically and mentally unhealthy days for residents.

These findings can be indicative of the state of health for residents of suburban areas. While past findings indicate that near-transit areas are more walkable (Marshall et al. 2009), areas farther away from transit stops are most likely the sprawled suburban areas, which are less inviting to active travel. This can lead to lower levels of walking and bicycling, and consequently, to higher levels of obesity and other health problems for residents of those areas.

Literature suggests that sprawl—a feature representative of suburban developments in the U.S.—is related to higher obesity rates (see e.g., McCann and Ewing 2003; Handy et al. 2006; Ewing et al. 2014). By promoting either sedentary or active behavior and increasing either social exclusion or an active social life, the degree of urban sprawl also has a potential to affect other physical and mental health outcomes (Cervero and Duncan 2003; Khattak and Rodriguez 2005; Næss 2005; Plantinga and Bernell 2007; Leslie et al. 2007; Melis et al. 2015). The results of the current analysis imply that living in sprawled suburban areas with lower levels of access to transit may lead to obesity and other adverse health effects.

The *Mean Total Road Network Density* variable does not show statistically significant path coefficients in any health model except in the premature death model where it shows a positive link with premature death of residents. This means that higher levels of road network density within the CBSA may lead to more premature deaths. The possible explanations for premature deaths to be linked with road network density within urban areas could be: *i*) fatalities due to vehicle crashes; *ii*) deaths due to diseases caused by long-term exposure and inhalation of pollutants emitted from vehicles on dense urban road networks; and *iii*) deaths due to diseases caused by the sedentary lifestyle and physical inactivity levels associated with increased automobile dependency and use in urban areas with dense road networks. It should be noted that although the effects of county-level ambient air pollution and automobile use have already been controlled for in the premature death model, the role of these factors at the macro level (i.e., CBSA level) have not been included in the model. Therefore, the extent of road network density within the CBSA can be acting as a proxy for any of the factors mentioned above.

Accordingly, the positive link between road network density within the CBSA and the rate of premature deaths as found in this analysis is probably capturing one or more of the following effects:

i) higher rates of vehicle-crash fatalities occurring on denser and more congested road networks within urbanized areas;

ii) higher rates of premature deaths associated with higher levels of exposure to polluted air resulted from vehicle emissions on dense and more congested urban road networks; and/or

iii) higher rates of premature deaths associated with higher levels of physical inactivity due to driving on denser and more congested urban road networks.

The Nonmotorized Mode Share Equation Findings

In the multilevel SEM equation system for each of the six health outcomes, the second equation (i.e., Equation I-2) estimates the effects of county-level social and built environment factors on county-level nonmotorized travel (i.e., active travel) mode share. Due to the possibility of reverse causality between health outcomes and health behavior such as walking and bicycling (Schauder and Foley 2015), this equation also includes a direct link to the particular health outcomes being modeled by the set of equations in the SEM system.

This model framework allows for estimating bidirectional effects between health outcomes and nonmotorized travel behavior (see Figure I-7). By applying the MLE estimation method for multilevel SEMs, this model framework also deals with any endogeneity bias that may exist in the county-level models. This is because in estimating bidirectional relationships, potential endogeneity bias can be statistically corrected by using MLE (Cervero and Murakami 2010).

The results of the *Nonmotorized Mode Share Equation* for all of the six health outcome models are consistent and they corroborate findings of the nonmotorized travel behavior models developed and estimated in Chapter 4 of this dissertation as well as findings of previous studies (see Chapter 2 and Appendix B). These results are discussed below.

Social Environment Variables Findings

The results of the multilevel SEMs indicate that a county's social environment factors influence the level of nonmotorized mode share within the county. As expected (and consistent with the results of the person-level nonmotorized mode share model developed in Chapter 4), the *Median Age* variable exhibits a statistically significant and negative link with the nonmotorized travel mode share in all models (except in the *Number of Poor Mental Health Days* model). This means that as the median age within the county increases, the nonmotorized travel mode share within the county decreases. Age has also been found in previous research to negatively correlate with nonmotorized travel (see e.g., Boarnet et al. 2008; Siu et al. 2012).

Moreover, the negative sign of the path coefficient of the *Median Annual Household Income* variable in all of the six health outcome models implies that higher median incomes within the county are linked with lower levels of county-level nonmotorized mode shares. This result is in line with past studies that found an association between higher income levels and lower levels of nonmotorized travel (e.g., Plaut 2005; Bento et al. 2005; Boarnet et al. 2008; Schneider 2015).

A county's racial composition also affects the level of nonmotorized travel mode share within that county. Results indicate that as the percentage of the White population increases within the county, so does the county's nonmotorized travel mode share. A few past studies suggested that non-Whites were more likely to make nonmotorized trips (see e.g., Hess et al. 1999; Cervero and Duncan 2003; Scuderi 2005; Yarlagadda and Srinivasan 2008; Pucher et al. 2011). Nonetheless, the result of the present analysis is consistent with those of the Florida person-level nonmotorized travel behavior models developed in Chapter 4.

Built Environment Variables Findings

The results of the SEM models also indicate that a county's built environment characteristics including the extent of compactness (i.e., activity density), mixed land use, and pedestrian friendliness of the street network impact the level of nonmotorized travel mode share within that county. These variables were found to be three key county-level (i.e., meso-level) built environment factors in estimating nonmotorized travel behavior in Chapter 4.

The county-level *Activity Density* variable shows a positive link with the county-level nonmotorized travel mode share in a few models, meaning that higher levels of compactness within the county are linked with higher levels of nonmotorized travel mode share within the county.

This finding is consistent with those of many past studies that found higher density and compactness to be positively correlated with nonmotorized travel (see e.g., Frank and Pivo 1994; Badoe and Miller 2000; Ewing et al. 2003b; Zhang 2004; Kerr et al. 2007; Wang 2013).

The extent of mixed-use development within the county is positively linked with the county-level nonmotorized mode share in all six models. This finding is consistent with those of past studies that found a higher extent of mixed land use had a positive association with nonmotorized travel (see e.g., Cervero and Duncan 2003; Kerr et al. 2007; Lin and Chang 2010).

Finally, results indicate that the extent of walkability and pedestrian friendliness of the street network within the county positively affects the nonmotorized travel mode share within the county. This is evidenced by the positive sign of the path coefficient of the *Mean Pedestrian-friendly Network Density* and the *Walk Score* variables in the models. These results are in line with the findings in Chapter 4 as well as those of previous research (see e.g., Ewing et al. 2004; Boer et al. 2007; Ewing and Cervero 2010; Mahmoudi and Zhang 2018a).

Reverse Causality Between Health and Nonmotorized Travel

Literature suggests that reverse causality may exist between health outcomes and health behavior such as walking and bicycling (i.e., nonmotorized travel) (Schauder and Foley 2015). Past research also suggests that individuals with poor health may perform lower rates of physical activity (Joshu et al. 2008), and that being overweight or obese can have a negative influence on physical activity levels (Trost et al. 2002).

To account for the possibility of reverse causality between nonmotorized travel—a typical form of physical activity—and health outcomes, the framework of the multilevel SEM models included bidirectional links between each of the six county-level health outcomes and the nonmotorized travel mode share within the county. The results of the models indicate that reverse causality does exist between health status of residents of a county and the extent of their nonmotorized travel.

More specifically, the results show that higher prevalence of obesity, higher prevalence of diabetes, higher prevalence of fair/poor health, as well as increased numbers of physically or mentally unhealthy days lead to lower levels of nonmotorized travel mode share within the county. These results are in line with those of Wasfi et al. (2016) who reported that healthier individuals were more likely to walk for utilitarian purposes.

These findings imply that the healthier the residents of a county are, the more they engage in health behavior such as active travel, which in turn, can help them sustain their healthy status. The opposite effect can also hold: an increased number of county residents with physical and mental health problems may lead to a reduction in active travel rates within the county, which in turn, may lead to even more adverse health effects for residents.

These findings shed light on the crucial role of reverse causality between health outcomes and active travel—an issue most often ignored in research probing the link between health and walking/bicycling modes of travel.

Random Effects

The variance of the CBSA-level random intercept is estimated by all the models to be statistically insignificant. Therefore, it can be inferred that CBSA-level random effects (i.e., random differences between urban areas) do not play an important role in health outcomes for the residents.

Further research may be needed to clarify the role of metropolitan/micropolitan random effects on health outcomes.

I.1.4.3 Summary of Findings and Conclusions: County-level Health Outcome Models

Through employment of multilevel Structural Equation Modeling (multilevel SEM) techniques, the county-level health outcome models examine the link between county-level health status indicators and the built as well as social environment attributes at two spatial scales: the county (i.e., the meso level) and the CBSA (i.e., the macro level).

Further, the framework of the county-level models includes bidirectional links between health outcomes and nonmotorized travel behavior to account for the possibility of reverse causality. The MLE estimation method was applied to the analysis. Together, the model design and the estimation method allow for examination of the causal links between health outcomes, nonmotorized travel behavior, and the built environment. Concurrently, the models address potential endogeneity bias issues, which may exist in the analysis.

The results provide evidence that contextual effects—such as those of the residential location's environmental attributes at various levels of influence—play a role in residents' health. More specifically, the results indicate that county-level health outcomes are linked with built and social environment attributes at the meso level (i.e., county) and the macro level (i.e., CBSA). The results also indicate that statistically significant paths exist between county-level travel behavior (including telecommuting behavior) and county-level health indicators.

Among meso-level (i.e., county-level) social environment attributes, the median age of the county population shows a positive link with prevalence of obesity, prevalence of diabetes, prevalence of fair/poor health, number of poor physical health days, number of poor mental health days, and premature death within the county. Also, a higher percentage of White residents within the county is linked with lower levels of obesity, diabetes, and premature death. Higher median household incomes are found to be linked to lower rates of obesity, diabetes as well as lower prevalence of fair/poor health, and premature death.

In addition, higher percentages of telecommutable jobs within the county are related to adverse health outcomes for the county population such as higher levels of obesity as well as higher numbers of physically and mentally unhealthy days. These findings imply that meso-level social environment characteristics such as the median age, median household income, racial composition, and the extent of telecommutability of employment opportunities within the county can affect the physical and psychological health status of residents.

Findings also indicate that macro-level social environment factors such as income levels can impact the health status of communities (i.e., counties). Higher rates of obesity, diabetes, and premature death are found to be related to higher average percentages of low-income workers within the CBSA, which suggests that higher income levels within the urban area of residence may lead to better community health outcomes. Based on the model estimations, however, the percentage of minority population within the CBSA does not exert any effects on community health status—a finding that may need further examination.

Moreover, the results of the county-level health impact models provide evidence that travel behavior of residents of a community (i.e., county) influences the health profile of that community. The model estimations reveal that a higher nonmotorized travel mode share within the county is linked with lower rates of obesity, diabetes, fair/poor health, premature death, as well as decreased numbers of poor physical and mental health days for residents. These findings suggest that increased levels of nonmotorized travel by residents of a community (i.e., county) may lead to improved physical and psychological health outcomes for them, and thereby to a better overall health status for the community.

The findings also suggest that telecommuting affects both physical and psychological health outcomes. An increased level of telecommuting mode share within the county is linked with higher rates of obesity and poor/fair health as well as higher numbers of poor physical and mental health days. These results suggest that higher rates of telecommuting within the county can lead to adverse physical and mental health effects for residents. With respect to obesity as a physical health outcome, these findings are not consistent with those of two previous studies that found non-telecommuters to be at greater risk for being obese (Henke et al. 2015), or did not find a statistically significant association between telecommuting and obesity (Tajalli and Hajbabaie 2017). The inconsistency in findings suggests a need for further investigation into the link between obesity and telecommuting. In terms of mental health, the findings of the present study, albeit consistent with the existing literature (see e.g., Baruch 2001; Tajalli and Hajbabaie 2017), are in contradiction with at least one study which suggested that employees who did not telecommute were at a higher risk of experiencing depression (i.e., mental unhealthiness) than those who telecommuted (Henke et al. 2015). These inconsistencies in study findings suggest a need for further investigation into the role of telecommuting in psychological health.

Additionally, the findings indicate that higher levels of private vehicle usage are linked with adverse health outcomes as a higher level of private vehicle mode share within the county is related to higher rates of obesity and poor/fair health as well as increased numbers of poor physical and mental health days. In contrast, a higher public transit mode share within the county is related to lower rates of obesity and diabetes. However, increased public transit usage may lead to adverse general health outcomes as according to the results, a higher public transit mode share is related to higher levels of fair/poor health as well as higher numbers of poor physical and mental health days. These findings indicate that traveling by public transportation influences physical and psychological health outcomes; but, the direction of these effects vary based on the health indicator under investigation and the ultimate effect may not be favorable in terms of the general health of residents. Based on these findings, further examination of the role of public transportation in communities' general health status may be required.

The results of the county-level health impact models also provide evidence that the built environment at two spatial levels (i.e., the meso or county level and the macro or CBSA level) influences communities' health outcomes. Among the meso-level built environment factors, county compactness (i.e., mean activity density) shows a positive link with prevalence of fair/poor health as well as the number of poor physical and mental health days. This indicates that higher densities within a county can lead to adverse physical and mental health effects. Nevertheless, county compactness does not show a statistically significant link with rates of obesity and diabetes within the county. Also, increased levels of compactness within the county of residence may lead to lower rates of premature death according to the model results.

The extent of a county's mixed-use development does not seem to affect health outcomes within the county. Also, a pedestrian-friendly network design within the county is linked with lower rates of obesity, poor/fair health, and premature death, as well as fewer numbers of unhealthy physical and mental days. These findings suggest that network designs that are supportive of active travel promote both physical and mental health for residents of communities.

The findings also provide evidence that as the number of primary care physicians per 100,000 county population increases, the rates of obesity, diabetes, fair/poor health, and premature death within the county decline. Increased access to primary care physicians within the county also leads to fewer number of physically or mentally unhealthy days for the county residents. These findings imply that access to clinical healthcare positively influences health outcomes for the population, as one would expect.

With respect to unhealthy food, the results indicate a positive link between prevalence of fast food restaurants and prevalence of obesity and the rate of premature death within the county. The links between prevalence of fast food restaurants and other county-level health outcomes are statistically insignificant. Further, according to model estimations, higher levels of liquor stores density within the county can lead to higher rates of diabetes and premature death for residents. Increased access to recreational facilities is negatively linked with prevalence of fair or poor health as well as with the average number of physically or mentally unhealthy days within the county. This implies that having better access to recreational facilities within the county can improve residents' physical and psychological health status. Findings also suggest that increased ambient air pollution is positively linked to premature death of residents of a county.

Among the macro-level built environment factors, CBSA compactness (i.e., mean activity density) is negatively linked with prevalence of premature death, meaning that higher levels of compactness within CBSAs may lead to lower rates of premature death for residents. On the other hand, increased mixed-use development within the CBSA is positively linked with higher rates of obesity, diabetes, and fair/poor health, as well as increased numbers of physically or mentally unhealthy days for county population. These findings suggest that increased levels of mixed land use within metropolitan/micropolitan areas may lead to adverse physical and psychological health outcomes for residents. Further research may be needed to confirm these findings and to investigate the health impacts of macro-level mixed-use development.

Increased average distance to the nearest transit stop within the entire CBSA of residence is linked to higher rates of obesity, diabetes, fair/poor health, as well as increased numbers of unhealthy physical and mental days for residents. These findings indicate that the extent of transit accessibility within the entire urban area affects the health status of residents. Particularly, residing in sprawled suburban areas with lower levels of access to transit (greater distances to transit stops) may lead to adverse physical and psychological health effects.

Results also show that higher levels of road network density within the CBSA may lead to more premature deaths—a finding that is probably capturing a combination of effects associated with using denser and more congested road networks within urbanized areas. These can include but may not be limited to: higher rates of fatalities due to vehicle crashes, higher rates of premature deaths due to more exposure to vehicle emissions and other transportation-related air pollutants, and higher rates of premature deaths due to higher levels of physical inactivity caused by long-duration commutes using the automobile mode. Together, the results of the multilevel SEM models provide evidence that the built environment attributes of CBSAs (i.e., macro-level built environment factors) play a role in health status of residents.

Additionally, the results of the county-level health impact models provide further evidence that social and built environment characteristics influence nonmotorized travel behavior. In terms of social environment factors, findings imply that increased median age and increased median household incomes within the county are linked with lower nonmotorized mode share within the county. Also, having a higher percentage of White residents within the county is linked with higher levels of county-level nonmotorized mode shares. A county's built environment factors including the extent of compactness, mixed land use, and pedestrian friendliness of the street network also impact the level of nonmotorized mode share within the county. Results suggest that higher levels of compactness, mixed lad use, walkability and pedestrian friendliness of the street network within the county are linked with higher levels of nonmotorized travel mode share within the county.

Results also confirm existence of reverse causality between health outcomes for residents of a county and the extent of their nonmotorized travel. Considering that reverse causality is often ignored in research examining the link between health and active travel, this is a notable finding. The model estimations show that higher rates of obesity, diabetes, fair/poor health, as well as increased numbers of physically or mentally unhealthy days for the county population are linked to lower levels of nonmotorized travel mode share within the county. Finally, results reveal that CBSA-level random effects (i.e., random differences between CBSAs) do not seem to affect health outcomes for residents. Nevertheless, further research may be required to clarify the role of metropolitan/micropolitan random differences on health outcomes for residents.

I.1.5 County-level Health Outcome Models: The Counties

The counties included in the county-level health models are listed in Table I-4. Data in the table indicates that the five most highly populated counties in the sample all locate in Florida (counties of Orange, Hillsborough, Palm Beach, Broward, and Miami-Dade). The average median age is highest in Florida counties of Highlands, Sarasota, Citrus, Charlotte, and Sumter, whereas five Virginia counties seem to have the lowest average median age within the sample (i.e., counties of Radford, Harrisonburg, Williamsburg, Montgomery, and Charlottesville).

Petersburg County, Virginia as well as Prince George's and Baltimore Counties, Maryland have the highest average percentage of minority population, whereas a few West Virginia counties have the lowest percentage of their population being of the minority races (counties of Lincoln, Clay, Wayne, Wirt, Boone, and Marshall).

Median income levels are highest in Virginia counties of Arlington, Fairfax, Falls Church, Loudoun, and Howard County, Maryland. The lowest median incomes within the sample belong to the Martinsville County, Virginia; Fayette County, West Virginia; and Dixie County, Florida.

Table I-4. Counties Included in the County-level Health Models

	County FIPS Code	County Name	State	County Population	County Average Median Age	County Average % Minority	County Average % Foreign Born	County Median Household Income	CBSA Code	CBSA Name	Metro/ Micro Area	CBSA Population	CBSA Average Median Age	CBSA Average % Minority	CBSA Average % Foreign Born
1	11001	District of Columbia	DC	601,723	33.8	61.50	15.37	60,729	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
2	12001	Alachua	FL	247,336	29.7	26.26	9.27	40,656	23540	Gainesville	Metro	260,930	29.4	26.26	9.27
3	12003	Baker	FL	27,115	36.1	28.67	7.14	45,802	27260	Jacksonville	Metro	1,319,195	36.7	28.67	7.14
4	12005	Bay	FL	168,852	38.7	17.36	5.19	44,364	37460	Panama City-Lynn Haven-Panama City Beach	Metro	166,798	38.9	17.36	5.19
5	12009	Brevard	FL	543,376	44.6	15.68	8.24	46,331	37340	Palm Bay-Melbourne-Titusville	Metro	540,583	43.8	15.68	8.24
6	12011	Broward	FL	1,748,066	39.2	28.94	36.73	47,917	33100	Miami-Fort Lauderdale-Pompano Beach	Metro	5,478,869	39.4	28.94	36.73
7	12013	Calhoun	FL	14,625	38.4	17.36	5.19	34,054	37460	Panama City-Lynn Haven-Panama City Beach	Metro	166,798	38.9	17.36	5.19
8	12015	Charlotte	FL	159,978	54.8	9.83	9.65	41,991	39460	Punta Gorda	Metro	159,385	52.8	9.83	9.65
9	12017	Citrus	FL	141,236	53.5	6.68	5.49	36,174	26140	Homosassa Springs	Micro	140,686	51.4	6.68	5.49
10	12019	Clay	FL	190,865	37.5	28.67	7.14	57,913	27260	Jacksonville	Metro	1,319,195	36.7	28.67	7.14
11	12021	Collier	FL	321,520	45.8	13.50	22.86	53,341	34940	Naples-Marco Island	Metro	316,931	44.8	13.50	22.86
12	12023	Columbia	FL	67,531	39.5	22.01	12.65	34,870	29380	Lake City	Micro	66,964	37.7	22.01	12.65
13	12027	DeSoto	FL	34,862	37	19.37	23.68	33,966	11580	Arcadia	Micro	34,557	36.0	19.37	23.68
14	12029	Dixie	FL	16,422	44.5	26.26	9.27	30,967	23540	Gainesville	Metro	260,930	29.4	26.26	9.27
15	12031	Duval	FL	864,263	35.4	28.67	7.14	46,112	27260	Jacksonville	Metro	1,319,195	36.7	28.67	7.14
16	12033	Escambia	FL	297,619	37.3	23.39	5.20	41,428	37860	Pensacola-Ferry Pass-Brent	Metro	445,778	37.8	23.39	5.20
17	12035	Flagler	FL	95,696	47.2	15.11	12.19	45,685	37380	Palm Coast	Metro	91,806	45.8	15.11	12.19
18	12037	Franklin	FL	11,549	43.6	38.13	5.83	34,522	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
19	12039	Gadsden	FL	46,389	38.2	38.13	5.83	35,704	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
20	12041	Gilchrist	FL	16,939	39.5	26.26	9.27	38,517	23540	Gainesville	Metro	260,930	29.4	26.26	9.27
21	12045	Gulf	FL	15,863	42.5	17.36	5.19	39,403	37460	Panama City-Lynn Haven-Panama City Beach	Metro	166,798	38.9	17.36	5.19

22	12047	Hamilton	FL	14,799	37.5	22.01	12.65	31,820	29380	Lake City	Micro	66,964	37.7	22.01	12.65
23	12049	Hardee	FL	27,731	33.4	17.86	12.65	33,732	48100	Wauchula	Micro	27,521	32.6	17.86	12.65
24	12051	Hendry	FL	39,140	31.7	30.98	28.13	37,220	17500	Clewiston	Micro	39,030	30.6	30.98	28.13
25	12053	Hernando	FL	172,778	47	18.34	12.01	37,867	45300	Tampa-St. Petersburg-Clearwater	Metro	2,745,350	40.7	18.34	12.01
26	12055	Highlands	FL	98,786	50.7	14.97	11.50	34,469	42700	Sebring	Micro	98,807	48.6	14.97	11.50
27	12057	Hillsborough	FL	1,229,226	35.8	18.34	12.01	46,043	45300	Tampa-St. Petersburg-Clearwater	Metro	2,745,350	40.7	18.34	12.01
28	12059	Holmes	FL	19,927	41.5	18.99	12.68	33,696	18880	Crestview-Fort Walton Beach-Destin	Metro	182,076	41.0	18.99	12.68
29	12061	Indian River	FL	138,028	48.1	12.47	10.10	47,525	42680	Sebastian-Vero Beach	Metro	135,518	46.3	12.47	10.10
30	12063	Jackson	FL	49,746	40.2	38.13	5.83	37,351	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
31	12065	Jefferson	FL	14,761	44.7	38.13	5.83	39,113	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
32	12067	Lafayette	FL	8,870	35.1	26.26	9.27	36,001	23540	Gainesville	Metro	260,930	29.4	26.26	9.27
33	12069	Lake	FL	297,052	45.2	28.16	15.77	42,343	36740	Orlando-Kissimmee-Sanford	Metro	2,083,626	36.3	28.16	15.77
34	12071	Lee	FL	618,754	44.6	15.21	14.68	44,377	15980	Cape Coral-Fort Myers	Metro	606,165	43.4	15.21	14.68
35	12073	Leon	FL	275,487	29.3	38.13	5.83	42,393	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
36	12077	Liberty	FL	8,365	37	38.13	5.83	37,815	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
37	12079	Madison	FL	19,224	40.2	38.13	5.83	31,942	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
38	12081	Manatee	FL	322,833	45	18.99	12.68	44,990	35840	North Port-Bradenton-Sarasota	Metro	694,819	41.0	18.99	12.68
39	12083	Marion	FL	331,298	46.7	17.12	7.21	37,162	36100	Ocala	Metro	326,833	44.5	17.12	7.21
40	12085	Martin	FL	146,318	48.9	19.92	13.65	49,539	38940	Port St. Lucie	Metro	413,981	43.4	19.92	13.65
41	12086	Miami-Dade	FL	2,496,435	37.7	28.94	36.73	40,145	33100	Miami-Fort Lauderdale-Pompano Beach	Metro	5,478,869	39.4	28.94	36.73
42	12087	Monroe	FL	73,090	45.7	10.24	16.45	50,388	28580	Key West	Micro	73,065	46.3	10.24	16.45
43	12089	Nassau	FL	73,314	42.2	28.67	7.14	57,605	27260	Jacksonville	Metro	1,319,195	36.7	28.67	7.14
44	12091	Okaloosa	FL	180,822	37.6	18.99	12.68	51,173	18880	Crestview-Fort Walton Beach-Destin	Metro	182,076	41.0	18.99	12.68
45	12093	Okeechobee	FL	39,996	39	15.12	12.65	35,417	36380	Okeechobee	Micro	39,883	36.6	15.12	12.65
46	12095	Orange	FL	1,145,956	33.4	28.16	15.77	45,105	36740	Orlando-Kissimmee-Sanford	Metro	2,083,626	36.3	28.16	15.77
47	12097	Osceola	FL	268,685	35.2	28.16	15.77	42,165	36740	Orlando-Kissimmee-Sanford	Metro	2,083,626	36.3	28.16	15.77

48	12099	Palm Beach	FL	1,320,134	43.1	28.94	36.73	49,891	33100	Miami-Fort Lauderdale-Pompano Beach	Metro	5,478,869	39.4	28.94	36.73
49	12101	Pasco	FL	464,697	43.4	18.34	12.01	42,184	45300	Tampa-St. Petersburg-Clearwater	Metro	2,745,350	40.7	18.34	12.01
50	12103	Pinellas	FL	916,542	45.6	18.34	12.01	42,628	45300	Tampa-St. Petersburg-Clearwater	Metro	2,745,350	40.7	18.34	12.01
51	12105	Polk	FL	602,095	39.4	22.15	10.31	41,184	29460	Lakeland-Winter Haven	Metro	590,116	38.5	22.15	10.31
52	12107	Putnam	FL	74,364	42.4	20.55	12.65	33,300	37260	Palatka	Micro	74,715	41.1	20.55	12.65
53	12109	St. Johns	FL	190,039	41.8	28.67	7.14	60,841	27260	Jacksonville	Metro	1,319,195	36.7	28.67	7.14
54	12111	St. Lucie	FL	277,789	41.9	19.92	13.65	39,378	38940	Port St. Lucie	Metro	413,981	43.4	19.92	13.65
55	12113	Santa Rosa	FL	151,372	38.7	23.39	5.20	51,208	37860	Pensacola-Ferry Pass-Brent	Metro	445,778	37.8	23.39	5.20
56	12115	Sarasota	FL	379,448	51.7	18.99	12.68	46,047	35840	North Port-Bradenton-Sarasota	Metro	694,819	41.0	18.99	12.68
57	12117	Seminole	FL	422,718	37.7	28.16	15.77	57,381	36740	Orlando-Kissimmee-Sanford	Metro	2,083,626	36.3	28.16	15.77
58	12119	Sumter	FL	93,420	61.4	16.03	12.65	45,165	45540	The Villages	Micro	85,891	46.8	16.03	12.65
59	12123	Taylor	FL	22,570	40	38.13	5.83	35,343	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
60	12127	Volusia	FL	494,593	44.4	15.90	7.54	41,368	19660	Deltona-Daytona Beach-Ormond Beach	Metro	496,053	42.9	15.90	7.54
61	12129	Wakulla	FL	30,776	39.2	38.13	5.83	47,566	45220	Tallahassee	Metro	360,391	32.1	38.13	5.83
62	12131	Walton	FL	55,043	42	18.99	12.68	44,622	18880	Crestview-Fort Walton Beach-Destin	Metro	182,076	41.0	18.99	12.68
63	12133	Washington	FL	24,896	41.2	17.36	5.19	35,378	37460	Panama City-Lynn Haven-Panama City Beach	Metro	166,798	38.9	17.36	5.19
64	24001	Allegany	MD	75,087	40.9	10.80	2.20	37,083	19060	Cumberland	Metro	102,434	42.4	5.93	0.92
65	24003	Anne Arundel	MD	537,656	38.4	24.60	8.61	80,908	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
66	24005	Baltimore	MD	805,029	39.1	35.40	12.19	62,300	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
67	24009	Calvert	MD	88,737	40.1	18.60	3.04	86,536	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
68	24013	Carroll	MD	167,134	41.1	7.10	3.62	80,291	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
69	24015	Cecil	MD	101,108	38.9	10.80	3.30	61,506	37980	Philadelphia-Camden-Wilmington	Metro	5,911,638	38.9	10.80	3.30
70	24017	Charles	MD	146,551	37.4	49.70	6.32	83,078	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
71	24019	Dorchester	MD	32,618	43.3	32.40	3.95	39,630	15700	Cambridge	Micro	32,287	43.3	32.40	3.95
72	24021	Frederick	MD	233,385	38.6	18.50	10.32	80,216	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02

73	24025	Harford	MD	244,826	39.4	18.80	5.54	71,848	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
74	24027	Howard	MD	287,085	38.4	37.80	21.34	100,992	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
75	24029	Kent	MD	20,197	45.6	19.90	4.25	49,017	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
76	24031	Montgomery	MD	971,777	38.5	42.50	34.44	88,559	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
77	24033	Prince George's	MD	863,420	34.9	80.80	22.24	69,524	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
78	24035	Queen Anne's	MD	47,798	42.6	11.30	3.95	78,503	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
79	24037	St. Mary's	MD	105,151	36	21.40	4.58	81,559	30500	Lexington Park	Micro	102,086	44.9	29.83	4.04
80	24039	Somerset	MD	26,470	36.5	46.50	4.99	38,134	41540	Salisbury	Metro	123,362	36.1	38.90	6.79
81	24041	Talbot	MD	37,782	47.4	18.60	5.88	56,806	20660	Easton	Micro	37,361	47.4	18.60	5.88
82	24043	Washington	MD	147,430	39.7	14.90	5.29	51,610	25180	Hagerstown-Martinsburg	Metro	264,648	40.8	9.93	3.54
83	24045	Wicomico	MD	98,733	35.7	31.30	8.58	47,702	41540	Salisbury	Metro	123,362	36.1	38.90	6.79
84	24047	Worcester	MD	51,454	48.1	18.00	4.59	55,492	36180	Ocean Pines	Micro	51,133	46.4	26.35	5.56
85	24510	Baltimore	MD	620,961	34.4	70.40	7.81	38,186	12580	Baltimore-Towson	Metro	2,683,160	39.7	27.28	7.92
86	51003	Albemarle	VA	98,970	38.2	19.40	10.45	61,845	16820	Charlottesville	Metro	197,279	40.3	20.29	5.43
87	51007	Amelia	VA	12,690	42.7	26.50	0.24	49,057	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
88	51009	Amherst	VA	32,353	42	21.40	1.69	42,063	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
89	51011	Appomattox	VA	14,973	42.8	22.50	0.95	44,479	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
90	51013	Arlington	VA	207,627	33.4	28.30	24.77	93,231	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
91	51015	Augusta	VA	73,750	42.9	6.60	1.94	50,534	44420	Staunton-Waynesboro	Micro	117,892	44.7	8.86	2.28
92	51019	Bedford	VA	68,676	44.3	8.60	2.47	51,656	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
93	51023	Botetourt	VA	33,148	44.9	5.10	2.66	63,528	40220	Roanoke	Metro	304,995	44.1	9.65	2.50
94	51031	Campbell	VA	54,842	41.1	17.90	2.63	42,158	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
95	51033	Caroline	VA	28,545	38.9	34.70	2.97	52,779	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
96	51036	Charles City	VA	7,256	46.6	59.10	1.63	45,916	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
97	51041	Chesterfield	VA	316,236	37.6	31.70	8.34	69,190	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
98	51043	Clarke	VA	14,034	44.9	9.80	3.56	67,962	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
99	51045	Craig	VA	5,190	44.8	1.30	0.02	44,882	40220	Roanoke	Metro	304,995	44.1	9.65	2.50
100	51047	Culpeper	VA	46,689	38.2	24.90	8.03	56,897	19020	Culpeper	Micro	45,749	41.6	18.60	4.94
101	51049	Cumberland	VA	10,052	41.6	36.10	0.42	39,394	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
102	51053	Dinwiddie	VA	28,001	40.7	36.10	2.90	50,535	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67

103	51059	Fairfax	VA	1,081,726	37.3	37.30	31.74	102,726	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
104	51061	Fauquier	VA	65,203	41.3	14.70	6.56	83,176	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
105	51065	Fluvanna	VA	25,691	41.1	19.30	2.88	63,869	16820	Charlottesville	Metro	197,279	40.3	20.29	5.43
106	51067	Franklin	VA	56,159	44.1	11.50	2.17	40,931	40220	Roanoke	Metro	304,995	44.1	9.65	2.50
107	51069	Frederick	VA	78,305	39.1	10.70	6.31	62,173	49020	Winchester	Metro	125,382	40.5	10.44	5.76
108	51071	Giles	VA	17,286	43.2	3.30	0.78	40,773	13980	Blacksburg-Christiansburg-Radford	Metro	161,013	39.2	7.86	3.72
109	51073	Gloucester	VA	36,858	42.6	12.80	2.22	58,893	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
110	51075	Goochland	VA	21,717	45.2	22.50	3.54	81,938	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
111	51079	Greene	VA	18,403	39.3	12.40	4.71	57,592	16820	Charlottesville	Metro	197,279	40.3	20.29	5.43
112	51085	Hanover	VA	99,863	41	13.30	3.53	72,319	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
113	51087	Henrico	VA	306,935	37.5	40.80	12.44	59,128	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
114	51089	Henry	VA	54,151	44.7	27.10	2.74	32,669	32300	Martinsville	Micro	68,889	44.2	38.60	2.83
115	51093	Isle of Wight	VA	35,270	43.8	28.20	2.00	62,224	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
116	51095	James City	VA	67,009	44.9	19.70	7.17	74,241	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
117	51097	King and Queen	VA	6,945	45.2	32.90	2.79	44,277	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
118	51101	King William	VA	15,935	39.4	22.80	1.91	64,205	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
119	51107	Loudoun	VA	312,311	34.8	31.30	27.13	119,075	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
120	51109	Louisa	VA	33,153	42.6	21.60	3.31	50,101	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
121	51115	Mathews	VA	8,978	50.1	12.00	1.30	53,418	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
122	51121	Montgomery	VA	94,392	26.6	12.40	8.71	42,827	13980	Blacksburg-Christiansburg-	Metro	161,013	39.2	7.86	3.72
123	51125	Nelson	VA	15,020	47.6	16.70	3.28	47,368	16820	Charlottesville	Metro	197,279	40.3	20.29	5.43
124	51127	New Kent	VA	18,429	42.4	18.30	3.01	67,979	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
125	51143	Pittsylvania	VA	63,506	44.2	24.50	2.15	41,031	19260	Danville	Metro	106,934	43.4	38.40	2.67
126	51145	Powhatan	VA	28,046	41.6	16.20	2.20	70,025	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
127	51149	Prince George	VA	35,725	38	38.90	4.48	59,346	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
128	51153	Prince William	VA	402,002	33.5	42.20	25.16	91,290	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
129	51155	Pulaski	VA	34,872	44.1	7.50	1.33	41,184	13980	Blacksburg-Christiansburg-	Metro	161,013	39.2	7.86	3.72
130	51161	Roanoke	VA	92,376	43.3	10.00	5.61	57,720	40220	Roanoke	Metro	304,995	44.1	9.65	2.50

131	51165	Rockingham	VA	76,314	40.4	6.70	5.43	49,158	25500	Harrisonburg	Metro	122,328	36.8	10.70	7.83
132	51169	Scott	VA	23,177	44.7	2.10	0.95	33,797	28700	Kingsport-Bristol-Bristol	Metro	307,637	41.8	5.64	1.64
133	51177	Spotsylvania	VA	122,397	36.4	24.50	7.58	72,463	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
134	51179	Stafford	VA	128,961	34.6	27.50	9.50	93,185	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
135	51181	Surry	VA	7,058	45	48.70	0.62	46,112	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
136	51183	Sussex	VA	12,087	40.6	60.70	2.81	37,019	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
137	51185	Tazewell	VA	45,078	43.2	4.90	0.79	35,485	14140	Bluefield	Micro	106,550	43.3	5.50	1.04
138	51187	Warren	VA	37,575	39.7	9.10	3.32	55,758	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
139	51191	Washington	VA	54,876	43.7	3.00	1.60	39,690	28700	Kingsport-Bristol-Bristol	Metro	307,637	41.8	5.64	1.64
140	51199	York	VA	65,464	39.4	23.60	8.26	77,070	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
141	51510	Alexandria	VA	139,966	35.6	39.10	30.06	78,023	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
142	51515	Bedford city	VA	6,222	42.9	23.60	1.58	35,664	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
143	51520	Bristol	VA	17,835	41.3	9.10	1.24	33,149	28700	Kingsport-Bristol-Bristol	Metro	307,637	41.8	5.64	1.64
144	51540	Charlottesville	VA	43,475	27.8	30.90	12.73	42,686	16820	Charlottesville	Metro	197,279	40.3	20.29	5.43
145	51550	Chesapeake	VA	222,209	37	37.40	5.21	67,674	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
146	51570	Colonial Heights	VA	17,411	41.9	17.70	7.56	48,883	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
147	51590	Danville	VA	43,055	42.6	52.30	3.20	31,153	19260	Danville	Metro	106,934	43.4	38.40	2.67
148	51600	Fairfax	VA	22,565	39.1	30.40	29.30	83,413	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
149	51610	Falls Church	VA	12,332	39	20.10	18.15	105,124	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
150	51630	Fredericksburg	VA	24,286	28.8	35.80	10.50	43,460	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
151	51650	Hampton	VA	137,436	35.5	57.30	4.60	50,923	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
152	51660	Harrisonburg	VA	48,914	22.7	21.60	17.62	37,179	25500	Harrisonburg	Metro	122,328	36.8	10.70	7.83
153	51670	Hopewell	VA	22,591	36.5	44.60	4.50	37,226	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
154	51680	Lynchburg	VA	75,568	30.3	35.60	6.10	36,397	31340	Lynchburg	Metro	248,742	39.2	22.54	2.21
155	51683	Manassas	VA	37,821	32.1	38.30	30.12	64,274	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
156	51685	Manassas Park	VA	14,273	30.9	44.10	36.85	67,948	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
157	51690	Martinsville	VA	13,821	43.6	50.10	2.92	29,887	32300	Martinsville	Micro	68,889	44.2	38.60	2.83
158	51700	Newport News	VA	180,719	32.3	51.00	7.13	49,228	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26

159	51710	Norfolk	VA	242,803	29.7	52.90	7.20	41,015	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
160	51730	Petersburg	VA	32,420	39.8	83.90	3.42	32,435	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
161	51735	Poquoson	VA	12,150	43.5	4.90	2.95	79,229	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
162	51740	Portsmouth	VA	95,535	35.7	58.40	2.72	42,740	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
163	51750	Radford	VA	16,408	22.4	13.00	3.84	34,009	13980	Blacksburg-Christiansburg-	Metro	161,013	39.2	7.86	3.72
164	51760	Richmond	VA	204,214	32	59.20	6.89	39,214	40060	Richmond	Metro	1,235,365	40.6	39.58	3.67
165	51770	Roanoke	VA	97,032	38.5	35.80	7.52	37,486	40220	Roanoke	Metro	304,995	44.1	9.65	2.50
166	51775	Salem	VA	24,802	40.5	11.80	3.24	46,636	40220	Roanoke	Metro	304,995	44.1	9.65	2.50
167	51790	Staunton	VA	23,746	42.2	16.30	3.13	40,855	44420	Staunton-Waynesboro	Micro	117,892	44.7	8.86	2.28
168	51800	Suffolk	VA	84,585	37.9	47.70	3.83	62,419	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
169	51810	VA Beach	VA	437,994	34.9	32.30	9.30	63,354	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
170	51820	Waynesboro	VA	21,006	38.8	17.80	5.14	40,256	44420	Staunton-Waynesboro	Micro	117,892	44.7	8.86	2.28
171	51830	Williamsburg	VA	14,068	23.8	26.00	9.66	46,285	47260	VA Beach-Norfolk-Newport News	Metro	1,663,070	40.6	35.30	4.26
172	51840	Winchester	VA	26,203	35.1	25.50	12.16	41,008	49020	Winchester	Metro	125,382	40.5	10.44	5.76
173	54003	Berkeley	WV	104,169	37.6	12.20	3.58	50,923	25180	Hagerstown-Martinsburg	Metro	264,648	40.8	9.93	3.54
174	54005	Boone	WV	24,629	40.7	1.50	0.25	38,126	16620	Charleston	Metro	304,033	42.1	2.90	0.58
175	54009	Brooke	WV	24,069	44.8	3.00	0.92	38,197	44600	Steubenville-Weirton	Metro	125,101	45.1	3.65	1.22
176	54011	Cabell	WV	96,319	38.7	8.40	1.69	36,274	26580	Huntington-Ashland	Metro	287,112	40.0	4.90	1.14
177	54015	Clay	WV	9,386	41.5	1.20	0.23	31,232	16620	Charleston	Metro	304,033	42.1	2.90	0.58
178	54017	Doddridge	WV	8,202	42.4	3.00	0.82	34,444	17220	Clarksburg	Micro	93,257	42.0	4.30	0.91
179	54019	Fayette	WV	46,039	43	6.50	0.68	30,856	36060	Oak Hill	Micro	46,138	43.0	6.50	0.68
180	54027	Hampshire	WV	23,964	42.6	2.80	0.64	33,991	49020	Winchester	Metro	125,382	40.5	10.44	5.76
181	54029	Hancock	WV	30,676	45.3	4.30	1.52	38,501	44600	Steubenville-Weirton	Metro	125,101	45.1	3.65	1.22
182	54033	Harrison	WV	69,099	41.8	4.00	0.89	40,441	17220	Clarksburg	Micro	93,257	42.0	4.30	0.91
183	54037	Jefferson	WV	53,498	38.9	12.40	5.30	63,156	47900	Washington-Arlington-Alexandria	Metro	5,416,691	37.2	30.05	16.02
184	54039	Kanawha	WV	193,063	42.4	10.90	1.65	43,110	16620	Charleston	Metro	304,033	42.1	2.90	0.58
185	54043	Lincoln	WV	21,720	41.2	1.00	0.28	34,119	16620	Charleston	Metro	304,033	42.1	2.90	0.58
186	54049	Marion	WV	56,418	41	5.70	1.15	38,856	21900	Fairmont	Micro	56,356	41.0	5.70	1.15

187	54051	Marshall	WV	33,107	44.3	2.00	0.91	37,206	48540	Wheeling	Metro	148,354	44.2	3.37	1.02
188	54053	Mason	WV	27,324	42.4	2.30	0.64	36,279	38580	Point Pleasant	Micro	57,959	42.4	2.30	0.64
189	54055	Mercer	WV	62,264	42.5	8.40	1.06	32,366	14140	Bluefield	Micro	106,550	43.3	5.50	1.04
190	54057	Mineral	WV	28,212	42.3	4.70	0.50	38,629	19060	Cumberland	Metro	102,434	42.4	5.93	0.92
191	54061	Monongalia	WV	96,189	29.1	9.00	5.79	42,247	34060	Morgantown	Metro	125,691	40.0	3.73	2.16
192	54065	Morgan	WV	17,541	45	2.70	1.73	40,636	25180	Hagerstown-Martinsburg	Metro	264,648	40.8	9.93	3.54
193	54069	Ohio	WV	44,443	43.5	6.80	1.71	38,997	48540	Wheeling	Metro	148,354	44.2	3.37	1.02
194	54073	Pleasants	WV	7,605	42.4	2.70	0.14	40,416	37620	Parkersburg-Marietta-Vienna	Metro	162,214	43.6	1.97	0.51
195	54077	Preston	WV	33,520	42	2.40	1.01	42,529	34060	Morgantown	Metro	125,691	40.0	3.73	2.16
196	54079	Putnam	WV	55,486	40.9	3.20	1.13	52,942	16620	Charleston	Metro	304,033	42.1	2.90	0.58
197	54081	Raleigh	WV	78,859	41.1	11.50	1.66	37,915	13220	Beckley	Micro	78,513	43.1	6.77	0.77
198	54091	Taylor	WV	16,895	42.3	2.50	0.75	36,846	17220	Clarksburg	Micro	93,257	42.0	4.30	0.91
199	54099	Wayne	WV	42,481	41.3	1.40	0.59	36,360	26580	Huntington-Ashland	Metro	287,112	40.0	4.90	1.14
200	54105	Wirt	WV	5,717	44.4	1.50	0.00	36,037	37620	Parkersburg-Marietta-Vienna	Metro	162,214	43.6	1.97	0.51
201	54107	Wood	WV	86,956	42.2	3.60	0.99	39,456	37620	Parkersburg-Marietta-Vienna	Metro	162,214	43.6	1.97	0.51

Table I-5. Variable Labels for Multilevel SEM Structure

(County-level Health Models—Figure I-7)

Variable (Units)	Label
Dependent (i.e., endogenous) Variables: County Level	
Prevalence of Adult Obesity (% of adults that report a BMI ≥ 30)	ho_1_co
Prevalence of Adult Diabetes (% of adults aged 20 and above with diagnosed diabetes)	ho_2_co
Prevalence of Fair or Poor Health (% of adults reporting fair or poor health)	ho_3_co
Number of Poor Physical Health Days (average number in past 30 days)	ho_4_co
Number of Poor Mental Health Days (average number in past 30 days)	ho_5_co
Premature Death (years of potential life lost before age 75 per 100,000 population)	ho_6_co
Independent (i.e., exogenous) Variables: County Level	
Social Environment	
Meso Level: The County	
Median Age (years)	ave_ma_co
Median Annual Household Income (dollars)	ave_hi_co
Percent White (%)	ave_pw_co
Percent of Telecommutable Jobs (%)	ave_ptpj_co
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area	
Average Percentage of Low-Wage Workers (workers earning ≤ $1250/month) (%)	ave_plw_cbsa
Average Percentage of Minority Population (%)	ave_pmp_cbsa
Travel Behavior	
Meso Level: The County	
Nonmotorized Travel Mode Share (%)	nmms_co
Private Vehicle Travel Mode Share (%)	pvms_co
Public Transit Travel Mode Share (%)	ptms_co
Telecommuting Mode Share (%)	tcms_co
Built Environment	
Meso Level: The County	
Mean Activity Density [average (employment + housing units)/acres)]	ave_ad_co
Mean Entropy (dimensionless)	ave_en_co
Mean Pedestrian-friendly Network Density [average (facility miles of ped.-oriented links/mi^2)]	ave_pf_co
Walk Score (dimensionless)	ws_co
Primary Care Physician Rate (primary care provider rate per 100,000 population)	pcpr_co
Percentage of Fast Food Restaurants (percent of all restaurants that are fast food establishments)	pffr_co
Liquor Store Density (number of liquor stores per 10,000 population)	lqsd_co
Recreational Facilities Density (number of recreational facilities per 100,000 population)	recd_co
Ambient Air Pollution (annual number of unhealthy air quality days due to Ozone and Fine PM)	ave_aad_co
Macro Level (Core Based Statistical Area): The Metropolitan/Micropolitan Area	
Mean Activity Density [average (employment + housing units)/acres)]	ave_ad_cbsa
Mean Entropy (dimensionless)	ave_en_cbsa
Mean Total Road Network Density [average (total road network miles/mi^2)]	ave_rd_cbsa
Mean Local Transit Accessibility [average (distance to the nearest transit stop in meters)]	ave_dt_cbsa
CBSA-level Random Intercept	$CBSA_2$

Appendix J

Summary of Study Findings and Discussion

A summary of the findings of the analysis conducted and models developed in the main body of this dissertation is provided and discussed below.

Florida Household-level Nonmotorized Travel Behavior Models*: *Linear Mixed-effects Models

In Chapter 4, the Florida household-level mixed-effects (i.e., multilevel) models examine the link between walking and bicycling travel behavior and social as well as built environment factors at multiple levels of influence. The results of the models show that nonmotorized travel behavior is correlated with household-level socioeconomic characteristics including the number of adults living in the household, the number of vehicles owned by the household, and the annual income of the household. These findings are consistent with results obtained by previous studies as well as those of the Baltimore-D.C. case study, the latter of which are presented in Appendix C.

In addition, the analysis shows that at various levels of influence, the most important socioeconomic factor determining the extent of household walking and bicycling is vehicle ownership. At the household level, the variable representing the number of household vehicles is significantly and negatively correlated with the number of daily per capita nonmotorized trips. At the neighborhood level, the variable representing the percentage of households with no vehicles has a significant and positive correlation with walking. At the metropolitan area, the variable representing the percentage of households that own more than two vehicles is negatively correlated with the number of daily per capita nonmotorized trips generated from households locating in that metropolitan area.

These results add to the body of empirical knowledge by providing evidence that the influence of vehicle ownership on walking and bicycling goes beyond the household and potentially operates at multiple levels of influence including at the neighborhood and metropolitan area levels.

These findings imply that the role of vehicle ownership in nonmotorized travel behavior may be far more important and complex than previously considered. As the highest elasticities in the bicycling model belong to the metropolitan area-level car ownership and worker income variables, the results also emphasize the key role that social environment factors at the metropolitan area level play in bicycling trips of residents.

The present case study also corroborates previous findings on the effects of the micro-level (i.e., neighborhood) built environment on nonmotorized travel behavior. The results indicate that increased numbers of walking and bicycling are associated with higher levels of neighborhood mixed land use, higher levels of pedestrian friendliness of the street network within the neighborhood, higher frequencies of local transit service as well as higher gross activity (residential and employment) density and intersection density within the neighborhood. Among these factors, neighborhood mixed land use and the pedestrian friendliness of the street network are the most important ones in terms of the elasticity of nonmotorized trips with respect to the neighborhood-level factors. Consistent with the Baltimore-D.C. case study (see Appendix C), the results of the Florida household-level analysis also suggest that random differences between neighborhoods may play a small but statistically significant role in walking/bicycling of residents.

The analysis further adds to the body of knowledge by providing evidence that meso-level (i.e., county) built environment also plays a significant role in nonmotorized travel behavior. The results indicate that higher numbers of daily walking trips are correlated with living in more compact counties (where activity density is higher) as well as a higher extent of county-level mixed-use development, a higher extent of pedestrian friendliness of the county street network, and increased transit service frequency within the county. In terms of bicycling trips, county-level compactness shows a negative correlation with these trips, whereas a higher extent of county-level pedestrian friendliness of the street network and increased intersection density have positive correlations with bicycling trips. Further, higher county-level automobile accessibility to employment opportunities is negatively correlated with both nonmotorized travel modes.

Compared to the Baltimore-D.C. case study (see Appendix C), the Florida household-level study adds macro level (i.e., metropolitan area level) factors to the analysis of nonmotorized travel behavior. The results indicate that metropolitan area-level built environment attributes are associated with walking but do not seem to have a strong association with bicycling. Most notably, the correlation of the entropy variable (i.e., extent of mixed land use) with walking trips switches direction and becomes negative as mixed land use increases within the entire metropolitan area. This is probably an indication of the destination choice effect. Higher mixed land use within the metropolitan area means that additional destinations within longer distances become available to residents. This may encourage more driving trips, and thereby may lead to a reduction in the number of walking trips that would otherwise have been made to nearby destinations.

Further, improved street connectivity (i.e., smaller blocks) throughout the entire metropolitan area is strongly and positively associated with walking. This metropolitan area-level variable also exhibits the highest elasticity in the walking model. Higher road network density within the metropolitan area shows a negative correlation with walking.

The findings also indicate that higher transit accessibility to employment opportunities throughout the metropolitan area is negatively correlated with bicycling. Also, based on the results, compactness of activities (i.e., higher residential and employment density) throughout the entire metropolitan area does not seem to be associated with nonmotorized travel behavior of residents.

Florida Household-level Nonmotorized Travel Behavior Models: Ordered Probit Models

Results of the Florida household-level ordered probit models, which are developed and estimated in Chapter 4 of this dissertation, are in line with those of the Florida household-level mixed-effects models (also presented in Chapter 4) in terms of the effects of multiple levels of social and built environment influence.

The results of the ordered probit models confirm that walking and bicycling are correlated with household-level socioeconomic attributes including the number of adults and workers living in the household, the number of vehicles owned by the household, and household's annual income. These findings are also consistent with results obtained in the Baltimore-D.C. case study (see Appendix C).

As in the mixed-effects models, vehicle ownership proves to be the most important socioeconomic factor at various levels of influence in the ordered probit nonmotorized travel behavior models. These results support the statement that in influencing walking and bicycling, vehicle ownership operates at multiple levels of the social environment including the household, the neighborhood, and the metropolitan area levels.

The ordered probit model estimates also confirm the results of the mixed-effects models regarding the effects of the micro-level (i.e., neighborhood) built environment on nonmotorized travel behavior.

Increased numbers of daily walking and bicycling trips are associated with residing in neighborhoods with a higher level of mixed-use development and higher extent of pedestrian friendliness of the street network. Further, higher numbers of daily walking trips are associated with compact neighborhoods (i.e., higher activity density) as well as neighborhoods with higher frequencies of local transit service. Increased numbers of bicycling trips are also correlated with a higher intersection density within the neighborhood.

The results of the ordered probit models also indicate that micro-level entropy variable (i.e., neighborhood mixed land use) may be the most important neighborhood-level built environment factor with respect to households' daily number of nonmotorized trips due to having the largest average marginal effects among the neighborhood-level built environment variables in the models.

Among the meso-level (i.e., county) built environment factors, higher compactness, higher density of pedestrian-friendly street network, higher levels of mixed land use are correlated with higher numbers of daily walking trips.

Increased transit accessibility to employment opportunities within 45 minutes of transit commute is correlated with fewer daily walking trips. Compactness at the county level is negatively correlated with the number of household bicycling trips. On the other hand, a higher extent of county-level pedestrian-friendly street network density and higher intersection density are positively correlated with these trips.

The results of the ordered probit models further indicate that macro-level (i.e., metropolitan area-level) built environment attributes are associated with walking but not with bicycling.

Consistent with results of the mixed-effects models, the correlation of the macro-level entropy variable with the number of walking trips is negative. The negative direction of the correlation can be capturing the effects of having additional destination choices within the metropolitan area, which may lead to more vehicular travel to more distant destinations and fewer walking trips to nearby neighborhood destinations.

The number of walking trips are also negatively correlated with higher road network density within the metropolitan area and positively correlated with better street network connectivity and walkability (i.e., higher percentage of smaller blocks) throughout the entire metropolitan area.

The largest average marginal effect for the built environment factors at the macro level in the walking model belongs to the entropy variable indicating that mixed land use within the metropolitan area is an important built environment element in the daily number of walking trips generated from households.

As in the mixed-effects models, the only macro-level built environment variable exhibiting a significant coefficient in the bicycling model is the *Mean Temporal Transit Accessibility* variable. This indicates that higher transit accessibility to jobs within the metropolitan area is negatively correlated with households' number of bicycling trips.

These results are further indicative of the role that macro-level (metropolitan area-level) built environment characteristics plays in nonmotorized travel behavior of residents, especially in their walking activities.

Overall, the results of the Florida household-level mixed-effects models and those of the Florida household-level ordered probit models provide additional evidence for the results obtained in the Baltimore-D.C. case study (Appendix C).

The findings further confirm the main hypothesis of this study that nonmotorized travel behavior is correlated with meso-level (i.e., county-level) as well as macro-level (i.e., metropolitan area-level) built and social environment attributes, and not just with the micro-level (i.e., neighborhood-level) environmental attributes.

Florida Person-level Nonmotorized Travel Behavior Models: Multilevel Structural Equation Models (Multilevel SEMs)

Guided by the existing literature on nonmotorized travel behavior and the framework of the ecological model of behavior and through employment of multilevel Structural Equation Modeling (multilevel SEM) techniques, the Florida person-level nonmotorized travel behavior models are developed and estimated in Chapter 4.

These models examine the relationship between walking and bicycling mode shares at the individual level with consideration of the effects of built and social environment factors at multiple levels. These models also include individual-level socioeconomic and demographic characteristics to incorporate the ecological model's emphasis on the impact of factors representing the intrapersonal level of influence on behavior. Further, the person-level models control for the residential self-selection effect (i.e., endogeneity bias) in the link between nonmotorized travel behavior and the built environment.

The results show that individuals' socioeconomic and demographic characteristics (i.e., the intrapersonal level of ecological influence) such as their age, race, gender, employment status, and educational attainment impact their nonmotorized travel mode share. As age increases, the daily walking and bicycling mode shares decrease for individuals. Being of the White race leads to increased levels of daily walking mode share, whereas being male leads to increased levels of daily bicycling mode share. Also, having a college degree is linked to higher walking mode shares, whereas being employed is linked to lower person-level daily walking and bicycling mode shares.

The results also indicate that contextual effects—such as those of the residential location's environmental factors at various levels of influence—play a role in people's nonmotorized travel behavior.

Specifically, social environment factors (i.e., the interpersonal level of ecological influence) at multiple levels (i.e., micro, meso, macro levels) impact individuals' nonmotorized travel mode share.

Among the socioeconomic and sociodemographic factors, increased car ownership at the household and neighborhood levels (i.e., micro level) as well as at the metropolitan area level (i.e., macro level) influences individuals' nonmotorized travel mode share in a negative direction.

Increased household income (i.e., micro level) shows a positive influence on individuals' walking mode share, whereas the direction of the effects of the income variable at the metropolitan area (i.e., macro level) implies that increased income levels within the metropolitan area negatively affect individuals' walking mode share.

Additionally, the results show that a higher average gasoline price within the metropolitan area (i.e., macro level) encourages higher person-level walking and bicycling mode shares. Further, as the average median age within the metropolitan area (i.e., macro level) increases, the person-level bicycling mode share decreases.

With respect to sociocultural factors, increased numbers of household (i.e., micro level) transit trips lead to more nonmotorized trips by individuals—perhaps highlighting the positive influence of a household "transit travel culture" on its members' walking and bicycling travel behavior.

In addition, variables representing the county-level (i.e., meso-level) and metropolitan area-level (i.e., macro-level) average walking and bicycling density show positive effects on individuals' nonmotorized travel behavior. This suggests that people who frequently see others walk and bicycle (as a result of living in counties or metropolitan areas with higher walking/bicycling densities) engage in such activities at higher rates.

Moreover, the variable measuring the annual public transportation passenger-miles within the metropolitan area (i.e., macro level) exhibits a positive effect on both walking and the bicycling mode shares of individuals. This implies that metropolitan areas with a "public transportation travel culture" may promote nonmotorized travel.

Overall, these results mean that walking and bicycling are influenced by the "cultural effects" of the social norms toward nonmotorized travel and public transit existing within the area of residence.

Further, the results of the Florida person-level nonmotorized travel behavior models provide evidence that higher percentages of foreign-born population living within the metropolitan area (i.e., macro level) influence individuals' walking mode share in a positive direction—perhaps capturing the influence of the cultural norms of the country of origin on nonmotorized travel behavior of people.

The metropolitan area-level (i.e., macro-level) crime variable does not show significant effects on residents' daily walking and bicycling mode shares.

The model estimations also confirm the impact of the built environment characteristics at multiple levels of geography (micro, meso, macro levels) on person-level walking and bicycling mode shares.

Activity density at the neighborhood level (i.e., micro level) as well as the county level (i.e., meso-level) influences individuals' walking mode share in a positive direction, meaning that compactness promotes walking as also found in many past studies (see Chapter 2). Neighborhood or county-level compactness, however, acts as a deterrent to bicycling trips as evidenced by the negative direction of influence of the variables representing activity density in the models.

Increased mixed-use development (i.e., entropy) within the neighborhood (micro-level variable) is linked to higher walking and bicycling mode shares for residents; however, increased regional diversity (i.e., meso-level variable) and increased mixed-use development throughout the entire metropolitan area (i.e., macro-level variable) are linked to lower walking and bicycling mode shares. The latter findings can be a result of increased vehicular trips to additional destination options within the county and metropolitan area instead of making walking or bicycling trips to neighborhood destinations.

These findings imply that with regards to nonmotorized trips, mixed-use development may be a stimulating factor at lower geographical scales such as the neighborhood. However, as metropolitan areas become more diverse in terms of land use, residents may be encouraged to drive to various additional destinations rather than using nonmotorized travel modes to reach the destinations located within their neighborhoods.

Therefore, perhaps an optimal threshold exists for mixed-use development within metropolitan areas; one that allows sufficient diversification of land use within neighborhoods to promote trips using sustainable modes of travel but does not attract vehicular trips from distant locations due to providing very different and more unique destination options.

Higher intersection density at the neighborhood and county levels (i.e., micro and meso levels) positively affects person-level bicycling mode share, whereas higher percentage of smaller blocks throughout the entire metropolitan (i.e., macro level) positively affects person-level walking mode share. These results suggest that improved street connectivity at various scales of geography encourages walking and bicycling.

Also, more pedestrian-friendly networks and more walkable environments at the micro, meso, and macro levels of geography promote individuals' nonmotorized mode share. This is evidenced by the positive direction of effects of the neighborhood-level and county-level *Pedestrian-friendly Network Density* variables and the metropolitan area-level *Walk Score* variable in the person-level nonmotorized travel behavior models. Moreover, increased person-level walking mode share is linked to higher frequency of local transit service (i.e., micro-level variable).

The results also provide evidence that higher levels of automobile accessibility to jobs within the county as well as higher levels of automobile and transit accessibility to jobs within the metropolitan area are related to decreased levels of nonmotorized mode shares for residents.

Also, having lower levels of mobility (i.e., higher levels of roadway congestion) within the metropolitan area encourages nonmotorized trips by residents.

Many significant paths in the person-level nonmotorized travel behavior multilevel SEM models make theoretical sense and confirm the results of the household-level models developed in this dissertation as well as those of the past empirical studies.

Model estimations also indicate that individuals' self-selection—shaped by their households' social environment (i.e., household's socioeconomic status as well as the transit and nonmotorized travel culture within the household)—influences their choice of residential location. These findings mean that, as found in many previous studies (see Appendix B), nonmotorized travel behavior is influenced by built environment characteristics as well as residential self-selection.

The impact of household-level random effects (i.e., random differences between households) also proves statistically significant in individuals' nonmotorized trip mode share, which further emphasizes the importance of the household's taste and role in individuals' nonmotorized travel behavior.

Person-level Health Outcome Models: Instrumental Variable Binary Probit Models and Multilevel Structural Equation Models (Multilevel SEMs)

Person-level health outcome models are developed in Chapter 5 of this dissertation to probe the factors that influence individuals' health. These models examine the link between individual-level health status indicators, travel behavior, built environment attributes within the residential area at two spatial scales: the county level (i.e., meso level), and the metropolitan area level (i.e., macro level) as well as social environment attributes at three levels of influence: the household (i.e., micro level), the county (i.e., meso level), and the CBSA (i.e., macro level). The person-level health models utilize data from the state of Florida.

Through comprehensive framework designs and employment of instrumental variable and multilevel Structural Equation Modeling (multilevel SEM) techniques, the person-level health outcome models also allow for addressing any potential spatial autocorrelation, endogeneity bias, and reverse causality between health outcomes and physical activity in the models.

The results provide evidence that individual-level health outcomes are linked with person and household attributes, health behavior, travel behavior, as well as built and social environment attributes at meso level (i.e., county) and macro level (i.e., CBSA).

Sociodemographic characteristics of the individual including age, race, gender, as well as the number of children in the household prove to play important roles in individuals' health. Adverse physical and psychological health outcomes are linked with older age. These include an increased number of poor mental health days; a higher likelihood of obesity, asthma, or diabetes; a lower likelihood of having a good or excellent general health; and a lower likelihood of meeting the CDC-recommended levels of physical activity. Being of the White race is generally associated with better health outcomes such as a lower likelihood of obesity or diabetes, an increased likelihood of having a good or excellent general health, and an increased likelihood of meeting the CDC-recommended levels of physical activity. Additionally, being male is associated with a higher likelihood of obesity, a lower likelihood of asthma, fewer numbers of poor mental health days, and a higher likelihood of meeting the CDC-recommended physical activity levels. Living with more children is associated with an increased likelihood of having a good or excellent general health and fewer numbers of poor physical health days. Due to some inconsistencies between findings of the present study and those of past research, further investigation into the role of presence of children in the household in health status of individuals is warranted.

Socioeconomic characteristics such as employment status, educational attainment, and household's income are also influential in individuals' general health. Being employed is associated with an increased likelihood of having good or excellent general health as well as fewer numbers of poor physical and poor mental health days. Having a college degree is related to a higher likelihood of having good or excellent general health, fewer numbers of poor physical health days, and a higher likelihood of meeting the CDC-recommended physical activity levels. Higher household income levels are associated with a lower likelihood of asthma or diabetes, an increased likelihood of meeting the CDC-recommended physical activity levels and having a good or excellent general health, as well as fewer numbers of poor physical and mental health days.

Moreover, results provide evidence that health-related behavior such as fruit and vegetable consumption, alcoholic beverages consumption, smoking habits, and level of physical activity can also impact individuals' health. Higher levels of fruit and vegetable consumption are associated with better health outcomes including a lower likelihood of obesity, a higher likelihood of having a good or excellent general health and meeting the CDC-recommended physical activity levels, and fewer numbers of poor physical and mental health days. Being a current smoker contributes to having a lower likelihood of being overweight or obese, and a lower likelihood of having diabetes. Nonetheless, being a smoker is associated with adverse health effects including a higher likelihood of asthma, a lower likelihood of having a good or excellent general health and meeting the CDC-recommended physical activity levels, as well as having an increased number of poor physical and mental health days. Former smokers have a higher likelihood of obesity, diabetes, or asthma; a lower likelihood of having a good or excellent general health; and increased numbers of poor physical and mental health days. Higher levels of alcohol consumption show a positive association with increased likelihood of being diagnosed with diabetes. Also, equally influencing individuals' health is their level of physical activity. Higher physical activity levels are associated with a lower likelihood of obesity, asthma, and diabetes; lower numbers of poor physical or mental health days; and an increased likelihood of good or excellent general health.

The results of the person-level health models also provide evidence that the built environment at two spatial levels (i.e., meso or county level and macro or metropolitan area level) influences individuals' health outcomes. Among the meso-level built environment factors, higher county compactness (i.e., density) is on the one hand, related to a higher likelihood of meeting the CDC recommendations on physical activity and a lower likelihood of asthma, and on the other hand, related to increased likelihood of obesity and perhaps diabetes, a lower likelihood of having a good or excellent general health, as well as to having more mentally unhealthy days. Further research is needed based on consistent definitions of compactness to clarify the role of county-level (i.e., meso-level) compactness as related to risks of obesity, diabetes and asthma for residents.

In addition, increased mixed land use within the county is associated with an increased likelihood of meeting the CDC physical activity recommendations, and a lower likelihood of obesity, but also with a few adverse health outcomes including a higher likelihood of asthma or diabetes, and having more unhealthy mental days. However, additional research may be needed to further clarify the impact of county-level mixed land use on residents' health outcomes.

Increased automobile-oriented intersection density within the county is associated with a higher likelihood of having a better general health, but also with a higher likelihood of asthma, and a lower likelihood of meeting the CDC-recommended physical activity levels. This factor does not show a statistically significant effect on other individual-level health outcomes including obesity—a finding consistent with that of a past study (Samimi and Mohammadian 2009) but in contrast with that of another (Samimi et al. 2009). Thus, further research into the role of meso-level (i.e., county-level) intersection density in individuals' health may be needed, particularly with regards to obesity. On the other hand, higher walkability (i.e., higher Walk Score) within the county is linked with a lower likelihood of obesity or asthma, a higher likelihood of having a good or excellent general health, and also with fewer numbers of poor physical health days.

Moreover, albeit associated with a lower likelihood of asthma, increased distances from transit stops (i.e., a lower level of accessibility to local transit) are related to adverse health effects such as a higher likelihood of obesity or diabetes, and a lower likelihood of having a good or excellent general health—findings that may be capturing the health profile of residents of sprawled suburban areas. On the other hand, higher temporal accessibility to jobs within the county by means of transit (i.e., number of employment opportunities within 45 minutes of transit travel time) is associated with fewer numbers of poor physical health days, a lower likelihood of obesity, and probably with a lower likelihood of diabetes. Although, due to the average marginal effects of the latter result not being statistically significant in the model, further research may be needed to clarify the role of temporal transit accessibility to jobs as related to risk of diabetes. Higher temporal accessibility to jobs within the county by means of automobile is related to fewer poor mental health days, a lower likelihood of meeting the CDC recommendations on physical activity levels, and an increased likelihood of obesity or diabetes. The findings on the adverse physical health effects of higher automobile accessibility to jobs may be capturing the effect of long automobile commutes. Results also suggest that increased levels of temporal accessibility to jobs by both automobile and transit may lead to increased risk of asthma. Cumulatively, the findings suggest that increased temporal automobile accessibility to employment opportunities within the county may lead to better psychological health, whereas increased temporal transit accessibility to employment opportunities may result in better physical health outcomes.

Other meso-level (i.e., county-level) built environment factors such as access to clinical care, access to healthy/unhealthy food outlets and parks also prove to play key roles in individuals' health. Higher access to clinical healthcare within the county is associated with a lower likelihood of obesity, a higher likelihood of having good or excellent general health, and fewer numbers of poor physical health days. Higher densities of fast food restaurants within the county are associated with a higher likelihood of obesity, diabetes, and asthma; a lower likelihood of meeting the CDC recommendations on physical activity; a lower likelihood of having a good or excellent general health; and increased numbers of poor physical health days. Increased access to healthy food outlets within the county, on the other hand, is associated with a lower likelihood of obesity, diabetes, and asthma; and a higher likelihood of meeting the CDC-recommended physical activity levels and having a good or excellent general health; as well as fewer poor mental health days.

Higher access to parks is associated with a lower likelihood of diabetes, a higher likelihood of meeting the CDC physical activity recommendations, fewer numbers of poor physical and mental health days, and may be associated with a lower likelihood of obesity (although, the average marginal effects does not reach a statistical significance threshold in the obesity model). Higher access to parks, however, is also linked with a higher risk of asthma. Furthermore, increased air pollution within the county is positively associated with the risk of asthma diagnosis, and is negatively associated with the likelihood of having a good or excellent general health as well as with more physical and mental unhealthy days.

Macro-level (i.e., metropolitan area-level) built environment factors including measures of compactness, mixed-use development, street design, distance to transit, regional accessibility, and mobility also influence health outcomes for residents. Higher compactness (i.e., activity density) within the entire metropolitan area is linked with increased numbers of poor mental health days, an increased risk of obesity, and may also be related to a higher risk of diabetes for residents (the average marginal effects is not significant in the diabetes model). A higher extent of mixed-use development throughout the metropolitan area is positively associated with the likelihood of meeting the CDC physical activity recommendations and having a good/excellent general health, but is also associated with adverse health outcomes such as higher risks of asthma and diabetes.

Increased automobile-oriented intersection density throughout the metropolitan area is on the one hand, associated with a higher likelihood of asthma and diabetes, and on the other hand, related to a higher likelihood of having a better general health status, and fewer number of poor physical health days. Increased distances to the nearest local transit stop (i.e., lower levels of accessibility to local transit) are associated with lower likelihood of asthma, but also with higher likelihood of obesity or diabetes, and increased numbers of physically or mentally unhealthy days.

Additionally, increased temporal accessibility to jobs within the metropolitan area by means of transit is associated with a lower likelihood of obesity, and perhaps diabetes (the average marginal effects is not significant in the case of diabetes), a higher likelihood of meeting the CDC-recommended physical activity levels, and a higher likelihood of having a good/excellent general health status. However, higher transit accessibility to jobs within a metropolitan area is also linked to an increased number of poor mental health days, and may be associated with a higher likelihood of asthma (the average marginal effects is not significant in the case of asthma). Increased temporal accessibility to jobs within the metropolitan area by means of automobile (i.e., number of employment opportunities within a 45-minute car commute) may be associated with an increased likelihood of obesity, asthma, or diabetes and a lower likelihood of good/excellent general health. However, due to the average marginal effects only being statistically significant in the general health model, further investigation into the link between metropolitan area-level automobile accessibility and health outcomes is warranted. Higher temporal accessibility to jobs within a metropolitan area by means of automobile is also linked with fewer poor mental health days.

Increased congestion levels within the metropolitan area are associated with a lower likelihood of meeting the CDC-recommended physical activity levels and having a good or excellent general health as well as with higher risks of obesity and asthma, and may also lead to an increased number of physically unhealthy days.

Social environment factors at two spatial levels (i.e., meso or county level and macro or metropolitan area level) also influence individuals' health outcomes. Among the meso-level social environment factors, sociodemographic factors such as the median age and racial composition within the county are influential. Increased median age within the county is associated with an increased likelihood of asthma and diabetes (average marginal effect is insignificant in the case of diabetes), a lower likelihood of having a good or excellent general health and meeting the CDC-recommended physical activity levels, as well as with more poor physical and mental health days.

A higher percentage of White residents within the county is associated with an increased likelihood of asthma, but also with an increased likelihood of meeting the CDC-recommended physical activity levels and having a good or excellent general health, and is also linked with a lower number of poor physical health days. As regards socioeconomic factors, higher county-level median household income is associated with a lower likelihood of asthma and/or diabetes.

Among the macro-level social environment factors, socioeconomic factors such as the percentage of low-wage workers, average gross regional product, and percentage of households with no automobiles prove to be important factors in residents' health outcomes. Cumulatively, the results on these variables suggest that a higher socioeconomic status within a metropolitan area is linked with a lower number of poor physical and mental health days, and is also associated with a lower likelihood of obesity and/or asthma, a higher likelihood of meeting the CDC recommendations on physical activity, and a higher likelihood of having a good or excellent general health status for residents. Higher crime rates within the metropolitan area are associated with a lower likelihood of meeting the CDC-recommended physical activity levels, having a good or excellent general health, and having asthma. Higher metropolitan-level crime rates may also be associated with a higher likelihood of obesity and/or diabetes; however, due to the corresponding average marginal effects not being statistically significant, further examination of the link between metropolitan area-level crime rates and the risk of obesity and diabetes for residents is needed.

Increased densities of active travel within a metropolitan area are associated with lower risks of asthma and/or diabetes, and a higher likelihood of having a good/excellent general health status, and are also linked with fewer number of poor mental health days. Further, increased public transit usage within the metropolitan area is associated with a lower likelihood of obesity and/or diabetes, a higher likelihood of asthma, a lower likelihood of having a good or excellent general health status, and an increased number of physically unhealthy days. An increased commuter stress index for residents of a metropolitan area is associated with a higher likelihood of obesity, a lower likelihood of having a good or excellent general health, and more physically unhealthy days.

Results also indicate that travel behavior factors also impact individuals' health outcomes. A higher nonmotorized travel mode share within the county is associated with a lower likelihood of obesity, a higher likelihood of having a good or excellent general health, as well as fewer numbers of poor physical and mental health days. An increased private vehicle travel mode share within the county is associated with a higher likelihood of asthma, and perhaps a higher likelihood of diabetes (the average marginal effects is statistically insignificant in the case of diabetes). The results also show a negative link between private vehicle travel mode share within a county and the number of poor mental health days for residents. A higher public transit mode share within the county is on the one hand, associated with a lower likelihood of obesity and/or diabetes, a higher likelihood of meeting the CDC recommendations on physical activity, and on the other hand, associated with a higher likelihood of asthma, a lower likelihood of having a good or excellent health, and an increased number of poor mental health days. Owing to inconsistencies among findings of a few previous studies and those of the present study regarding the role of public transit use within an area in general health of residents, additional research on this subject may be needed.

Moreover, a higher average frequency of telecommuting within the county is associated with a higher likelihood of obesity, a lower likelihood of having a good or excellent general health status, and a lower likelihood of meeting the CDC recommendations on physical activity. Increased average frequency of telecommuting within the county is also associated with a lower likelihood of asthma. Also, an increased percentage of the county population with an option to telecommute is associated with a lower likelihood of asthma, a lower likelihood of meeting the CDC recommendations on physical activity, and an increased number of poor mental health days.

Further examination of the relationship between telecommuting and health indicators—particularly obesity, physical activity, and mental health outcomes—may shed light on the inconsistencies between results of the present study and those of a few past studies. Other travel behavior measures including online shopping-related activities also prove to be of importance. Increased numbers of online purchases and/or deliveries are associated with a lower likelihood of asthma, but also with a lower likelihood of meeting the CDC-recommended physical activity levels, a lower likelihood of having a good or excellent general health, a higher likelihood of obesity, and an increased number of physically and mentally unhealthy days.

The results also provide evidence that individuals' attributes affect their physical activity. Older age is linked with fewer minutes of weekly physical activity by individuals, whereas being male and having a college education are linked with more minutes of weekly physical activity.

The results also confirm existence of endogeneity bias in the obesity, diabetes, and asthma models and the appropriateness of employment of instrumental variable techniques to account for the endogenous physical activity independent variable in modeling these health outcomes.

The results of the multilevel SEMs for the number of poor physical and mental health days imply that no reverse causality exists between these health outcomes and the extent of individuals' physical activity per week. This finding is somewhat inconsistent with the results of the county-level health models (see Appendix I), which indicate significant links between county-level active travel (i.e., physical activity) and health outcomes. Thus, further research is required to examine reverse causality between health outcomes and physical activity.

Lastly, results of the person-level health models indicate that random differences between metropolitan areas (i.e., metropolitan-level random effects) do not play a role in health outcomes for the residents; a result which is consistent with that of the county-level health outcome models.

Bibliography

Abbreviations

BTS Bureau of Transportation Statistics, U.S. Department of Transportation

CDC Centers for Disease Control and Prevention

DHHS U.S. Department of Health and Human Services

EPA U.S. Environmental Protection Agency

WHO World Health Organization

Aditjandra, P., Cao, X. and Mulley, C., 2016. Exploring changes in public transport use and walking, following residential relocation: a British case study. *Journal of Transport and Land Use*, *9*(3).

Agrawal, A.W. and Schimek, P., 2007. Extent and correlates of walking in the USA. *Transportation Research Part D: Transport and Environment*, *12*(8), pp.548-563.

Ajzen, I., 1991. The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), pp.179-211.

Akinbami, L.J. and Fryar, C.D., 2016. *Current asthma prevalence by weight status among adults: United States, 2001-2014* (pp. 1-8). DHHS, CDC, National Center for Health Statistics Data Brief, No. 239.

Albright, J.J. and Marinova, D.M., 2010. Estimating multilevel models using SPSS, Stata, SAS and R.

Andersen, L.B., Schnohr, P., Schroll, M. and Hein, H.O., 2000. All-cause mortality associated with physical activity during leisure time, work, sports, and cycling to work. *Archives of internal medicine*, *160*(11), pp.1621-1628.

Anderson, L.H., Martinson, B.C., Crain, A.L., Pronk, N.P., Whitebird, R.R., O'Connor, P.J. and Fine, L.J., 2005. Health Care Charges Associated With Physical Inactivity, Overweight, and Obesity. *Preventing chronic disease*, *2*(4).

Andrews, J.R., Morrow, C. and Wood, R., 2013. Modeling the role of public transportation in sustaining tuberculosis transmission in South Africa. *American journal of epidemiology*, *177*(6), pp.556-561.

Badoe, D.A. and Miller, E.J., 2000. Transportation–land-use interaction: empirical findings in North America, and their implications for modeling. *Transportation Research Part D: Transport and Environment*, *5*(4), pp.235-263.

Balaker, T., 2005. *The Quite Success: Telecommuting Impact on Transportation and Beyond* (No. PS338).

Bagley, M.N. and Mokhtarian, P.L., 2002. The impact of residential neighborhood type on travel behavior: a structural equations modeling approach. *The Annals of regional science*, *36*(2), pp.279-297.

Bandura., A., 1986. Social foundations of thought and action: A social cognitive theory. *NY.: Prentice-Hall*.

Banister, D. and Stead, D., 2004. Impact of information and communications technology on transport. *Transport Reviews*, 24 (5), pp. 611-632.

Barnes, R., Winters, M., Ste-Marie, N., McKay, H. and Ashe, M.C., 2016. Age and retirement status differences in associations between the built environment and active travel behaviour. *Journal of Transport & Health*, *3*(4), pp.513-522.

Barr, A., Bentley, R., Simpson, J.A., Scheurer, J., Owen, N., Dunstan, D., Thornton, L., Krnjacki, L. and Kavanagh, A., 2016. Associations of public transport accessibility with walking, obesity, metabolic syndrome and diabetes. *Journal of Transport & Health*, *3*(2), pp.141-153.

Baruch, Y., 2001. The status of research on teleworking and an agenda for future research. *International Journal of Management Reviews*, *3*(2), pp.113-129.

Baum, C.F., Schaffer, M.E. and Stillman, S., 2003. Instrumental variables and GMM: Estimation and testing. *Stata journal*, *3*(1), pp.1-31.

Baum, C.F., Schaffer, M.E., Stillman, S. and Wiggins, V., 2006. Overid: Stata module to calculate tests of overidentifying restrictions after ivreg, ivreg2, ivprobit, ivtobit, reg3. URL: http://ideas. repec. org/c/boc/bocode/s396802. html.

Bauman, A., Smith, B., Stoker, L., Bellew, B. and Booth, M., 1999. Geographical influences upon physical activity participation: evidence of a ‘coastal effect’. *Australian and New Zealand Journal of Public Health*, *23*(3), pp.322-324.

Ben-Akiva, M.E. and Lerman, S.R., 1985. *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Benoit, K., 2011. Linear regression models with logarithmic transformations. *London School of Economics, London*.

Boarnet, M, 2004, The built environment and physical activity: empirical methods and data resources, paper prepared for the Committee on Physical Activity, Health, Transportation, and Land Use, Transportation Research Board and Institute of Medicine, National Academy of Sciences, Washington, DC.

Boarnet, M.G. and Crane, R., 2001. *Travel by design: The influence of urban form on travel*. Oxford University Press on Demand.

Boarnet, M.G., Greenwald, M. and McMillan, T.E., 2008. Walking, urban design, and health toward a cost-benefit analysis framework. *Journal of Planning Education and Research*, *27*(3), pp.341-358.

Boarnet, M.G. and Sarmiento, S., 1998. Can land-use policy really affect travel behaviour? A study of the link between non-work travel and land-use characteristics. *Urban Studies*, *35*(7), pp.1155-1169.

Boer, R., Zheng, Y., Overton, A., Ridgeway, G.K. and Cohen, D.A., 2007. Neighborhood design and walking trips in ten US metropolitan areas. *American journal of preventive medicine*, *32*(4), pp.298-304.

Boniface, S., Scantlebury, R., Watkins, S.J. and Mindell, J.S., 2015. Health implications of transport: evidence of effects of transport on social interactions. *Journal of Transport & Health*, *2*(3), pp.441-446.

Boyd, J.P. and Butterfield, L.H., 1950. *The Papers of Thomas Jefferson*. Princeton University Press.

Braun, L.M. and Malizia, E., 2015. Downtown vibrancy influences public health and safety outcomes in urban counties. *Journal of Transport & Health*, *2*(4), pp.540-548.

BTS, 2016. Transportation Statistics Annual Report 2016 (Washington, DC: 2016). https://www.bts.gov/sites/bts.dot.gov/files/docs/TSAR_2016.pdf. Accessed May 18, 2019.

Buckinger, C., 1994. Picking the Participants: Guidelines for Selecting a Telecommuting Team (No. UCD-ITS-RR-94-11).

Buehler, R., Pucher, J., Merom, D. and Bauman, A., 2011. Active travel in Germany and the US: contributions of daily walking and cycling to physical activity. *American Journal of Preventive Medicine*, *41*(3), pp.241-250.

Burbidge, S.K. and Goulias, K.G., 2008. Active Travel Behavior. *University of California Transportation Center*.

Cao, X., 2010. Exploring causal effects of neighborhood type on walking behavior using stratification on the propensity score. *Environment and Planning A*, *42*(2), pp.487-504.

Cao, X., Handy, S.L. and Mokhtarian, P.L., 2006. The influences of the built environment and residential self-selection on pedestrian behavior: evidence from Austin, TX. *Transportation*, *33*(1), pp.1-20.

Cao, X., Mokhtarian, P.L. and Handy, S.L., 2007. Do changes in neighborhood characteristics lead to changes in travel behavior? A structural equations modeling approach. *Transportation*, *34*(5), pp.535-556.

Cao, X., Mokhtarian, P.L. and Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. *Transport Reviews*, *29*(3), pp.359-395.

Cao, X., Mokhtarian, P.L. and Handy, S.L., 2010. Neighborhood design and the accessibility of the elderly: An empirical analysis in Northern California. *International Journal of Sustainable Transportation*, *4*(6), pp.347-371.

Carr, L.J., Dunsiger, S.I. and Marcus, B.H., 2010a. Walk score™ as a global estimate of neighborhood walkability. *American journal of preventive medicine*, *39*(5), pp.460-463.

Carr, L.J., Dunsiger, S.I. and Marcus, B.H., 2010b. Validation of Walk Score for estimating access to walkable amenities. *British Journal of Sports Medicine*, p. bjsports69609.

Carver, A., Veitch, J., Sahlqvist, S., Crawford, D. and Hume, C., 2014. Active transport, independent mobility and territorial range among children residing in disadvantaged areas. *Journal of Transport & Health*, *1*(4), pp.267-273.

CDC, 1999. Neighborhood safety and the prevalence of physical inactivity--selected states, 1996. *MMWR. Morbidity and mortality weekly report*, *48*(7), p.143.

CDC, 2002. Barriers to children walking and biking to school-United States, 1999. *MMWR: Morbidity and mortality weekly report*, *51*(32), pp.701-704.

CDC, 2013. The BRFSS Data User Guide. https://www.cdc.gov/brfss/data_documentation/PDF/UserguideJune2013.pdf. Accessed April 22, 2019.

CDC, 2018. Defining Adult Overweight and Obesity. https://www.cdc.gov/obesity/adult/defining.html. Accessed April 30, 2019.

CDC, 2019. Physical Activity. https://www.cdc.gov/physicalactivity/index.html. Accessed May 07, 2019.

Cervero, R., 1996. Mixed land-uses and commuting: evidence from the American Housing Survey. *Transportation Research Part A: Policy and Practice*, *30*(5), pp.361-377.

Cervero, R., 2001. Walk-and-ride: factors influencing pedestrian access to transit. *Journal of Public Transportation*, *7*(3).

Cervero, R., 2002. Built environments and mode choice: toward a normative framework. *Transportation Research Part D: Transport and Environment*, *7*(4), pp.265-284.

Cervero, R. and Duncan, M., 2003. Walking, bicycling, and urban landscapes: evidence from the San Francisco Bay Area. *American journal of public health*, *93*(9), pp.1478-1483.

Cervero, R. and Gorham, R., 1995. Commuting in transit versus automobile neighborhoods. *Journal of the American planning Association*, *61*(2), pp.210-225.

Cervero, R. and Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), pp.199-219.

Cervero, R. and Murakami, J., 2010. Effects of built environments on vehicle miles traveled: evidence from 370 US urbanized areas. *Environment and planning A*, *42*(2), pp.400-418.

Cervero, R. and Radisch, C., 1996. Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy*, *3*(3), pp.127-141.

Chatman, D.G., 2009. Residential choice, the built environment, and nonwork travel: evidence using new data and methods. *Environment and Planning A*, *41*(5), pp.1072-1089.

Chen, C., Gong, H. and Paaswell, R., 2008. Role of the built environment on mode choice decisions: additional evidence on the impact of density. *Transportation*, *35*(3), pp.285-299.

Chung, J.H., Kim, S., Lee, Y.K. and Choi, Y.S., 2004. Multilevel structural equation model for activity participation and travel behavior: Data from the Puget sound transportation panel. *Transportation Research Record: Journal of the Transportation Research Board*, (1898), pp.52-60.

Cidell, J., 2010. Concentration and decentralization: the new geography of freight distribution in US metropolitan areas. *Journal of Transport Geography*, *18*(3), pp.363-371.

Clifton, K.J. and Dill, J., 2005. Women’s Travel Behavior and Land Use: Will New Styles of Neighborhoods Lead to More Women Walking? In *Transportation research board conference proceedings* (No. 35).

Corburn, J., 2015. Inclusive and healthy cities: Commentary on transport, social exclusion and health. *Journal of Transport & Health*, *2*(4), pp.618-619.

Craig, C.L., Brownson, R.C., Cragg, S.E. and Dunn, A.L., 2002. Exploring the effect of the environment on physical activity: a study examining walking to work. *American journal of preventive medicine*, *23*(2), pp.36-43.

Croucher, K., Wallace, A. and Duffy, S., 2012. The influence of land use mix, density and urban design on health: A critical literature review. *University of York*.

D'amato, G., Vitale, C., De Martino, A., Viegi, G., Lanza, M., Molino, A., Sanduzzi, A., Vatrella, A., Annesi-Maesano, I. and D'amato, M., 2015. Effects on asthma and respiratory allergy of climate change and air pollution. *Multidisciplinary respiratory medicine*, *10*(1), p.39.

Dannenberg, A.L. and Sener, I.N., 2015. Why Public Health and Transportation: Setting the Stage. *TR News*, (299).

Davis, G.A. and Wicklatz, T., 2001. Sample-based estimation of bicycle miles of travel (BMT). Minnesota Department of Transportation.

Daykin, A.R. and Moffatt, P.G., 2002. Analyzing ordered responses: A review of the ordered probit model. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences*, *1*(3), pp.157-166.

De Bourdeaudhuij, I., Sallis, J.F. and Saelens, B.E., 2003. Environmental correlates of physical activity in a sample of Belgian adults. *American journal of health promotion*, *18*(1), pp.83-92.

De Croon, E., Sluiter, J., Kuijer, P.P. and Frings-Dresen, M., 2005. The effect of office concepts on worker health and performance: a systematic review of the literature. *Ergonomics*, *48*(2), pp.119-134.

Delmelle, E.C., Thill, J.C. and Ha, H.H., 2012. Spatial epidemiologic analysis of relative collision risk factors among urban bicyclists and pedestrians. *Transportation*, *39*(2), pp.433-448.

Demetsky, M.J. and Perfater, M.A., 1975. Assessment of pedestrian attitudes and behavior in suburban environments. *Transportation research record*, *540*, pp.46-55.

Demidenko, E. *Mixed Models, Theory and Applications*, John Wiley & Sons, Hoboken, N.J., 2004.

Desyllas, J., Duxbury, E., Ward, J. and Smith, A., 2003. Pedestrian demand modelling of large cities: an applied example from London.

DHHS, 1996. *Physical activity and health: A report of the Surgeon General*. diane Publishing.

DHHS, 2008. 2008 physical activity guidelines for Americans: Be active, healthy, and happy! https://health.gov/paguidelines/pdf/paguide.pdf. Accessed April 23, 2019.

DHHS, 2018. 2018 physical activity guidelines for Americans, 2nd edition. https://health.gov/paguidelines/second-edition/pdf/Physical_Activity_Guidelines_2nd_edition.pdf. Accessed April 30, 2019.

Dieleman, F.M., Dijst, M. and Burghouwt, G., 2002. Urban form and travel behaviour: micro-level household attributes and residential context. *Urban Studies*, *39*(3), pp.507-527.

Dill, J. and Carr, T., 2003. Bicycle commuting and facilities in major US cities: if you build them, commuters will use them. *Transportation Research Record: Journal of the Transportation Research Board*, (1828), pp.116-123.

Dill, J. and Voros, K., 2007. Factors affecting bicycling demand: initial survey findings from the Portland, Oregon, region. *Transportation Research Record: Journal of the Transportation Research Board*, (2031), pp.9-17.

Duncan, D.T., J. Aldstadt, J. Whalen, S. J. Melly, and S.L. Gortmaker., 2011. Validation of Walk Score® for Estimating Neighborhood Walkability: An Analysis of Four US Metropolitan Areas. *International Journal of Environmental Research and Public Health*. Vol. 8, No. 11, pp. 4160–4179.

Durand, C.P., Tang, X., Gabriel, K.P., Sener, I.N., Oluyomi, A.O., Knell, G., Porter, A.K., Hoelscher, D.M. and Kohl, H.W., 2016. The association of trip distance with walking to reach public transit: data from the California household travel survey. *Journal of Transport & Health*, *3*(2), pp.154-160.

Ellaway, A., Macintyre, S., Hiscock, R. and Kearns, A., 2003. In the driving seat: psychosocial benefits from private motor vehicle transport compared to public transport. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*(3), pp.217-231.

EPA, A., 2017. Inventory of US greenhouse gas emissions and sinks: 1990-2015. Environmental Protection Agency 2017.

Evans, G.W. and Wener, R.E., 2006. Rail commuting duration and passenger stress. *Health Psychology*, *25*(3), p.408.

Evans, G.W., Wener, R.E. and Phillips, D., 2002. The morning rush hour: Predictability and commuter stress. *Environment and behavior*, *34*(4), pp.521-530.

Ewing, R., 1995. Beyond density, mode choice, and single-purpose trips. *Transportation Quarterly*, *49*(4), pp.15-24.

Ewing, R. and Cervero, R., 2001. Travel and the built environment: a synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, (1780), pp.87-114.

Ewing, R. and Cervero, R., 2010. Travel and the built environment: a meta-analysis. *Journal of the American planning association*, *76*(3), pp.265-294.

Ewing, R. and Greene, W., 2003. Travel and environmental implications of school siting. *Washington, DC: US Environmental Protection Agency*.

Ewing, R., Meakins, G., Hamidi, S. and Nelson, A.C., 2014. Relationship between urban sprawl and physical activity, obesity, and morbidity–update and refinement. *Health & place*, *26*, pp.118-126.

Ewing, R., Pendall, R. and Chen, D., 2003a. Measuring sprawl and its transportation impacts. *Transportation Research Record: Journal of the Transportation Research Board*, (1831), pp.175-183.

Ewing R, Schmid T, Killingsworth R, Zlot A, Raudenbush S., 2003b. Relationship between urban sprawl and physical activity, obesity, and morbidity. *Am J Health Promotion* 18(1), pp 47–57.

Ewing, R., Schmid, T., Killingsworth, R., Zlot, A. and Raudenbush, S., 2008. Relationship between urban sprawl and physical activity, obesity, and morbidity. In *Urban Ecology* (pp. 567-582). Springer, Boston, MA.

Ewing, R., Schroeer, W. and Greene, W., 2004. School location and student travel analysis of factors affecting mode choice. *Transportation Research Record: Journal of the Transportation Research Board*, (1895), pp.55-63.

Fabozzi, F.J., Focardi, S.M., Rachev, S.T. and Arshanapalli, B.G., 2014. *The basics of financial econometrics: Tools, concepts, and asset management applications*. John Wiley & Sons.

Fan, Y., 2007. *The built environment, activity space, and time allocation: An activity-based framework for modeling the land use and travel connection*. The University Of North Carolina At Chapel Hill.

Fichter, K., 2002. E-commerce: Sorting out the environmental consequences. *Journal of Industrial Ecology*, *6*(2), pp.25-41.

Frank LD, Andresen MA, Schmid TL., 2004. Obesity relationships with community design, physical activity, and time spent in cars. *American Journal Preventive Medicine* 27(2), pp. 87–96.

Frank, L., Bradley, M., Kavage, S., Chapman, J. and Lawton, T.K., 2008. Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, *35*(1), pp.37-54.

Frank, L., Giles-Corti, B. and Ewing, R., 2016. The influence of the built environment on transport and health. *Journal of Transport & Health*, *3*(4), pp.423-425.

Frank LD, Schmid TL, Sallis JF, Chapman J, Saelens BE., 2005. Linking objectively measured physical activity with objectively measured urban form. *American Journal Preventive Medicine* 28(2), pp. 117–125.

Frank, L.D. and Pivo, G., 1994. Impacts of mixed use and density on utilization of three modes of travel: single-occupant vehicle, transit, and walking. *Transportation research record*, 1466, pp.44-52.

Franke, G.R., 2010. Multicollinearity. *Wiley International Encyclopedia of Marketing*.2.

Friedman, B., Gordon, S.P. and Peers, J.B., 1994. Effect of neotraditional neighborhood design on travel characteristics. *Transportation Research Record*: *Journal of the Transportation Research Board*, (1466), pp. 63–70.

Forsyth, A., Hearst, M., Oakes, J.M. and Schmitz, K.H., 2008. Design and destinations: factors influencing walking and total physical activity. *Urban Studies*, *45*(9), pp.1973-1996.

Foster, S. and Giles-Corti, B., 2008. The built environment, neighborhood crime and constrained physical activity: an exploration of inconsistent findings. *Preventive medicine*, *47*(3), pp.241-251.

Founders Online, National Archives, "*From Thomas Jefferson to Peter Carr, 19 August 1785"*. https://founders.archives.gov/documents/Jefferson/01-08-02-0319. Accessed April 17, 2019.

Galovski, T.E. and Blanchard, E.B., 2004. Road rage: a domain for psychological intervention?. *Aggression and Violent Behavior*, *9*(2), pp.105-127.

Garson, G.D., 2013. Fundamentals of hierarchical linear and multilevel modeling. Hierarchical linear modeling: Guide and applications, pp.3-25.

Gatersleben, B. and Appleton, K.M., 2007. Contemplating cycling to work: Attitudes and perceptions in different stages of change. *Transportation Research Part A: Policy and Practice*, *41*(4), pp.302-312.

Gehl J. 1987. Life between Buildings: Using Public Space Copenhagen: The Danish Architecture Press.

Gelman, A. and Hill, J., 2007. *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press.

Geurs, K.T. and van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport geography*, *12*(2), pp.127-140.

Giles-Corti, B. and Donovan, R.J., 2002. Socioeconomic status differences in recreational physical activity levels and real and perceived access to a supportive physical environment. *Preventive medicine*, *35*(6), pp.601-611.

Giles-Corti, B. and Donovan, R.J., 2003. Relative influences of individual, social environmental, and physical environmental correlates of walking. *American journal of public health*, *93*(9), pp.1583-1589.

Giles-Corti, B., Kelty, S.F., Zubrick, S.R. and Villanueva, K.P., 2009. Encouraging walking for transport and physical activity in children and adolescents. *Sports medicine*, *39*(12), pp.995-1009.

Gochman, D.S., 1997. Handbook of health behavior research 1: personal and social determinants.

Goddard, T., Handy, S., Cao, X. and Mokhtarian, P., 2006. Voyage of the SS Minivan: Women's travel behavior in traditional and suburban neighborhoods. *Transportation Research Record: Journal of the Transportation Research Board*, (1956), pp.141-148.

Godwin, Ariel, and Anne M. Price., 2016. Bicycling and walking in the Southeast USA: Why is it rare and risky?. *Journal of Transport & Health* 3, no. 1: 26-37.

Gordon-Larsen, P., Boone-Heinonen, J., Sidney, S., Sternfeld, B., Jacobs, D.R. and Lewis, C.E., 2009. Active commuting and cardiovascular disease risk: the CARDIA study. *Archives of internal medicine*, *169*(13), pp.1216-1223.

Greenwald, M. and Boarnet, M., 2001. Built environment as determinant of walking behavior: Analyzing nonwork pedestrian travel in Portland, Oregon. *Transportation Research Record: Journal of the Transportation Research Board*, (1780), pp.33-41.

Grilli, L. and Rampichini, C., 2012. Multilevel models for ordinal data. *Modern Analysis of Customer Surveys: with Applications using R*, pp.391-411.

Griswold, M.G., Fullman, N., Hawley, C., Arian, N., Zimsen, S.R., Tymeson, H.D., Venkateswaran, V., Tapp, A.D., Forouzanfar, M.H., Salama, J.S. and Abate, K.H., 2018. Alcohol use and burden for 195 countries and territories, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. The Lancet, 392(10152), pp.1015-1035.

Guo, J.Y. and Bhat, C.R., 2007. Operationalizing the concept of neighborhood: Application to residential location choice analysis. *Journal of Transport Geography*, *15*(1), pp.31-45.

Hamilton, L.C., 2013. Multilevel and mixed-effects modeling. *Statistics with STATA: Updated for version*, *10*, pp.387-421.

Hammen, C. Stress and Depression, Annual Review, *Clinical Psychology*. 2005. 1:293–319.

Hancock, G.R. and Mueller, R.O., 2006. In: Hancock, G.R. and Mueller, R.O. (Eds.), *Structural equation modeling: A second course*, pp. 1-9. Information Age Publishing Inc.

Handy, S., 1993. Regional versus local accessibility: Implications for nonwork travel. *University of California Transportation Center*.

Handy, S., 1996a. Urban form and pedestrian choices: study of Austin neighborhoods. *Transportation Research Record: Journal of the Transportation Research Board,* (1552), pp.135-144.

Handy, S.L., 1996b. Understanding the link between urban form and nonwork travel behavior. *Journal of planning education and research*, *15*(3), pp.183-198.

Handy, S., 1996c. Methodologies for exploring the link between urban form and travel behavior. *Transportation Research Part D: Transport and Environment*, *1*(2), pp.151-165.

Handy, S., 2005. Critical assessment of the literature on the relationships among transportation, land use, and physical activity. Transportation Research Board and the Institute of Medicine Committee on Physical Activity, Health, Transportation, and Land Use. *Resource paper for TRB Special Report, 282(1)*, pp.1-81.

Handy, S., Cao, X. and Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), pp.427-444.

Handy, S., Cao, X and P. Mokhtarian., 2006. Self-selection in the Relationship Between the Built Environment and Walking. *Journal of the American Planning Association*, Vol. 72, No. 1, pp. 55–74.

Handy, S.L. and Clifton, K.J., 2001. Local shopping as a strategy for reducing automobile travel. *Transportation*, *28*(4), pp.317-346.

Handy, S.L. and Mokhtarian, P.L., 1996. The future of telecommuting. Futures, 28(3), pp.227-240.

Handy, S.L. and Xing, Y., 2011. Factors correlated with bicycle commuting: a study in six small US cities. *International Journal of Sustainable Transportation*, *5*(2), pp.91-110.

Hansen, W.G. How accessibility Shapes Land Use. *Journal of the American Institute of Planners*, Vol. 25, No. 2, 1959, pp. 73–76.

Hansson, E., Mattisson, K., Björk, J., Östergren, P.O. and Jakobsson, K., 2011. Relationship between commuting and health outcomes in a cross-sectional population survey in southern Sweden. *BMC public health*, *11*(1), p.834.

Harkey, D.L., Reinfurt, D.W., Knuiman, M., Stewart, J.R. and Sorton, A., 1998. *Development of the bicycle compatibility index: A level of service concept, final report* (No. FHWA-RD-98-072,).

Harms, L., Bertolini, L. and Te Brömmelstroet, M., 2014. Spatial and social variations in cycling patterns in a mature cycling country exploring differences and trends. *Journal of Transport & Health*, *1*(4), pp.232-242.

He, X. and Zhang, L., 2014. Quantifying the Self-Selection Effect in Residential Location and Vehicle Use Choices with a Structural Equation Model. *Bridges*, *10*, pp.9780784412442-361.

Healy, M., 2001. Multilevel data and their analysis. In: Leyland, A.H. and Goldstein, H., (Eds.), *Multilevel modelling of health statistics*. John Wiley and Sons, Inc, New York.

Heck, R.H., 2001. Multilevel modeling with SEM. In Marcoulides, G.A. and Schumacker, R.E. (Eds.), *New developments and techniques in structural equation modeling*, pp. 109-148.

Heinen, E., Van Wee, B. and Maat, K., 2010. Commuting by bicycle: an overview of the literature. *Transport reviews*, *30*(1), pp.59-96.

Henke, R.M., Benevent, R., Schulte, P., Rinehart, C., Crighton, K.A. and Corcoran, M., 2015. The Effects of Telecommuting Intensity on Employee Health. *American Journal of Health Promotion*.

Hershberger, S.L., 2006. The problem of equivalent structural models. In: Hancock, G.R. and Mueller, R.O. (Eds.), *Structural equation modeling: A second course*, pp.13-41. Information Age Publishing Inc.

Hess, P., Moudon, A., Snyder, M. and Stanilov, K., 1999. Site design and pedestrian travel. *Transportation Research Record: Journal of the Transportation Research Board*, (1674), pp.9-19.

Hirsch, J.A., Diez Roux, A.V., Moore, K.A., Evenson, K.R. and Rodriguez, D.A., 2014. Change in walking and body mass index following residential relocation: the multi-ethnic study of atherosclerosis. *American journal of public health*, *104*(3), pp. e49-e56.

Hoehner, C.M., Ramirez, L.K.B., Elliott, M.B., Handy, S.L. and Brownson, R.C., 2005. Perceived and objective environmental measures and physical activity among urban adults. *American journal of preventive medicine*, *28*(2), pp.105-116.

Hovell, M.F., Hofstetter, C.R., Sallis, J.F., Rauh, M.J. and Barrington, E., 1992. Correlates of change in walking for exercise: an exploratory analysis. *Research quarterly for exercise and sport*, *63*(4), pp.425-434.

Howard, A.A., Arnsten, J.H. and Gourevitch, M.N., 2004. Effect of alcohol consumption on diabetes mellitus: a systematic review. *Annals of internal medicine*, *140*(3), pp.211-219.

Jackson, L.E., 2003. The relationship of urban design to human health and condition. *Landscape and urban planning*, *64*(4), pp.191-200.

Jacobs, J., 1961. The death and life of great American cities. *New-York, NY: Vintage*.

Joh, K., Boarnet, M.G. and Nguyen, M.T., 2009. Interactions between race/ethnicity, attitude, and crime: Analyzing walking trips in the South Bay Area. 88th annual meeting of the Transportation Research Board. *Washington, DC*.

Joshu, C.E., Boehmer, T.K., Brownson, R.C. and Ewing, R., 2008. Personal, neighbourhood and urban factors associated with obesity in the United States. *Journal of epidemiology and community health*, *62*(3), pp.202-208.

Khan, A.M., 2015. Modeling Telecommuting Decisions in Diverse SocioEconomic Environments. The *Journal of Transportation of the Institute of Transportation Engineers*.

Khattak, A.J. and Rodriguez, D., 2005. Travel behavior in neo-traditional neighborhood developments: A case study in USA. *Transportation Research Part A: Policy and Practice*, *39*(6), pp.481-500.

Kelloway, E.K.,1998. "*Using LISREL for structural equation modeling: A researcher's guide*." Sage.

Kelly-Schwartz, A.C., Stockard, J., Doyle, S. and Schlossberg, M., 2004. Is sprawl unhealthy? A multilevel analysis of the relationship of metropolitan sprawl to the health of individuals. *Journal of Planning Education and Research*, *24*(2), pp.184-196.

Kent, J. and Thompson, S., 2012. Health and the built environment: exploring foundations for a new interdisciplinary profession. *Journal of environmental and public health*, *2012*.

Kerr, J., Frank, L., Sallis, J.F. and Chapman, J., 2007. Urban form correlates of pedestrian travel in youth: Differences by gender, race-ethnicity and household attributes. *Transportation Research Part D: Transport and Environment*, *12*(3), pp.177-182.

Kiecolt-Glaser, J. K., Habash, D.L., Fagundes, C.P., Andridge, R., Peng, J., Malarkey, B.W., and Belury., M.A. Daily Stressors, Past Depression, and Metabolic Responses to High-Fat Meals: A Novel Pathto Obesity, *Biological Psychiatry*, 2015.

Kim, N.S. and Susilo, Y.O., 2013. Comparison of pedestrian trip generation models. *Journal of Advanced Transportation*, *47*(4), pp.399-412.

Kitamura, R., Mokhtarian, P.L. and Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. *Transportation*, *24*(2), pp.125-158.

Kitamura, R., Robinson, J., Golob, T., Bradley, M., Leonard, J. and van der Hoorn, T., 1992. A comparative analysis of time use data in the Netherlands and California.

Kline, R.B., 2006. Reverse arrow dynamics: Formative measurement and feedback loops. In: Hancock, G.R. and Mueller, R.O. (Eds.), *Structural equation modeling: A second course*, pp.43-68. Information Age Publishing Inc.

Kline, R.B., 2011. *Principles and practice of structural equation modeling*. Third edition. Guilford publications.

Kockelman, K., 1997. Travel behavior as function of accessibility, land use mixing, and land use balance: evidence from San Francisco Bay Area. *Transportation Research Record: Journal of the Transportation Research Board*, (1607), pp.116-125.

Konrad, K. and Wittowsky, D., 2018. Virtual mobility and travel behavior of young people–Connections of two dimensions of mobility. *Research in Transportation Economics*, *68*, pp.11-17.

Krizek, K.J., 2003a. Neighborhood services, trip purpose, and tour-based travel. *Transportation*, *30*(4), pp.387-410.

Krizek, K.J., 2003b. Operationalizing neighborhood accessibility for land use-travel behavior research and regional modeling. *Journal of Planning Education and Research*, *22*(3), pp.270-287.

Krizek, K.J., 2003c. Residential relocation and changes in urban travel: does neighborhood-scale urban form matter?. *Journal of the American Planning Association*, *69*(3), pp.265-281.

Künn-Nelen, A., 2015. Does commuting affect health?. *Health economics*.

Kuzmyak, J.R., Walters, J., Bradley, M. and Kockelman, K.M., 2014. *Estimating bicycling and walking for planning and project development: A guidebook* (Project 08-78).

Langerudi, M.F., Abolfazl, M. and Sriraj, P.S., 2015. Health and transportation: Small scale area association. *Journal of Transport & Health*, *2*(2), pp.127-134.

Leckie, G., 2010. Module 5: Introduction to multilevel modeling. *London, England: Centre for Multilevel Modelling*.

Lee, C. and Moudon, A.V., 2004. Physical activity and environment research in the health field: implications for urban and transportation planning practice and research. *Journal of planning literature*, *19*(2), pp.147-181.

Lee, C. and Moudon, A.V., 2006. The 3Ds+ R: Quantifying land use and urban form correlates of walking. Transportation Research Part D: Transport and Environment, 11(3), pp.204-215.

Leslie, E., McCrea, R., Cerin, E. and Stimson, R., 2007. Regional Variations in Walking for Different Purposes. The South East Queensland Quality of Life Study. *Environment and behavior*, *39*(4), pp.557-577.

Levine, J., 1998. Rethinking accessibility and jobs-housing balance. *Journal of the American Planning Association*, *64*(2), pp.133-149.

Leyden, K.M., 2003. Social capital and the built environment: the importance of walkable neighborhoods. *American journal of public health*, *93*(9), pp.1546-1551.

Li, W., Joh, K., Lee, C., Kim, J.H., Park, H. and Woo, A., 2014. From car-dependent neighborhoods to walkers' paradise: estimating walkability premiums in the condominium housing market. *Transportation Research Record: Journal of the Transportation Research Board*, *2453*, pp.162-170.

Liao, Y., Tsai, H.H., Wang, H.S., Lin, C.P., Wu, M.C. and Chen, J.F., 2016. Travel mode, transportation-related physical activity, and risk of overweight in Taiwanese adults. *Journal of Transport & Health*, *3*(2), pp.220-225.

Liepmann, K.K., 1945. *The journey to work: its significance for industrial and community life*. K. Paul, Trench, Trubner & Company.

Limanond, T. and Niemeier, D.A., 2004. Effect of land use on decisions of shopping tour generation: A case study of three traditional neighborhoods in WA. *Transportation*, *31*(2), pp.153-181.

Lin, J.J. and Chang, H.T., 2010. Built environment effects on children's school travel in Taipai: independence and travel mode. *Urban Studies*, *47*(4), pp.867-889.

Lindström, M., 2008. Means of transportation to work and overweight and obesity: a population-based study in southern Sweden. *Preventive medicine*, *46*(1), pp.22-28.

Lister, K. and Harnish, T., 2011. The state of telework in the US Telework Research Network.

Litman, T., 2003. Measuring transportation: traffic, mobility and accessibility. *Institute of Transportation Engineers. ITE Journal*, *73*(10), p.28.

Litman, T. Measuring Transportation Traffic, Mobility and Accessibility, 2011. Victoria Transport Policy Institute: www.vtpi.org/measure.pdf. Accessed March 23, 2016.

Lloyd, C., Smith, J. and Weinger, K., 2005. Stress and diabetes: a review of the links. *Diabetes spectrum*, *18*(2), pp.121-127.

Long, J.S. and Freese, J., 2006. *Regression models for categorical dependent variables using Stata*. Stata press.

Lumsdon, L. and Mitchell, J., 1999. Walking, transport and health: do we have the right prescription?. *Health Promotion International*, *14*(3), pp.271-280.

Lund, H., 2002. Pedestrian environments and sense of community. *Journal of Planning education and Research*, *21*(3), pp.301-312.

Lund, H., 2003. Testing the claims of new urbanism: Local access, pedestrian travel, and neighboring behaviors. *Journal of the American Planning Association*, *69*(4), pp.414-429.

Ma, L. and Dill, J., 2015. Associations between the objective and perceived built environment and bicycling for transportation. *Journal of Transport & Health*, *2*(2), pp.248-255.

Mackett, R.L. and Thoreau, R., 2015. Transport, social exclusion and health. *Journal of Transport & Health*, *2*(4), pp.610-617.

Maddock, J., 2004. The relationship between obesity and the prevalence of fast food restaurants: state-level analysis. *American journal of health promotion*, *19*(2), pp.137-143.

Mahmoudi, J. and Clifton, K., 2019. The Role of Accessibility and Built Environment Characteristics in Usage of Information and Communication Technologies in Business. In International Conference on Transportation and Development (p.1).

Mahmoudi, J. and Zhang, L., 2018a. Impact of County-Level Built Environment and Regional Accessibility on Walking: A Washington, DC–Baltimore Case Study. *Journal of Urban Planning and Development*, *144*(3), p.04018020.

Mahmoudi, J and Zhang, L., 2018b. The Relationship between For-Hire Service Pickups and Built Environment Characteristics: Evidence from New York City. In International Conference on Transportation and Development (p. 1).

Manaugh, K. and El-Geneidy, A., 2011. Validating walkability indices: How do different households respond to the walkability of their neighborhood?. *Transportation Research Part D: Transport and Environment*, *16*(4), pp.309-315.

Marcus, M.J., 2008. Examining correlations with frequency of walking trips in Metropolitan areas. Georgia State University.

Mariani, M., 2000.Telecommuters. *Occupational Outlook Quarterly*, *44*(3), pp.10-17.

Marshall, J.D., Brauer, M. and Frank, L.D., 2009. Healthy neighborhoods: walkability and air pollution. *Environmental health perspectives*, *117*(11), p.1752.

Marshall, W.E., Piatkowski, D.P. and Garrick, N.W., 2014. Community design, street networks, and public health. *Journal of Transport & Health*, *1*(4), pp.326-340.

McAlister, A.L., Perry, C.L. and Parcel, G.S., 2008. How individuals, environments, and health behaviors interact: Social Cognitive Theory: *Health behavior and health education: Theory, research, and practice*, pp.169-188.

McCann, B.A. and Ewing, R., 2003. Measuring the health effects of sprawl: A national analysis of physical activity, obesity and chronic disease.

McDonald, N.C., 2005. Children's travel: patterns and influences. *University of California Transportation Center*.

McDonald, N.C., Brown, A.L., Marchetti, L.M. and Pedroso, M.S., 2011. US school travel, 2009: an assessment of trends. *American journal of preventive medicine*, *41*(2), pp.146-151.

McEwen, B.S., 1998. Protective and damaging effects of stress mediators. *New England journal of medicine*, *338*(3), pp.171-179.

McFadden, D., 1974. The measurement of urban travel demand. *Journal of public economics*, *3*(4), pp.303-328.

McFadden, D.L., 2002. The path to discrete-choice models. *ACCESS Magazine*, *1*(20).

McMillan, T.E., 2005. Urban form and a child's trip to school: the current literature and a framework for future research. *Journal of Planning Literature* 19 (4), pp. 440–456.

Meehan, L., 2015. Measuring the Health Benefits of Walking and Bicycling: Nashville Area Metropolitan Planning Organization Applies the Findings. *TR News,* (299).

Melis, G., Marra, G., Ferracin, E., Gelormino, E. and Costa, G., 2015. The impact of urban structure on mental health in Turin: the importance of public transport accessibility. *Journal of transport and health*, *2*(Suppl), pp. S8-S9.

Merom, D., van der Ploeg, H.P., Corpuz, G. and Bauman, A.E., 2010. Public health perspectives on household travel surveys: active travel between 1997 and 2007. *American journal of preventive medicine*, *39*(2), pp.113-121.

Miller, E. and Ibrahim, A., 1998. Urban form and vehicular travel: some empirical findings. *Transportation Research Record: Journal of the Transportation Research Board*, (1617), pp.18-27.

Milne, A. and Melin, M., 2014. Bicycling and Walking in the United States: 2014 Benchmarking Report.

Mindell, J.S., 2015. The impacts of national and local government actions on active travel. *Journal of transport and health*, *2*(2), pp.95-96.

Mitra, R. and Buliung, R.N., 2012. Built environment correlates of active school transportation: neighborhood and the modifiable areal unit problem. *Journal of Transport Geography*, *20*(1), pp.51-61.

Mokdad, A.H., Ford, E.S., Bowman, B.A., Dietz, W.H., Vinicor, F., Bales, V.S. and Marks, J.S., 2003. Prevalence of obesity, diabetes, and obesity-related health risk factors, 2001. *Jama*, *289*(1), pp.76-79.

Mokhtarian, P.L., 2002. Telecommunications and travel: The case for complementarity. *Journal of Industrial Ecology*, *6*(2), pp.43-57.

Montano, D.E. and Kasprzyk, D., 2008. Theory of reasoned action, theory of planned behavior, and the integrated behavioral model. *Health behavior and health education: Theory, research and practice*, pp.67-96.

Moudon, A.V. and Lee, C., 2003. Walking and bicycling: an evaluation of environmental audit instruments. *American Journal of Health Promotion*, *18*(1), pp.21-37.

Moudon, A.V., Lee, C., Cheadle, A.D., Collier, C.W., Johnson, D., Schmid, T.L. and Weather, R.D., 2005. Cycling and the built environment, a US perspective. *Transportation Research Part D: Transport and Environment*, *10*(3), pp.245-261.

Murga, M. 2004. Pedestrians as a critical target of metropolitan planning. Presented at the Fifth International Conference on Walking in the 21st Century, Copenhagen, Denmark.

Musselwhite, C., Holland, C. and Walker, I., 2015. The role of transport and mobility in the health of older people.

Næss, P., 2005. Residential location affects travel behavior—but how and why? The case of Copenhagen metropolitan area. *Progress in Planning*, *63*(2), pp.167-257.

Nakagawa, S. and Schielzeth, H., 2013. A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, *4*(2), pp.133-142.

Nasri, A. and Zhang, L., 2012. Impact of metropolitan-level built environment on travel behavior. *Transportation Research Record: Journal of the Transportation Research Board*, (2323), pp.75-79.

Nasri, A. and Zhang, L., 2014. Assessing the impact of metropolitan-level, county-level, and local-level built environment on travel behavior: Evidence from 19 US urban areas. *Journal of Urban Planning and Development*, *141*(3), p.04014031.

National Center for Health Statistics., 2017. Health, United States, 2016: with chartbook on long-term trends in health. https://www.cdc.gov/nchs/data/hus/hus16.pdf. Accessed May 18, 2019.

National Research Council (U.S.). Committee on Physical Activity, Land Use and Institute of Medicine (U.S.), 2005. *Does the built environment influence physical activity?: examining the evidence* (No. 282). Transportation Research Board.

Nehme, E.K., Oluyomi, A.O., Calise, T.V. and Kohl III, H.W., 2016. Environmental correlates of recreational walking in the neighborhood. *American journal of health promotion*, *30*(3), pp.139-148.

Ogden, C.L., Carroll, M.D., Fryar, C.D. and Flegal, K.M., 2015. *Prevalence of obesity among adults and youth: United States, 2011-2014* (pp. 1-8). DHHS, CDC, National Center for Health Statistics Data Brief, No. 219.

Ohta, M., Mizoue, T., Mishima, N. and Ikeda, M., 2007. Effect of the physical activities in leisure time and commuting to work on mental health. *Journal of occupational health*, *49*(1), pp.46-52.

Oja, P., Mänttäri, A., Heinonen, A., Kukkonen-Harjula, K., Laukkanen, R., Pasanen, M. and Vuori, I., 1991. Physiological effects of walking and cycling to work. *Scandinavian Journal of medicine & science in sports*, *1*(3), pp.151-157.

Oja, P., Titze, S., Bauman, A., De Geus, B., Krenn, P., Reger-Nash, B. and Kohlberger, T., 2011. Health benefits of cycling: a systematic review. *Scandinavian journal of medicine & science in sports*, *21*(4), pp.496-509.

Oja, P., Vuori, I. and Paronen, O., 1998. Daily walking and cycling to work: their utility as health-enhancing physical activity. *Patient education and counseling*, *33*, pp. S87-S94.

Pikora, T., Giles-Corti, B., Bull, F., Jamrozik, K. and Donovan, R., 2003. Developing a framework for assessment of the environmental determinants of walking and cycling. *Social science & medicine*, *56*(8), pp.1693-1703.

Pikora, T.J., Giles-Corti, B., Knuiman, M.W., Bull, F.C., Jamrozik, K. and Donovan, R.J., 2006. Neighborhood environmental factors correlated with walking near home: Using SPACES. *Medicine and Science in Sports and Exercise*, *38*(4), pp.708-714.

Pivo, G., and J. D. Fisher., 2011. The Walkability Premium in Commercial Real Estate Investments. *Real Estate Economics*. Vol. 39, No. 2, pp. 185–219.

Plantinga, A.J. and Bernell, S., 2007. The Association between Urban Sprawl and Obesity: Is It a Two-Way Street?. *Journal of Regional Science*, *47*(5), pp.857-879.

Plaut, P.O., 2005. Non-motorized commuting in the US. *Transportation Research Part D: Transport and Environment*, *10*(5), pp.347-356.

Pollock, M.L., Wilmore, J. H. and Fox, S.M., 1978. Health and fitness through physical activity.

Porter, C., Suhrbier, J. and Schwartz, W., 1999. Forecasting bicycle and pedestrian travel: state of the practice and research needs. *Transportation Research Record: Journal of the Transportation Research Board*, (1674), pp.94-101.

Pucher, J., Buehler, R., Merom, D. and Bauman, A., 2011. Walking and cycling in the United States, 2001–2009: evidence from the National Household Travel Surveys. *American Journal of Public Health*, *101*(S1), pp. S310-S317.

Pucher, J. and Dijkstra, L., 2003. Promoting safe walking and cycling to improve public health: lessons from the Netherlands and Germany. *American journal of public health*, *93*(9), pp.1509-1516.

Pucher, J., Dill, J. and Handy, S., 2010. Infrastructure, programs, and policies to increase bicycling: an international review. *Preventive medicine*, *50,* pp. S106-S125.

Pucher, J., Komanoff, C. and Schimek, P., 1999. Bicycling renaissance in North America?: Recent trends and alternative policies to promote bicycling. *Transportation Research Part A: Policy and Practice*, *33*(7), pp.625-654.

Rabe-Hesketh, Sophia, Anders Skrondal, and Andrew Pickles., 2004. GLLAMM manual.

Rabe-Hesketh, S. and Skrondal, A., 2012. *Multilevel and longitudinal modeling using Stata*. STATA press.

Rabe-Hesketh, S., Skrondal, A. and Zheng, X., 2007. Multilevel structural equation modeling. In *Handbook of latent variable and related models*, pp. 209-227. North-Holland.

Ramsey, K. and Bell, A., 2014. Smart location database. *Washington, DC*.

Reilly, M. and Landis, J., 2003. The influence of built-form and land use on mode choice. *University of California Transportation Center*.

Renne, J., Ewing, R. and Hamidi, S., 2015. Transit Commuting and the Built Environment in Station Areas Across the United States. In *Transportation Research Board 94th Annual Meeting* (No. 15-1966).

Rimm, E.B., Chan, J., Stampfer, M.J., Colditz, G.A. and Willett, W.C., 1995. Prospective study of cigarette smoking, alcohol use, and the risk of diabetes in men. *Bmj*, *310*(6979), pp.555-559.

Rissel, C., Petrunoff, N., Wen, L.M. and Crane, M., 2014. Travel to work and self-reported stress: findings from a workplace survey in south west Sydney, Australia. *Journal of Transport & Health*, *1*(1), pp.50-53.

Robertson, M.M., Maynard, W.S. and McDevitt, J.R., 2003. Telecommuting: managing the safety of workers in home office environments. *Professional Safety*, *48*(4), p.30.

Robinson, W.S., 1950. Ecological correlations and the behavior of individuals, *American Sociological Review* 15, pp. 351-357.

Rodríguez, D.A. and Joo, J., 2004. The relationship between non-motorized mode choice and the local physical environment. *Transportation Research Part D: Transport and Environment*, *9*(2), pp.151-173.

Rodríguez, D.A., Evenson, K.R., Roux, A.V.D. and Brines, S.J., 2009. Land use, residential density, and walking: the multi-ethnic study of atherosclerosis. *American journal of preventive medicine*, *37*(5), pp.397-404.

Rose, S. and Dhandayudham, A., 2014. Toward an understanding of Internet-based problem shopping behaviour: The concept of online shopping addiction and its proposed predictors.

Roshan Zamir, K., Nasri, A., Baghaei, B., Mahapatra, S. and Zhang, L., 2014. Effects of Transit-Oriented Development on Trip Generation, Distribution, and Mode Share in Washington, DC, and Baltimore, Maryland. *Transportation Research Record: Journal of the Transportation Research Board*, (2413), pp.45-53.

Ross, C.E., 2000. Walking, exercising, and smoking: does neighborhood matter?. *Social science & medicine*, *51*(2), pp.265-274.

Ryan, S. and Frank, L.F., 2009. Pedestrian environments and transit ridership. *Journal of Public Transportation*, *12*(1), p.3.

Salam, M.T., Islam, T. and Gilliland, F.D., 2008. Recent evidence for adverse effects of residential proximity to traffic sources on asthma. *Current opinion in pulmonary medicine*, *14*(1), pp.3-8.

Sallis, J., Bauman, A. and Pratt, M., 1998. Environmental and policy interventions to promote physical activity. *American journal of preventive medicine*, *15*(4), pp.379-397.

Sallis, J.F., Owen, N. and Fisher, E.B., 2008. Ecological models of health behavior. *Health behavior and health education: Theory, research, and practice*, pp.465-486.

Salon, D., 2006. *Cars and the city: an investigation of transportation and residential location choices in New York City* (Doctoral dissertation, University of California, Davis).

Samimi, A. and Mohammadian, A.K., 2009. Health impacts of urban development and transportation systems. *Journal of Urban Planning and Development*, *136*(3), pp.208-21.

Samimi, A., Mohammadian, A.K. and Madanizadeh, S., 2009. Effects of transportation and built environment on general health and obesity. *Transportation research part D: transport and environment*, *14*(1), pp.67-71.

Schauder, S.A. and Foley, M.C., 2015. The relationship between active transportation and health. *Journal of Transport & Health*, *2*(3), pp.343-349.

Schlossberg, M., J. Greene, P. P. Phillips, B. Johnson and B. Parker., 2006. School Trips: Effects of Urban Form and Distance on Travel Mode. *Journal of the American Planning Association*, Vol. 72, No. 3, pp. 337–346.

Schneider, R.J., 2015. Local environment characteristics associated with walking and taking transit to shopping districts. *Journal of Transport and Land Use*, *8*(2).

Schulz, A.J., Mentz, G., Lachance, L., Johnson, J., Gaines, C. and Israel, B.A., 2012. Associations between socioeconomic status and allostatic load: effects of neighborhood poverty and tests of mediating pathways. *American journal of public health*, *102*(9), pp.1706-1714.

Schürmann, C., Spiekermann, K. and Wegener, M., 1997. Accessibility indicators. *Berichte aus dem Institut für Raumplanung*, *39*.

Schwanen, T. and Mokhtarian, P.L., 2005. What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?. *Journal of transport geography*, *13*(1), pp.83-99.

Scuderi, M.G., 2005. *Bayesian approaches to learning from data how to untangle the travel behavior and land use relationships* (Doctoral dissertation).

Sener, I.N., Lee, R.J. and Elgart, Z., 2016. Potential health implications and health cost reductions of transit-induced physical activity. *Journal of Transport & Health*, *3*(2), pp.133-140.

Shay, E., Fan, Y., Rodríguez, D. and Khattak, A., 2006. Drive or walk?: Utilitarian trips within a neotraditional neighborhood. *Transportation Research Record: Journal of the Transportation Research Board*, (1985), pp.154-161.

Shephard, R.J., 2008. Is active commuting the answer to population health? *Sports Medicine*, *38*(9), pp.751-758.

Shriver, K., 1997. Influence of environmental design on pedestrian travel behavior in four Austin neighborhoods. *Transportation Research Record: Journal of the Transportation Research Board*, (1578), pp.64-75.

Siegel, P.Z., Brackbill, R.M. and Heath, G.W., 1995. The epidemiology of walking for exercise: implications for promoting activity among sedentary groups. *American journal of public health*, *85*(5), pp.706-710.

Siikavirta, H., Punakivi, M., Kärkkäinen, M. and Linnanen, L., 2002. Effects of E-Commerce on Greenhouse Gas Emissions: A Case Study of Grocery Home Delivery in Finland. *Journal of industrial ecology*, *6*(2), pp.83-97.

Siu, V.W., Lambert, W.E., Fu, R., Hillier, T.A., Bosworth, M. and Michael, Y.L., 2012. Built environment and its influences on walking among older women: use of standardized geographic units to define urban forms. *Journal of environmental and public health*, *2012*.

Smith, K.R., Brown, B.B., Yamada, I., Kowaleski-Jones, L., Zick, C.D. and Fan, J.X., 2008. Walkability and body mass index: density, design, and new diversity measures. *American journal of preventive medicine*, *35*(3), pp.237-244.

Snijders, T.A., und Roel J. Bosker. 2012. Multilevel analysis. An introduction to basic and advanced multilevel modeling.

Spinks, W.A., 2002. A Survey of Home-Based Workers in Japan: Emerging Health Issues. *Journal of Occupational Health*, *44*(4), pp.248-253.

Stapleton, L.M., 2006. Using multilevel structural equation modeling techniques with complex sample data. In: Hancock, G.R. and Mueller, R.O. (Eds.), *Structural equation modeling: A second course*, pp.345-383. Information Age Publishing Inc.

StataCorp, L.P., 2013. Stata Structural Equation Modeling Reference Manual Release 13. https://www.stata.com/manuals13/sem.pdf. Accessed April 23, 2019.

Steward, B., 2001. Health trade-offs in teleworking: an exploratory study of work and health in computer homebased working. *Indexer*, *22*(3), pp.142-146.

Stinson, M. and Bhat, C., 2004. Frequency of bicycle commuting: internet-based survey analysis. *Transportation Research Record: Journal of the Transportation Research Board*, (1878), pp.122-130.

Stokols, D., Novaco, R.W., Stokols, J. and Campbell, J. 1978. Traffic Congestion, Type A Behavior, and Stress, *Journal of Applied Psychology*, Vol. 63, No. 4, 467-480.

Tainio, M., 2015. Burden of disease caused by local transport in Warsaw, Poland. *Journal of transport & health*, *2*(3), pp.423-433.

Tajalli, M. and Hajbabaie, A., 2017. On the relationships between commuting mode choice and public health. *Journal of Transport & Health*, *4*, pp.267-277.

Targa, F. and Clifton, K.J., 2005. Built environment and nonmotorized travel: Evidence from Baltimore City using the NHTS. *Journal of Transportation and Statistics*, *8*(3), pp.55-70.

Timperio, A., Jeffery, R.W., Crawford, D., Roberts, R., Giles-Corti, B. and Ball, K., 2010. Neighbourhood physical activity environments and adiposity in children and mothers: a three-year longitudinal study. *International journal of behavioral nutrition and physical activity*, *7*(1), p.1.

Train, K.E., 2009. *Discrete choice methods with simulation*. Cambridge university press.

Troped, P.J., Saunders, R.P., Pate, R.R., Reininger, B., Ureda, J.R. and Thompson, S.J., 2001. Associations between self-reported and objective physical environmental factors and use of a community rail-trail. *Preventive medicine*, *32*(2), pp.191-200.

Trost, S.G., Owen, N., Bauman, A.E., Sallis, J.F. and Brown, W., 2002. Correlates of adults' participation in physical activity: review and update. *Medicine and science in sports and exercise*, *34*(12), pp.1996-2001.

Trost, Stewart, Russell Pate, Ruth Saunders, Dianne Ward, Marsha Dowda, and Gwen Felton. 1997. A prospective study of the determinants of physical activity in rural fifth-grade children. *Preventive Medicine* 26, pp. 257-63.

Tsunoda, K., Kitano, N., Kai, Y., Tsuji, T., Soma, Y., Jindo, T., Yoon, J. and Okura, T., 2015. Transportation mode usage and physical, mental and social functions in older Japanese adults. *Journal of Transport & Health*, *2*(1), pp.44-49.

Van Acker, V., Van Wee, B. and Witlox, F., 2010. When transport geography meets social psychology: toward a conceptual model of travel behaviour. *Transport Reviews*, *30*(2), pp.219-240.

van Loon, J. and Frank, L., 2011. Urban form relationships with youth physical activity: implications for research and practice. *Journal of Planning Literature*, p.0885412211400978.

van Wee, B. and Ettema, D., 2016. Travel behaviour and health: A conceptual model and research agenda. *Journal of Transport & Health*, *3*(3), pp.240-248.

Verbeke, G., and Molenberghs, G. 1997. *Linear Mixed Models in Practice – A SAS-Oriented Approach*. Springer-Verlag New York, Inc., New York, N.Y.

Walk Score.com. *Live Where You Love*. https://www.walkscore.com/. Accessed April 22, 2019.

Walk Score.com. *Walkibility, Real Estate and Public Health Data*. https://www.walkscore.com/professional/research.php. Accessed April 22, 2019.

Walk Score.com. *Walkibility Research*. https://www.walkscore.com/professional/walkability-research.php. Accessed April 22, 2019.

Wang, K., 2013. Causality Between Built Environment and Travel Behavior: Structural Equations Model Applied to Southern California. *Transportation Research Record: Journal of the Transportation Research Board*, (2397), pp.80-88.

Wannamethee, S.G., Camargo, C.A., Manson, J.E., Willett, W.C. and Rimm, E.B., 2003. Alcohol drinking patterns and risk of type 2 diabetes mellitus among younger women. *Archives of Internal Medicine*, *163*(11), pp.1329-1336.

Wasfi, R.A., Dasgupta, K., Eluru, N. and Ross, N.A., 2016. Exposure to walkable neighbourhoods in urban areas increases utilitarian walking: longitudinal study of Canadians. *Journal of Transport & Health*, 3(4), pp.440-447.

Weinberger, R. and Sweet, M., 2012. Integrating walkability into planning practice. *Transportation Research Record: Journal of the Transportation Research Board*, (2322), pp.20-30.

Wener, R.E. and Evans, G.W., 2011. Comparing stress of car and train commuters. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(2), pp.111-116.

White, S.M. and Rotton, J., 1998. Type of commute, behavioral aftereffects, and cardiovascular activity: A field experiment. *Environment and Behavior*, *30*(6), pp.763-780.

WHO, 2006. *Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide*. World Health Organization.

WHO, 2015. WHO Regional Office for Europe, OECD. Economic cost of the health impact of air pollution in Europe: Clean air, health and wealth. Copenhagen: WHO Regional Office for Europe.

WHO, 2017. Twelfth General Programme of Work: Not merely the absence of disease (2014-2019). *Geneva: World Health Organization*.

WHO, 2018a. Physical Activity. http://www.who.int/topics/physical_activity/en/. Accessed April 30, 2019.

WHO, 2018b. Physical Activity Fact Sheet. http://www.who.int/mediacentre/factsheets/fs385/en/. Accessed April 30, 2019.

Widener, M.J. and Hatzopoulou, M., 2016. Contextualizing research on transportation and health: A systems perspective. *Journal of Transport & Health*, *3*(3), pp.232-239.

Williams, R., 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata Journal*, *12*(2), p.308.

Wood, L., Frank, L.D. and Giles-Corti, B., 2010. Sense of community and its relationship with walking and neighborhood design. *Social science & medicine, 70*(9), pp.1381-1390.

Wooldridge, J.M., 2010. *Econometric analysis of cross section and panel data*. MIT press.

Yarlagadda, A.K. and Srinivasan, S., 2008. Modeling children's school travel mode and parental escort decisions. *Transportation*, *35*(2), pp.201-218.

Yoo, Y.S., Cho, O.H. and Cha, K.S., 2014. Associations between overuse of the internet and mental health in adolescents. *Nursing & health sciences*, *16*(2), pp.193-200.

Zacharias, J., 2005. Non-motorized transportation in four Shanghai districts. *International Planning Studies*, *10*(3-4), pp.323-340.

Zayed, K.N., Ahmed, M.D., Van Niekerk, R.L. and Ho, W.K.Y., 2018. The mediating role of exercise behaviour on satisfaction with life, mental well-being and BMI among university employees. *Cogent Psychology*, *5*(1), p.1430716.

Zhang, M., 2004. The role of land use in travel mode choice: evidence from Boston and Hong Kong. *Journal of the American planning association*, *70*(3), pp.344-36.

Zhang, M. and Kukadia, N., 2005. Metrics of urban form and the modifiable areal unit problem. *Transportation Research Record: Journal of the Transportation Research Board*, (1902), pp.71-79.

Zhao, J., Stockwell, T., Martin, G., Macdonald, S., Vallance, K., Treno, A., Ponicki, W.R., Tu, A. and Buxton, J., 2013. The relationship between minimum alcohol prices, outlet densities and alcohol-attributable deaths in B ritish C olumbia, 2002–09. *Addiction*, *108*(6), pp.1059-1069.

Zheng, Y., Wei, D., Li, J., Zhu, T. and Ning, H., 2016. Internet Use and Its Impact on Individual Physical Health. *IEEE Access*, *4*, pp.5135-5142.

Zick, C.D., Hanson, H., Fan, J.X., Smith, K.R., Kowaleski-Jones, L., Brown, B.B. and Yamada, I., 2013. Re-visiting the relationship between neighbourhood environment and BMI: an instrumental variables approach to correcting for residential selection bias. *International journal of behavioral nutrition and physical activity*, *10*(1), p.1.