ABSTRACT

Title of Document:	THE INFLUENCE OF URBAN FORM AT DIFFERENT GEOGRAPHICAL SCALES ON TRAVEL BEHAVIOR; EVIDENCE FROM U.S. CITIES
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Suburban lifestyle is popular among American families, although it has been criticized for encouraging automobile use through longer commutes, causing heavy traffic congestion, and destroying open spaces (Handy, 2005). It is a serious concern that people living in low-density suburban areas suffer from high automobile dependency and lower rates of daily physical activity, both of which result in social, environmental and health-related costs.

In response to such concerns, researchers have investigated the inter-relationships between urban land-use pattern and travel behavior within the last few decades and suggested that land-use planning can play a significant role in changing travel behavior in the long-term.

However, debates regarding the magnitude and efficiency of the effects of land-use on travel patterns have been contentious over the years. Changes in built-environment patterns is potentially considered a long-term panacea for automobile dependency and traffic congestion, despite some researchers arguing that the effects of land-use on travel behavior are minor, if any. It is still not clear why the estimated impact is different in urban areas and how effective a proposed land-use change/policy is in changing certain travel behavior. This knowledge gap has made it difficult for decision-makers to evaluate land-use plans and policies.

In addition, little is known about the influence of the large-scale built environment. In the present dissertation, advanced spatial-statistical tools have been employed to better understand and analyze these impacts at different scales, along with analyzing transit-oriented development policy at both small and large scales.

The objective of this research is to: (1) develop scalable and consistent measures of the overall physical form of metropolitan areas; (2) re-examine the effects of built-environment factors at different hierarchical scales on travel behavior, and, in particular, on vehicle miles traveled

(VMT) and car ownership; and (3) investigate the effects of transit-oriented development on travel behavior.

The findings show that changes in built-environment at both local and regional levels could be very influential in changing travel behavior. Specifically, the promotion of compact, mixed-use built environment with well-connected street networks reduces VMT and car ownership, resulting in less traffic congestion, air pollution, and energy consumption.

THE INFLUENCE OF URBAN FORM AT DIFFERENT GEOGRAPHICAL SCALES ON TRAVEL BEHAVIOR; EVIDENCE FROM U.S. CITIES

By

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Dedication

To my beloved son, Ilya, who is my pride and joy.

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Chapter 1: Introduction

1.1. Background and Research Motivations

Concerns over high energy consumption and pollution emissions in urban areas have increased in recent years. By itself, the transportation sector is responsible for a high portion of greenhouse gas (GHG) emissions and other pollutants. Additionally, statistics show that between 1970 and 2005, the average annual vehicle miles traveled (VMT) per American household increased by almost 50% (Cervero & Murakami, 2010).

These serious concerns have motivated researchers and urban transportation planners to think about long-term solutions to reduce the amount of automobile travel, through shortening trips (especially commuting) and by encouraging a more sustainable lifestyle by efficient and diverse use of public transit and non-motorized modes (Modarres, 2003). Researchers share a consensual belief about the significant impact of the physical form of urban areas, including their settlement pattern, size, population and employment distributions, as well as transportation infrastructure patterns on economic activities, housing, transportation, energy consumption, and health-related issues (Nasri and Zhang, 2012; Chatman, 2008).

Living in low-density, sprawling neighborhoods can be preferable for the many advantages they provide, such as lower crime rates, less congestion and air pollution, more green space availability, and high-quality educational services, compared to high-density neighborhoods. However, people who live in low-density, suburban areas may also suffer from problems caused by sprawl, such as high automobile dependency and lower rates of daily physical activity, which result in social, environmental and health-related costs (Kelly-Schwartz et al., 2004; Nasser &

Overberg, 2001). On the other hand, people in general prefer living in neighborhoods that offer a shorter commute, pleasant sidewalks, and amenities like retail stores, restaurants, libraries, schools, and public transportation within walking distance, compared to low-density areas with limited options for walking (Haughey, 2005).

Given the aforementioned dis-benefits of a sprawled urban structure and the important role of land use and smart growth strategies, policies promoting compact, mixed-use developments and high transit accessibility are often proposed to offer a more healthy and sustainable lifestyle, and thus considered a popular alternative to urban sprawl. However, there is still no perfect method or tool to compare and evaluate the costs and benefits of compact, mixed-use urban structure and the lifestyle associated with it. The construction and promotion of higher-density, mixed-use development is usually difficult, time-consuming, and expensive for many communities.

With these issues, the question arises of how exactly—and to what extent—the overall physical form of metropolitan areas and the geography of employment distribution affect how often and how far people drive or use transit for their daily trips, and whether or not promoting transit-oriented strategies would help reduce auto dependency and encourage transit use. Finding a reliable answer to these questions, and, in particular, estimating the magnitude of the effect, if any, helps to assess the costs and benefits of implementing long-term land use policy changes toward more infill and transit/non-motorized-friendly forms. Similarly, it would be beneficial to find more evidence on the extent to which the overall land use patterns influence travel behavior.

To answer the above-mentioned questions and find the linkage between land use—at multiple geographical levels—and travel behavior, the present research uses a two-pronged approach. First, it assesses the impact of land use at micro-levels (neighborhood and zone levels) on the amount of driving, using data from five metropolitan areas across the country. Then, it investigates the effects of land use at macro-levels (regional, county, and metropolitan levels), on households' VMT and car ownership. It proposes new methods and variables to comprehensively quantify the built environment at the regional level –as well as at the local level- and then links the measures with travel survey data across several metropolitan areas in the United States. An advanced structural equations modeling method is employed to capture the causal effects, rather than only observing statistical correlations among variables.

Moreover, this analysis addresses the issue of residential self-selection, which has long been the center of debate among researchers who believe that the correlation between travel behavior and land use is at least partially explained by residential self-selection (Kitamura et al., 1997; Krizek, 2003a; Schwanen & Mokhtarian, 2005; Handy et al., 2005; Mokhtarian & Cao, 2008). Residential self-selection is defined as the tendency for individuals and businesses to locate in areas that meet their travel preferences (e.g., those who tend to drive less are more likely to choose to live in transit-friendly neighborhoods). With the self-selection issue addressed, it is easier and more accurate to ascertain to what extent the observed correlation between the built environment and travel behavior represents a causal effect. In the present research, self-selection impact has been captured by pursuing the "instrumental variable" approach as the most appropriate method to address the issue, given data and resource availability. This method has been used as an advanced tool by a number of researchers (Boarnet & Sarmiento, 1998; Greenwald & Boarnet, 2001; Khattak & Rodriguez, 2005; Vance & Hedel, 2007), when attitudinal and direct questioning are not available options.

1.2. Research Objectives

The importance of effective and efficient land use planning in urban areas is undeniable. Many social, environmental, economic, and health-related costs and problems of high automobile dependency could be avoided by changing land use plans and policies and by reducing sprawl. This, of course, requires a thorough understanding of the current urban structure and settlement patterns, as well as how to restructure land use policies to promote sustainable transportation.

There is a lack of empirical research on the overall physical form of the urban environment, how to measure it at different scales and the connections between travel behavior and the multi-scale built environment and urban design. This dissertation attempts to examine the statistical association between travel behavior and the built environment using advanced spatial-statistical models. The knowledge developed from this research carried out over several case study areas. When integrated with existing literature on the relationship between neighborhood-level built environment and travel behavior, it could provide unique evidence for examining the overall influence of the built environment and urban sprawl on travel patterns in a detailed and comprehensive way.

This dissertation pursues three main objectives: first, to highlight the similarities/differences of metropolitan areas by size, urban morphology, population and employment distributions, socio-demographics, and land use and urban design patterns; second, to propose a new, unique method to quantitatively measure the micro-and macro-level built environment and multimodal accessibility, through the use of various land use characteristics that can be easily applied in different metropolitan areas, and; third, to perform a comprehensive analysis of the causal relationships between the built environment and travel behavior, using advanced modeling techniques and data from several case study areas across the country.

In addition, comprehensive models have been developed to analyze the effects of the popular planning strategy, transit-oriented development (known as TOD), on various travel behavior components including trip generation, distribution, VMT, and mode choice. The aim is to measure and investigate to what extent TOD policies have been successful in achieving their hypothesized goals of auto trip reduction through the promotion of transit use and non-motorized modes.

1.3. Research Contributions

Empirical research on the connection between travel behavior and the built environment at different scales is limited in the body of literature. To date, this study is one of the first disaggregate analyses that measures various dimensions of urban form at different hierarchical scales (micro versus macro levels) and develops advanced statistical modeling methods to fill in existing methodological gaps by capturing causality and self-selection effects using a wide range of built environment variables and household-level data. Therefore, the main contribution of this study is that it presents a more useful and rigorous method to systematically link urban form to travel choices than previous, similar studies.

This dissertation contributes to the body of literature by looking at the urban form in the entire metro area as a consolidated system, as opposed to a set of zones and neighborhoods. It addresses the question of how and to what extent the macro-level built environment and the overall structure of urban areas influence urban daily travel. It provides additional insights into both theoretical and empirical aspects of the broad topic of the relationship between the built environment and travel behavior.

From a theoretical point of view, the present study provides novel methods to better understand, define, and quantitatively measure the overall physical form of the built environment in U.S. cities. It also tries to comprehensively address the inter-relationships between land use and travel behavior by measuring various aspects of urban form and considering its relationship with different travel behavior indicators.

From a practical point of view, this research contributes to the literature by using very recent, detailed land use and travel behavior data for several metropolitan areas in the United States, and employing advanced econometric methods. Data has been collected by contacting individual state and local planning agencies to ask for the most up-to-date travel survey data and land use data. After receiving the data from several agencies around the country, it has been processed and compiled into one single consistent dataset for modeling purposes. This extensive data collection and processing effort has not been done before and makes the data used for this study a unique dataset which could be used for many other travel behavior analyses in the future.

Three hierarchical geographical levels to measure the built environment have been considered in this research; neighborhood/local level (measured by TAZ/Census Tract/Census Block Group), county/regional level, and the whole metro area as the highest level of analysis. Moreover, since the data used in the analysis consists of several case study areas located in various regions of the country, this analysis could be better generalized to the whole nation, compared to several other studies that only focus on a single or a few metropolitan areas.

Moreover, the present study contributes to the current literature on policy analysis by examining the popular urban design policy of transit-oriented development (TOD). It proposes new ideas on how to define TODs–both conceptually and quantitatively–and provides new mathematical, scalable methods for measurement and delimitation of TOD boundaries. It further applies this definition to case study areas followed by comprehensively modeling trip generation, distribution, mode choice, and VMT in the TOD versus non-TOD areas. Results of the TOD analysis show that households living in TOD areas are generally less auto-dependent. They produce more trips but lower VMT, compared to the residents of non-TOD areas, which implies shorter trips as well as higher use of public transit.

Furthermore, a nationwide analysis was conducted for all major fixed-guideway transit stations across the country, in order to investigate the mode share for residents living within walking distance from the stations. This study provides additional evidence on how transit-friendly urban design strategy could help reduce automobile use and promote more sustainable travel modes, such as transit and walking, and thus cope with ever-growing traffic congestion in urban areas.

1.4. Research Organization

The remaining chapters of this dissertation are organized as follows:

Chapter Two presents a comprehensive overview of the past research on the topic, and summarizes the major findings in the body of literature on the relationship between land use and travel behavior. It also outlines the proposed strategies and policy scenarios to cope with urban sprawl and improve accessibility, connectivity, and overall sustainability in urban design, as well as the main issues faced by the researchers over the years in the analysis of travel behavior in urban areas. Lastly, it provides a brief discussion of the main motivating issues and needs for performing the present study.

While the detailed data description and extensive calculation methods for the variables used in the present study have been provided in each chapter separately, chapter Three briefly introduces the various datasets used in the analysis (especially the travel survey data), and gives a general overview of the variables used in the models both directly or indirectly from the datasets. It also discusses the structure of the data and how various datasets were linked using spatial or statistical tools.

Chapter Four develops a multi-level, mixed effect regression model of per person VMT as a function of socio-demographic characteristics and land use characteristics at the neighborhood level in five U.S. cities: Seattle, WA; Richmond-Petersburg, VA; Norfolk-Virginia Beach, VA; Baltimore, MD; and Washington, D.C.

Chapter Five starts with an overview of the proposed measures of metropolitan-level land use and descriptive statistics of those measures for the 50 most populous metropolitan areas in the United States. Variables, their source of data, and calculation methods are introduced in detail, and a cluster analysis performed to group the metro areas based on their urban structure and land use pattern has been developed.

Chapter Six discusses how the macro-level built environment influences travel behavior of the residents in more detail. Using disaggregated travel survey data (at the household level) for 19 case study areas across the country, it develops a structural equations model for households' VMT and car ownership as endogenous and land use measures at zone, county, and metropolitan levels, as well as socio-demographic characteristics of the households as exogenous variables. It then provides a detailed discussion on the results and the issue of residential self-selection.

Chapter Seven introduces transit-oriented development (TOD) as a popular planning strategy to encourage transit use and reduce the amount of automobile trips, which anticipates improvement of traffic congestion in urban areas as well. It first proposes a new mathematical method to identify TOD zones in metropolitan areas, based on measures of transit accessibility and other land use characteristics of TODs. It then develops various statistical models of trip generation and distribution, households' VMT, and mode choice in Washington, D.C. and Baltimore Metropolitan areas with respect to TOD development, and discusses the potential effects this type of development has on travel behavior of those who live or work in TODs. Chapter Seven concludes with a nationwide analysis of transit-friendly neighborhoods and a statistical analysis of the commute mode share of residents in these neighborhoods for around 4,000 rail transit stations across the country.

Finally, Chapter Eight provides a summary of the major findings and conclusions, the main study's limitations, and a discussion of future research opportunities.

Chapter 2: Urban Form and Travel Behavior: A Comprehensive Literature Review

For decades, researchers have tried to understand and find the linkage between the physical form of urban settlements and the way people travel to reach destinations. In this chapter, an extensive literature review is provided on the influence of urban structure pattern on travel behavior and residential location choice. It discusses research findings on how the built environment, both at the local and regional level could affect how often and how far people drive, their choice of auto ownership, and the acknowledged benefits and drawbacks of a compact, mixed use land use pattern and urban design strategies. The review covers both theoretical and empirical works done in the past on this topic. In addition, previous research on issues related to this topic, such as the residential self-selection effect, spatial auto-correlation, inter-trip dependency, and geographic scales (Krizek 2003b; Bottai et al. 2006; Chen et al. 2008; Frank et al, 2008) are reviewed and summarized in this chapter and the following chapters.

This section is divided into three sub-sections. First, it discusses the literature focused on micro-level built environment effects. Second, it introduces the past research done on the overall impacts of urban form at higher geographical levels on travel behavior. The third sub-section shares the literature that examines how to address the effects of residential self-selection and how to separate these effects from the actual built environment impacts on travel patterns. In each sub-section, the reviewed literature is divided into two groups. The first group are those researchers who support the idea of compact, mixed development and claim that developing policies related to this idea and living in these types of urban neighborhoods will actually encourage less automobile use and promote more sustainable, less auto-dependent life-style.

Contrary to this claim is the other group of researchers, who believe that this effect is minor and negligible, if it exists at all. Both groups have provided various research approaches and techniques to investigate and support their beliefs.

Although the amount of literature on the topic is considerable (see Crane, 2000, Ewing and Cervero, 2001 & 2010, and TRB, 2009 for reviews of this literature), the very mixed nature of empirical findings does not allow for a consensus on the actual impact of built environment on travel pattern.

2.1. Introduction

The linkage between the built environment and travel behavior has been intensively studied since the 1980s. Despite many mixed findings, there has been a growing recognition that changes in built environment characteristics can potentially have a significant impact on people's travel behavior in urban areas. Recent research suggests that people who live in neighborhoods with transit- and pedestrian-oriented design—characterized by good street connectivity, mixed land use, and high population density—are encouraged to drive less and switch to other modes, such as transit, walking, and bicycling (Cervero, 1996; Frank, 2000; Kitamura et al., 1997).

Researchers criticize the sprawling pattern of urban areas in the United States, mainly because they promote auto dependence, generate longer commutes, worsen traffic congestion, cause air and water pollution, and are financially inefficient (Cao et al., 2007; Haughey, 2005). In contrast, they support infill development, which offers shorter commutes and provides easy access to restaurants, shopping, and schools within walking distance. However, some argue that this type of development may not be as successful in achieving the aforementioned goals as expected, and may even increase crime rates, worsen traffic congestion, and reduce property values (and thus, affect economic growth). More empirical analysis is required to investigate these issues and help planners and decision-makers in setting their long-term land use policies.

Over the years, debate about the potential impact of changing land use patterns on travel behavior has motivated researchers to produce numerous papers and journal articles on the topic. So far, this debate has reached no consensus due to the complex relationship between the built environment and travel patterns, and because of different views and conclusions on whether changing land use policies significantly and effectively influence people's travel behavior (Crane, 2000). Hundreds of empirical studies, varied in methodology and data, have tried to explore this relationship, as well as the short and long-term travel behavior indicators they modeled. Most of these studies argue that residents of high-density, pedestrian-friendly neighborhoods where transit is easily and efficiently accessible, and where jobs and retail spaces are closer to residential places, tend to drive less and live a more healthy sustainable life (Frank & Pivo, 1994; Kitamura et al., 1997; Cervero & Murakami, 2010; Bento et al., 2005).

2.2. Micro-Level Built Environment and Travel Behavior

The linkage between the built environment and travel behavior was not highlighted or intensively analyzed until the 1980s. In theory, built environment characteristics can influence travel behavior on different time scales and through various mechanisms. Boarnet and Crane (2001) suggested that the built environment influences the price/generalized cost of travel through its short-run impact on travel time and other factors, which then influences the consumption of travel. Long term, the built environment can influence the location choices of households and businesses, and consequently, their travel decisions. Land use dynamics can also have a less immediate and more indirect effect on travel behavior through their impact on activity-travel attitudes over time.

Early studies focused on the connection between land use density and transit use (Pushkarev & Zupan, 1977). Driven by recent policy debates related to new urbanism and smart growth, a number of studies have examined the effect of the built environment on travel behavior at a disaggregate level. In general, these studies attempted to quantify the correlation and understand the structure between the two. Plenty of studies have found statistically significant impacts of various built environment factors on travel behavior, such as mode choice, trip generation, trip length, trip chaining, and VMT (Cervero, 1996; Cervero & Kockelman, 1997; Ewing & Cervero, 2001; Frank et al., 2007; McMullen et al., 2008). Built environment characteristics examined include density, diversity, block size, sprawl indicators, and network connectivity. In contrast, a number of studies have shown insignificant or negligible impacts of certain land use patterns on certain travel behavior (Boarnet & Sarmiento 1998; Boarnet & Crane 2001). Other studies have empirically examined the reverse impact of transportation on land use (e.g., Hanson & Genevieve 2004; Zhang 2010), which is not the focus of this research.

After a comprehensive review of the literature, the present study builds hypotheses about the impacts of the built environment on travel behavior in urban areas. The underlying hypotheses about the influence of various dimensions of urban form (known as the 5-Ds) on travel behavior (vehicle miles of travel) have been outlined in Table 2-1. Higher residential and employment densities, and a better mixture of residential and various types of employment in neighborhoods are thought to be associated with lower VMT. The level of street connectivity and walkability are positively linked to the amount of auto travel, and encourage more non-motorized activities, especially for non-work trips (Cervero and Kockelman, 1997). Also, living in neighborhoods with higher destination accessibility (closer to CBD or regional employment centers) and easier access to transit, facilitates transit use and discourages automobile use.

Table 1-1 Hypothesized Effects of Built Environment Factors (the 5-Ds) on VMT

Measure	Definition/quantitative measures	Hypothesized impact on VMT
Residential **D**ensity	Population/Area size	Negative*
Employment **D**ensity	Employment/Area size	Negative
Jobs/Housing **D**iversity (Land use mix)	Mixture of residential, retail employment, service employment, and other employment land use types	Negative
Walkable **D**esign (Street connectivity)	Average block size/Intersection density	Positive**
Destination accessibility	Distance from the CBD/ regional employment subcenters	Positive
Distance to Transit	Transit-oriented Development Analysis/ Distance to rail or bus station	Positive

* "Negative" herein means higher residential density leads to lower VMT per person, which is desirable.
** "Positive" herein means larger block sizes leads to higher VMT per person, which is undesirable.

Previous studies have typically used census block, tract, and Traffic Analysis Zone (TAZ) as the geographic units, probably because land use and travel data are usually available at these levels. Several studies have shown that land use patterns measured at different geographic resolutions can produce different empirical estimates (Zegras, 2010; Boarnet & Crane, 2001). It is conceivable that some significant effects may only be found at certain geographic levels. For instance, while non-motorized trips are mostly sensitive to local neighborhood characteristics, the characteristics of auto commuting trips are influenced more by regional land use patterns. In the neighborhood-level analysis presented in this dissertation (see Chapter 4), TAZ and census tract (in one case) have been used as the spatial units of analysis for data and model consistency. The census tracts used in one case study area are approximately similar in size to TAZs in the remaining cases.

Several well-known methodology issues arise when the impacts of built environment on travel behavior are examined. First, the correlation between travel behavior and neighborhood characteristics is at least partially explained by residential, or spatial, self-selection (Kitamura et al., 1997; Krizek, 2003a; Schwanen & Mokhtarian, 2005; Handy et al., 2005; Mokhtarian & Cao, 2008). Spatial self-selection is defined as the tendency for individuals and businesses to locate in areas that meet their travel preferences (e.g., those who tend to drive less are more likely to choose to live in transit-friendly neighborhoods). With self-selection, it is difficult to ascertain to what extent the observed association between the built environment and travel behavior represents a cause-effect relationship. Studies found that failing to account for self-selection results in overestimation of the influence of the built environment on travel. A more detailed discussion on the issue has been provided in a separate section (section 2.4).

In addition to self-selection problems, other issues that can confound the relationship between the built environment and travel behavior include spatial auto-correlation, inter-trip dependency, and geographic scales (Krizek, 2003b; Bottai et al., 2006; Chen et al., 2008; Frank et al., 2008). Spatial auto-correlation is a problem in geographic analysis, since individuals and firms located in the same spatial unit are likely to be similar in ways not accounted for by their observable characteristics. Spatial heterogeneity is also an issue in geography, wherein relationships between variables differ across spatial contexts. Ignoring these issues can result in model misspecification and biased estimates of standard errors in linear models.

Finally, it is interesting to note that Burchell and Lahr (2008) studied land use policies for several major U.S. cities and found that the institutional structure for land use decision-making is different in each location. For instance, in some cases, cities and other local governments have autonomous and dominant control over land use decisions (e.g., Maryland, Virginia, and many other East Coast and New England states), while in other cases, state and regional governments have much stronger control over land use policies. It is reasonable to hypothesize that centralized and decentralized land use decision-making processes can lead to different impacts of land use on travel behavior.

2.3. Macro-Level Built Environment and Travel Behavior

Recent research suggests that people who live in neighborhoods with pedestrian-oriented design—characterized by good street connectivity, mixed land use, and high population density—are encouraged to drive less and switch to other modes, such as transit, walking, and bicycling (Cervero, 1996; Frank, 2000; Kitamura et al., 1997).

In general, studies that explore the connections between the built environment and travel behavior have taken two approaches, based on different spatial scales that are used to characterize the built environment. One employs the macro approach and examines the regional urban development characteristics of metropolitan areas. The other follows the micro approach that concentrates on the influence of neighborhood design characteristics.

The majority of the existing research has taken the micro approach, with a primary focus on built environment and land use characteristics at the local and neighborhood level, such as residential and employment density, land use mix, street connectivity, accessibility, and so forth. Therefore, these studies suffer from significant methodological issues. Researchers believe that, as a consequence of improved mobility, travel behavior has become more connected to large-scale land use and the overall spatial form of metropolitan areas (Nasri & Zhang 2012). As a result of increased mobility, activity space is shaped around home and work locations, as well as along the commute route (See Figure 6-1). With larger activity spaces, the connection between macro-level built environment patterns becomes more important and ignoring such connections makes the analyses less reliable. However, most of the studies in the past only looked at land use patterns in the immediate neighborhood of residence and neglected the overall composition of the surrounding metropolitan area.

Relatively limited empirical analyses are provided on how the built environment at regional and city levels could affect people's travel behavior (Boarnet & Sarmiento 1998; Bento et al. 2005), and almost all of them found that the effect of land-use at higher levels are more or at least equally significant as the neighborhood-level built environment. Those who pursued the macro approach addressed the rapid process of urbanization in the United States, which has recently changed from city or urban formation, to the agglomeration of urban areas, into metropolitan areas or large mega-regions, as a leading factor in increased automobile-based mobility (Berube, 2007; Ross, 2009). Because of the increased mobility, individuals or households who are looking for jobs, entertainment, and shopping opportunities are no longer restricted to opportunities located in their own residential neighborhoods and cities, and are more likely to travel to destinations that are further away within a relatively constant travel time (Schafer 1998). Therefore, the physical form of metropolitan areas, including their land use and settlement patterns, their size, population, employment, and transportation infrastructure patterns, could potentially have a significant impact on economic activities, housing, transportation, and energy consumption (Gomez-Ibanez et al, *2009*).

Hence, travel frequency, travel time, mode choice, and destination choice for daily travel have become more dependent on large-scale built environment characteristics. Empirical research suggests that the metropolitan structure—such as the degrees of concentration and decentralization, the regional employment centers, the overall density, and the job-housing balance—could be more influential in travel, and especially commuting behavior, than the typical neighborhood-level built environment features (Newman & Kenworthy, 1999; Horner, 2002; Shen, 2000; Yang, 2008; Yang & Ferreira, 2008). Therefore, it is necessary to examine how people's travel behavior is affected by the metropolitan-scale built environment, in addition to local-level land use characteristics.

In recent years, a few studies have introduced the impact of sprawl as one of the main factors of the metropolitan-level built environment (Nasser & Overberg, 2001; Ewing, Pendall, & Chen, 2002; McCann & Ewing, 2003; Kelly-Schwartz et al., 2004). However, to measure sprawl, the majority of these studies only focused on density and its change over time; little is known about other characteristics of the metropolitan-level built environment and its potential impacts on transportation-related issues in urban areas.

Studies in the past have failed to fully measure the large-scale characteristics of the built environment. The Kain and Fauth study (1976) was one of the earliest studies to use disaggregate data from 125 metropolitan areas to explain travel behavior as a function of urban form, by considering the overall arrangement of land uses, density, juxtaposition of homes and workplaces, in combination with the transit and highway networks. Their measures of the built environment at the metropolitan level included central city density, CBD employment, percentage of single-family housing stock, workplace composition, and highway and transit service supply in each area. Despite the novelty of considering the overall form of metropolitan areas, this study–similar to several other recent studies–does not go farther than the measures of decentralization to address the overall metro-level urban form.

On the other hand, most studies to date confirmed only an association between the built environment and travel behavior. Few have tried to capture causality, especially the direction of causality, which has two ends: one establishes the "true" effect of land use pattern on travel behavior, while the other is the endogeneity issue emphasizing residential location choice based on behavior and personal taste—widely addressed as self-selection. Those who provided cause-effect analyses found that the effect of the built environment on travel pattern is both statistically and practically significant, even after controlling for taste and attitude (Cao et al., 2007; Ewing & Cervero, 2010).

2.4. Residential Self-Selection in the Literature

The argument on the true effect of the built environment on travel behavior, regardless of geographical level, has been going on for so long because of the complex nature and various issues involved. One of the very controversial issues involved in this discussion is the issue of "residential self-selection." It is argued that the observed relationship between living in high-density, transit- and pedestrian-friendly neighborhoods, and lower rates of automobile use among

American households, is partly because households who prefer transit and active transportation over automobiles seek out these neighborhoods and somehow “self-select” to live in them. If this effect is large and is not statistically controlled, estimations of the effect of the built environment on travel behavior will be biased. If that is the case, as some researchers have argued, it implies that changing land use policies and developing more high-density, mixed-use areas might not have the intended influence on changing people’s travel behavior toward less automobile use and more transit ridership. On the other hand, if the supply of such neighborhoods is limited, and the number of self-selector households is large–which means that more people are responsive to built environment characteristics– changing land use policies would be even more effective in changing travel behavior.

Given the significance of this issue, it has received much scholarly attention over the years and researchers have tried to quantify this effect using several different approaches (Cao et al., 2009). There exists mixed findings on the significance and magnitude of the effect of taste and attitude on travel behavior. Several studies that performed cause-effect analyses found that the effect of the built environment on travel pattern is both statistically and practically significant, even after controlling for taste and attitude (Cao et al., 2007; Ewing & Cervero, 2010), while many other studies claimed the opposite. For example, Kitamura et al. (1997) was probably the first study to address the issue of self-selection–without calling it so—by adding data on personal attitudes as explanatory variables. They found that the effect of self-selection is quite significant and can explain behavior even better than the land use characteristics. More recently, several other studies found this effect significant, and in some cases, even more significant than the true effect of land use; ignoring such impact can result in the over-estimation of the effect of land use on travel (Bagley & Mokhtarian, 2002; Cao et al., 2007; Chatman, 2005).

Self-selection can be controlled in various ways, as it is categorized in Cao et al. (2009), such as incorporating a rich set of socioeconomic factors that correlate with travel attitude (Brownstone & Golob, 2009; Brownstone, 2008); travel attitudinal variables (Kitamura et al.,1997; Chatman, 2009 ; Handy & Clifton, 2001); structural models that consider two-way effects (Grazi et al., 2008; Vance & Hedel, 2007; Boarnet & Sarmiento, 1998); and longitudinal behavior analysis that focuses on observed behavior changes, rather than relying on stated preference surveys or reported changes (Cao et al., 2009).

In the present research, cross-sectional data is used; among the case study areas that were analyzed, only a few have behavior/attitude data (e.g., attitudinal factors) that allow for the direct control of self-selection effects. Therefore, I had to pursue approaches other than direct questioning and longitudinal analysis methods to address this issue. A rich set of households' socio-demographic characteristics was used in all statistical models developed, and those variables can explain the taste/attitude and expected travel preferences of households to some extent. Also, in the structural models, I used an instrumental variable method in order to better capture the possible effect of residential self-selection. Detailed results, interpretation and discussion are provided in Chapter Six.

Chapter 3: Data

3.1. Introduction

To test the hypotheses discussed in previous sections, this study employs advanced spatial/statistical tools using variables to capture the built environment dimensions at several hierarchical levels. Data is obtained and spatially processed for 50 metropolitan areas across the United States.

The data used in the present research includes various factors that capture trip information, travelers' characteristics, land use and employment characteristics, transit accessibility (rail and bus), and road network data. Therefore, several primary fields such as household and person ID, trip ID, and geocoded location ID were used to spatially link all the variables together and prepare them for the final modeling steps. The data was collected from multiple sources. The primary data source was the National Household Travel Survey (NHTS) 2009 and the NHTS add-on data for the cities of Atlanta, GA, Phoenix, AZ, and New York City, the states of Virginia, Florida, California, and North Carolina, as well as travel survey data from local and state agencies, and Metropolitan Planning Organizations (MPOs) for the rest of the study areas. These datasets contain detailed traveler characteristics and trip information, as well as vehicle characteristics, and are geocoded at census tract or TAZ levels.

Land use data contains population and employment information by employment type, as well as the transit station location information and road network for all road types. Five primary land use factors were calculated using the land use data at zone or census tract levels: residential density, employment density, land use mix (entropy), distance from CBD, and average block size.

Residential and employment densities were calculated by dividing the number of residents or jobs within a certain zone by the area of that zone by acre. Entropy measure indicates the extent of mixed-land development (e.g., houses, shops, restaurants, offices) and was computed using the following equation:

$$\text{Entropy} = -\sum_j \frac{P_j{}^* * \ln(P_j{}^*)}{\ln(J)}$$

where P_j =The proportion of land use in the jth land use category,

J= The number of different land use type classes in the area

This entropy measure ranges from zero (homogeneous land use such as housing-only divisions, often found in rural and suburban areas) to 1 (most diverse and equally mixed land use, sometimes found in city centers).

The distance from CBD as a measure of destination accessibility was calculated by measuring the straight line from each zone's centroid to the centroid of the central business district in ArcGIS. In order to measure street connectivity and the degree of pedestrian-friendliness, average block size was calculated using the census block shapefiles from the Census TIGER website. Clearly, zones closer to downtown areas indicate smaller average block size, whereas zones located farther away in the suburbs indicate larger average block size and thus less street connectivity.

Also, to calculate many other variables such as historical gas price, lane mile density, and congestion level (index), data were obtained from private sources. In the following subsections, the data structure, data sources, and a detailed list of all variables used in the study, along with their definition/calculation method, are presented.

This chapter introduces the various travel survey, land use, and other related datasets used in the present research, along with their sources. An elaborative list of variables included in the datasets and their calculation methods have been provided in two separate sub-sections for both travel characteristics and the built environment measures.

3.2. Data Sources

The National Household Travel Survey (NHTS) is a national database funded by the U.S. Department of Transportation, which periodically collects information regarding purpose of trips, trip time and duration, travel mode used on a trip, time of day and day of week when the trip was made, etc., for a two-day period, from thousands of American households.

The most recent survey was conducted in 2009 and is the main source of travel behavior data used in the present study. The NHTS 2009 surveyed 150,000 households across the country about their travel information, along with detailed information regarding their socioeconomic and demographic status such as age, income, household size, race, employment status, vehicle ownership, etc. In addition to the national file, there exists some add-on data for 16 states[1] that includes an additional 125,000 households surveyed. This add-on survey has more detailed information on households and travel characteristics, such as geocoded home and work locations,

[1] Participating states include Arizona, California, Florida, Georgia, Indiana, Iowa, Texas, Nebraska, New York, North Carolina, South Carolina, South Dakota, Tennessee, Vermont, Virginia, and Wisconsin.

and geocoded trip origin and destination location. There are also several additional questions in the survey regarding attitude and behavior. Figure 3-1 highlights the 16 states that participated in the NHTS add-on program. This study uses the NHTS national data and the add-on data from Arizona, Georgia, Florida, North Carolina, Virginia, and New York. Travel survey data for a few metropolitan areas was obtained from their local planning agencies. As a result, 19 metropolitan areas are included for the disaggregate-level travel behavior analysis.

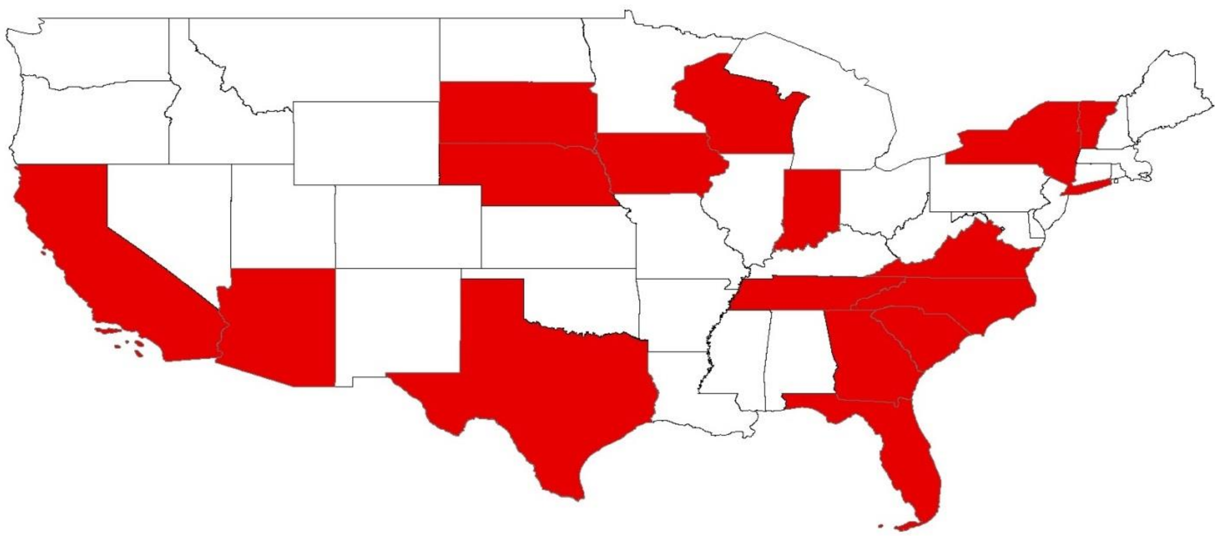

Figure 2-1 NHTS Add-On States

Land use data, including geocoded population and employment information, was also obtained from the local and state agencies by contacting them directly. Table 3-1 lists the agencies that provided the land use/travel survey data specifically for the present study. In addition, land use data for the policy analysis part of this research was obtained from the Smart Location Database (SLD) developed by the Environmental Protection Agency (EPA), and provides demographics, employment, and built environment measures at the census block group level. This rich, nationwide dataset uses the five *D*s, including residential and employment *density*, land use *diversity*, *design* of the built environment, access to *destinations*, and *distance* to transit, as the main built environment characteristics, using several different data sources[2]. These include the following five major sources:

1) Census datasets, such as TIGER/Line shapefiles, 2010 Summary file 1, American Community Survey, and Longitudinal Employer-Household Dynamics (LEHD);
2) NAVTEQ highway/streets and parks data;
3) Protected Areas Database for the United States (PAD-US);
4) Fixed-guideway transit station locations from the national TOD database; and
5) Local transit service data from the General Transit Feed Specification (GTFS).

Table 2-1 Metropolitan Planning Agencies and Data Sources/Dates

Metropolitan Area	Planning Agency	Travel Survey	Land use
Atlanta, GA	Atlanta Regional Commission	ARC Survey 2001	2009
Baltimore, MD	Baltimore Metropolitan Council	TPB/BMS 2008	2005
Binghamton, NY	Binghamton Metropolitan Transportation Study	BMTS Survey 2008	2009
Cleveland, OH	Northeast Ohio Areawide Coordinating Agency	NHTS 2009-National	2010
Daytona Beach, FL	Volusia County MPO- Daytona Beach, FL	NHTS 2009-National	2010
Houston, TX	Houston-Galveston Area Council	NHTS 2009-National	2010
Jacksonville, FL	First Coast MPO- Jacksonville, FL	NHTS 2009-National	2010
Los Angeles, CA	Southern California Association of Governments	NHTS 2009-National	2010
Nashville, TN	Nashville Area MPO	NHTS 2009-National	2008
Philadelphia, PA	Delaware Valley Regional Planning Commission	NHTS 2009-National	2010
Rapid City, SD	City of Rapid City	NHTS 2009-National	2008
Richmond, VA	Virginia DOT	NHTS 2009- Add-On	2010
San Diego, CA	The San Diego Association of Governments	NHTS 2009-National	2008
San Francisco, CA	Metropolitan Transportation Commission, Oakland, CA	NHTS 2009-National	2000

[2] Please see the SLD User's guide at: http://www.epa.gov/smartgrowth/pdf/sld_userguide.pdf

Seattle, WA	Puget Sound Regional Council	PSRC Survey 2006	2005
Sioux Falls, SD	City of Sioux Falls	NHTS 2009-National	2008
Tallahassee, FL	Capital Region Transportation Planning Agency- Tallahassee, FL	NHTS 2009-National	2007
Virginia Beach, VA	Virginia DOT	NHTS 2009 Add-On	2010
Washington, D.C.	Transportation Planning Board at the MWCOG	TPB/BMC 2008	2005

The National TOD Database was also obtained and used in order to get geocoded information for all fixed-guideway transit stations in the country. This publicly available dataset provides geocoded information on existing, planned, and proposed fixed-guideway stations in 50 metropolitan areas across the entire country, along with aggregated, demographic and travel information in the quarter and half-mile buffer around those stations.[3] The present study only uses the data for the existing stations.

Household travel survey data from local and state planning agencies was either obtained directly from the local/state planning agencies or downloaded from the "Metropolitan Survey Archive" website.[4] This website provides free access to the most recent travel survey data for about 45 metropolitan areas across the country. The Bureau of Transportation Statistics and the Federal Highway Administration funded and—with collaborations from the University of Minnesota—created this website to store and preserve the travel surveys conducted by metropolitan areas, states, and localities, while making it publicly available for free.

[3] National TOD Database website: http://toddata.cnt.org/
[4] http://www.surveyarchive.org/index.html

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3.3. Data Structure and Variables

3.3.1. Personal and Travel Characteristics

The 2009 NHTS data was used as the main source of travel behavior information and contains four separate datasets, including household, person, trip, and vehicle datasets. Each contains detailed information for each observation regarding the socioeconomic and demographic characteristics, as well as travel information (see Figure 3-2).

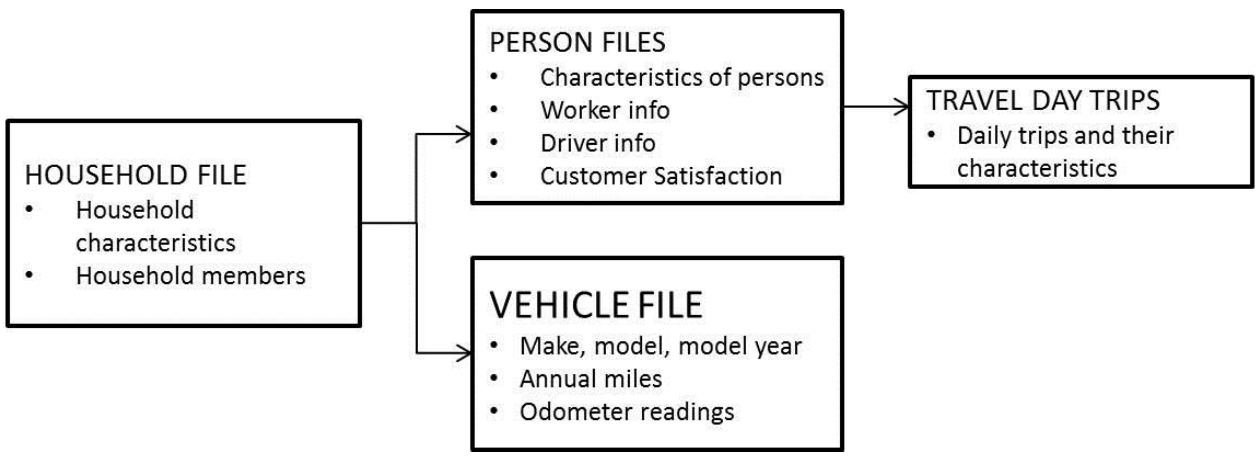


Figure 2-2 NHTS Data Structure/Components

ID numbers have been assigned to each household, person, and each trip reported by the respondents; these ID numbers enable us to join these separate data files together for the purpose of modeling travel behavior. Table 3-2 lists a summary of the main information each of these files contains and briefly describes their definition/explanation.[5] In addition to these main

[5] Source: NHTS codebook/data dictionary

variables in the national NHTS data, there are several other variables in the add-on data regarding individuals' attitudes and travel preferences toward various predefined scenarios, in order to estimate their taste/lifestyle. For example, the respondents were asked why they think public transit is a good option for commuter/non-commuter trips, their reasons for not biking, whether or not their medical conditions require them not to drive/use public transit/use special transit services, etc. For transit riders, questions were asked regarding the safety, reliability, cost, and comfort of using public transit. In addition, people were given a set of scenarios (such as facility improvements) and if, under these scenarios, they would walk/bike more often. For walking/cycling respondents, questions were asked regarding the reason for walk/bike trips and the issues they face while walking/biking, such as long distance between destinations, safety issues, amount/speed of traffic along the route, etc. Respondents were also asked about reasons for not walking/biking.

In the NHTS add-on data, the geocoded home location, work location, and the trip end location has also been provided (at both block group level and the exact point location). This allows for investigating the effect of the built environment on travel behavior, not only at the origin, but also at the trip destination location.

Table 2-2 NHTS Data Structure and Variables' Description-Summary

Variable's Name	Variable Description	Code/Range
HOUSEHOLD (HH)		
HHSIZE	Count of HH members	1-13
HHFAMINC	Total HH income last 12 months	01-18
HHVEHCNT	Count of HH vehicles	0-99
DRVRCNT	Count of drivers in HH	0-8
HHR_RACE	Race of HH respondent	--
HOMEOWN	Housing unit owned or rented	01=owned, 02=rented, 03=occupied without payment of rent
HOMETYPE	Type of housing unit	Single family detached etc./ 6 types
LIF_CYC	HH life cycle	--
WRKCOUNT	Count of HH members with jobs	1-6
HHSTATE/	HH location; state and county	FIPS code for home address

HHCNTYFP		
HHCT	HH Census tract	Tract FIPS code
HHBG	HH block group	Add-on only
PERSON		
R_AGE	Respondent Age	0-115
R_SEX	Respondent gender	01=Male, 02=Female
EDUC	Highest grade completed	01-05
EVERDROV	Has been a driver in the past	01=Yes, 02=No
WORKER	Worker Status	01=Yes, 02=No
WKFTPT	Work full or part-time	01=Full-time, 02=Part-time, 03=Multiple jobs
WORKLOC	Respondent work location	01=Workplace, 02=Only at home, 03=No fixed workplace
WRKTRANS	Transportation mode to work last week	01=Car, 02=Van, 03=pickup truck, etc.
DISTTOWK	One-way distance to workplace (miles)	Distance in mile
PRMACT	Primary activity last week	01=working, etc. 01-07
DISTTOSC	Distance home to school	01=less than ¼ mile, etc.
TRIP		
ENDAMPM	Travel day trip end time AM/PM	--
STRTAMPM	Travel day trip start time AM/PM	--
ENDTIME	Trip END time in military	--
HH_ONTD	Derived number of HHMs on trip	0-10
NUMONTRP	Count of total people on trip	0-16
PUBTRANS	Respondent Used Public Transportation on trip	--
TRIPPURP	General Trip Purpose (Home-Based Purpose types)	--
TRPMILES	Calculated Trip distance converted into miles	0.11-11050
TRPTRANS	Transportation mode used on trip	25 modes
TRVL_MIN	Derived trip time - minutes	0-200
WAIT_MIN	Length of wait for public transit - minutes	0-200
TRACC1	1st mode used to get to public transit	25 modes
TREGR1	1st mode used from public transit to destination	25 modes
DROP_PRK	Parked or dropped off at public transit	01=Parked, 02=Dropped off
VEVICLE		
MAKENAME	Vehicle make name	Text/ vehicle make name
MODLNAME	Vehicle model name	Text/vehicle model name
VEHYEAR	Vehicle Model year	1923-2009
VEHTYPE	Vehicle type	Text
OD_READ	Odometer reading	0-999999
OWNUNIT	How long vehicle owned - unit	01=Days, 02=Weeks, 03=Months, 04=Years
ORNLMPG	Adjusted miles per gallon	--
GSYRGAL	Annual fuel consumption in gasoline-	--

	equivalent gallons,	
ANNMILES	Self-reported annualized mile estimate	--
FUELTYPE	Type of fuel, FUELTYPE	--

3.3.2. Urban Form and Transit Accessibility Measures

Geocoded land use data was obtained from several sources, including individual local agencies, the U.S. Census website, EPA's Smart Location Database, and the National TOD database. Land use data obtained from individual state/local planning agencies includes population and employment information at TAZ/Census tract level, and were used to generate the five key land use measures at the corresponding level. Table 5-3 in Chapter Five provides a detailed list of land use variables at different geographical levels used in this analysis, as well as their calculation methods.

Table 3-3 (below) summarizes the key land use variables included in the SLD dataset, along with a brief description and data sources used to calculate and spatially process the variables. Employment and employment density have been provided in both five-tier and eight-tier classifications. The five-tier classification breaks down employment into the following employment types: retail, office, service, industrial, and entertainment. The eight-tier classification includes education, healthcare, and public administration, in addition to the ones in a five-tier setting. To measure the land use diversity, variables of job-housing balance (measured by total employment divided by the number of housing units) and employment mix (entropy score) were provided in the dataset.

It should be noted, however, that the variables representing diversity in this dataset do not show how different activities are spatially distributed within a particular census block group. For instance, a very large block group in an area of low-density development may include a variety of different activities. However, those activities may be spatially separated within the block group area (i.e., an actual low level of land use diversity), while the mixed-use score shows a high level of diversity in this particular zone. Similarly, for a case of a very small residential block group adjacent to several well-mixed areas, the score shows a relatively low level of mixed-use, while in reality, the land use diversity is greater.

The employment and household entropy, based on trip production and attraction (D2c_TrpMx1), is also provided in the dataset using the following formula. The vehicle trip productions and attractions are derived by multiplying average vehicle trip generation rates by employment types and households provided by the Institute of Transportation Engineers (ITE). The trip generation rates were used as a proxy for trip activity.

$$\text{D2c\_TrpMx1} = -\frac{H(VT)+E(VT)}{\ln(6)} \tag{1}$$

where:

H(VT) + E(VT) = (HH*11/ TotVT)*ln(HH*11/ TotVT) + (E5_Ret10*22/TotVT)*ln(E5_Ret10*22/TotVT) + (E5_Off10*3/ TotVT)*ln(E5_Off10*3/ TotVT) + (E5_Ind10*2/TotVT)*ln(E5_Ind10*2/ TotVT) + (E5_Svc10*31/ TotVT)*ln(E5_Svc10*31/ TotVT) + (E5_Ent10*43/ TotVT)*ln(E5_Ent10*43/ TotVT)

And:

TotVT = Total trips generated (production and attraction) for all activity categories in the block group based on ITE Trip Generation Rates (rates shown in equation above)

Trip equilibrium index (D2c_TripEq) was derived by calculating trip production and attractions by block group. It ranges from zero to one, and the closer to one, the more balanced the trip making at the census block group level. The following formula was used to calculate the index:

D2c_TripEq = exp(- |[H(VT)/E(VT)]-1|) (2)

where:

H(VT) = Productions: total occupied household units in CBG * ITE Vehicle Trip (VT) Generation
E(VT) = Total trip attractions for the 5 employment categories based on ITE Trip Generation Rate

Regional diversity (D2r_JobPop) was calculated based on total population and total employment by CBG. It quantifies the deviation of the CBG ratio of jobs/population from the regional average ratio of jobs/population using the following formula:

$$D2rJobPop = 1 - \left|\frac{b*(TotPop - TotEmp)}{b*(TotPop + TotEmp)}\right| \quad (3)$$

where:

b= CBSA_Pop/CBSA_Emp

In terms of street design, D3a measures the road network density using the total block group area, while D3b measures the intersection density using total land area. While intersection density is often used as an indicator of more walkable urban design, it should be noted that the source data (NAVTEQ) provides no information regarding the presence or quality of sidewalks.

In calculating design variables, first streets were grouped into three categories: auto-oriented links, multi-modal links, and pedestrian-oriented links. What follows are the various link types that fall under each of the three groups:

Auto-oriented facilities:

- Any controlled access highway, tollway, highway ramp, or other facility on which automobiles are allowed but pedestrians are restricted
- Any arterial street having a speed category value of 3 or lower (speeds are 55+ mph)
- Any arterial street having a speed category value of 4 (between 41 and 54 mph), where car travel is restricted to one-way traffic

- Any arterial street having four or more lanes of travel in a single direction (implied eight lanes bi-directional – turn lanes and other auxiliary lanes are not counted)
- For all of the above, ferries and parking lot roads are excluded

Multi-modal facilities:

- Any arterial or local street having a speed category of 4 (between 41 and 54 mph), where car travel is permitted in both directions
- Any arterial or local street having a speed category of 5 (between 31 and 40 mph)
- Any arterial or local street having a speed category of 6 (between 21 and 30 mph), where car travel is restricted to one-way traffic
- For all of the above, autos and 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 bi-directional) are excluded

Pedestrian-oriented facilities:

- 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 bi-directional) are excluded

D3b was calculated by creating a weighted sum of component intersection density metrics. Auto-oriented intersections were given zero weight to reflect that these intersections usually restrict pedestrian and bicycle mobility. Since three-way intersections do not promote street connectivity as effectively as do four-way intersections, their weight was reduced as well. The following formula represents how the intersection density was calculated in the SLD database:

$$D3b = (D3bmm3 * 0.667) + Dbmm4 + (D3bpo3 * 0.667) + D3bpo4$$

(4)

where:

D3bmm3: Intersection density in terms of multi-modal intersections having three legs per sq mi

Dbmm4: Intersection density in terms of multi-modal intersections having four or more legs per sq mi

D3bpo3: Intersection density in terms of multi-modal intersections having four or more legs per sq mi

D3bpo4: Intersection density in terms of multi-modal intersections having four or more legs per sq mi

Table 2-3 SLD Variable List and Data Source(s)*

Variables	**Description**	**Data Source(s)**
Demographics		
CountHU	Housing units, 2010	2010 decennial Census
HH	Households (occupied housing units), 2010	2010 decennial Census
TotPop	Population, 2010	2010 decennial Census
Pct_AO0	Percent of zero-car households in CBG	ACS
Pct_AO1	Percent of one-car households in CBG	ACS
Pct_AO2p	Percent of two-plus-car households in CBG	ACS
Workers	# of workers in CBG (home location), 2010	Census LEHD, 2010
R_PctLowWage	% LowWageWk of total #workers in a CBG (home location), 2010	Census LEHD, 2010
Employment		
TotEmp	Total employment, 2010	LEHD, 2010 ; InfoUSA, 2011 (MA only)
E5_	Number of jobs by type within a 5-tier employment classification	LEHD, 2010 ; InfoUSA,

	scheme (LEHD: CNS07)	2011 (MA only)
E8_	Number of jobs by type within a 8-tier employment classification scheme (LEHD: CNS07)	LEHD, 2010 ; InfoUSA, 2011 (MA only)
E_lowwagewk	# of workers earning $1250/month or less (work location), 2010	Census LEHD, 2010
E_medwagewk	# of workers earning more than $1250/month but less than $3333/month (work location), 2010	Census LEHD, 2010
E_HiWageWk	# of workers earning $3333/month or more (work location), 2010	Census LEHD, 2010
E_PctLowWage	% LowWageWk of total #workers in a CBG (work location), 2010	Census LEHD, 2010
Density		
D1b	Gross population density (people/acre) on unprotected land	Derived from other variables
D1c	Gross employment density (jobs/acre) on unprotected land	Derived from other variables
D1c5	Gross employment density (jobs/acre) by type- 5-tier	Derived from other variables
D1c8	Gross employment density (jobs/acre) by type- 8-tier	Derived from other variables
D1d	Gross activity density (employment + HUs) on unprotected land	Derived from other variables
Diversity		
D2a_JpHH	Jobs per household	Derived from other variables
D2b_E5MixA	5-tier employment entropy	Derived from other variables
D2a_EpHHm	Employment and household entropy	Derived from other variables
D2c_TrpMx1	Employment and household entropy (based on vehicle trip production and attractions including all 5 employment categories)	Derived from other variables
D2c_TripEq	Trip productions and attractions equilibrium index; the closer to one, the more balanced the trip making	Derived from other variables
D2r_JobPop	Regional diversity. Deviation of CBG ratio of jobs/pop from regional average ratio of jobs/pop	Derived from other variables
D2r_WrkEmp	Household workers per job, Deviation of CBG ratio of household workers/job from regional average ratio of HH workers/job	Derived from other variables
D2a_WrkEmp	Household workers per job, by CBG	$\frac{Eorkers}{TotEmp}$
D2c_WrEmIx	Household workers per Job Equilibrium Index; the closer to one the more balanced the resident workers and jobs in the CBG.	$\exp(-\left\|\left(\frac{Eorkers}{TotEmp}\right)-1\right\|)$
Design		
D3a	Total road network density	NAVSTREETS
D3amm	Network density in terms of facility miles of multi-modal links/sq mi	NAVSTREETS
D3b	Street intersection density (weighted, auto-oriented intersections eliminated)	NAVSTREETS
D3bao	Intersection density in terms of auto-oriented intersections per sq mi	NAVSTREETS
(Distance to) Transit		
D4a	Distance from population-weighted centroid to nearest transit stop	GTFS; TOD Database 2012
D4b025	Proportion of CBG employment within ¼ mile of fixed-guideway transit stop	TOD Database 2012, SLD polygons
D4b050	Proportion of CBG employment within ½ mile of fixed-guideway transit stop	TOD Database 2012, SLD polygons
D4d	Aggregate frequency of transit service (D4c) per square mile	Derived from other SLD variables
Destination Accessibility		
D5ar	Jobs within 45 minutes auto travel time, time-decay (network travel time) weighted	NAVSTREETS
D5br	Jobs within 45-minute transit commute, distance decay (walk network travel time, GTFS schedules) weighted	NAVSTREEETS, GTFS
D5cr	Proportional accessibility to regional destinations - Auto: Employment accessibility as a ratio of total MSA accessibility	Derived from other variables

D5cri	Regional Centrality Index – Auto: CBG D5cr score relative to max CBSA score	Derived from other variables
D5cei	Regional Centrality Index – Auto: CBG D5ce score relative to max CBSA D5ce score	Derived from other variables
D5dr	Proportional accessibility of regional destinations - Transit: Employment accessibility as a ratio of total MSA accessibility	Derived from other variables
D5dri	Regional Centrality Index – Transit: CBG D5dr score relative to max CBSA score	Derived from other variables
D5dei	Regional Centrality Index – Transit: CBG D5de score relative to max CBSA score	Derived from other variables

* This table is a summarized version of Table 1 in the Smart Location Database User's Guide

Another set of variables in the SLD dataset measure the level of transit availability, proximity, service frequency, and density. The SLD obtained transit station location data from the National TOD Database created by The Center for Transit Oriented Development, which is a collaboration of the Center for Neighborhood Technology, Reconnecting America and Strategic Economics; the SLD obtained information regarding service and coverage from the GTFS website.

D4a measures the minimum walking distance between the population-weighted CBG centroid and the nearest transit stop. To calculate the D4b variables, which roughly measure the proportion of housing units and employment with easy access to rapid transit, transit station locations were buffered at a distance of one-quarter and one-half of a mile. Each respective set of buffers was then intersected with the CBG unprotected areas polygons. The area of each polygon was compared to the unprotected area of its corresponding CBG to determine the proportion of the polygon's unprotected area that is found within one-quarter or one-half mile of a rapid transit station.

D4d measures transit frequency per square mile of land area and was calculated by dividing the aggregate frequency of transit service per hour during evening peak period by the total land area (acre), then converting to units per square mile.

To calculate destination accessibility, SLD includes variables that measure the number of jobs or working-age population within a 45-minute commute via automobile or transit. A travel-time decay formula was used to weigh jobs/population closer to the origin block group stronger than those farther away.

SLD also includes an additional set of accessibility variables to measure accessibility relative to other block groups within the same metropolitan region (CBSA). CBG accessibility was first measured as a ratio of total CBSA accessibility. For instance, D5cr was calculated by dividing the CBG's D5ar score by the sum of all D5ar scores for CBG within the same CBSA. Additionally, EPA calculated CBG accessibility relative to the CBG, with greatest accessibility within the same CBSA. For instance, D5cri was calculated by dividing the CBG's D5cr score by the maximum D5cr score within the same CBSA.

Chapter 4: Neighborhood-Level Land Use Impacts on Travel; VMT

4.1. Introduction

Mixed findings have been reported in previous research regarding the impact of built environment on travel behavior—i.e., statistically and practically significant effects found in a number of empirical studies and insignificant correlations shown in many other studies. It is not clear why the estimated impact is stronger or weaker in certain urban areas and how effective a proposed land use change/policy will be in changing certain travel behavior. This knowledge gap has made it difficult for decision makers to evaluate land use plans and policies according to their impact on vehicle miles traveled (VMT), and consequently, their impact on congestion mitigation, energy conservation, and pollution and greenhouse gas emission reduction.

This chapter has several objectives: (1) re-examine the effects of built-environment factors at the neighborhood level on travel behavior, in particular, on per person VMT, in five U.S. metropolitan areas grouped into four case study areas; (2) develop consistent models in all case study areas with the same model specification and datasets to enable direct comparisons; (3) identify factors such as existing land use characteristics and land use policy decision-making processes that may explain the different impacts of built environment on VMT in different urban areas; and (4) provide a prototype tool for government agencies and decision makers to estimate the impact of proposed land use changes on VMT.

The five case study areas include Seattle, WA; Richmond-Petersburg and Norfolk-Virginia Beach, VA; Baltimore, MD; and Washington, D.C. This empirical analysis employs Bayesian multilevel modeling method with various person-level socioeconomic and demographic variables, and five built-environment factors including residential density, employment density, entropy (measuring level of mixed-use development), average block size (measuring transit/walking friendliness), and distance to city center (measuring decentralization and level of infill development).

4.2. Data and Built Environment Measures- Neighborhood-Level Land Use

Several data sources in the case study areas are employed for this study. For Seattle, the 2006 Household Activity Survey (HAS) and 2005 building and parcel land use data are used. The Puget Sound Region Council (PSRC) has conducted several travel surveys since 1985. Data includes 4,746 households—approximately 0.5% of all households in the metropolitan area. The HAS contains household/person-level activity and travel information for two days.

The data for the Washington, D.C. and Baltimore cases are obtained from the Metropolitan Washington Council of Governments (MWCOG) and the Baltimore Metropolitan Council (BMC), respectively. The travel and land-use datasets in these two cases are similar to each other. The travel surveys containing travel behavior information were conducted in 2007 by the Transportation Planning Board (TPB)—part of the MWCOG—and the Baltimore Metropolitan Council (BMC), which included 11,000 households in Washington, D.C. and 4,650 households in the Baltimore metropolitan area. Land use information in the same survey year was collected for both cases.

For the Virginia case that includes two metropolitan areas (Richmond-Petersburg and Norfolk-Virginia Beach), the 2009 National Household Travel Survey (NHTS) add-on data was used, along with the matching 2009 land use data obtained from the Virginia Department of

Transportation (VDOT). The NHTS add-on data contain 5,428 households in the two chosen metropolitan areas in Virginia.

After removing household and person observations with missing variable values, the travel survey files include 6,582 persons in Seattle, 7,215 persons in Virginia, 6,089 persons in Baltimore, and 12,963 persons in Washington, D.C. for subsequent modeling tasks. The home location information for all persons is available at the TAZ, census tract, or even smaller geographic levels, and is used to link built environment measures to travel behavior in GIS environment. For each of the cases, all continuous variables are standardized by the sample mean and two standard deviations in that case study area. Two standard deviations are used rather than one (which is more common), because it ensures coherence with binary covariates in the analysis (Gelman & Hill, 2007).

Weighted VMT was measured by dividing total travel distance for each reported trip by the number of people in the vehicle used for the trip. In other words, I calculated VMT per person to capture the effects of switching to public transit or High Occupancy Vehicle (HOV) from Single Occupancy Vehicle (SOV). For travelers who reported bus trips, I divided the trip distance by the national average passenger load in a conventional bus in 2006, which is 9.22 according to Rubin et al. (2010). Since per capita VMT often has a skewed distribution, the naturally logged per capita VMT was used as the travel behavior variable for all cases.

For the land use variables, I used population and employment information aggregated by census tract for Seattle and by TAZ for Virginia, Baltimore, and Washington, D.C. The sizes of these census tracts and TAZs are roughly equal in the case study areas. In particular, residential density, employment density, entropy,[6] average block size, and distance from city center (central business district/CBD) are measured to represent built environment characteristics. Methods of calculation have been explained in detail in the Chapter Three.

4.3. Modeling Framework: Multilevel Bayesian Regression Model

The Bayesian multilevel model is considered an extension of regression models that produce different coefficients by subject groups (Hong et al., 2011; Shen et al., 2011). Subjects in the same level/group are likely to be similar to each other in terms of their observable characteristics. For example, persons living in the same census tract can share similar characteristics (e.g., attitudes) that are not included in statistical models. By adding group indicators, one can resolve this auto-correlation problem. However, including all group indicators will cause collinearity problems. In the multilevel model developed for this research, a group-level model and a person-level model were estimated simultaneously. This approach requires the simultaneous estimation of group-level indicators (i.e., varying intercepts and slopes for different groups) from group-level predictors and person-level indicators (i.e., VMT) from person-level variables.

In addition to considering the aforementioned five built-environment variables, I also take into account many socioeconomic and demographic factors. Previous studies have found that the inclusion of sufficient socioeconomic and demographic variables can help control for the residential self-selection effect (e.g., NAS 2009). The final model specification is as follows:

$$y_i \sim N(\alpha_{j[i]} + \beta_{SES}^{\mathrm{T}} X_{iSES}, \sigma_y^2), \text{ for i= } 1, \ldots, n \tag{5}$$

[6] Four land use types are considered to calculate the entropy: residential, service, retail, and other.

where:

$\alpha_j \sim N(\gamma + \gamma_{BE}^{\mathrm{T}}\ \gamma_{BE} X_{jBE}, \sigma_\alpha^2)$, for j=1, … , J

y_i represents naturally logged VMT for person *i*. $X_{SES}$and X_{BE} indicate various socioeconomic factors and built environment measures respectively. *j* is the group indicator. Varying intercept α_j is estimated from group level predictors (e.g., built environment variables at the TAZ and census tract levels) and assumed to be normally and independently distributed. Since the Bayesian estimation approach is employed, prior distributions are needed to be assigned for all model coefficients. Non-informative prior distributions for *β, γ* and uniform prior distributions for σ_y and σ_α are assigned. The posterior distribution density function therefore is:

$$\mathrm{P}(\alpha, \beta_{SES}^{\mathrm{T}}, \gamma_{BE}^{\mathrm{T}}, \sigma_y, \sigma_\alpha | y, X_{SES}, X_{BE}) \propto \tag{6}$$

$$\prod_{j=1}^{J} \prod_{i=1}^{n_j} N\left(y_{ij} | \alpha_j + \beta_{SES}^{\mathrm{T}} X_{ijSES} \sigma_y^2\right) \prod_{j=1}^{J} N(\alpha_j | \gamma + \gamma_{BE}^{\mathrm{T}} X_{jBE}, \sigma_\alpha^2).$$

The Bayesian approach does not require the direct estimation of the mean and standard deviation of model coefficients. Instead, the posterior distribution for each model coefficient (which is a random variable) is estimated. One can easily compute distribution parameters, such as mean and standard deviation, from the posterior distribution. It is also possible to apply the posterior distributions to conduct policy analysis.

4.4. Summary Statistics

Table 4-1 presents the descriptive statistics for major land use and socio-demographic variables in all case study areas. In general, the characteristics of travelers are similar in all case studies. Seattle and Washington, D.C. residents have slightly higher average income (standard deviation of income is not computed because income is reported in categories in all cases). Residents in the Virginia case have slightly larger family sizes, more vehicles, and older residents. All samples contain slightly more females than males (0.5 would indicate a 50-50 split). The built environment characteristics are quite different in these cases. Washington, D.C. has the highest residential and employment density, while Virginia has the lowest density (much lower than the other three case study areas, probably due to much smaller city sizes). The differences in other land use factors are also significant. These descriptive statistics are encouraging because cases with similar travelers, but different built environment features, are ideal for this study.

Table 3-1 Descriptive Statistics: Socio-demographic and Land Use Characteristics

	Seattle		Virginia		Washington, D.C.		Baltimore	
Sample Size	6582		7215		12,963		6089	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
HH income	$ 70,000-80,000		$60,000-64,999		$75,000-99,999		$60,000-74,999	
HH size	2.56	1.24	2.70	1.25	2.53	1.27	2.58	1.28
Worker 1	0.36	0.48	0.33	0.47	0.36	0.48	0.34	0.47
Worker 2	0.44	0.5	0.43	0.49	0.51	0.5	0.5	0.5
# of vehicles	2.13	1.07	2.50	1.16	1.98	1.06	2.12	1.09
Age	50.13	15.06	53.87	15.70	47.56	15.76	48.79	15.78
Gender	0.46	0.5	0.47	0.50	0.48	0.5	0.47	0.5
Residential density (persons/sq. mi.)	4017	4382	1950	1783	7015	8610	5309	5846
Employment density (jobs/sq. mi.)	2014	8395	766	1049	3990	13128	2623	9597
Entropy (no unit)	0.32	0.14	0.60	0.16	0.41	0.22	0.47	0.21
Average block size (sq. mile)	0.08	0.14	0.15	0.17	0.14	0.31	0.10	0.15

Distance from CBD (mile)	15.32	10.20	18.15	12.16	15.40	12.87	13.71	8.72

4.5. Results and Interpretations

Table 4-2 summarizes model estimation results in all cases and presents empirical evidence of the impact of urban form on VMT per person. All models include the same control covariates and built environment measures, except for the inclusion of distance-to-bus stop in the Seattle case, and the exclusion of education levels in the Baltimore and D.C. cases, because of data limitations. One of the benefits of the Bayesian estimation approach is that one can directly simulate posterior distributions of model coefficients, rather than employing the asymptotic distribution assumption. Therefore, the 95% and 90% confidence intervals were computed for each coefficient estimate. If zero does not fall in the 95% (90%) confidence interval for a coefficient estimate, the coefficient is statistically significant at the 95% (90%) level (see Tables A-1 and A-2 in appendix A). Conventional regression models produce a single R^2 to indicate the model goodness of fit. With the multilevel methods, it is required to measure two different R^2s at the group and person levels, respectively. Gelman and Pardoe (2006) developed R^2 for Bayesian multilevel models at different levels, as follows:

$$\theta_k = u_k^T + \epsilon_k, \ for\ k = 1,\ \ldots,\ K$$

$$R^2 = 1 - \frac{E(V_{k=1}^K \epsilon_k)}{E(V_{k=1}^K \theta_k)} \qquad (7)$$

where u_k^T is the batch of linear predictors, ϵ_k is the errors from distribution of mean 0; standard deviation *б*, Θ_k refers to individual data points, and *E* stands for the posterior distribution mean.

Table 3-2 Multilevel Linear Regression Results

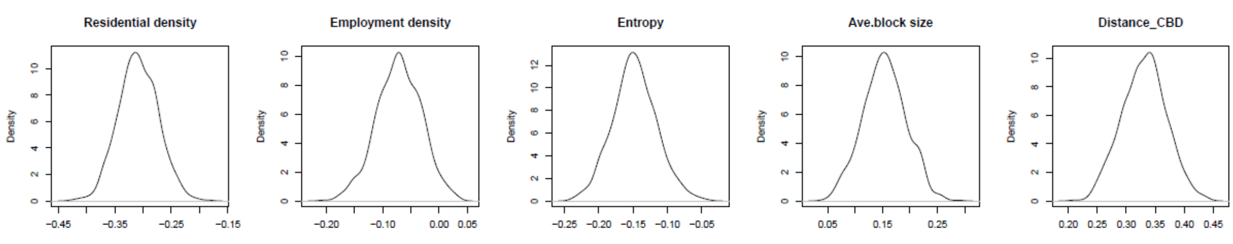
	Seattle, WA		**Virginia**		**Washington, D.C.**		**Baltimore, MD**	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Intercept	3.065	0.046	2.756	0.045	2.192	0.038	2.285	2.381
Age of householder	1.221	0.137	0.935	0.153	1.631	0.113	1.459	0.150
Age_sq	-1.313	0.142	-1.042	0.156	-1.576	0.116	-1.521	0.156
Education (H.S.)	-0.184	0.040	-0.141	0.041	N/A	N/A	N/A	N/A
Education (college)	-0.012	0.030	0.007	0.034	N/A	N/A	N/A	N/A
Gender of householder	0.151	0.023	0.213	0.025	0.198	0.021	0.242	0.028
Household size	-0.230	0.029	-0.224	0.032	-0.325	0.027	-0.472	0.035
Number of vehicles	0.346	0.030	0.255	0.03	0.581	0.029	0.365	0.038
Household income	0.158	0.029	0.203	0.03	0.184	0.025	0.381	0.036
Worker 1	0.240	0.042	0.015	0.039	0.159	0.039	0.343	0.053
Worker 2+	0.294	0.045	0.088	0.042	0.129	0.043	0.395	0.059
Distance to bus stop	0.036	0.032	N/A	N/A	N/A	N/A	N/A	N/A
Residential density	**-0.308**	**0.035**	**-0.262**	**0.060**	**-0.444**	**0.030**	**-0.344**	**0.047**
Employment density	**-0.071**	**0.039**	**0.034**	**0.093**	**-0.010**	**0.036**	**-0.085**	**0.049**
Entropy	**-0.149**	**0.033**	**-0.003**	**0.049**	**-0.195**	**0.031**	**-0.074**	**0.038**
Avg. block size	**0.153**	**0.040**	**0.220**	**0.051**	**0.021**	**0.029**	**0.089**	**0.048**
Distance from CBD	**0.331**	**0.037**	**-0.043**	**0.043**	**0.456**	**0.032**	**0.264**	**0.048**
sigma.a	0.196	0.019	0.169	0.022	0.282	0.016	0.256	0.026
sigma.y	0.948	0.009	1.063	0.009	1.174	0.007	1.098	0.011
R^2(person level)	0.238		0.112		0.278		0.264	
R^2(group level)	0.768		0.585		0.685		0.596	

The overall model explanatory power is good, but not great. Adding variables such as commuting trip distance and built environmental factors at destinations will increase the model's goodness of fit, but such information is not available in datasets used for this analysis.

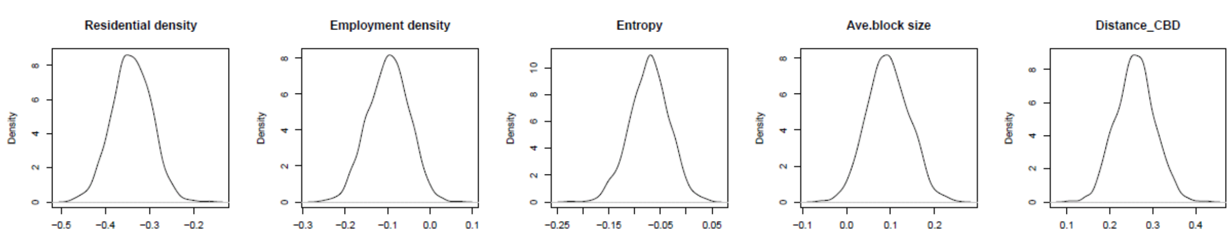
The selected socio-economic and demographic variables have statistically significant influences on per-person VMT in all cases. As people age, they tend to drive more, most likely because of work and family-related travel needs. However, the effect of age is non-linear, indicating that older people will eventually drive less after they reach certain ages. Highly educated people drive more (post-graduate education is the reference case). Education level is an important determinant of job placement. It seems from the findings that jobs requiring high levels of education tend to require more spatially dispersed business activities. It is also possible that highly educated people are more likely to engage in more spatially dispersed social and recreational activities. In terms of gender effects, males travel more than females. Individuals from larger households tend to drive less. This is expected, since household travel demand can be spread among more household members. Persons in households with one or more workers drive more than households with no workers, which is also expected. The relationship between per-person VMT in households with two or more workers and per-person VMT in households with just one worker is different across the four cases. On the one hand, if two or more workers live together, their commuting distances may become longer on average, since they need to consider multiple work places in residential location choices. On the other hand, multi-worker households enjoy greater carpool opportunities and transit use flexibilities. Both vehicle ownership and high income encourage people to drive more. Public transit accessibility does not statistically influence per-person VMT in the Seattle case.

Built environment measures significantly influence per-person VMT in all case study areas. All four models show that *residential density* has a statistically significant, negative impact on VMT. This is consistent with previous findings. *Employment density* is statistically negatively correlated with VMT only in the Seattle and Baltimore cases. *Entropy,* or level of mixed development, has a statistically significant, negative impact on VMT in all but the Virginia case. These results indicate that people living in more compact/mixed-development neighborhoods tend to drive less. *Average block size* has a positive relationship with VMT. In general, a smaller block size indicates better street connectivity and walkability. *Distance from CBD* is also positively associated with VMT in all cases except the Virginia case, which shows that people living further away from the CBD tend to drive more.

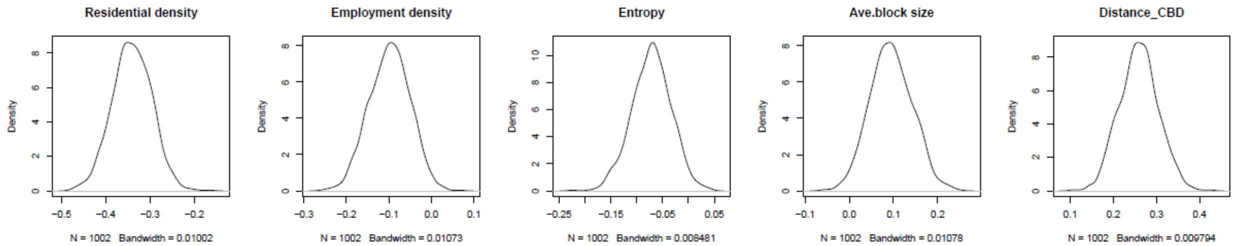
Figure 4-2 below shows the estimated posterior distributions of all five built environment factors for each case study area (from left to right: residential density, employment density, entropy, block size, and distance to CBD). This further demonstrates the feasibility of the Bayesian multilevel modeling approach. All model coefficients used for the above analysis are derived from these simulated posterior distributions.



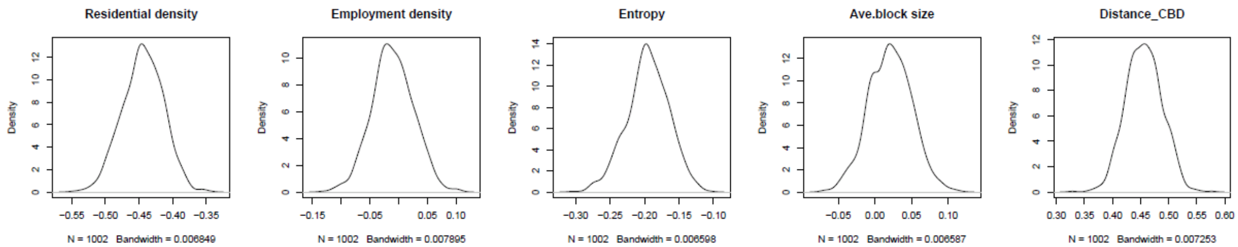
Seattle, WA



Virginia



Baltimore, MD



Washington, D.C.

Figure 3-1 Posterior Distribution of Built Environment Factors

<u>4.6. Sensitivity Analysis</u>

Since all continuous variables have been standardized with mean and two standard deviations, and the VMT variable is naturally lagged, it is not very straightforward to interpret the coefficient estimates. For instance, the coefficient for residential density is –0.308 in the Seattle case. This implies that if the residential density increases from the sample mean (4,017 persons/square mile) to two standard deviations above the sample mean (12,781 persons/square mile), VMT per person would decrease by 26.5%, i.e., [exp(–0.308*0) – exp(–0.308*1)]/ exp(–0.308*0). Table 4-3 and Figure 4-1 have been developed to better interpret the model coefficients and enable easy comparison across the four cases.

Table 4-3 shows the percentage of change in VMT per person in response to a one-standard-deviation increase of built environment variable values from their respective sample means. Again, I use the residential density in the Seattle case as an example. The mean residential density in Seattle is 4017 persons per square mile. An increase in residential density by one standard deviation from the mean represents a 109% density increase from the mean. This residential density increase is predicted by the Bayesian multilevel model to reduce VMT per person by 14.27%, i.e., [exp(–0.308*0) – exp(–0.308*0.5)]/ exp(–0.308*0). In general, the impact of residential density increase on VMT reduction is much more significant than the impact of employment density increase. The D.C. case with the best existing transit services and highest existing density is the urban area, where compact (higher density), mixed-use (higher entropy), and in-fill (lower distance to the CBD) land use is the most effective in reducing VMT in all four cases.

Table 3-3 Interpretation of Built Environment Variables Coefficient Estimates

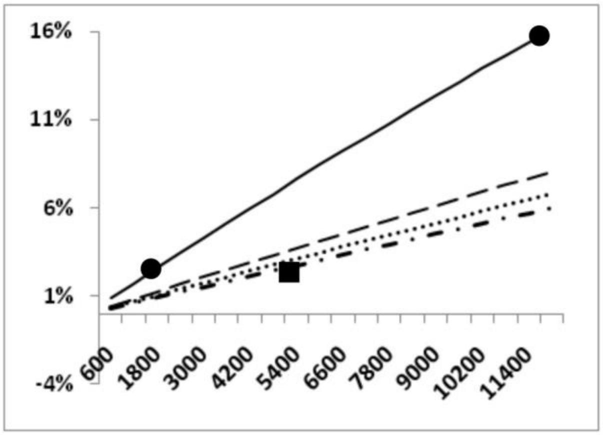
	Seattle		Virginia		Baltimore		Washington, D.C.	
	Base %change	%VMT change	Base %change	%VMT change	Base %change	%VMT change	Base %change	%VMT change
Residential density	4017 109%	-14.27%	1950 91%	-12.28%	5309 110%	-15.80%	7015 123%	-19.91%
Employment density	2014 417%	-3.49%	765 137%	1.71%	2623 366%	-4.16%	3990 329%	-0.50%
Entropy	0.32 44%	-7.18%	0.60 27%	-0.15%	0.47 45%	-3.63%	0.41 0.54%	-9.29%
Avg block size	0.08 175%	7.95%	0.15 113%	11.63%	0.10 150%	4.55%	0.14 221%	1.06%
Distance from CBD	15.32 67%	18.00%	18.15 67%	-2.13%	13.71 64%	14.11%	15.4 84%	25.61%

The impact of the built environment on VMT is very different in the Virginia case than the other three cases. Notably, in the Virginia case, which happens to have much smaller urban areas than the other three cases, mixed land development is much less effective. This is probably because in smaller urban areas, even residents living in neighborhoods with well-mixed land development may still need to travel far to reach work and non-work destinations. In other words, mixed development areas are less likely to be self-sufficient in smaller urban areas.

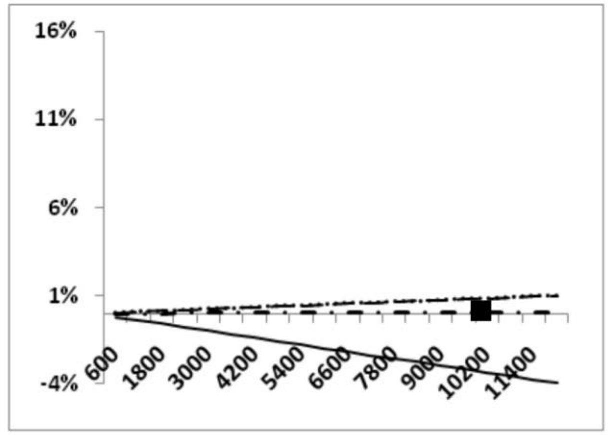
Centralized development (reducing distance from the CBD) is also the least effective in the Virginia case, which may be explained by semi-rural areas near the fringes of the Virginian cities, where residents already travel less than their urban center counterparts. Reducing the average block size turns out to be the most effective in the Virginia case with the largest existing average block size.

The impact of land use changes on VMT depends on both current built environment characteristics and proposed land use change. This is illustrated in Figure 4-1, which shows that the impact of a 20% land use change from various existing built environment statuses results in a VMT reduction in all four case study areas (a. increased residential density; b. increased employment density; c. increased level of mixed-use development; d. reduced average block size; and e. reduced distance to the CBD). In each of the five graphs, the horizontal axis represents various current built-environment patterns (from zero to two standard deviations above the mean values). The vertical axis denotes the percentage reduction in VMT per person that corresponds to the 20% land use change. For instance, from the residential density graph (see the two round dots in Figure 4-1a), it can be observed that for Virginia (solid line), a 20% increase of residential density in an area with an existing density of 11,400 persons/sq mi (right-hand side of the horizontal axis) can produce about a 16% reduction in per-person VMT. The same 20% increase in residential density in an area with an existing density of 1,950 persons/sq mi (the average density in the Virginia case) will only produce about a 3% reduction in VMT. While findings from Figure 4-1 are largely similar to those from Table 4-3, the 20% land use changes in Figure 4-1 are much more attainable than the much larger land use changes in Table 4-3. Similar graphs can be plotted for any percentage change in land use patterns, not just 20%.

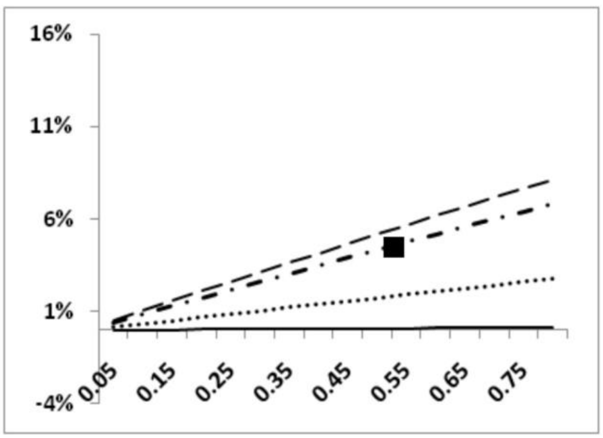
For government agencies and the stakeholders who routinely decide whether to approve and/or financially support land use development projects or plans to reduce VMT, results such as the ones found in Figure 4-1 can be very useful. For instance, a proposed local land use plan may lead to 20% increases in residential density, employment density, and mixed-use entropy in a specific subarea of the D.C. region with the following existing built environment characteristics: 2000 residents, residential density of 5,400 persons/sq mi, employment density of 10,200 jobs/sq mi, and mixed-use entropy of 0.55. By applying model coefficients (see squared dots in Figures 4-1a, 4-1b, and 4-1c), the reduction in VMT per person in that sub-area is estimated to be 7.58% (2.75% + 0.08% + 4.76%). Despite the reduction in VMT per person, total VMT will still increase by 10.91% due to the influx of 20% more residents. In other cases, two land use plans may be compared with one another. For instance, Plan A may produce an average block size of 0.51 mile and a distance to CBD of 30 miles in Baltimore, while Plan B (that includes smaller blocks and more infill developments) reduces both measures by 20%. Results show that Plan B can reduce VMT per person by 11.66% (2.98% + 8.68%; see triangular dots in Figures 4-1d and 4-1e).



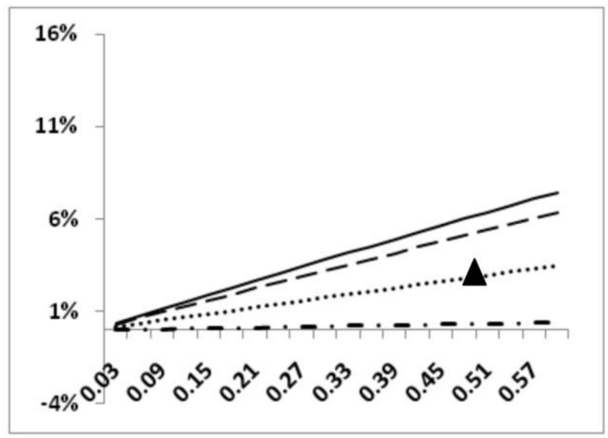
a. Residential Density (persons/sqm)



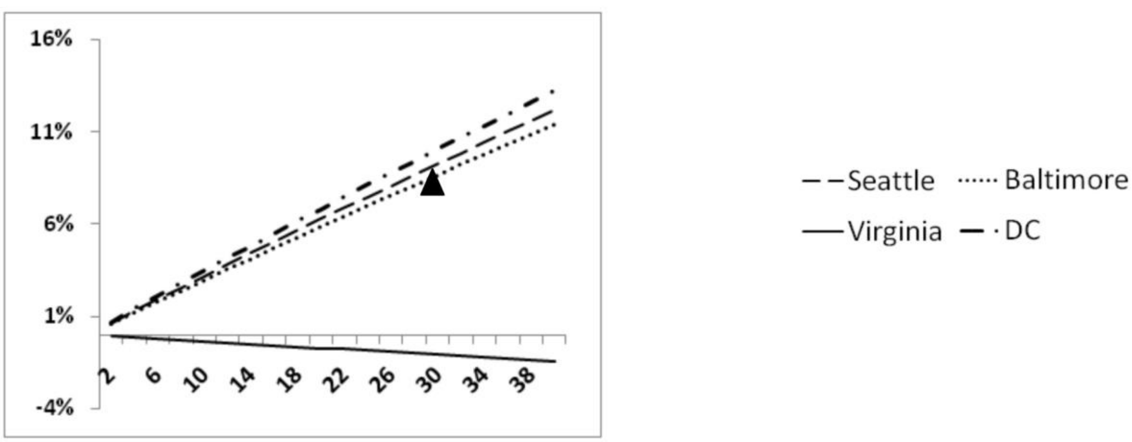
b. Employment Density (jobs/sqm)



c. Entropy: Level of Mixed Development (no unit)



d. Average Block Size (mile)



e. Distance to CBD (mile)

Figure 3-2 VMT Reduction with 20% Change in Built Environment Measures

4.7. Summary and Conclusions

In this chapter, the results from Bayesian multilevel regression models developed to compare the different impacts of local-level built environment on VMT were presented. These models, developed for five case study areas across the country (grouped into four), allow analysts and decision-makers to estimate the VMT reduction effects of various proposed built environment changes (e.g., higher residential/employment density, mixed-use developments, smaller block sizes, and compact infill developments), and devise alternative land use plans given existing land use characteristics.

In general, findings show that promoting compact, mixed-use, infill developments and smaller city blocks with various planning and policy tools can be effective in reducing VMT per person in all case study areas, and therefore, can be effective in addressing traffic congestion, energy consumption, and environmental quality issues. However, the effectiveness of these land use policies differs both across case study areas and within the same case study area. Several factors have been identified that potentially influence the connection between built environment shifts and VMT changes, including urban area size, existing built environment status, transit service coverage and quality, and land use decision-making processes. Certain land use policies, such as increasing employment density without promoting mixed-use developments and increasing residential density in areas with low existing residential density, may not reduce VMT at all. This comparative analysis also shows that mixed-use and urban infill developments in smaller urban areas are much less effective than those in larger urban areas.

However, the effect of urban form on travel behavior cannot be fully analyzed if it is measured only at one geographical scale, since several urban form characteristics operate only at certain levels (such as the job-housing balance, metropolitan area size, and the overall employment distribution/centralization). On the other hand, some built environment variables, such as density, could affect travel behavior differently at different geographical scales (Tsai 2005). Therefore, by using four case study areas and looking only at the built environment characteristics at a neighborhood-level, it is difficult to accurately and quantitatively attribute the impacts of urban form on VMT to various influencing factors. It is, however, feasible to conduct similar analyses in additional U.S. cities for a meta-analysis; this could provide the opportunity to examine the effect of land use at larger scales. Further analysis could also potentially shed light on important policy debates—e.g., the relative effectiveness of compact, mixed-use, infill, and small-street-block developments under local-level versus regional-level land use decision making—in large urban areas versus small to medium urban areas, in one region of the United States versus another region, and/or given various existing land use patterns. The next two chapters will elaborate more on these issues.

Chapter 5: Measuring the Spatial Structure of U.S. Metropolitan Areas

For many years, attempts to measure the urban structure and physical form of metropolitan areas have been focused on a limited set of attributes, mostly density and density gradients. However, the complex nature of urban form requires consideration of many other dimensions in order to provide a comprehensive measure, which includes all aspects of the urban structure and growth pattern at different hierarchical levels. In this chapter, a multi-dimensional method of measuring urban form and development patterns in the United States' urban areas is presented. The innovative methodology presented here develops a full range of scores and indices, contributing to the characterization and quantification of the overall physical form of urban areas at various hierarchical levels. This comprehensive quantification of urban form allows for a better understanding and visualization of various aspects of urban form, and could potentially be used in various analyses on the relationship between land use and transportation, environment, housing market, etc. Also, it facilitates planning and evaluation of various land use policy scenarios, such as transit-oriented development, smart growth, and polycentricity. The proposed measures and indices have been calculated for the 50 most populous urban areas in the U.S., and the consistency of the values allows for several comparative analyses in these metropolitan areas. In addition, a cluster analysis has been performed in order to group the urban areas with similar land use pattern together. This better utilizes land use-transportation planning and policy analyses used by planners and researchers. The clustering of urban areas will eventually help policymakers and stakeholders in their decision-making process to evaluate land use-transportation policies, identify similar patterns, and understand how similar policies implemented in urban areas with similar urban form structure would result in a more efficient and successful planning for the future.

5.1. Introduction and Case Study Areas Selection

The top 50 metropolitan areas in the United States in terms of 2010 population—according to US Census 2010—are selected as case study areas to measure the overall urban form and metropolitan-level built environment pattern. Table 5-1 lists all of these metropolitan areas, along with their 2010 population and employment. Among these cases, New York is the ranked first in terms of both population (18,897,109) and employment (8,022,279), and Birmingham, AL and Salt Lake City, UT have the lowest employment (477,549) and population (1,124,197), respectively. In terms of geometric area, Riverside, CA (17,548,869.82 acre) is the largest and Hartford, CT (1,028,311.86 acre) is the smallest metro area among all.

Although the metropolitan areas of study all share high population and employment, they are not similar in every characteristic, especially in terms of their urban form and built environment patterns. They vary in size (i.e., developable land area), densities, accessibilities, housing characteristics, road network structure, etc. This section attempts to address these differences and find potential relationships among urban structure pattern, travel behavior, and transportation system performance (e.g., level of congestion and transit ridership rates). To achieve this goal, cluster analysis method is used to investigate the similarities/differences among the cities, in terms of their urban structure and transportation supply patterns. Cases will be grouped based on their spatial and urban form characteristics into three categories of 1) compact, well-mixed and high-accessible, 2) moderate-density, reasonable accessibility and connectivity pattern and 3) a sprawled, low-density, suburban setting. These measurements and classifications could facilitate research on various aspects of land use-transportation interactions in different urban areas. They could also help facilitate policy analysis and the decision-making process for urban planners and policy makers, based on the results of comparative analyses in similar cities implementing different planning/policy strategies.

Table 4-1 Case Study Areas

Metropolitan area	Population	Employment	Metropolitan area	Population	Employment
Atlanta, GA	5,268,860	2,203,331	Minneapolis-St. Paul, MN	3,279,833	1,679,161
Austin, TX	1,716,289	800,514	Nashville, TN	1,589,934	742,661
Baltimore-Towson, MD	2,710,489	1,212,756	New Orleans, LA	1,167,764	495,052
Birmingham-Hoover, AL	1,128,047	477,549	New York, NY-NJ	18,897,109	8,022,279
Boston-Cambridge, MA	4,552,402	2,338,890	Oklahoma City, OK	1,252,987	546,958
Buffalo-Niagara Falls, NY	1,135,509	542,353	Orlando, FL	2,134,411	978,967
Charlotte, NC	1,758,038	770,971	Philadelphia, PA	5,965,343	260,046
Chicago, IL	9,461,105	4,161,510	Phoenix, AZ	4,192,887	1,661,476
Cincinnati, OH	2,130,151	944,787	Pittsburgh, PA	2,356,285	1,093,445
Cleveland, OH	2,077,240	957,557	Portland, OR	2,226,009	974,858
Columbus, OH	1,836,536	865,988	Providence, RI	1,600,852	661,822
Dallas, TX	6,371,773	2,871,213	Raleigh-Cary, NC	1,130,490	548,185
Denver, CO	2,543,482	1,212,658	Richmond, VA	1,258,251	571,928
Detroit, MI	4,296,250	1,657,054	Riverside, CA	4,224,851	1,183,673
Hartford, CT	1,212,381	599,586	Sacramento, CA	2,149,127	840,310
Houston, TX	5,946,800	2,530,059	Salt Lake City, UT	1,124,197	592,557
Indianapolis-Carmel, IN	1,756,241	864,558	San Antonio, TX	2,142,508	801,317
Jacksonville, FL	1,345,596	653,161	San Diego, CA	3,095,313	1,230,279
Kansas City, MO-KS	2,035,334	941,315	San Francisco, CA	4,335,391	1,953,826
Las Vegas-Paradise, NV	1,951,269	806,758	San Jose, CA	1,836,911	866,354
Los Angeles, CA	12,828,837	5,566,994	Seattle, WA	3,439,809	1,600,098
Louisville/Jefferson County, KY-IN	1,283,566	586,897	St. Louis, MO-IL	2,812,896	1,261,547
Memphis, TN-MS-AR	1,316,100	570,014	Tampa, FL	2,783,243	1,046,561
Miami, FL	5,564,635	2,118,833	Virginia Beach-Norfolk, VA-NC	1,671,683	674,996
Milwaukee, WI	1,555,908	794,235	Washington, DC	5,582,170	2,781,078

Land use data at the census block group level and the corresponding GIS shapefiles have been used to conduct spatial analysis of the urban form and calculate built environment variables. Using spatial statistics tools in ArcGIS 10.1, I first performed a high/low clustering (Getis-Ord General G) test to measures the degree of clustering for either high values or low values, using the Getis-Ord General G statistic. This tool will help to assess the overall pattern and trend of data. Figure 5-1[7] below shows how high/low values of a particular feature of the date are clustered within the study area and how this tool detects these clustering patterns.

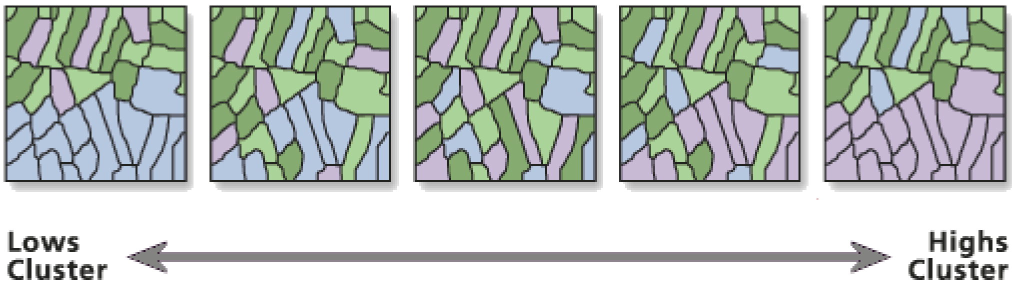


Figure 4-1 Illustration of Clustering of High/Low Values in Data

When the test is performed, five values are returned as output: Observed General G, Expected General G, Variance, z-score, and p-value. The z-score and p-value are measures of statistical significance to determine whether to reject the null hypothesis. For this tool, the null hypothesis states that there is no spatial clustering of feature values and the values are randomly distributed. Figure 5-2 shows what the result looks like and how the four values are reported. As it indicates, when the p-value is small and statistically significant, the null hypothesis can be rejected. In this case, and if the z-score value is positive, the observed General G index is larger than the expected General G index, indicating clustering of high values in the study area. If the z-score value is negative, the observed General G index is smaller than the expected index, indicating clustering of low values in the study area. The higher (or lower) the z-score, the stronger the intensity of the clustering. A z-score near zero indicates no apparent clustering within the study area.

[7] Source: ArcGIS 10.1 Help

The General G statistic of overall spatial association is given as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}, \forall j \neq i$$

Where x_i and x_j are attribute values for features *i* and *j*, *and* w_{ij} is the spatial weight between feature *i* and *j*. *n* is the number of features in the dataset and $\forall j \neq i$ indicates that features *i* and *j* cannot be the same feature. As shown in the formula above, the only difference between the numerator and the denominator is the weighting (w_{ij}).

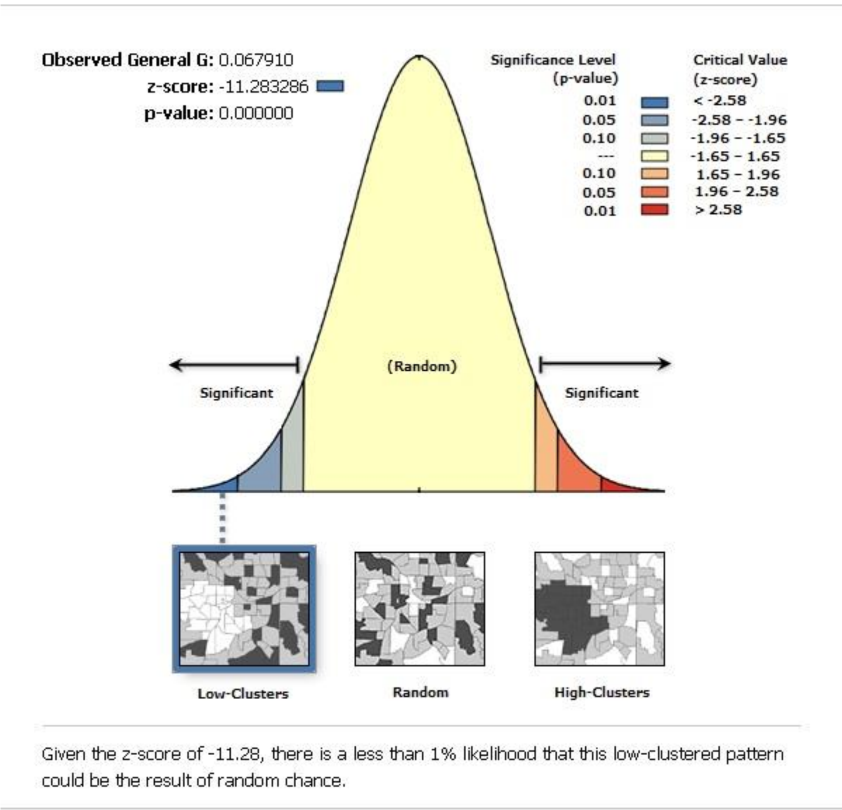


Figure 4-2 General G (High/Low Clustering) Report Summary

The test was performed for each metropolitan area separately to explore the concentration of high and/or low values for the four variables of population, employment, population density, and employment density. The results are summarized in the table 5-2, below. High, low, and random show clustering of high values, clustering of low values, and random distribution (no clustering pattern), respectively. The test results for population and employment densities are not shown in the table, since they were all high-clustered for all 50 metropolitan areas.

As shown in the table, except for a few cases with random pattern and only one case with high values clustered, all other cases have low population clustering pattern. This confirms the suburban setting for these cases, where people live in low-density decentralized residential zones, and which—consequently—is associated with an auto-oriented life style.

In terms of employment, as expected, clustering of high values is observed in 33 of the case study areas. The other 17 cases show a random pattern for employment distribution, which indicates there is not a specific pattern of employment distribution detected in these areas; there exists areas with high, low, and medium employment concentration, but none of them necessarily dominates others in these metropolitan areas, which leads to a random employment distribution pattern.

Table 4-2 Clustering Analysis Test Results

Metropolitan area	Employment	Population	Metropolitan area	Employment	Population
Atlanta, GA	High	Low	Minneapolis-St. Paul, MN	High	Low
Austin, TX	High	Low	Nashville, TN	High	Low
Baltimore-Towson, MD	Random	Low	New Orleans, LA	Random	Low
Birmingham-Hoover, AL	High	Low	New York, NY-NJ	High	Low
Boston-Cambridge, MA	High	Low	Oklahoma City, OK	High	Low
Buffalo-Niagara Falls, NY	Random	Low	Orlando, FL	High	Low
Charlotte, NC	high	Low	Philadelphia, PA	Low	Low
Chicago, IL	Random	Low	Phoenix, AZ	High	Low
Cincinnati, OH	High	Low	Pittsburgh, PA	High	Low
Cleveland, OH	Random	Low	Portland, OR	High	Low
Columbus, OH	Random	Low	Providence, RI	Random	Low
Dallas, TX	High	Low	Raleigh-Cary, NC	High	Low
Denver, CO	High	Low	Richmond, VA	High	Low
Detroit, MI	Random	Low	Riverside, CA	Random	Random
Hartford, CT	High	Low	Sacramento, CA	High	Low

Houston, TX	High	Low	Salt Lake City, UT	Random	High
Indianapolis-Carmel, IN	Random	Low	San Antonio, TX	High	Low
Jacksonville, FL	High	Low	San Diego, CA	High	Low
Kansas City, MO-KS	High	Low	San Francisco, CA	Random	Low
Las Vegas-Paradise, NV	Random	Random	San Jose, CA	Random	Random
Los Angeles, CA	Random	Low	Seattle, WA	High	Low
Louisville/Jefferson County, KY-IN	High	Low	St. Louis, MO-IL	High	Low
Memphis, TN-MS-AR	High	Low	Tampa, FL	High	Low
Miami, FL	High	Random	Virginia Beach-Norfolk, VA-NC	High	Low
Milwaukee, WI	Random	Low	Washington, DC	High	Low

5.2. Variables and Calculation Process

In this section, the built environment variables calculated at local/neighborhood and regional/metropolitan levels are introduced, and the calculation and measurement methods are explained in detail. Measure of urban form introduced in this section belongs to two separate groups: those measured at the local and neighborhood levels and then aggregated/averaged to represent the macro-scale characteristics; and those directly measured for the region/metro area as a whole. It includes more than 50 variables listed in Table 5-3 under five categories: socioeconomic and demographic, housing and urban morphology, density and centrality, diversity and urban design, and network and destination accessibility.

Table 4-3 Variable Description and Data Sources

Variables	**Description**	**Data Source**
Socioeconomic and Demographics		
EmpTot	Employment, 2010	SLD
PopTot	Population, 2010	SLD
HHs	Number of households (occupied housing units), 2010	SLD
Workers	# of workers (home location), 2010	SLD
Avg_HH_size	Average household size/aggregated from CBGs	SLD
P_WrkAge	Percent of working-age population, 2010	SLD
MedHHInc	2010 median household income in the CBSA	HUD*
P_AutoOwn0	Percent households with zero cars in the CBSA	SLD
P_AutoOwn1	Percent households with one car in the CBSA	SLD
P_AutoOwn2+	Percent households with 2+ cars in the CBSA	SLD
P_LowWage	Percent workers earning $1250/month or less (home location), 2010	Derived from SLD

P_MedWage	Percent workers earning more than $1250/month but less than $3333/month (home location), 2010	Derived from SLD
P_HiWage	Percent workers earning $3333/month or more (home location), 2010	Derived from SLD
P_CrossCommuter	Percent of employment that commutes in/out of metro area	Derived from SLD
Housing and Urban Morphology		
HH_type1_h	Housing cost as % of income for a median-income family	LAI**
HH_type7_h	Housing cost as % of income for a moderate-income family	LAI
HH_type8_h	Housing cost as % of income for a high-income family	LAI
P_unprotected	Percent geometric area (acres) that is not protected from development (i.e., not a park or conservation area)	Derived from SLD
P_occupied	Percent of occupied housing units in the CBSA	Derived from SLD
Avg_Occupation	Average percent of occupied housing units (from CBGs)	Derived from SLD
Density and Centrality		
ResDens_Avg	Average residential density	Derived from SLD
EmpDens_Avg	Average employment density	Derived from SLD
StDev_Popdens	Standard deviation of population density	Derived from SLD
StDev_Empdens	Standard deviation of employment density	Derived from SLD
CoV_Popdens	The coefficient of variation of population density	Derived from SLD
CoV_Empdens	The coefficient of variation of employment density	Derived from SLD
P_ResOnly	Percent population living in residential-only CBGs	Derived from SLD
P_LowResDens	Percent population living in low-residential-density zones	SLD- Spatial analysis
P_Hi_ResDens	Percent population living in high-residential-density zones	SLD-Spatial analysis
P_ LowEmpDens	Percent population living in low-employment-density zones	SLD-Spatial analysis
P_ HiEmpDens	Percent population living in high-employment-density zones	SLD-Spatial analysis
E_LowEmpDens	Percent employment in low-employment-density zones	SLD-Spatial analysis
E_HiEmpDens	Percent employment in high-employment-density zones	SLD-Spatial analysis
Diversity and Urban Design		
Entropy_Avg	CBG land use mix score/averaged for metropolitan area	Derived from SLD
Job_HH_Avg	Jobs per HH at CBG level/averaged for metropolitan area	Derived from SLD
%SmallBlocks	Percent blocks smaller than 0.01 sq. mi	Census/TIGER 2010
Block_Size_Avg	Average block size/aggregated from CBGs	Census/TIGER 2010
Network and Destination Accessibility		
Rd_metro	Total road network density	Census/TIGER 2010
IntDens_metro	Total intersection density	Derived from SLD
P_Trans_Pop	Percent population living within ½ mile of transit	Derived from SLD
P_Trans_Emp	Percent jobs located within ½ mile of transit stops	Derived from SLD
PJ_45_auto	Percent jobs within 45 minutes auto travel time	Derived from SLD
PJ_45_transit	Percent jobs within 45-minute transit travel time	Derived from SLD
PW_45_auto	Percent working age population within 45 minutes auto travel	Derived from SLD

	time	
PW_45_transit	Percent working-age population within 45-minute transit travel time	Derived from SLD
RetAcc_avg	Average ratio of residential population to retail employment	Derived from SLD
P_NoRet	Percent population living in no-retail zones	Derived from SLD
WalkScore	Walk score/ walkability at the metropolitan level	WalkScore Inc.
Congestion_Index	Level of congestion in a metro area	TTI***

* U.S. Department of Housing and Urban Development
** Location Affordability Index Data
*** Texas Transportation Institute

Most of the socioeconomic and demographic variables listed in the table above are available at the CBG level in the SLD database, and have been used to obtain the aggregated value at the metropolitan level. Percent of workers in different income group (low, median, and high wage groups) have been calculated by summing up the number of workers in each group and then dividing that value by the total number of workers in the metropolitan area. The percentage of cross-commuters has been calculated by subtracting the number of workers from the total employment in a metropolitan area. If that number is positive, it implies that workers from outside regions have to commute and fill in the excess employment opportunities (commuters-in). Similarly, if the number is negative and the number of workers is greater than the total employment, the excess workers have to commute to outside regions for work (commuter-out). If the number of workers and the total employment in the metro area are equal, there are no cross-commuters and the value for this variable would be equal to zero.

Spatial analysis was done in ArcGIS in order to calculate several variables under density and centrality category. For each of the case study areas, the spatial statistics tool in ArcMap 10.1 was used to identify clusters of high and low population, and employment density zones. Spatial statistics use various techniques for describing and modeling spatial data, especially by assessing spatial patterns, distributions, trends, processes, and relationships (Schott and Getis 2008;

Fischer and Getis 2009). In ArcGIS 10.1, statistical functions are grouped into six toolsets: analyzing patterns, mapping clusters, measuring geographic distributions, modeling spatial relationships, rendering, and utilities. These tools were used in this analysis to calculate several variables that needed spatial analysis prior to calculation. Table 5-4[8] summarizes the various tools that can be used within this toolset (only the ones related to this study are listed).

Table 4-4 Summary of the Tools in the Analyzing Pattern Toolset

Tool	**Description**
Analyzing Pattern Toolset	
Average Nearest Neighbor	Calculates the average distance from every feature to its nearest neighbor based on feature centroid
High/low Clustering (Getis-Ord general G)	Measures concentrations of high or low values for a study area
Spatial Autocorrelation (global Moran's *I*)	Measures spatial autocorrelation (clustering or dispersion) based on feature locations and attribute values
Multi-distance Spatial Cluster Analysis (Ripley's *K* function)	Assesses spatial clustering/dispersion for a set of geographic features over a range of distances
Mapping Clusters Toolset	
Cluster and Outlier Analysis (Anselin's local Moran's *I*)	Given a set of weighted features, identifies clusters of high or low values as well as spatial outliers
Grouping Analysis	Given a set of weighted features, identifies groups based on feature attributes and spatial/temporal constraints
Hot Spot Analysis (Getis-Ord G)	Given a set of weighted features, identifies clusters of features with high values (hot spots) and clusters of features with low values (cold spots)

The Spatial Autocorrelation (Global Moran's I) tool assesses the overall pattern and trend of the data used. It is most effective when the spatial pattern is consistent across the study area, whereas the local statistics (like the Hot Spot Analysis tool) assess each feature within the context of neighboring features, and compare the local situation to the global situation. For example, when we are taking an average for a set of values (all near a certain value, like 50), the

[8] From Fischer and Getis, 2009

mean value would also be something near 50, and that number would be a very good representation/summary of the dataset as a whole. However, if half of the values are near 1 and the other half of the values are near 100, the mean will again be near 50. Clearly, in this case, the mean value is not a good representation of the dataset as a whole. Similarly, global spatial statistics, including the Spatial Autocorrelation (Global Moran's I) tool, are not effective when the variable being measured is not consistent across the entire study area. As a result, the High/Low Clustering (Getis-Ord general G) tool is the most appropriate when we are looking for unexpected spatial spikes of high/low values. It identifies the concentration of high and low values of a certain feature and computes a z-score describing the degree of spatial concentration or dispersion for a certain variable. The High/Low Clustering (Getis-Ord General G) tool is an inferential statistic, which means that the results of the analysis are interpreted within the context of the null hypothesis. The null hypothesis states that there is no spatial clustering of feature values. When the test is finished, and the p-value returned by this tool is small and statistically significant, the null hypothesis can be rejected. Once the null hypothesis is rejected, then we look at the sign of the z-score. The positive values for the z-score indicate the hot spots (clusters of high values), and the negative values for the z-score indicate the cold spots (clusters of low values) of a certain feature.

The tools in the Analyzing Patterns toolset are used to answer the question of whether or not there is statistically significant spatial clustering of high/low values in the data. Once the existence of such clusters is confirmed, in the next step, the Mapping Clusters tool can be used to identify where the spatial clustering/outliers are located within an urban area.

The Hot Spot Analysis (Getis-Ord G_i) tool was applied to each of the metropolitan areas to identify the clusters of high and low values for population and employment densities. Once those clusters are identified, the overall population and employment located within the high-density zones was calculated. The resulting six variables are: P_LowResDens, P_Hi_ResDens, P_ LowEmpDens, P_ HiEmpDens, E_LowEmpDens, and E_HiEmpDens (see Table 5-3 for variable descriptions).

The congestion index variable was obtained from the Texas Transportation Institute (TTI). They calculated this index for about 500 metropolitan areas nationwide using a variety of data sources on traffic volume, speed, and average travel time. The traffic speed was obtained from INRIX, a private company that provides travel time information for each section of road for every 15 minutes of each day, for a total of 672 day/time period cells (24 hours x 7 days x 4 periods per hour). For road segments and the time of day for which the INRIX data was not available, estimated speed was used instead of the actual speed. Using this detailed data, a dataset of average speed for each road segment is compiled by the TTI team.

According to the Urban Mobility Report, what TTI team needs includes actual and free-flow travel speed, vehicle volume on the road segments, and vehicle occupancy (to calculate person-hour travel delay). Their calculation process is as follows:

1. Obtain HPMS traffic volume data by road section;
2. Match the HPMS road network sections with the traffic speed dataset road sections;
3. Estimate traffic volumes for each hour time interval from the daily volume data;
4. Calculate average travel speed and total delay for each hour interval; and

5. Establish free-flow (i.e., low volume) travel speed using overnight speeds as comparison standard.

The commute mode share for three modes of auto, transit, and non-motorized has been obtained from the American Community Survey “Journey to Work” data. The data was first driven at the county level and then aggregated to the metropolitan level to obtain numbers for each of the 50 metropolitan areas. The complete list of the 50 metropolitan areas and their counties can be found in Appendix C (see Table C-1).

The total annual VMT for each metropolitan area was calculated using the database provided by the Highway Performance Monitoring System (HPMS) from the Federal Highway Administration. This dataset provides traffic volume data by road segments for all road types. Similar to the mode share calculation, the annual VMT for the year 2008 (the most recent data available) was first calculated for each county, and then aggregated to the entire metropolitan area to obtain the actual VMT number. The following formula shows how the annual VMT at the metropolitan level was calculated:

$$VMT_i = \sum_{j=1}^{n} \sum_{k=1}^{n} AADT_k L_k * 365$$

where:

VMT_i= Annual VMT for the metropolitan area i, $1 \leq i \leq 50$

$AADT_k$ = Average annual daily traffic for the road segment k

L_k = Segment length, mile

j is the county’s identifier and ranges from one to the number of counties in metropolitan area i.

__5.3. Summary and Cluster Analysis__

After the land use measures are calculated for each of the case study areas, it is observed that although the metropolitan areas of study all share high population and employment, they are not similar in every characteristic, especially in terms of their urban form and built environment pattern. They vary in size (i.e., developable land area), densities, accessibilities, housing characteristics, road network structure, etc. The next two sections attempt to address the similarities/differences among the case study areas in terms of their overall urban form structure, and find potential relationships among urban structure pattern, travel behavior, and transportation system performance (e.g., level of congestion and transit ridership rates). To achieve this goal, cluster analysis is performed to group similar cities together based on their overall urban form pattern, and investigate the similarities within and differences between the groups in terms of their urban structure, transportation supply patterns, and aggregate-level travel behavior.

Cluster analysis is a data reduction technique to find groups of similar observations within a data, according to certain characteristics of those observations. It is used to better analyze the data, to find relationships among observations, develop new hypotheses concerning the nature of the data, as well as test previously stated hypotheses. It has a wide range of applications in many research fields, such as marketing, insurance, biology, psychiatry, and land use and city planning. For example, in marketing, identifying groups of similar, targeted customers would help to develop more efficient marketing programs. In psychiatry, cluster analysis technique is used to group patients based on symptoms in order to better identify appropriate therapy. Similarly, in land use planning and policy-making, cluster analysis could be very useful to identify areas with similar land use patterns in order to propose, implement, and evaluate land use policies more efficiently.

In cluster analysis, similarity represents the degree of correspondence among observations across all of the variables used in the clustering. It is a set of rules for grouping or separating observations. Distance measures are used as measures of similarity or dissimilarity among observations. High values of distance measures between observations represent greater dissimilarity. Euclidean distance is one the very popular distance measures used in many cluster analysis methods. It is calculated by:

$$d(i,j) = \sqrt{(|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \cdots + |x_{ip} - x_{jp}|^2}$$

Clustering algorithms can be categorized into several groups, such as partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods. In this analysis, I only describe partitioning methods and hierarchical methods. Introducing and analyzing the rest of the methods is beyond the scope of this analysis.

In the partitioning approach, the database is partitioned into a set of *n* clusters with the minimum sum of squared distance. The process begins with *n* initial group centers; each observation is assigned to the cluster group to which its mean or median is the closest. The process is repeated until all the observations belong to the cluster group with the closest mean/median to the center, and no observation changes group. There are two main methods in this approach; k-means and k-median. In the k-means method, each cluster is represented by the center of the cluster. The algorithm iteratively estimates the cluster group means and assigns each observation to the cluster for which its distance to the cluster mean is the smallest. The process is continued until no observation changes group (see Figure 5-3). In k-median method, each cluster is represented by one of the observations in in the cluster (the most centrally located observation in a cluster).

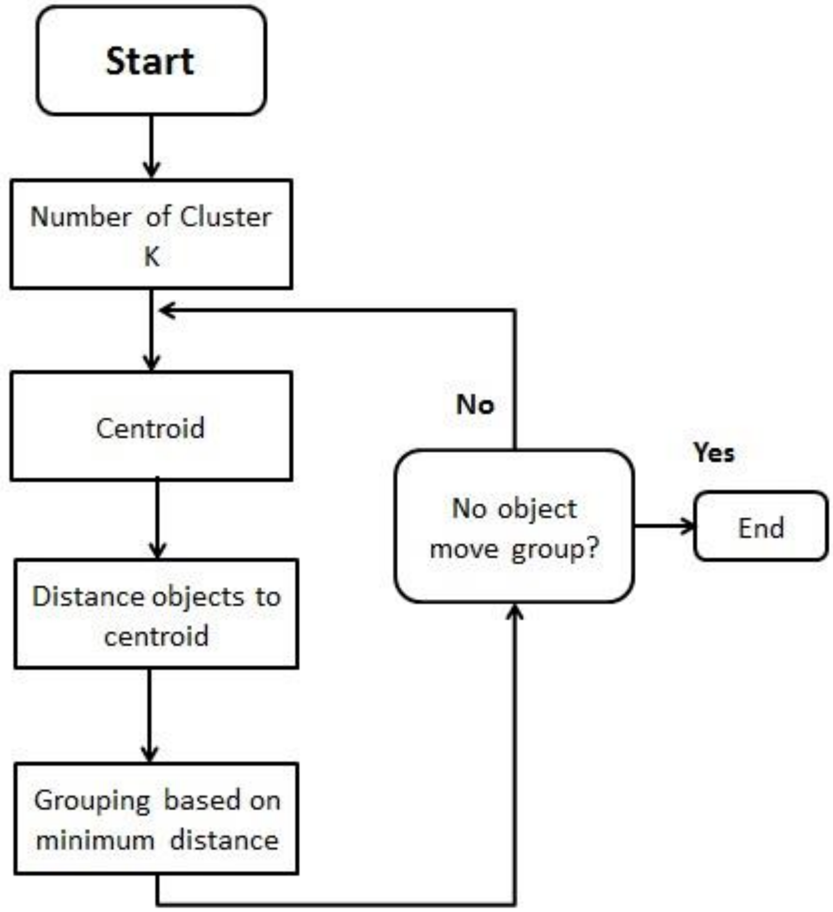


Figure 4-3 K-means Process Flow Chart

In the hierarchical clustering approach, distance matrix is used as clustering criteria. It is not required to specify the number of clusters in advance. Instead, it needs a termination condition. In this method, data is deconstructed into several levels of nested partitioning which is called dendrogram. Figure 5-4 illustrates a schematic dendrogram of clustering of a data with 30 objects. As it is shown in the figure, a clustering of observations is obtained by cutting the dendrogram at a desired level (based on the number of clusters needed). Each connected component in the dendrogram forms a cluster. If the dendrogram is cut at position A, there will be three cluster groups, and if it is cut at position B, the number of groups would be five.

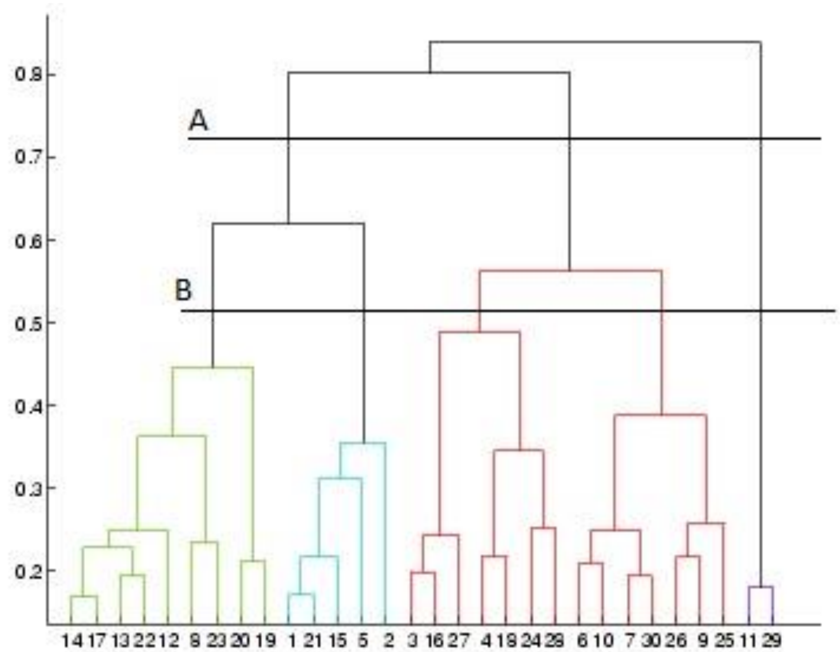


Figure 4-4 Schematic Dendrogram- Clustering of 30 Observations

Hierarchical clustering is categorized, based on the distance measure used, into several methods such as single linkage, average linkage, complete linkage etc. (see Table 5-5 for a complete list and description of clustering methods).

Table 4-5 Cluster Analysis Methods Summary and Descriptions

Method	Description	# of Clusters
Partition clustering methods		
Kmeans	Each cluster is associated with a centroid/ Construct various partitions in which each observation belongs to the cluster with the nearest mean.	User-specified mandatory
Kmedians	A variation of kmeans clustering. The same process is followed except that medians, instead of means, are computed to represent the group centers at each step.	

Hierarchical clustering methods		
Single linkage (Nearest-neighbor method)	The closest two groups are determined by the closest observations between the two groups.	Optional/ Done in post-clustering
Average linkage (Arithmetic-average clustering)	The closest two groups are determined by the average (dis)similarity/distance between the observations of the two groups.	
Complete linkage (Furthest-neighbor method)	The closest two groups are determined by the farthest observations between the two groups.	
Weighted average linkage (Weighted group-average method)	Similar to average-linkage clustering, except that it gives each group of observations equal weight, while average linkage gives each observation equal weight.	
Median linkage (Weighted pair method)	A variation on centroid linkage; treats groups of unequal size differently. It gives each group of observations equal weight, meaning that with unequal group sizes, the observations in the smaller group will have more weight than the observations in the larger group.	
Centroid linkage (Unweighted pair-group centroid method)	Merges the groups whose means are closest. Gives each observation equal weight.	
Ward's linkage (Minimum-variance method)	Produces clusters of similar numbers of observations and with a minimal amount of within-cluster variance.	

Several cluster analysis methods—including k-means, average linkage, complete linkage, and ward's linkage methods, in addition to different numbers of clusters—were applied and tested on the data. A combination of k-means method, the Euclidean distance measure, and using six, main land use variables was selected, as it produced the most logical clustering of metropolitan areas of study (based on the output's similarity indices). Cities have been grouped based on several of their spatial and urban form characteristics into three cluster categories: A) compact, well-mixed, high-accessible, B) moderate-density, average accessibility, random clustering pattern and C) sprawled, low-density, suburban setting. This reasonable set of classification could facilitate research on various aspects of land use-transportation interactions in different urban areas, and serve as a guideline to help urban planners and policy-makers better understand the relationships between the overall land use pattern and travel outcomes in certain urban areas. It is also very useful for the decision-making process, and the development and evaluation of various land use policy scenarios, based on comparative analyses results that consider the similarities/differences of cities in the same cluster groups.

The clustering was based on the following land use variables: average employment density in the metro area, average population density in the metro area, average entropy score, retail accessibility in the metro area, average block size, and proportion of metro area's employment within ½ mile of major transit stops (transit accessibility). Table 5-6 represents the three cluster types obtained by the k-means clustering method and lists the metropolitan areas falling under each of the three types. As it is indicated, Cluster type A (compact, well-mixed, high-accessible cities) consists of seven cases, most of which are among the top ten metropolitan areas in terms of the overall population and employment. However, it also shows that not necessarily all the cases with high population and employment have an overall dense and highly-accessible urban structure. For example, Los Angeles and Dallas, which are among the top five metropolitan areas both in terms of population and employment, are not categorized under cluster type A. The cluster type B consists of 25 cases and is identified as a group of moderate-density cities with reasonably good job accessibility and street connectivity. Cases in this group range from Los Angeles and Dallas with overall high population and employment, to Buffalo and New Orleans, which are among the smaller, low-population and employment cities. Finally, cluster type C with 18 cases is identified as the group of suburban style cities with an overall sprawled, low-density pattern, low job accessibility and walkability.

Table 4-6 Cluster Analysis Results and Summary

K-means Cluster Method	Metropolitan Areas
Cluster A	Washington, DC; New York, Northern New Jersey, NY-NJ; San Jose-Santa Clara, CA; Chicago, IL; Boston-Cambridge, MA; San Francisco-Oakland, CA; Philadelphia-Camden, PA
Cluster B	Atlanta, GA; Austin, TX; Baltimore, MD; Buffalo-Niagara Falls, NY; Charlotte,

	NC; Cleveland, OH; Dallas, TX; Denver, CO; Houston, TX; Kansas City, MO-KS; Las Vegas-Paradise, NV; Los Angeles, CA; Memphis, TN; Miami, FL; Minneapolis, MN; New Orleans, LA; Phoenix, AZ; Pittsburgh, PA; Portland, OR; Sacramento, CA; Salt Lake City, UT; San Diego, CA; Seattle-Tacoma, WA; St. Louis, MO-IL; Virginia Beach, VA
Cluster C	Birmingham-Hoover, AL; Cincinnati, OH; Columbus, OH; Detroit, MI; Hartford, CT; Indianapolis, IN; Louisville-Jefferson County, KY-IN; Milwaukee, WI; Nashville, TN; Oklahoma City, OK; Orlando, FL; Providence, RI; Raleigh-Cary, NC; Richmond, VA; Riverside, CA; San Antonio, TX; Tampa, FL; Jacksonville, FL

Figure 5-6, below, illustrates where the metropolitan areas belonging to the same cluster groups are geographically located within the entire country. As shown in this figure, while cities of all three groups are distributed all around the country, they are not evenly distributed. Figure 5-5 illustrates the distribution of cluster groups in the four main U.S. regions.[9] In the Midwest and Southern regions, the highest share belongs to cluster type C, which is the group of sprawled low-density cities. The Southern region also has the same number of cities belonging to cluster type B and only one city from the type A.

[9] According to the United States Census Bureau

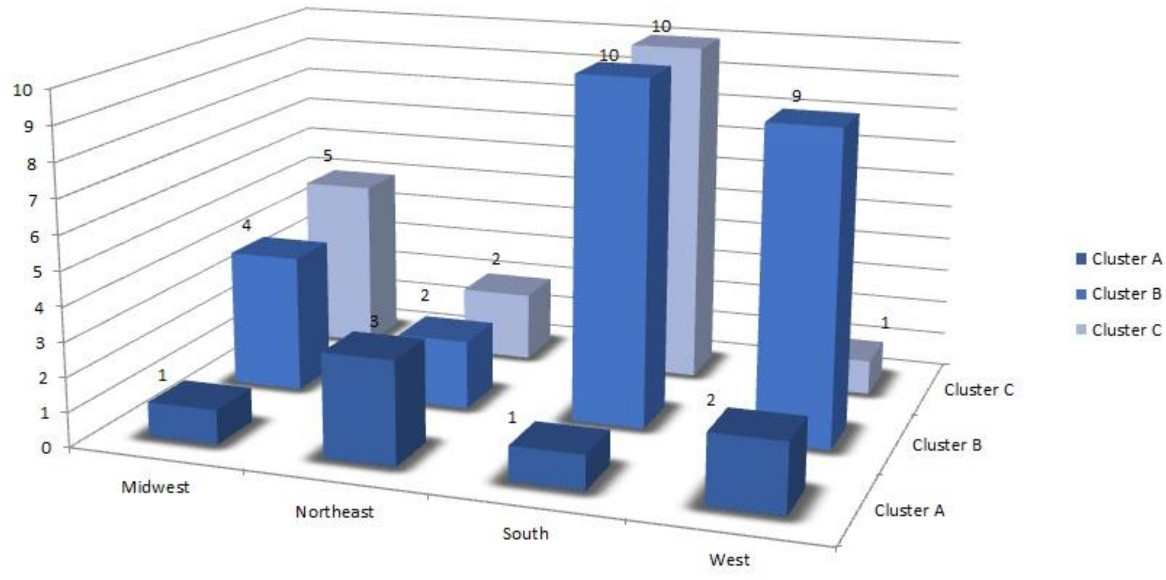


Figure 4-5 Distribution of Cluster Groups by U.S. Regions

This implies that in the Southern region, most metropolitan areas follow the medium-to-low density pattern. In the Western region, the majority of cases belong to the cluster type B—moderate-density cities with average accessibility and street connectivity.

There is no generally-accepted rule or measure to evaluate a clustering method based on the output. However, cluster methods can be evaluated based on the similarity within and/or dissimilarity between the identified cluster groups. The cluster centroid, a mean of the cluster on each clustering variable, is very useful in evaluating the clustering. Interpretation of clustering involves examining the characteristics of each cluster and identifying the similarities/differences. A good method will produce clusters with high intra-group similarity and low inter-group similarity. A method that fails to show substantial variation among the clusters is not recognized as an efficient method; it does not help in understanding the data nor does it identify common groups within it, failing to meet the initial goal. Toward this goal, summary statistics of the main socio-demographic characteristics, as well as the land use measures for each cluster group, are provided in Table 5-7. As it indicates, cluster A shows higher population and employment densities than the other two groups with a considerable distance. Mean population density in cluster A (21.70) is more than twice as high as cluster B (8.64) and about four times higher than cluster C (5.85). Similarly, mean employment density in cluster A is more than double than that in cluster B and C. The percentage of population living in residential-only zones is a lot higher in cluster C (0.92%) than it is in cluster B (0.76%) and A (0.53%). The higher this percentage, the lower the accessibility to various destinations, and the higher the automobile dependency.

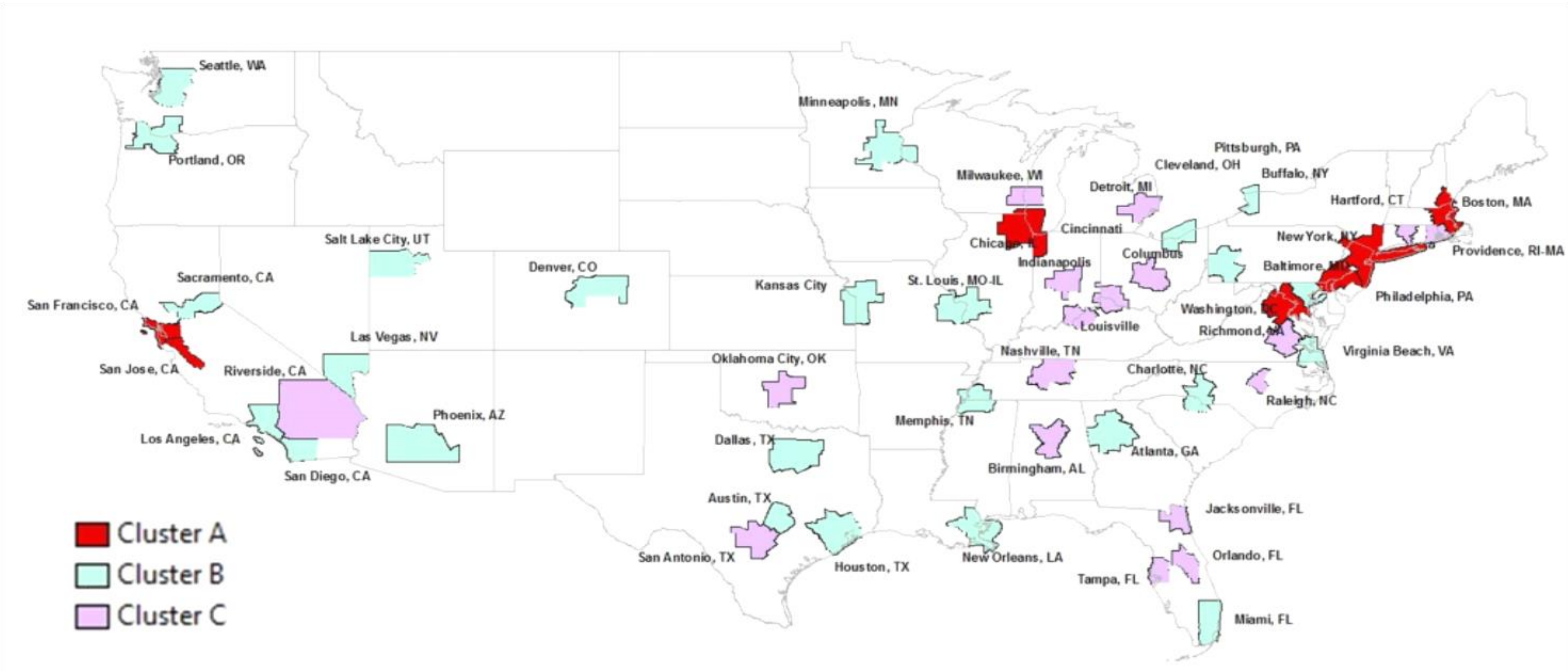


Figure 4-6 Location Distribution of Cluster Groups

Table 4-7 Summary Statistics by Cluster Groups

	Cluster A		Cluster B		Cluster C	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Socioeconomic and Demographic Characteristics						
Total Employment	3,246,340	2,325,194	1,408,364	1076108	806,993.7	288,623.7
Total Population	7,232,919	5,628,019	3,229,618	2515438	1,925,678	957,611.8
HHs	2,676,953	2,054,958	1,193,101	835,621.4	730,700.3	334,697.6
Workers	2,869,077	2,587,500	1,354,001	1,011,600	776,342.9	336,076.7
Avg_HH_size	2.71	.12	2.65	.17	2.61	.18
P_WrkAge	76.82	1.41	75.35	2.14	75.58	1.84
MedHHInc	86,614.29	15,111.74	69,184	7,733.73	66,622.22	7,482.26
P_AutoOwn0	15.14	8.64	8.66	2.59	7.74	1.78
P_AutoOwn1	35.77	2.81	38.26	4.36	37.97	4.26
P_AutoOwn2+	56.13	8.51	63.44	4.24	65.28	4.23
P_LowWage	22.06	3.17	24.01	2.35	24.81	1.48
P_MedWage	29.21	2.55	35.75	3.07	36.85	3.61
P_HiWage	48.73	5.50	40.24	4.21	38.33	4.39
Built Environment Characteristics						
ResDens_Avg	21.70	13.92	8.64	3.65	5.85	2.11
EmpDens_Avg	7.33	3.96	3.00034	.94	2.18	.64
Entropy_Avg	.46	.050	.46	.048	.48	.065
P_ResOnly	.53	.48	.76	.77	.92	.74
P_LowResDens	36.56	15.83	21.49	14.88	20.83	8.82
P_Hi_ResDens	52.81	20.75	55.86	22.095	50.52	15.19
P_ LowEmpDens	19.13	18.88	5.19	8.28	1.75	2.011
P_ HiEmpDens	35.73	20.69	38.27	21.46	31.54	15.33
E_LowEmpDens	17.29	17.62	3.83	7.28	1.039	2.044
E_HiEmpDens	41.80	19.50	48.78	22.81	46.27	18.59
%SmallBlocks	59.99	5.50	50.91	8.28	48.55	7.76
Block_Size_Avg	.050	.014	.13	.171	.107	.046
Walkscore	74.93	12.81	50.86	14.028	42.13	14.62
Roadnetworkdensity	18.15	32.30	6.026	8.20	16.19	47.29
JobHH_avg	11.29	4.37	12.86	9.58	8.41	10.31
P_D4b050_metro	34.42	7.54	15.49	5.22	1.86	2.57
P_D5br_avg	.65	.42	1.22	2.34	.63	.64
Travel Behavior Characteristics						
VMT*	42,258.72	22,380.78	25,024.99	19,971.65	16,825.69	8,557.73
VMT per capita	6,639.40	1,378.57	7,659.41	853.41	8,787.82	1,024.33
Auto_Commute	75.45	9.45	88.04	3.21	90.99	1.70
Transit_Commute	13.69	8.57	3.49	1.81	1.82	.94
WalkBike_Commute	4.91	1.34	2.80	1.12	2.17	.68
# of observations	7		25		18	

* VMT is measured in million miles

The three cluster groups are somehow similar in terms of average entropy, the percentage of population living in high-residential-density zones and high-employment-density zones, and the proportion of employment located in high-employment-density zones. However, the proportion of employment concentrated in low-employment-density zones is a lot higher in cluster A (17.29% vs. 3.83% and 1.039%), which is an indicator of a more evenly distributed pattern for employment. In terms of street connectivity and walkability, cluster A is again in better shape than the other two groups. The percentage of small blocks in cluster A is about 60%, whereas this number is around 50% in the other two cluster groups. In addition, the average block size is smaller and the walkscore is larger in cluster A, compared to the other two cluster groups.

Looking at transit accessibility measures in Table 5-7, again it is observed that cluster A has a higher level of transit accessibility (the percentage of a metro area's employment located within a ½ mile of transit stations) than the other two groups. The transit accessibility level is twice as high in cluster A than cluster B, and in comparison with cluster C, this ratio is about 1/17.

In terms of socio-demographic characteristics, Cluster A has the highest ($86,614) and Cluster C has the lowest ($66,622) median household's income. Similarly, the percentage of high-wage workers in cluster A is higher (48.73%) and the percentage of low-wage workers is lower (22.06%), compared to the other two cluster groups.

In cluster A, there are more households with no automobiles (15.14%) and fewer households with more than 2 automobiles (56.13%). The number of households who do not have private cars is almost double in cluster A compared to the other cluster groups. These are important findings, especially for policy-makers looking for ways to restrict automobile ownership and use; in metropolitan areas with higher accessibility and a more compact, transit-friendly pattern, the percentage of households who decide not to own a car increases. Meanwhile, the median income and percentage of high-wage workers in these areas is higher, compared to the other groups with a more sprawled and less-connected land use pattern.

In addition to the car ownership pattern, clusters are also compared based on their VMT and the overall commute mode share pattern. Cluster A has a higher overall VMT compared to the other clusters, but lower per capita VMT. The share of auto commute in cluster A is about 75% while in cluster B it is 88%. In cluster C, it is about 91%. Similarly, the share of transit commute in cluster A is about 14%, which is about three times higher than that in cluster B and about seven times higher than that in cluster C. The same pattern exists for the share of walk/bike mode for commuting trips.

Therefore, it can again be implied that cities with a more compact land use pattern have an overall lower automobile dependency, and a higher level of transit and non-motorized mode share. The higher overall VMT in cluster A is a direct result of the size of the metro areas in this group and the larger population living in these cities.

Overall, these findings are potentially significant to future land-use and transportation planning projects, and will better utilize land use-transportation planning and policy analyses employed by planners and researchers. Clustering of urban areas would eventually help policy- makers in their decision-making process, by examining new and old land use-transportation policies and planning scenarios, identifying similar patterns, and understanding how similar policies implemented in urban areas with similar urban form structure would result in more efficient and successful planning in the future.

Chapter 6: Metropolitan-Level Land Use Impacts on Travel; VMT and Car Ownership

In this chapter, disaggregated household travel survey data for 19 metropolitan areas across the country has been collected and linked to the urban form measures at multiple hierarchical levels, in order to investigate the cause-effect relationship among urban form, households' auto ownership, and the amount of driving.

6.1. Introduction

There has been growing recognition of the significant impact that land use patterns have on travel behavior; changes in built environment patterns could potentially be considered a long-term solution in changing people's travel behavior, particularly their vehicle miles traveled (VMT). However, the existing literature has mainly focused on local and neighborhood characteristics of the built environment, and little is known about the unique or relative influence of the metropolitan-level built environment. In this section, an empirical analysis is provided that highlights the impact of built environment characteristics on travel behavior at different scales, using an extensive database for 19 major metropolitan areas in the United States. It employs a structural equations model to investigate whether or not changes in built environment measures, not only at local and neighborhood levels, but also at larger metropolitan and regional levels, could be influential in changing people's travel behavior.

Because of increased mobility, research shows that travel behavior is influenced by both the local land use pattern, as well as the overall form of metropolitan area, regional employment accessibility and growth pattern, and job-housing balance in the entire metro area (Nasri &

Zhang 2012). Figure 6-1 illustrates how increased mobility results in home and work locations being farther apart, and how various daily activities such as work, shopping, entertainment, and personal business are done in places not necessarily located in the neighborhood of residence, but rather in various locations in the entire metropolitan area of residence. It also illustrates how urban form at origin, destination, and along the chosen travel path can influence travel pattern. For example, someone who lives in a mixed-use, pedestrian-friendly neighborhood might do some of his/her shopping on foot. Another person, who chooses to drive to work, might stop by various locations along the way to do grocery shopping, personal business, and other non-work activities. As a result, land use pattern at the immediate neighborhood, the county of residence, and the entire metro area becomes important for travel behavior analysis.

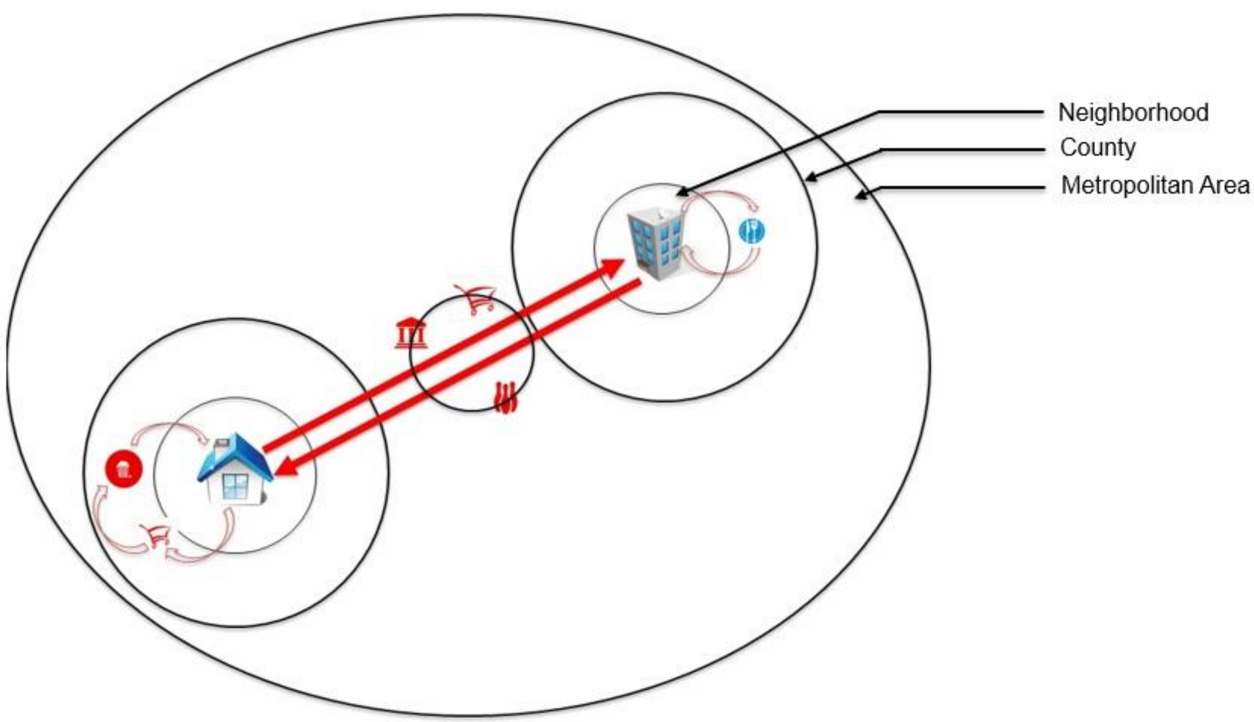


Figure 5-1 Increased Mobility: Larger Activity Spaces

The present study attempts to shed some light on the overlooked impacts of metropolitan-level built environment on travel behavior. It presents results from structural equations modeling (SEM) analysis using data from 19 metropolitan areas across the United States, to construct a systematic cause-effect relationship among macro-level land use, regional mobility, and travel behavior. The results provide evidence on the direction and magnitude of these impacts, and confirm the hypothesis that changing land use policies at the neighborhood/local level alone does not result in a significant change in people's travel behavior towards less driving. Effective land use policies are those that consider the overall form of urban areas, and the composition of jobs and services in the entire region.

Concerns over high-energy consumption and pollution emissions in urban areas have increased in recent years. By itself, the transportation sector is responsible for a high portion of greenhouse gas (GHG) emissions and other pollutants. Additionally, statistics show that between 1970 and 2005, the average annual VMT per American household increased by almost 50% (Cervero & Murakami 2010).

These serious concerns have motivated researchers to think about long-term solutions to reduce the amount of automobile travel and encourage a more sustainable lifestyle. There is a consensual belief among researchers about the significant impact of the physical form of urban areas, including their settlement pattern, size, population, employment, and transportation infrastructure pattern on economic activities, housing, transportation, energy consumption, and health-related issues (Nasri & Zhang, 2012; Chatman, 2008).

Living in low-density, sprawling neighborhoods can be preferable for the many advantages they provide, such as lower crime rates, less congestion and air pollution, more green space availability, and higher-quality educational services, compared to high-density neighborhoods.

However, people who live in low-density, suburban areas may also suffer from problems caused by sprawl, such as high automobile dependency and lower rates of daily physical activity, which result in social, environmental and health-related costs (Kelly-Schwartz et al., 2004; Nasser & Overberg 2001). On the other hand, people generally state a preference for living in neighborhoods offering a shorter commute, nice sidewalks, and amenities like retail stores, restaurants, libraries, schools, and public transportation within walking distance, compared to the low-density areas with limited options for walking (Haughey, 2005).

Given the aforementioned dis-benefits of sprawled urban structure, policies promoting compact mixed-use developments are supposed to offer a more healthy and sustainable lifestyle, and therefore are considered a popular alternative to urban sprawl. However, there is still no perfect method or tool to compare and evaluate the costs and benefits of compact mixed-use urban structure and the lifestyle associated with it. The construction and promotion of higher-density, mixed-use development is usually difficult, time-consuming, and expensive for many communities.

With these issues, the question arises of how exactly—and to what extent—the overall physical form of metropolitan areas affect how often and how far people drive or use transit for their daily trips. Finding a reliable answer to this question, and estimating the magnitude of the effect, if any, helps to assess the costs and benefits of implementing long-term land use policy changes toward more infill, transit, and non-motorized-friendly forms. In addition, it would be beneficial to find more evidence on the impact of land use patterns on travel behavior.

The present study first started with six cities to conduct the local-level analysis of land use on travel behavior (see Chapter four). In the next step, the surveyed sites were expanded to 19 metropolitan areas and employed an advanced, structural equations modeling method to capture the causal effects—rather than only correlations—among variables and addressing self-selection. Moreover, I have used a combination of hierarchical land use measures and introduced many additional regional-level built environment factors, which, altogether, influence households' travel behavior.

In the following section, various datasets used in the model are introduced, along with the description of data processing efforts. It is followed by methodology and modeling approach, results, and interpretation of the results. In the last section, conclusions, policy recommendations, and the study's limitations are discussed.

6.2. Data Collection and Processing

By performing meticulous data collection and processing, this analysis tries to provide a comprehensive set of variables hypothesized to have an influence on travel behavior, including household-level socio-demographic factors, built environment attributes at various hierarchical levels, and other factors, such as congestion levels and gasoline prices. ArcGIS has been employed to geographically link the various datasets together to use in the final model.

The study area covers 19 metropolitan areas located in more than 14 states (see Figure 6-2). Table 6-1 lists the case study areas with the corresponding sample size, total population, and the population group they fall into (according to the U.S. Census website), as well as the source of travel survey data (whether from NHTS or a local agency). The sample sizes are proportionate to the population and there are case study areas from all different population groups. Also, the selected cases come from several states and regions with different cultures, geographic characteristics, and climates, which makes this sample a fair representation of the population in the whole country.

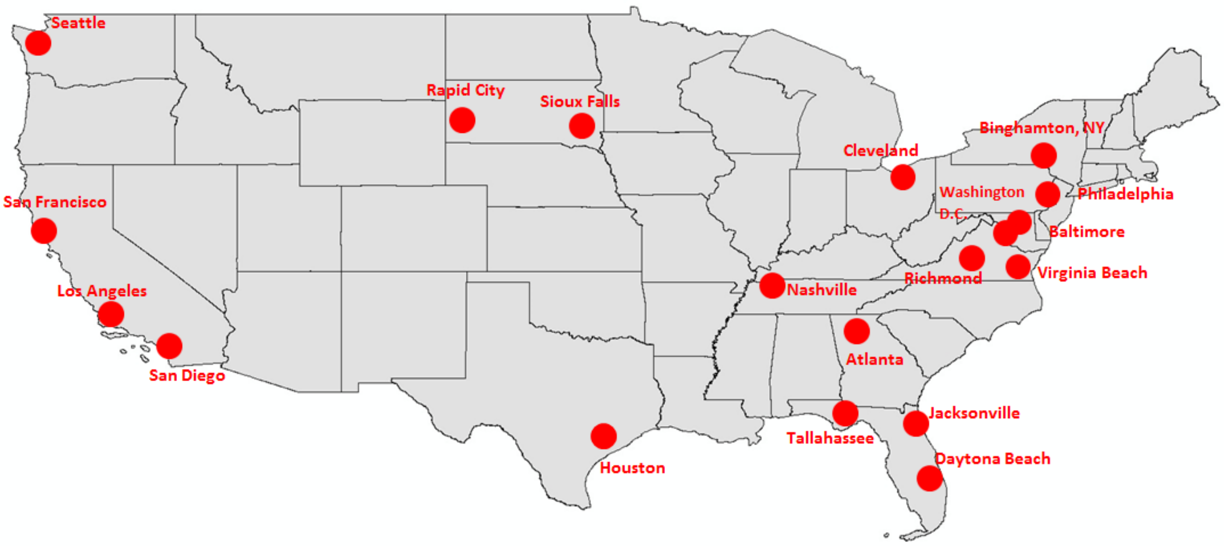


Figure 5-2 Location Distribution of Case Study Areas

Household travel survey data used in this analysis contains socioeconomic status and trip information, such as trip duration, distance, mode, trip purpose, etc., for each trip, at both household and person levels. Surveys are all geocoded at TAZ or census tract level and the GIS shapefiles are used for spatial processing of the datasets prior to statistical modeling. The households' VMTs were obtained by summing up all household members' VMTs and calculated using the weighted distance of each trip made by each person. Since this study analyzes the impact of land use on motorized urban travel, non-motorized trips and air travel were excluded from the dataset, as well as automobile trips longer than 50 miles (which are considered long–distance trips, according to NHTS 2009).

The exogenous variables fall into four groups: 1) Socio-demographic variables coming from the households' travel survey data, 2) Neighborhood-level land-use variables, 3) Regional-level land use and road network variables, and 4) Metropolitan-level land use and control variables.

Table 5-1 List of Case Study Areas

Metropolitan area	Sample size	Population (2010)	Population Group	Travel Survey Data Source
Atlanta, GA	6231	5,269,000	Very large	ARC[10]
Baltimore, MD	3991	2,710,000	Large	BMC[11]
Binghamton, NY	836	186,000	Small	BMTS[12]
Cleveland, OH	1560	2,080,000	Large	NHTS
Daytona Beach, FL	530	494,593	Small	NHTS
Houston, TX	7175	5,946,800	Very large	NHTS
Jacksonville, FL	1554	1,345,596	Large	NHTS
Los Angeles, CA	12275	12,829,000	Very large	NHTS
Nashville, TN	1840	1,353,000	Large	NHTS
Philadelphia, PA	6240	5,965,400	Very large	NHTS
Rapid City, SD	125	112,000	Small	NHTS
Richmond, VA	1891	1,208,101	Medium	NHTS Add-on
San Diego, CA	3338	3,095,000	Very large	NHTS
San Francisco, CA	5668	4,335,391	Very large	NHTS
Seattle, WA	3945	3,440,000	Very large	PSRC[13]
Sioux Falls, SD	422	212,000	Small	NHTS
Tallahassee, FL	474	367,556	Small	NHTS
Virginia Beach, VA	2461	1,676,822	Large	NHTS Add-on
Washington, D.C.	8537	6,276,000	Very large	MWCOG

This study calculates built environment variables on a small scale and then aggregates them into larger levels to prevent measurement biases that other studies have suffered from. Land-use characteristics were measured using three units of analysis to capture the effect of changes at micro- versus-macro levels, and their impacts on travel behavior. The following table (6-2) lists all the variables used in the model, along with brief descriptions, method of calculation, and data sources. The five main land use variables include population density, employment density, level of mixed-use (entropy), distance from CBD, and average block size.

[10] Atlanta Regional Commission
[11] Baltimore Metropolitan Council
[12] Binghamton Metropolitan Transportation Study
[13] Puget Sound Regional Council

Density variables at three geographical levels represent the level of sprawl in urban areas. An entropy score varying from zero to one represents how different land use types are mixed in a neighborhood, and is used as a measure of accessibility to various destinations. Two variables of average block size and lane-mile density are used to represent street connectivity, pedestrian-friendliness, and accessibility.

To measure the level of decentralization, one can use the percentage of population living within 5, 10, or 15 miles of the CBD. However, this measurement is highly dependent upon the overall size of the metropolitan area and thus cannot be a good indicator of the level of decentralization. Instead, I used two other variables measuring the percentage of employment in CBD and in regional employment sub centers, as it is very likely that the distribution of employment in an urban area is an influential factor in modeling trip distribution and length (Bento et al., 2005).

As the first step to measure polycentricity, employment subcenters were defined as a set of contiguous TAZs, and applied the minimum cutoff point method using GIS data processing. The method was proposed by Giuliano and Small (1991) and has been widely used for its simplicity and applicability in different studies (Small & Song, 1994; McMillen & McDonald, 1998; Cervero & Wu 1998; and Bogart & Ferry, 1999). It considers an employment density threshold of 10 jobs per acre in each zone and the overall 10,000+ jobs in the whole area, as the main criteria to identify subcenters (Giuliano & Small, 1991).

Table 5-2 Variable Descriptions and Data Sources

Variable	Variable description	Computation	Data source
Local level land use- TAZ or census tract level			
ResDens	Residential density	persons/acre	Local/state planning agency
EmpDens	Employment density	jobs/acre	Local/state planning agency
Dist_CBD	Distance from CBD (mi)[14]	Straight line from zone centroid to CBD	Local/state planning agency/ Census 2000
Entropy	level of mixed use development	Entropy formula	Local/state planning agency
Block_size	Street connectivity[15]/ walkability measurement	Avg block size for each TAZ (sq. mile)	Census 2000/Tiger block shapefiles
Regional level land use variables- county level			
Resdens_cnty	Mean residential density	TAZ density averaged for the county	Aggregated from TAZ-level data
Empdens_cnty	Mean employment density	TAZ density averaged for the county	Aggregated from TAZ-level data
Entropy_cnty	Mean entropy	TAZ entropy averaged for the county	Aggregated from TAZ-level data
Block_cnty	Mean block size	TAZ block size averaged for the county	Aggregated from TAZ-level data
Metropolitan level land use variables- metropolitan level			
Resdens_metro	Mean residential density	TAZ density averaged for the metro area	Aggregated from TAZ-level data
Empdens_metro	Mean employment density	TAZ density averaged for the metro area	Aggregated from TAZ-level data
Entropy_metro	Mean entropy	TAZ entropy averaged for the metro area	Aggregated from TAZ-level data
Blocks01	Walkability/connectivity measurement	% Blocks smaller than 0.01 sq. miles	Aggregated from TAZ-level data
subcenter	Decentralization measure #1	% Employment concentrated in subcenters	Employment data at TAZ level/ GIS shapefiles
Empshare_CBD	Decentralization measure #2	% Employment concentrated in CBD	Employment data at TAZ level/ GIS shapefiles
Transit_trips	Metro level transit accessibility	Avg # of transit trips in the metro area	Survey data
Transportation supply- Metropolitan level			
Lanemile_dens	Lane-mile density		Private agency
Control variables- Metropolitan level			
Gas_price	Gas price (cents)- 2008	Aggregated from county level data	Private agency
Congestion	Congestion index	Avg congestion index of the metro area	TTI[16] congestion index dataset
Size*	Metropolitan area size	Population 2010/million	Census Website

[14] Regional accessibility: The site location relative to the regional urban centers, the number of jobs and public services available within a certain travel time.

[15] Degree to which roads are connected and allow direct travel between destinations

[16] Texas Transportation Institute

* Does not appear in the final model because it was statistically insignificant.

6.3. Modeling Framework- Structural Equations Modeling (SEM)

In the present SEM framework, households' VMT and car ownership were used as the two endogenous travel behavior indicators. The hypothesis is that urban form influences households' travel behavior by either the number of cars households own or the total miles they drive (Bento et al., 2005), and these two variables are interrelated as well.

The SEM approach is the most advanced tool available to address various endogeneity issues and multilevel, cause-effect relationships, as it allows for complex interdependencies among variables. Therefore, it is the perfect modeling approach to test the relationship among built environment, regional accessibility, and travel demand, given the complex relationship among all these variables.

I tried several different model specifications and finally selected the best model representing logical, cause-effect relationships with a reasonably good statistical fit. This specification is based on the hypothesis that households' VMT and auto ownership are functions of socioeconomic and demographic characteristics of the households, built environment factors of households' residence location at different levels, as well as some other control variables (i.e., gas price, congestion level, transit use, etc.).

In figure 6-2 (below), the detailed path diagram used in SEM is shown with observed variables in rectangles and the latent variable in oval. Arrows, have connected endogenous and exogenous variables, specifying the direction of influence coming from the exogenous (independent) variables and heading toward the endogenous (dependent) variables.

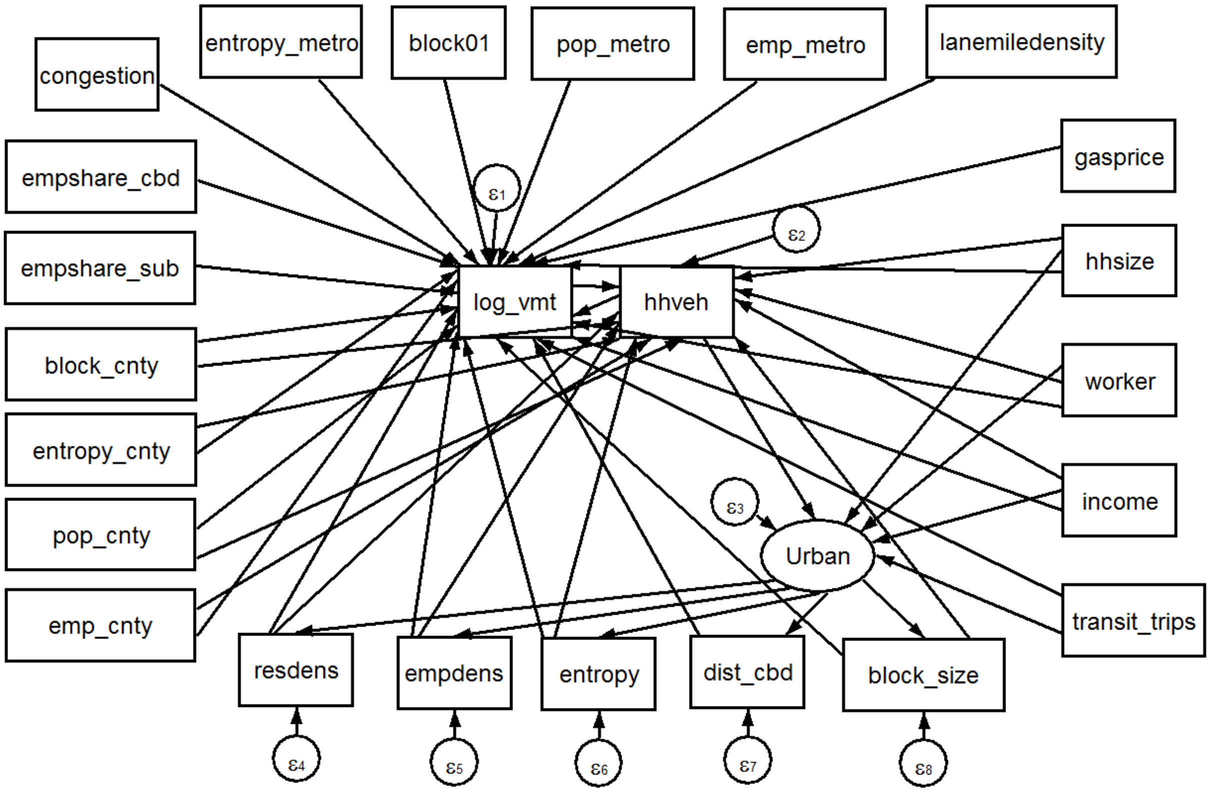


Figure 5-3 SEM Model Structure

Because of the nature of cross-sectional data used and the lack of attitudinal survey data for all case study areas, the ability for the present study to thoroughly capture the effect of self-selection is limited. However, SEM allows us to investigate the existence of this effect and estimate its magnitude relative to the impact of built environment, with a good approximation. A single, latent variable was created, representing the overall form of urban area estimated from the main neighborhood-level land use factors. Including this latent variable allows us to explicitly capture the unreliability of measurement in the model, as well as estimate the self-selection effect without having attitudinal data. To do so, similar to many previous studies (Abreu e Silva & Goulias, 2009; Cervero & Murakami, 2010; Bagley & Mokhtarian, 2002; Cao et al., 2007), I constructed causal relationships between households' characteristics (taste) and the urban form of their residence location, assuming that the overall households' characteristics and social class, to a great extent, influence their travel behavior and residential location choice. A high-income household is more likely to choose living in a single-family home in a low-density, residential neighborhood, and take advantage of affluent land and parking. In contrast, a typical low-income household with no children and no or fewer cars, tends to live in a walkable, transit-oriented neighborhood (Nasri & Zhang, 2013; Wang, 2013).

As mentioned above, the latent variable "*Urban Form*" is measured using five main land use variables as its indicators. The measurement model for "Urban Form" is specified as follows:

$$D_{res} = a_1 UF + e_1 \tag{8}$$

$$D_{emp} = a_2 UF + e_2 \tag{9}$$

$$Dist_{CBD} = a_3 UF + e_3$$

(10)

$$Entropy = a_4 UF + e_4 \tag{11}$$

$$Block = a_5 UF + e_5 \tag{12}$$

Where:

$UF: Urban\ Form\ variable$

$D_{res}: Residential\ density$

$D_{emp}: Employment\ density$

$Dist_{CBD}: Distance\ to\ CBD$

$Entropy: Mixed\ use\ score$

$Block: Average\ block\ size$

$a_1, a_2, a_3, a_4 and\ a_5: regression\ coefficients$

$e_1, e_2, e_3, e_4, and\ e_5 : measurement\ errors$, and

$$(UF, D_{res}, D_{emp}, Dist_{CBD}, Entropy, Block, e_1, e_2, e_3, e_4, e_5) \sim N\ (\mu, \Sigma)$$

I assume that all variables, both observed and latent, follow a multivariate, normal distribution. Observations are assumed to be independent. Also, measurement errors are assumed independent of the latent factor, *Urban Form*.

6.4. Results and Interpretations

6.4.1. Summary Statistics

In Table 6-3, the descriptive statistics for land use factors at neighborhood-level are shown for each metro area separately. The numbers indicate that in all metropolitan areas, the mean residential density is higher than the employment density (twice or more). The lowest mean residential and employment densities belong to Cleveland, with 0.43 persons/acre and 0.20 jobs/acre. Entropy has the lowest mean (0.33) in Seattle and Sioux Falls and the highest in Cleveland and Philadelphia. Rapid City and Daytona Beach have the highest average block size of them all, which implies lower street connectivity and pedestrian-friendliness in these cities.

Table 5-3 Descriptive Statistics- Neighborhood Level Land Use Characteristics*

Metropolitan Area	Residential density		Employment density		Entropy		Avg. block size	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Atlanta, GA	4.37	2.45	2.26	3.01	0.71	0.24	0.088	0.081
Baltimore, MD	8.83	9.32	4.72	17.22	0.47	0.21	0.097	0.145
Binghamton, NY	4.24	3.79	1.88	2.88	0.41	0.23	0.075	0.120
Cleveland, OH	0.43	0.42	0.20	0.19	0.85	0.11	0.102	0.124
Daytona Beach, FL	4.25	6.2	1.68	2.65	0.52	0.17	0.381	0.398
Houston, TX	5.15	4.61	2.37	4.55	0.71	0.20	0.107	0.161
Jacksonville, FL	8.80	6.58	4.88	6.67	0.51	0.17	0.136	0.176

Los Angeles, CA	13.51	38.59	4.09	7.54	0.68	0.21	0.090	0.099
Nashville, TN	2.06	1.84	1.24	1.99	0.56	0.19	0.157	0.117
Philadelphia, PA	37.90	69.64	22.64	49.56	0.85	0.15	0.049	0.052
Rapid City, SD	1.76	1.63	0.98	1.20	0.57	0.16	0.435	0.444
Richmond, VA	2.57	2.80	1.17	1.85	0.60	0.18	0.155	0.164
San Diego, CA	9.04	7.36	2.90	6.26	0.65	0.22	0.071	0.189
San Francisco, CA	11.33	13.29	3.83	7.10	0.69	0.22	0.076	0.191
Seattle, WA	6.64	7.45	3.71	14.83	0.33	0.15	0.078	0.133
Sioux Falls, SD	10.95	10.70	6.12	7.28	0.33	0.08	0.162	0.169
Tallahassee, FL	4.53	4.67	2.96	4.96	0.73	0.19	0.079	0.144
Virginia Beach, VA	3.58	2.77	1.31	1.83	0.59	0.15	0.134	0.169
Washington, D.C.	11.95	14.58	7.22	22.63	0.42	0.22	0.107	0.177

** Distance to CBD is excluded as it is largely dependent on the metro area size*

6.4.2. SEM Results

The results from SEM model–as expected–show that promoting compact, mixed-use, built environment with well-connected street networks and a lower concentration of employment in CBD is very effective in reducing VMT and encouraging other modes. It confirms the same direction of influence as many other studies; that is, residents of cities with better job-housing balance, overall higher densities and transit accessibility produce lower VMT and own fewer private cars.

The results from the VMT and car ownership equations in the SEM model are shown in Tables 6-4 and 6-5, respectively, indicating direct, indirect, and total effects. Blank cells represent either no direct path between variables, or the coefficients constrained to be zero. The effect of built environment has been categorized by local/TAZ level, regional (county) level, and metropolitan area as a whole. This contributes to a better understanding of these effects and what kinds of land use changes would influence people’s short and long-term travel behavior. Results suggest that income, household size, and number of workers (i.e., commuters) within the household are all positively correlated with VMT and car ownership, meaning larger households who have higher annual income and more commuters, exhibit higher VMT and own more private cars. Also, households who have higher numbers of transit trips show lower VMT, which indicates switching among modes.

Table 5-4 Structural Equations Model Results- VMT Equation

Independent variables	Direct coefficients	*p-value*	Indirect Coefficients	*p-value*	Total coefficients	*p-value*
Households Characteristics						
HH size	.088	0.000	.009	0.416	.096	0.000
HH income	.056	0.000	.0021	0.421	.058	0.000
HH worker	.353	0.000	.0077	0.435	.361	0.000
Transit trips	-.0028	0.000	-9.93e-06	0.318	-.0028	0.000
Auto	.034	0.428	.00051	0.003	.035	0.423
TAZ-level variables						
ResDens	-.0015	0.000	.00001	0.101	-.0015	0.000
EmpDens	.0022	0.002	.00044	0.000	.0027	0.000
Entropy	-.214	0.000	-.0011	0.282	-.214	0.000
Dist_CBD	.013	0.000	.00005	0.000	.014	0.000
Avgblock	.384	0.000	.0213	0.000	.405	0.000
Regional (county) level variables						
Resdens_cnty	-.000014	0.000	1.73e-07	(constrained)	-.000014	0.000
Empdens_cnty	.00027	0.000	-4.04e-06	0.444	.00027	0.000
Avgblock_cnty	.094	0.033	.011	0.421	.105	0.010
Entropy_cnty	-.701	0.000	-.022	0.429	-.723	0.000
Lanemile density	-.0012	0.365	-4.21e-06	0.479	-.0012	0.365
Metropolitan level variables						
Resdens_metro	.002	0.000	6.92e-06	0.357	.0020	0.000
Empdens_metro	-.0019	0.000	-6.65e-06	0.366	-.0019	0.000
Block01	-.018	0.000	-.00006	0.351	-.018	0.000
Entropy_metro	-.125	0.305	-.00043	0.495	-.125	0.305
Gas price	-.036	0.278	.00012	0.504	-.036	0.279
Congestion	-.124	0.006	-.00043	0.343	-.124	0.006
Empshare_CBD	.031	0.000	.00011	0.359	.031	0.000
Empshare_sub	-.018	0.000	-.00006	0.350	-.018	0.000

There is a two-way relationship between the endogenous variables of VMT and car ownership, and the results show that—as hypothesized—these two variables positively affect each other. Higher VMT encourages vehicle ownership; having more automobiles available encourages households to drive more. However, model shows that the effect of car ownership on households' VMT is not statistically significant.

As previous studies show, high residential density and mixed-use development are associated with lower VMT at the local/neighborhood level. However, at the metropolitan level, residential density seems to have a positive and significant relationship with VMT. The employment density significantly influences both VMT and car ownership at larger levels, with a negative direction at higher levels and positive direction at a smaller scale of the built environment. These findings are not consistent with aforementioned hypothesis and might be because entropy has a statistically significant, negative impact on households' VMT and car ownership at all three levels, with the exception of the local-level, which is positive. The effect of entropy is highest in terms of magnitude at the county level for both equations.

Table 5-5 Structural Equations Model Results- Car Ownership Equation

Independent variables	Direct coefficients	*p-value*	Indirect Coefficients	*p-value*	Total coefficients	*p-value*
Households Characteristics						
HH size	.236	0.000	-.0065	0.069	.229	0.000
HH income	.054	0.000	.0030	0.017	.057	0.000
HH worker	.188	0.000	.044	0.000	.232	0.000
Transit trips	--	--	-.0002	0.000	-.00019	0.000
HH VMT (logged)	.098	0.000	-.0072	0.000	.0909	0.000
TAZ-level variables						
ResDens	.00049	0.016	-.00018	0.000	.00031	0.101
EmpDens	.012	0.000	-.00071	0.000	.0117	0.000
Entropy	-.011	0.706	-.0186	0.000	-.029	0.282
Dist_CBD	--	--	.0012	0.000	.0012	0.000
Avgblock	.57	0.000	-.0073	0.175	.563	0.000
Regional (county) level variables						
Resdens_cnty	6.31e-06	0.000	-1.73e-06	--	4.58e-06	0.000
Empdens_cnty	-.00014	0.000	.000035	0.000	-.00011	0.000
Avgblock_cnty	.313	0.000	-.0146	0.112	.298	0.000
Entropy_cnty	-.570	0.000	-.0216	0.438	-.5918	0.000
Lanemile density	--	--	-.00011	0.381	-.00011	0.381
Metropolitan level variables						

Resdens_metro	--	--	.00018	0.000	.00018	0.000
Empdens_metro	--	--	-.00018	0.000	-.00018	0.000
Block01	--	--	-.0016	0.000	-.0016	0.000
Entropy_metro	--	--	-.011	0.310	-.011	0.310
Gas price	--	--	-.0032	0.275	-.0032	0.275
Congestion	--	--	-.0113	0.020	-.0113	0.020
Empshare_CBD	--	--	.0028	0.000	.0028	0.000
Empshare_sub	--	--	-.0016	0.000	-.0016	0.000

The employment density's coefficients follow an opposite trend. In the literature, mixed findings have been reported in terms of the relationship between a neighborhoods' employment density and the amount of driving, and it has been a center of debates for several years. Findings show a significant positive direction of influence of employment density at smaller scales and a negative direction at higher levels, in both VMT and car ownership equations.

In terms of the influence of street connectivity, the coefficients in the VMT equation imply that larger blocks (at both local and regional levels), farther distance from the city center, and a concentrated, higher employment share in the city center all lead to higher household VMT. The effect of block size (street connectivity/pedestrian friendliness) is larger at the local level, compared to that at the regional/county level.

Moreover, increased gas prices, congestion, and level of decentralization all have negative effects on VMT and car ownership. According to estimated equations, households' VMT and vehicle ownership decrease when the price of gasoline, congestion level in the network, or share of employment by regional employment sub centers, increase. This finding is especially interesting, as the effect of decentralization and growth of regional employment sub centers, both in terms of number and share of employment, have been very controversial among planners and policymakers. It suggests that the higher the share of employment centers and the stronger they are in terms of economic activities, the less people drive, probably because their commute distance becomes shorter, especially for those who live in suburban areas far from downtowns.

Looking at the coefficients, the effects of residential and employment densities on VMT are found to be small, compared to the coefficients of mixed-use and street connectivity (block size). This implies that building higher-density neighborhoods alone cannot be very effective in reducing automobile travel and promoting sustainable modes of transportation. This type of development is more effective in the context of a mixed-use, pedestrian-friendly neighborhood with easy access to transit.

The indirect results represent all effects occurring because of the existence of intervening variables in-between two variables. Results show that the indirect effects of the built environment variables on travel behavior are weak, and in most cases, statistically insignificant; thus, they are negligible. This might also imply that although statistical models prove the existence of statistically significant self-selection effect, or household's taste as an indirect effect, it is not as high as to frustrate the true effect of built environment on travel behavior. A more detailed discussion on the self-selection effect is presented in the next section. The proposed model specification provides no direct path from metropolitan-level built environment variables on car ownership, as I assume the decision of purchasing a private car is more of a long-term decision. While there is a correlation between car ownership and the physical form of urban areas at neighborhood and regional levels, there is a nonexistent or negligible relationship between the overall form of urban environment and the decision of auto ownership. If a household lives in a neighborhood where there is access to various destinations within walking distance, or if transit service is provided extensively and efficiently, there may be a higher chance of deciding to own no or fewer automobiles. The results from the indirect coefficients confirm the hypothesis and reveal that although these indirect effects exist and are statistically significant, they are quite small in terms of magnitude, as compared to the local and regional level land-use coefficients.

6.4.3. Self-Selection Effects

I created one latent variable representing the overall form of urban environment from all five land use variables at the TAZ level, and hypothesized that this latent variable is influenced by households' characteristics, such as size, income, number of workers, car ownership, and transit usage. The overall results from the self-selection effect analysis indicate a small but statistically significant influence of households' taste on residential location choice. Table 5-6 (below) shows all coefficients and relationships in detail.

Table 5-6 Urban Form Estimation- Self-selection Effects

To		From	Coefficient	*P-value*
Latent variable: Urban				
ResDens	←	Urban	1 (constrained)	--
EmpDens	←	Urban	.973	0.000
Entropy	←	Urban	.0024	0.000
Dist_CBD	←	Urban	-.029	0.000
Avgblock	←	Urban	-.0006	0.000
Self-selection effect				
Urban	←	Auto	-6.86	0.000
Urban	←	HH size	.26	0.225
Urban	←	HH income	.17	0.000
Urban	←	HH worker	2.26	0.000
Urban	←	Transit trips	.0059	0.000

Similar to several other studies, I found that both built environment characteristics and residential self-selection influence travel behavior and car ownership jointly, reinforcing the effects of each other. However, standardized coefficients show that household car ownership is the most influential factor in determining residential location choice. It shows a far larger effect than any other household characteristics on the latent variable urban form. The negative effect of car ownership suggests that households with more automobiles tend to live in suburban neighborhoods where they can enjoy free parking and less congested roads, along with quiet residential areas and more spacious homes.

6.5. Conclusions and Study Limitations

Understanding and analyzing the complex relationships between land use and travel behavior thoroughly is a key factor in sustainable planning, and the main goal of the present study. A more detailed understanding of these relationships would help researchers and planners to propose and implement the types of changes in land use that would eventually result in lower rates of automobile travel and shorter trips, and thus, less traffic congestion and environmental pollution.

This analysis suggests that the built environment at larger scales, and the overall form of urban areas as a whole, play an important role in determining people's travel patterns. At the neighborhood level, results show that compact development patterns, higher employment opportunities, and better mixed neighborhoods encourage less driving. However, the effect of land use on a regional scale is larger and more significant, according to modeling results. Residents of metropolitan areas with smaller city centers, more regional employment subcenters, and higher transit accessibility, will drive less and own fewer automobiles. This is similar to what Ewing and Cervero (2001) suggested; that VMT is more influenced by regional accessibility rather that density at local level: "…dense, mixed-use developments in the middle of nowhere may offer only modest regional travel benefits."

High residential density and mixed-use development at the local/neighborhood level, as many previous studies have shown, are both associated with lower VMT. However, at the metropolitan level, residential density seems to have a positive and significant relationship with VMT. It implies that, as cities become denser in terms of the overall metropolitan-wide residential areas, the overall form of cities requires residents to drive more to reach various destinations. It could be said that there is an optimal threshold for the cities to become dense (by attracting more population and developing more high-density residential neighborhoods), and still remain sustainable in terms of travel behavior. The findings here confirm this claim by indicating the positive relationship between the amount of driving and the metropolitan-wide residential density.

The employment density's coefficients follow an opposite trend. In the literature, mixed findings have been reported in terms of the relationship between neighborhood employment density and the amount of driving, and it has been a center of debate for several years. Findings show a significantly positive direction of influence of employment density at smaller scales and a negative direction at higher levels, in both VMT and car ownership equations. The observed positive influence at smaller levels may be because higher employment density in the neighborhood of residence (including more retail stores, service, recreational, and office spaces) gives auto-dependent people (often the majority of the population) more incentives and choices for travel, increasing VMT by generating more trips, even though the trips are shorter in length (the induced demand). At the metropolitan level, the overall higher employment density indicates there are more jobs available throughout the entire metro area, which largely reduces the number of people who need to commute relatively long distances across metropolitan area boundaries to reach jobs (i.e., fewer super-commuters), and reduces the overall VMT at the household and individual levels.

However, a more detailed analysis is needed to understand the underlying reasons behind these findings, especially since there is no specific pattern for the residential and employment densities of cases with respect to their population and size. One can investigate these issues by including more cities and employing more sophisticated modeling methods, in order to find a more detailed explanation for these findings in the future. Entropy has a statistically significant negative impact on households' VMT and car ownership at all three levels, except for the effect of local-level entropy on car ownership, which is positive. The effect of entropy is highest in terms of magnitude at the county level for both equations.

The findings suggest that urban design policies should definitely be considered as part of the solution to current, highly debated transportation and environmental problems. The findings presented in this research can potentially provide guidelines for decision-makers to set or evaluate these land use and urban design policies and improve them for more sustainable neighborhoods.

However, this study has several limitations. First, cross-sectional data was used in this study, which is not strong enough to fully investigate a causal relationship. An analysis based on longitudinal data will potentially offer more reliable evidence of the causal relationship between the built environment and travel behavior, with the clear establishment of temporal precedence (Finkel, 1995; Cao et al., 2007; Bagley & Mokhtarian, 2002). Second, due to a lack of attitudinal survey data for all case study areas, the impact of self-selection was not captured thoroughly. Instead, I modeled the overall urban form as a function of residents' characteristics, assuming that household socio-demographic factors, to some extent, represent households' tastes and therefore influence their residential location choices.

The other limitation of the present study is that several factors influencing travel behavior at the metropolitan and regional levels have not been included. For instance, the crime rate around transit stations and through the entire metropolitan area could potentially affect the transit ridership rate and non-motorized mode share, thus indirectly influencing the VMT and car ownership (Bento et al., 2005). This possible effect is neglected in the present study due to data limitation and measurement complexity. However, in future studies, these factors could be taken into account, along with other safety measures.

In future research, longitudinal data should be employed in order to fully capture the causal relationships, along with the use of attitudinal survey data to control for the issue of self-selection. The model structure could also be improved by including more travel behavior indicators and BE variables in the work locations—in addition to residential neighborhoods—to more deeply investigate the determinants of commuter trips.

Chapter 7: Policy Analysis: Transit-Oriented Development (TOD)

Several land use policies have been proposed and implemented in the last few decades, which all favor high-density and pedestrian-friendly design in the hope of reducing auto use and encourage transit ridership. In this chapter, a comprehensive analysis of a popular land use strategy, known as "transit-oriented development," or TOD, is provided, along with a comprehensive modeling framework to investigate the effects of living and working in TOD areas on travel pattern.

At the disaggregate (i.e., household) level, models for VMT, trip generation, trip distribution, and mode choice were developed to perform this analysis, using data from TOD zones in two metropolitan areas: Washington, D.C. and Baltimore.

At the aggregate level, using data from all rail transit stations across the United States, an analysis of commute mode share in the station areas' precinct has been performed, in order to better understand how promoting high-density, mixed-use developments, combined with high transit and job accessibility, could influence people's commute behavior towards more transit use and less auto dependency.

At the end of this chapter, a summary of the work completed and the key points found in the analyses for the planners and policy-makers has been provided, along with concluding remarks.

7.1. Introduction to Transit-Oriented Development

Transit-oriented development (TOD) is a type of development that is designed to encourage the use of public transit and create a pedestrian-friendly, urban environment. Various terms such as “transit village,” “transit-friendly design,” and “transit-supportive development” have been used over the years to refer to this concept (Cervero, Ferrell, & Murphy, 2002). However, TOD is the most widely used and popular among all of these terms.

TOD is primarily focused on providing transit service along with high density and mixed-use development to encourage transit ridership. The Maryland Department of Transportation defines TOD as, “a place of relatively higher density that includes a mixture of residential, employment, shopping, and civic uses and types, located within an easy walk of a bus or rail transit center.” TOD is a fast-growing development strategy and is becoming more popular among city planners, land developers, and government officials for its potential to increase transit ridership and reduce VMT by shortening trips. However, there has not been enough research on the success of TODs in providing sustainable transportation modes, which will eventually result in less energy consumption, environmental pollution, and traffic congestion in urban areas. The present study tries to understand how travel behavior is different for TOD residents in the two metropolitan areas of Washington, D.C. and Baltimore. This is done by examining the changes in trip generation, trip distribution, mode share, and vehicle miles traveled (VMT), in order to analyze the effectiveness of TODs in encouraging riders to swap driving for transit, walking, biking, and other sustainable modes of transportation.

The question, “Can transit-oriented development reduce automobile travel and encourage transit ridership?” has been asked frequently, ever since TODs were first proposed and implemented in urban areas. In this section, I summarize the work I have done to try to find a viable answer to this question.

In general, transit-oriented development provides an environment where residents live within walking distance of a major transit station and other amenities. TODs are primarily designed to promote transit ridership and use through several different features. First, by living near transit, residents are connected to the entire transit network. This feature aims to increase transit ridership and use, while granting access to more job centers, educational opportunities, and cultural facilities (Arrington & Cervero, 2008). TOD also aims to provide a pedestrian-friendly, mixed-use environment, and better accessibility, therefore promoting pedestrian activities.

Contemporary research shows that one of the key factors in lowering levels of automobile use in transit-served neighborhoods is the presence of in-neighborhood retail sites between residences and stations, which promotes "rail-pedestrian" trip-chaining. An analysis of the American Housing Survey suggests that the presence of retail near rail stations can boost transit commute mode share by as much as 4% (Cervero, 1996). Thus, "well designed, concentrated, mixed-use development around transit nodes can boost transit use around five to six times higher than comparable development away from transit" (Cervero et al., 2004).

In North America, there are about 200 established TODs with nearly 4,000 sites offering potential for various forms of TOD practice.[17] TOD has recently received a lot more attention as a tool to promote smart growth strategies, revitalize areas, enhance the economy, and improve quality of life, by enabling suitable transportation arrangements for people. Many cities have implemented smart growth initiatives in order to resurrect neighborhoods and stimulate their economy (Cervero, Ferrell, & Murphy, 2002). Smart growth policy encourages economic revitalization by creating mixed-land uses that increase business opportunities, such as additional housing, nightlife services, shopping, and various other activities.

[17] Reconnecting America

As mentioned above, proponents of transit-oriented development policies hope that TODs will promote walking, biking, and transit ridership for daily trips in many different ways and consequently, will reduce the amount of driving. This hypothesis, however, has not been examined adequately in the previous literature about TOD. There is a lack of knowledge, especially regarding the extent to which TOD may reduce total VMT, particularly since a reduction in total VMT translates into less energy consumption and vehicle emissions. The purpose of this analysis is to examine how travel behavior changes within the context of TOD, and whether or not it is successful in achieving its aforementioned goals and objectives. The focus of the disaggregated study here is on the Washington, D.C. and Baltimore metropolitan areas, where there is a growing interest among policymakers and planners to promote transit-oriented and joint development policies (Washington Metropolitan Area Transit Authority-WMATA). Specifically, by performing this analysis, I have tried to answer the key question of how transit-oriented development (TOD) affects vehicle miles of travel, trip generation and distribution, and mode choice. First, a comprehensive definition for TOD is provided along with the way its design features can be quantitatively measured. Then, based on the proposed measurement criteria, this analysis presents findings from a comprehensive travel behavior analysis in TOD vs. non-TOD areas of the two metropolitan areas of study.

In the next step, an aggregated-level analysis of the commuting mode share in all rail transit station areas across the country has been performed. Data is gathered for residents who live in a ½ mile buffer zone of rail transit stations. Their commute mode share is modeled as a function of the main land use characteristics and level of employment accessibility at three levels: station area, neighborhood, and metropolitan area (for details, see section 7.5).

7.2. TODs in Literature

This section provides a brief overview on the conceptual framework for TOD, as well as the main findings of past studies related to the performance of TODs and their effectiveness on changing travel behavior along with its environmental impacts. I reviewed the body of literature on transit-oriented development both in terms of how it has been conceptualized over time, and what the policy requirements are for designing the TOD areas. Also, TOD performance and its impact on travel behavior, environment, and affordable housing in urban areas after implementation were extensively reviewed.

7.2.1. TOD Definitions and Conceptual Framework

The research community's present state of knowledge provides various definitions for TOD, based on different viewpoints and perspectives. Some define it simply as a high-density area located within walking distance of a transit station (CTOD);[18] others highlight the walkability factors as well as high-density and mixed-use aspects (Calthorpe, 1993; Parker et al., 2002). By doing so, they define TOD as a high-density area where there are shopping, housing and employment opportunities available, designed for pedestrians without excluding the automobile (Parker, 2002). Others focus on how well the collaboration of land uses and transit can work, and identify TOD as, "development with a functional relationship to transit, allowing it to achieve synergies that enhance the value of both."[19]

Most of the theoretical definitions proposed for TOD include some common elements, such as compact mixed-use development pattern, pedestrian-friendliness, and being well -served by

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[18] Center for Transit-Oriented Development
[19] Fastracks, 2008; page 3

transit (Cervero, Ferrell, & Murphy, 2002). In practice, there are different approaches proposing different quantitative measurement criteria for TOD. Bernick and Cervero (1997) have specified a half-mile buffer zone around a transit station as TOD. They defined TOD as, “a compact, mixed-use community, centered around a transit station that—by design—invites residents, workers, and shoppers to drive their cars less and ride mass transit more. The transit village extends roughly a quarter mile from a transit station, a distance that can be covered in about 5 minutes by foot. The centerpiece of the transit village is the transit station itself, and the civic and public spaces that surround it. The transit station is what connects village residents to the rest of the region” (Bernick & Cervero, 1997).

Lund, et al. (2004) also emphasizes TOD design for both motorized and non-motorized modes, and suggests that encouraging pedestrian trips without having to discourage automobile traffic is possible, by creating street networks that allow safe and efficient interaction among all these modes (Lund, Cervero, & Willson, 2004).

7.2.2. Empirical Analyses of TOD

In addition to studies that built theoretical frameworks for TOD definition, characteristics, design guidelines, and expected benefits, there are empirical works analyzing TODs that perceive how effective they are in terms of increasing transit ridership, reducing emissions, and encouraging more active transportation.

Since the time TODs were first proposed and implemented, the academic community has been interested in investigating the benefits and dis-benefits of this kind of development, and evaluating the influence of TOD on economic growth, housing markets, traffic congestion, and environmental issues. Among these, transportation and travel behavior-related impacts of TOD, and methodologies to model these impacts, have received the most attention. Researchers and travel behavior analysts found that TODs in general have the potential to reduce the number of automobile trips by providing easy access to transit and commercial/retail destinations and encourage non-motorized modes (Lund et al. 2004; Cervero 2008).

One of the earliest studies of this kind, by Robert Cervero, showed that TOD residents are around five times more likely to take transit to work. In addition, those who work in TOD areas are about three times more likely to use transit to get to work, compared to all workers in the city (Cervero, 1993). Another, more recent study by Arrington and Cervero (2008) analyzed 17 TOD projects of varying sizes in 4 urbanized areas, and found that people living in TOD areas use transit 2 to 5 times more often for commuting trips, compared to those living in non-TOD areas. They claimed that automobile travel is reduced in TOD areas for three main reasons: 1) residential self-selection, 2) the availability of retail stores in neighborhoods and the short distance to the transit stations, and 3) reduced car ownership rate, as a result of residing in transit-served neighborhoods. Lund et al. (2004) also found that transit shares for TOD residents is higher, compared to the other surrounding areas by a factor of 4.9.

Within TOD areas, transit share is higher for commute trips than for non-work travel. In a very interesting piece of research, Renne (2005) found that over the 30-year period from 1970 to 2000, transit mode share for work trips has increased amongst TOD residents from 15.1% to 16.7%, while it has decreased across all regions from 19% to 7.1%. Despite regions becoming increasingly auto-dependent for work trips, the proportion of TOD residents using transit for commuting was more than twice as high than that of the regional average (16.7% versus 7.1%) in 2000 (Renne, 2005).

There are different views among researchers about the importance of specific land use characteristics, such as high density and mixed-use, in TOD areas. Some claim that presence of a transit station alone can be a very effective factor in encouraging residents to use transit. Cervero (1993) found that for TOD residents, proximity to a transit station is more strongly associated with transit use than land use mix or high-quality walking facilities. He claimed that, “as long as one lived near a rail station, other design factors are unlikely to deter them from using transit.” Others take the opposing view by saying that all else being equal, the higher the residential and employment densities around transit stations, and the higher the mix of land uses, the greater the transit ridership—and that is even more significant than being close to a transit facility (Tumlin & Millard-Ball, 2003; Chatman, 2013). There is a third viewpoint saying that for non-work trips, shifting to transit is largely dependent on the degree of mixed-use, the scale of the development, and the high residential and retail densities (Lund et al., 2004), while for work trips these factors are not as important. Arrington and Cervero (2008) also believe that the mixed-use nature of the built environment in TOD areas allows transit use for a variety of trip purposes and accommodates non-work trips throughout the day and week. This study also found that the combination of high densities and small block size significantly increased transit ridership among TOD residents in the San Francisco Bay Area in 2000. However, the land use features of TOD seem to be more effective in shorter distance, non-work trips. In other words, having offices, shops, restaurants, and other amenities around a major transit station in high-density areas encourages less driving and more non-motorized travel (Arrington & Cervero, 2008).

In addition to the land use characteristics in the immediate neighborhood of residence, some researchers also believe that travel behavior is significantly related to the entire metropolitan area’s built environment pattern. Nasri and Zhang (2012) claimed that having high residential and employment densities, along with mixed-use development throughout the entire metropolitan area, aims to lower VMT and encourages transit use. Thus, transit-oriented planning and design for a person's lifestyle in his/her entire activity space is considered, instead of just the neighborhood of residence or work and in the half-mile buffer zone.

Lund et al. (2004) suggested that the success of TOD in terms of increased transit ridership is also linked to the length of residency for TOD residents. Their results show that longer residencies are associated with higher rates of transit use. They hypothesized that longer-term residents tend to use transit more often, as they are more familiar with the transit services in and around the area, and therefore have more opportunity to adjust their workplace and other trip destination locations to take advantage of transit accessibility. For work trips only, their results show that the pattern of increased transit use appears for those in the 6-10 year residency group, and even more for those having a length of residency longer than 10 years. However, the "drive vehicle, alone" share is similar among different lengths of residency (Lund et al., 2004).

Zhang (2010) studied the traffic outcomes in TOD areas by applying the traditional four-step travel demand modeling. In this paper, the congestion relief was analyzed in two scenarios of "Rail-Only" TOD and "All-Systems-Go" TOD, as opposed to the base case "no TOD." The study estimated a reduction in congested roadways by 513 lane miles and a decrease in VMT by 9.6 million from the base of No-TOD scenario. He claimed that having higher population and employment densities in TOD areas typically generate more traffic and worsen congestion, rather than improve traffic conditions in TOD and surrounding areas. Also, the concentration of jobs in TOD areas may increase traffic density on local roads, even though residents in TOD drive less and take transit more. This result contradicts the general belief about TOD, saying that even though this policy encourages high-density development, it eventually aims to reduce traffic congestion by promoting other modes of transportation (Zhang, 2010).

There are several studies in the body of literature focused on the effect of TOD and different land developments on overall and mode-specific trip generation. Lapham (2001) developed several regression models with data gathered from eight TODs located in the Portland metropolitan region, relating TOD attributes to the trip generation. In Transit Cooperative Research Program (TCRP) report 128, the weighted average vehicle trip rate was computed for 17 TOD built projects in Philadelphia, Portland, Washington, D.C., and East Bay (Arrington & Cervero, 2008). Results of these studies showed that the average trip generation rate in TOD areas is well below the proposed Institute of Transportation Engineers' (ITE) trip generation rate. Chatman (2013) modeled weekly grocery-shopping auto trip generation as a function of built environment attributes and transit proximity, and found that the TODs benefit does not depend very much on rail access (Chatman 2013).

Elasticity factors of "3Ds," "4Ds," and "5Ds," including density, diversity, design, destination, and distance to transit stations, have been used to estimate auto trip generation rates (Cervero & Kockelman, 1997; Lee & Cervero, 2007). Colman et al. (1992) modeled auto trip generation rates in TOD zones of Sacramento County, indirectly using the change in vehicle ownership due to improvement in transit service and urban structure.

Unlike trip generation, there is not as much research completed in the previous studies on trip length and trip distribution of TOD residents. In theory, developing high-density, mixed-use areas makes destinations closer together and thus reduces the average trip length (Crane, 2000). Empirically, most of the literature in this area includes only descriptive statistical analysis. McCormack et al. studied two mixed-use neighborhoods in Seattle (McCormack et al., 2001).

Their analysis showed that residents of these two areas traveled 28-120% fewer kilometers than residents of nearby suburbs. Lund et al. (2004) compared the mean commute time for station area residents and the surrounding cities, and found that station area residents spend twice as much time commuting to work as residents of surrounding cities. Another study in Austin, Texas showed that the average length and duration of trips that originate or end in mixed-use developments are less than the ones that start and end in other areas, for both commuting and non-work trips (CAMPO, 2009). Muley et al. (2012) compared mode share and length of trips made by residents of a fully planned, mixed-use development located in Brisbane, Australia to the residents of Brisbane as a whole, and found that mixed-use area residents have lower average trip lengths, use automobiles for farther destinations and public transport for relatively closer destinations.

7.3. Mathematical Framework for TOD Identification and Delimitation

As discussed in the previous section, there have been several different definitions for TOD proposed by planners, researchers, and practitioners. However, there is no clear path or generally accepted definition or standard to follow in terms of both theoretical and practical aspects of TOD. In theory, a TOD neighborhood often consists of a center with a major public transit station, surrounded by high-density development with a mixture of residential, employment, shopping and civic uses, and lower-density development gradually spreading outward from the center (Holmes & Hemert, 2008). In practice, many TOD studies defined its boundaries using a half-mile buffer around selected transit stops (Reconnecting America, 2009; Dittmar & Ohland, 2003; Austin & Fogarty, 2011; Soursourian, 2010; TCRP Report 95, 2007).

I formalize a quantitative methodology to identify TOD areas. It comprehensively considers all of the generally accepted theoretical aspects of TOD, such as the presence of one or more transit centers surrounded by high residential and employment densities, and mixed-use development. The proposed methodology contains three main factors: 1) walkability and high density; 2) walking distance to a transit station; and 3) collaboration of mixed uses and transit.

A Traffic Analysis Zone (TAZ) is identified as a TOD if it meets the following conditions:

$$TAZ \in TOD\ iff \tag{13}$$

$$\left(D^{TAZ}_{Residential} \geq D^{Avg}_{Residential}\ OR\ D^{TAZ}_{Employment} \geq D^{Avg}_{Employment}\right)$$

$$B_{TAZ} \leq B_{Avg}$$

$$Rank^{Entropy}_{TAZ}/n \geq 0.30$$

$$TAZ \in U_{1 \leq i \leq n} Ball^{T_i}_{0.5}$$

where:

$D^{TAZ}_{Residential}$ = Residential density of *TAZ*= $\text{residential population/area (acre)}$

$D^{TAZ}_{Employment}$ = Employment density of *TAZ*= $\text{employment population/area (acre)}$

$D^{Avg}_{Residential}$= Average residential density for the entire metropolitan area

$D^{Avg}_{Employment}$= Average employment density for the entire metropolitan area

B_{TAZ}= Average block size of TAZ (sq mi)

B_{Avg} = Average block size for the entire metropolitan area

$Rank^{Entropy}_{TAZ}$ is the rank of *Entropy (TAZ)* when sorted decreasingly according to entropy

$Ball_{0.5}^{T_i}$ is the circle of radius 0.5 mile around point T_i

$T_i, 1 \leq i \leq n$ is the point where the transit station is located

This methodology is applied in both the Washington, D.C. and Baltimore metropolitan areas, separately. The results have been used in the model as a binary variable called TOD, with a value 1 for the TAZ to be considered as a TOD area and zero otherwise.

The methodology presented above is an arbitrary method that has been chosen based on our knowledge, experience, and data availability, and for its ability to be applied to other metropolitan areas. Various other definitions and quantitative methods can certainly be applied in the future to test the sensitivity of the results to those other types of methodologies and definitions for TOD.

To define TOD boundaries based on criteria explained in the previous section, I used the Washington, D.C. and Baltimore major transit station data obtained from the National TOD database, created by the Center for Transit-Oriented Development (CTOD). This dataset includes geocoded information for all fixed guideway transit stations in the Washington, D.C. and Baltimore metropolitan areas.[20] For analyzing conditions around the transit stations, a half-mile buffer was created around each station to represent the transit zone (TOD). This was used as the basis for identifying whether a particular TAZ can be considered as a TOD area. Figures 7-1 and 7-2, below, illustrate the location of TOD zones in the two cities identified, using the proposed mathematical framework, as well as their position with respect to the major arterials and roadways. Most of the TOD zones are concentrated either in downtown areas, where higher

[20] http://toddata.cnt.org/

employment opportunities and better transit service are provided, or in close proximity to the major roads and arterials, where there is easy access to various destinations.

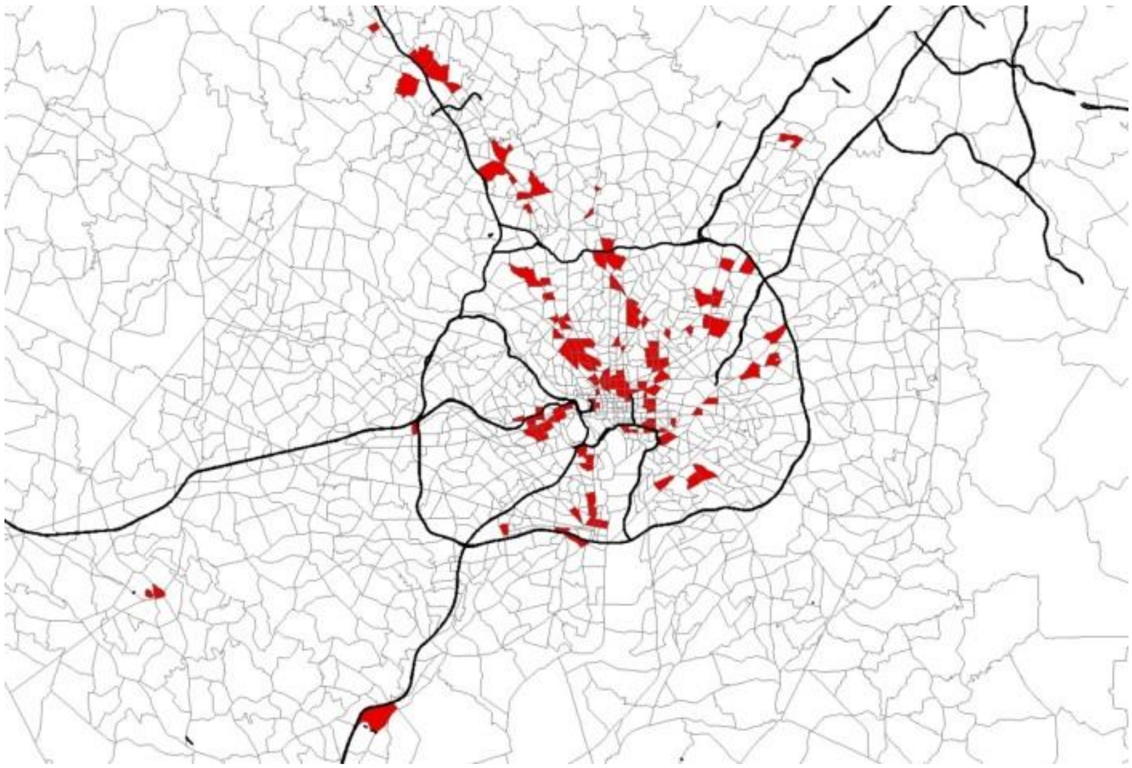


Figure 6-1 Location of TOD Zones: Washington, D.C.

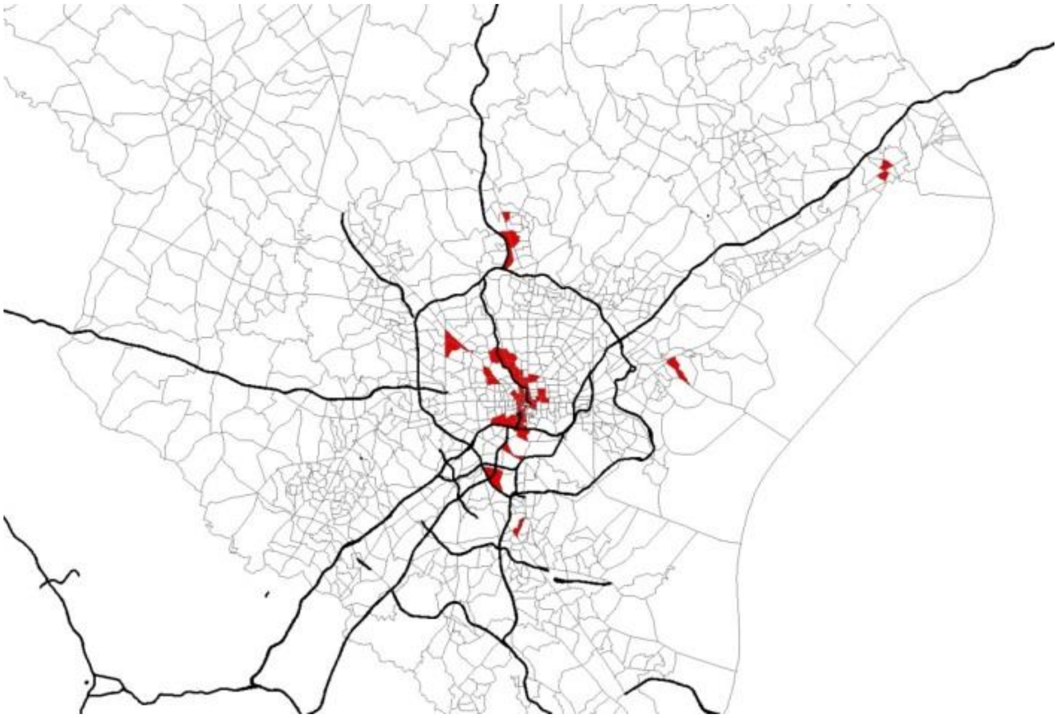


Figure 6-2 Location of TOD Zones: Baltimore, MD

7.4. Modeling Travel Behavior in TOD Areas

It is claimed that TODs have the ability to reduce the vehicle miles travelled (VMT), the number and average length of auto trips, by providing better non-auto accessibility to jobs and other destinations, and encourage sustainable modes (i.e., transit, walking, and biking) by facilitating pedestrian-friendly environment and transit services (Cervero,1996; Arrington andCervero,2008). I perform a comprehensive analysis of TODs in the Washington, D.C. and Baltimore metro areas to investigate if TODs actually have these hypothesized impacts. I model VMT, trip generation, trip length, and mode share in the two case study areas using the most recent local household travel survey data and advanced statistical methods.

Findings show that, overall, people living in TODs make more trips, but fewer trips by automobiles. Results also show that TOD residents tend to travel shorter distances by all modes of transportation, which implies the selection of closer destinations for their activities. In terms of mode choice, trips originating from TODs have substantially higher non-auto mode share in both Baltimore and Washington D.C., after relevant socioeconomic and demographic factors are controlled.

In the following sections, summary statistics of the travel behavior of residents in the two case study areas are presented. Detailed results of the statistical travel behavior models and a brief discussion and interpretation of the results are provided for each of the case study areas.

7.4.1. Summary Statistics

Descriptive statistics have been completed in order to obtain general information about both TOD and non-TOD residents, comparison of their socioeconomic and demographic characteristics, and to better understand and track their travel patterns. Table 7-1 summarizes the results and shows that people living in TOD areas have smaller households, which most likely consists of childless singles, couples, or older "empty-nester" couples who are either unable to drive or do not feel comfortable doing so. As expected, TOD residents have lower car ownership rates compared to the non-TOD areas, and lower annual income rates. The percentage of households with zero vehicles is 20% and 23% in TOD areas in D.C. and Baltimore, respectively, while it is only 5% and 9% in non-TOD areas. This substantial difference—coupled with the average car ownership rates in TOD and non-TOD areas—shows that, in general, people living in TODs tend to drive less and have fewer automobiles. This is probably due to fewer needs or to parking space availability in high-density urban areas, which are not as prolific as in low-density suburban areas.

Table 6-1 Comparison of Socioeconomic Characteristics in TOD vs. Non-TOD Areas

	Washington, D.C.	Baltimore, MD

	TOD	Non-TOD	TOD	Non-TOD
Average household size	1.81	2.29	1.74	2.20
Average auto ownership	1.12	1.86	1.19	1.68
Average annual income	$92,000	$93,000	$56,000	$82,000
Average # of workers/household	1.13	1.22	0.97	1.13
Percentage of HHs with 0 vehicle	0.20	0.05	0.23	0.09

Table 7-2 summarizes the travel characteristics in TOD and non-TOD areas. The table also separates work and non-work trips to understand how living in TODs encourages transit use for shopping, recreational, and other non-work trips. The percentages of transit/walk/bike trips are much higher in TOD areas compared to non-TOD areas, especially in Washington, D.C., where the rate is almost triple. However, this difference is not as high in the Baltimore area. It shows that in the Washington, D.C. area, the percentage of commute trips made by transit or non-motorized modes is almost half of all the work trips in TOD areas, and twice the percentage of transit work trips in non-TOD areas. The number of trips made by transit is much lower for non-work trips in both TOD and non-TOD areas in the Washington, D.C. metropolitan area. This might be because, for shopping, recreational, and personal business trips, it is always easier to drive, especially as people usually have company—such as a couple or parents with children—when making these kinds of trips. The results in Baltimore are somehow different than in D.C. area; in Baltimore, people living in non-TOD areas commute by transit more than those in TOD areas (25% versus 21%). However, in Baltimore TOD areas, the percentage of non-work trips made by transit is higher compared to the percentage of work trips. Again, similar to the pattern in Washington, D.C., the percentage of non-work trips made by transit, walk, and bike is lower in non-TOD areas in Baltimore, compared to the TOD areas where transit is more accessible and easier to use.

The auto mode share for all trips, regardless of trip purpose, is 62% and 74% in TOD, and 83% and 79% in non-TOD areas, in D.C. and Baltimore, respectively. Again, the automobile mode share is higher in non-TOD compared to TOD areas as expected, though the difference is much greater in Washington, D.C. than in Baltimore. The same pattern is observed if work and non-work trips are separated. In Washington, the difference of auto mode share between TOD and non-TOD areas is around 20% for both work and non-work trips, though the share is higher for non-work trips (65% versus 54% and 84% versus 78%). In Baltimore, there is not that much of a difference observed among automobile mode share for work and non-work trips in TOD and non-TOD areas, except a slightly small difference between non-work trips auto share in TOD and non-TOD. This might be because Baltimore does not have as extensive a transit network as the D.C. area, and, the parking availability is much higher, which encourages people to drive more. It also reflects the fact that a considerable portion of workers living in Baltimore might actually have to commute to the D.C. area for work, and this prevents them from using transit, as there is not a fast and efficient transit service connecting the two cities. This makes driving almost the only option for commuters.

Table 6-2 Comparison of Travel Characteristics in TOD vs. Non-TOD Areas

	Washington, D.C.		Baltimore, MD	
	TOD	Non-TOD	TOD	Non-TOD
% all trips made by transit/walk/bike	35.65	13.49	22.22	17.87
% all trips made by auto*	61.79	82.57	73.56	78.73
% work trips made by transit/walk/bike	44.93	21.29	20.82	25.23
% non-work trips made by transit/walk/bike	32.79	11.18	23.78	15.62
% of work trips made by auto*	53.70	77.60	73.61	73.45
% of non-work trips made by auto*	64.63	84.15	73.54	80.41

* Auto trips considered both “as driver” or “as a passenger” cases

The statistics presented in Table 7-2 help us to understand the travel behavior of people living in different areas with different land use characteristics and transit accessibility. However, it should be noted that these numbers alone do not necessarily prove that living in TOD reduces automobile travel and increases transit use, as several other factors such as self-selection and cultural identity are involved in people's mode choice decisions for different trip purposes.

In both case study areas, TOD zones on average have a lower number of auto trips, compared to non-TOD areas. These statistics show that, in general, TOD promotes non-auto mode choices such as transit and walk/bike modes.

The summary statistics of the trip length and duration have been presented in Table 7-3. Trips are divided into four categories: home-based work (HBW), home-based shopping (HBS), home-based other (HBO), and non-home-based (NHB) trips. The non-home-based trips are excluded from the analysis since the effect of living in TOD on these trips was negligible.

TODs are shown to have lower average trip length in both cities. Although the average trip length of TOD residents in Washington, D.C. is reduced by 40% for total trips, their travel duration is only slightly smaller compared to non-TOD residents. For the Baltimore area, average travel time of trips is higher in TOD compared to non-TOD zones. This might be because of higher non-auto mode share.

In general, the statistics show that HBW trips are longer in both travel distance and time spent on trips compared to other home-based trips, although in both cases, TOD residents seem to spend less time on commute trips. Comparing HBW trips of Washington, D.C. to that of Baltimore, overall, trip length is shorter in Washington, D.C. However, the statistics show that this is not necessarily associated with shorter trip time. In fact, average travel time shows to be approximately the same in both cities. This might be due to higher transit use in Washington

D.C., which is a slower mode compared to automobile. The descriptive statistics of mode share shows that 39% of commute trips of TOD residents in Washington, D.C. are made by transit, whereas this number is only 13% for the Baltimore area. Similarly, for HBS and HBO trips, it is observed that shorter trips are in most cases not associated with shorter travel time in either of TOD and non-TOD areas.

Table 6-3 Trip Length and Duration Summary Statistics

	Washington, D.C.	Baltimore	Washington, D.C.	Baltimore
	Average Trip Length (mi)			
	Total Trips		**HBW Trips**	
TOD	4.3	6.1	7.0	9.9
Non-TOD	7.6	6.9	12.6	11.5
	HBS Trips		**HBO Trips**	
TOD	2.64	3.38	3.80	5.42
Non-TOD	4.83	4.41	6.31	5.94
	Average Trip Time (min)			
	Total Trips		**HBW Trips**	
TOD	25.3	27.7	34.9	34.2
Non-TOD	25.8	26	37.8	36.9
	HBS Trips		**HBO Trips**	
TOD	17.94	19.91	23.65	27.77
Non-TOD	18.25	18.86	22.71	23.75

The mode share of auto, transit and walk/bike are compared in figure 6-6 for TOD and Non-TOD areas at the zone level. Non-TOD residents have 17% higher auto mode share in Washington, D.C. and 14% higher in Baltimore. Baltimore demonstrates to be a more auto-oriented city compared to Washington, D.C., probably because of the existence of a more efficient subway system in the Capitol City. The summary statistics also confirm the hypothesis that proximity to transit stations and living in a mixed and high-density neighborhood results in higher transit use. Also, Washington, D.C. has about 5% higher transit mode share in both TOD and Non-TOD areas than Baltimore. Descriptive statistics also indicate that among three modes, walk/bike is most influenced by TOD designation. In both Washington, D.C. and Baltimore, living in transit-oriented neighborhoods results in about 9% higher walk/bike mode share. However, these results only show the aggregate comparison between TOD and non-TOD, and do not distinguish the effect of different land use and household characteristics.

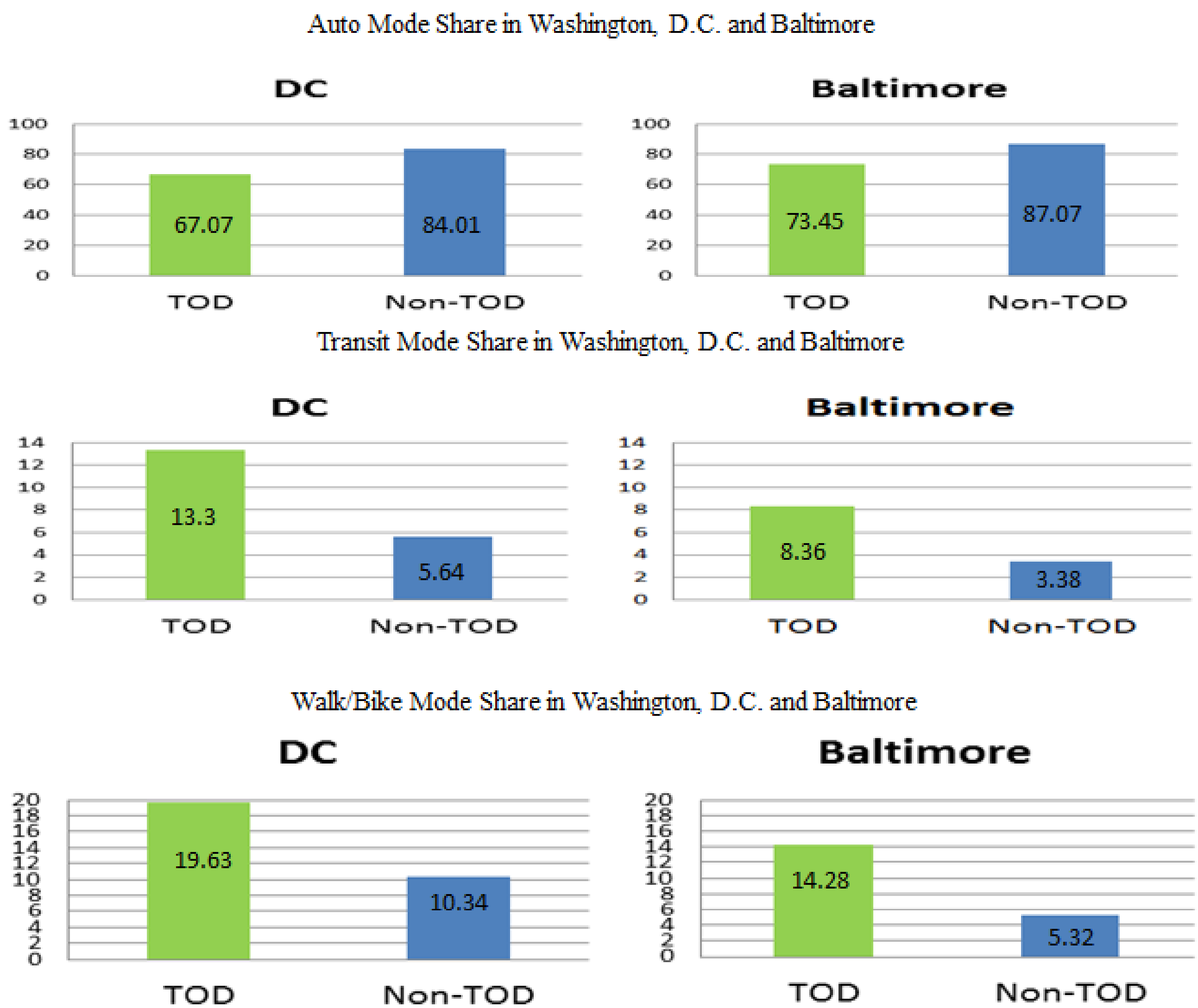


Figure 6-3 Mode Share Distributions

7.4.2. Trip Generation and Trip Length Models

For modeling the trip generation and length within TOD and non-TOD areas, I decided to follow the multilevel, mixed-effect regression modeling approach. A mixed-effect model is a statistical model that contains fixed and random effects, and could be viewed as a generalization of the variance component and regression analysis models. When the number of clusters is small and the number of observations per cluster is large, the cluster-specific coefficients are treated as fixed and ordinary regression analysis with dummy variables applies, as with the analysis of variance model. Such a model is called a fixed-effects model. When the number of clusters is large but the number of observations per cluster is relatively small, a random effects model would be more adequate, because in this scenario, the cluster-specific coefficients are random (Demidenko, *2004*).

The mixed model is well suited for this analysis because, on the one hand, there are households of the same category (i.e., that live in the same TAZ), but on the other hand, the households have different characteristics (i.e., different socioeconomic and demographic characteristics). The mixed-effect model allows there to be different coefficients by subject group. Subjects in the same level or group are likely to be similar to one another in terms of their observable characteristics, meaning households living in the same TAZ (whether or not it is a TOD) tend to have similar travel patterns; this model is able to capture these similarities and their magnitude. Consequently, there are two sources of variation: the variation between different TAZs (inter-subject variance) and the variation within a particular TAZ (intra-subject variance).

The mixed model can be represented as:

$$y = X\beta + Zu + \varepsilon \tag{14}$$

where:

- y is a vector of observations, with mean $E(y) = X\beta$
- β is a vector of fixed effects
- u is a vector of independent identically-distributed random effects with mean E(u) = 0 and variance-covariance matrix $\text{var}(u) = G$
- ε is a vector of random error terms with mean $E(\varepsilon) = 0$ and variance $\text{var}(\varepsilon) = R$
- X and Z are matrices of regressors relating the observations y to β and u

The effect of socio-demographic factors and some selected land use characteristics were considered a fixed effect, while living in a particular TAZ was considered a random effect. This is because both the households in the survey and the TAZs are randomly selected from the entire population of households living in the same TAZ, and all the TAZs in the whole metro area, respectively. The above justification is that the errors within each randomly sampled group level are likely correlated, thereby necessitating the estimation of a random effects model.

Equation 15 represents the structure of trip generation model developed using two sets of predictors; the households' characteristics and whether or not the household's residential location is TOD. Inclusion of households' characteristics into the model controls for the possible effects of those variables can also provide better estimates, in terms of the effects of built environment variables on travel behavior in TOD areas. It makes the results more reliable when compared to the analyses in the past that did not include these factors, due to either lack of data or their scope of analysis. The dependent variables include number of auto, non-auto, and total trips, respectively. The socio-economic variables included in the models are household size, number of vehicles, a household's annual income, number of children, and number of workers in the household.

$$Trips = f(SES_{ij}, TOD_j)$$

(15)

where:

$Trips = number\ of\ trips\ by\ mode$

$SES_{ij} = socioeconomic\ attributes\ of\ HH\ i\ living\ in\ zone\ j$

$TOD_j = dummy\ variable\ indicating\ whether\ zone\ j\ is\ TOD\ or\ not$

The specification for the trip length model is similar to that of trip generation, using socio-demographic characteristics of the households and the binary variable representing TOD.

The results of trip generation for total, non-auto (i.e., transit, bike, and walk), and auto trips are presented in table 7-4. It shows that when socioeconomic attributes of households are controlled, living in TODs is associated with higher numbers of total trips, which confirms that people in TOD areas do not make fewer trips, but rather switch to other modes (e.g., transit). The results indicate that TOD residents make about 0.51 and 0.28 more trips in Washington, D.C., and Baltimore, respectively.

Households living in TOD areas make about 1.71 and 0.74 more non-auto trips in Washington, D.C., and Baltimore, respectively. The results from the regression model for auto trips show that households living in TOD make about 1.2 and 0.6 less auto trips in Washington, D.C., and Baltimore, respectively. These numbers, divided by average number of auto trips obtained from descriptive statistics (6.6 for Washington, D.C. and 6.2 for Baltimore), gives us about a 10% and 18% reduction in auto trips in these types of development. Overall, the results indicate TODs in D.C. are more successful in reducing auto mode share and promoting non-auto modes, compared to TODs in Baltimore.

All socio-economic variables have the expected sign and direction of influence on trips made by various modes. Larger households with higher levels of annual income tend to make more trips, regardless of mode choice. Vehicle ownership and number of children both have positive impacts on the number of auto trips and negative effects on non-auto trips, since having children makes it harder to coordinate transit trips and car ownership inevitably encourages driving. Households with a higher number of commuters make fewer auto trips and use transit more often. This could be because transit systems are more efficient during the morning/evening commute hours, and using transit for commuting is easier, compared to other trip purposes.

Table 6-4 Results for Trip Generation Model

	Washington, D.C.	**Baltimore**	**Washington, D.C.**	**Baltimore**	**Washington, D.C.**	**Baltimore**
Dependent Variable	**Total Trips/HH**		**Transit, Bike, &Walk Trips/HH**		**Auto Trips/HH**	
Household size	2.51	2.3	0.65	0.81	1.82	1.44
Household's income	0.21	0.23	0.11	0.15	0.10	0.08
# of Children	0.88	0.97	-0.33	-0.41	0.75	1.03
# of Vehicles	0.23	0.32	-0.83	-1.05	1.06	1.38
# of Workers	-	0.11	0.33	0.28	-0.34	-0.18
Household living in TOD	0.51	0.28*	1.71	0.74	-1.22	-0.59
R-squared	0.81	0.81	0.34	0.32	0.74	0.73

* All coefficients are significant at 95% level except this one

In table 7-5, results of the multilevel, mixed-effect model for trip length of total, HBW, HBS, and HBO trips have been presented. The results show that living in TODs will significantly decrease the trip length by 40% for TOD residents in Washington, D.C. and by 25% for TOD residents in Baltimore. The results suggest that this effect is larger in magnitude than the effect of households' socioeconomic characteristics, though they are all statistically significant. HBW trips are 40% shorter for TOD residents in D.C. and 37% for TOD residents of Baltimore.

Living within TOD reduces average length of HBS trips by 46% for TOD residents in Washington, D.C., and by 41% for TOD residents in Baltimore. For HBO trips, this number is 40% and 18% for Washington, D.C., and Baltimore, respectively. Vehicle ownership and income have a positive effect on the length of all trips. This is reasonable, since auto is a more convenient mode for longer trips and lower-income families prefer not to choose distant destinations, due to the corresponding costs.

There might be several reasons for the disparities observed between the two metropolitan areas, in terms of model coefficients and descriptive statistics of trip length. First, both population and employment densities are higher in Washington, D.C., and it may be the case that more people are attracted to live and work in the D.C.-area to enjoy its various benefits. In fact, many people living in Baltimore travel to Washington, D.C. on a daily basis. This portion of the Baltimore population must drive to D.C., as there is not a fast and efficient transit service connecting the downtown of Washington, D.C., to Baltimore. That could be a probable cause of longer trip length for TOD residents of Baltimore. However, HBW trips in Baltimore are shorter in duration, probably due to the higher share of auto mode (which is faster). Also, parking is not as limited and expensive in Baltimore as it is in the Washington, D.C. area, and neighborhoods are not as pedestrian-friendly and physically diverse. Therefore, people make fewer walking trips—which intuitively are shorter than other modes—and more auto trips to reach farther destinations. Last, trips are longer in general in the Baltimore area, in part because policies in place in the Baltimore area are more driving-supportive compared to the Washington, D.C. area, making it more attractive for automobile users (the issue of self-selection). Moreover, the transit system in Washington, D.C. is more efficient than Baltimore, providing more frequent service and coverage to different parts of the city. Average trip length for shopping purposes is less for residents of TODs in Washington, D.C. compared to the Baltimore area, due to the existence of more shopping opportunities near transit.

Table 6-5 Results for Trip Length Model

	Washington	**Baltimore**	**Washington**	**Baltimore**	**Washington**	**Baltimore**	**Washington**	**Baltimore**
Dependent Variable	**Ln(Avg Trip Length per HH)**		**Ln(Avg Length of HBW Trips per HH)**		**Ln(Avg Length of HBS Trips per HH)**		**Ln(Avg Length of HBO Trips per HH)**	
Household size	-0.09	-0.08	-0.05	-0.05	-	-	-0.09	*0.04
Ln(Household's income)	0.12	0.1	0.16	0.15	0.05	0.04	0.12	0.08
# of Children	-	-	0.13	0.13	-	-	-	-0.17
# of Vehicles	0.18	0.21	0.2	0.24	0.27	0.28	0.18	0.19
# of Workers	0.2	0.19	-	-	-0.08	-0.07	0.2	-0.04
Household living in TOD	-0.5	-0.28	-0.5	-0.46	-0.6	-0.52	-0.5	-0.2
R-squared	0.79	0.77	0.84	0.81	0.45	0.4	0.79	0.57

All coefficients are significant at 95% confidence level

7.4.3. Vehicle Miles of Travel (VMT) Models

The multi-level, mixed effect modeling approach was again followed for modeling households' VMT, with respect to land use pattern of the neighborhood of residence (i.e., TOD vs. non-TOD). . As it is shown in the equation 16 below, VMT is assumed to be a function of the households' characteristics, as well as built environment factors and transit accessibility factors (TOD impact).

$$VMT_{ln} = f\left(SES_{ij}, BE_j, TOD_j, Bus_j, Rail_j\right) + \varepsilon \quad (16)$$

where:

VMT_ln = *households' VMT, naturally logged*

$SES_{ij} = socioeconomic\ attributes\ of\ HH\ i\ living\ in\ zone\ j$

BE_j = *land use characteristics of zone j*

$TOD_j = dummy\ variable\ indicating\ whether\ zone\ j\ is\ TOD\ or\ not$

Bus_j =*density of bus stops in zone j*

$Rail_j$ = *dummy variable indicating whether zone j is a non-TOD but rail accessible zone*

ε is a vector of random error terms with mean E(ε) = 0 and variance var(ε)=R

The results show a strong association among VMT, built environment, and living in TOD. Tables 7-6 and 7-7 attempt to summarize the modeling results for the D.C. and Baltimore metropolitan areas, respectively, and are divided into three main sections: 1) households' socioeconomic variables impacts; 2) local-level land use factor impacts; and 3) transit accessibility-TOD impacts. The "within" and "between" TAZ variation is presented at the bottom of each table.

Table 6-6 Results for VMT Model: Washington, D.C.

Variables	Coefficient	Standard error	*p-value*
Dependent variable: Household's VMT-logged			
Socioeconomic and control factors			
Constant	1.76	0.058	0.000
Household size	0.12	0.010	0.000
Household income	0.051	0.005	0.000
# of vehicles	0.29	0.013	0.000
# of workers	0.21	0.016	0.000
Built environment variables at local level			

Residential density	-0.012	0.0014	0.000
Employment density	-0.0004	0.0007	0.535
Land use mix (entropy)	-0.053	0.056	0.348
Distance from CBD	0.0037	0.0013	0.004
Average block size	0.434	0.075	0.000
Transit accessibility- TOD impact			
Household living in TOD	-0.32	0.054	0.000
Household living in a rail-accessible zone	-0.13	0.055	0.016
Bus stop density	-3.63	0.358	0.000
Covariance parameter estimates (random effect)			
TAZ	0.246	0.0157	
Residual	1.022	0.0075	

The potential effects of socioeconomic status was controlled using households' size, annual income, number of workers in the household, and vehicle ownership in the model. The results show that in both cities, the socioeconomic variables significantly influence the amount of driving or the households' VMT in a positive direction. This implies that VMT increases with larger households who have higher annual income and car ownership. More workers in the household typically means different work locations, which forces household members to travel to different daily destinations. These numbers all can be reasonably explained from the hypothetical point of view, as it is highly expected that households with these characteristics drive more, and therefore, generate higher vehicle miles of travel.

Table 6-7 Results for VMT Model: Baltimore, MD

Variables	Coefficient	Standard error	*p-value*
Socioeconomic and control factors			
Constant	1.442	0.070	0.000
Household size	0.050	0.015	0.001
Household income	0.093	0.007	0.000
# of vehicles	0.255	0.019	0.000
# of workers	0.276	0.024	0.000
Built environment variables at local level			
Residential density	-0.0002	0.0023	0.941

Employment density	-0.001	0.0012	0.220
Land use mix (entropy)	-0.046	0.092	0.614
Distance from CBD	0.018	0.003	0.000
Average block size	0.379	0.143	0.008
Transit accessibility- TOD impact			
Household living in TOD	-0.19	0.099	0.058
Household living in a rail-accessible zone	0.088	0.099	0.375
Bus stop density	-3.65	0.848	0.000
Covariance parameter estimates (random effect)			
TAZ	0.25	0.026	
Residual	0.98	0.012	

As shown in Tables 7-6 and 7-7, land-use variables at the neighborhood level, such as residential density, employment density, and the level of mixed-use (entropy) have negative relationships with VMT, while the distance from CBD and average block size (street connectivity) are positively linked to VMT. Overall, the coefficients of the land-use variables in the model—consistent with previous studies—show that people living in areas with compact development patterns, higher employment opportunities, and higher levels of mixed uses in neighborhoods tend to drive less, as they can reach closer destinations by choosing non-motorized modes and transit. Distance to the central business district also has a positive association with VMT, as people living farther from city centers have to drive more to reach various destinations. The average block size, as a measure of street network connectivity, has a positive significant relationship with household's VMT in both cities as well. This is also because with lower block size and/or higher street connectivity, the distance to various types of destinations would be lower, and as a result, people would drive less to reach those destinations. Also, smaller block size aims to encourage more non-motorized trips, as it is faster and more convenient for pedestrians and cyclists to reach destinations with smaller blocks.

The two variables of bus and rail accessibility have been included in the model to measure transit service accessibility (proximity to transit) in a specific neighborhood, regardless of being a TOD. Results show that, in addition to the effects of land use patterns, transit accessibility—measured by the density of bus stops and accessibility to rail transit stations in neighborhoods—has a negative impact on households' VMT in Washington, DC area, and this effect is statistically significant. In Baltimore, the effect of rail accessibility is statistically insignificant, as opposed to the negative effect of bus accessibility. This is expected, as there is only one light-rail line in Baltimore and one commuter rail line that connects D.C. and Baltimore. There is not much difference observed between the two case study areas in terms of the effect of bus accessibility on households' VMT, as both urban areas have similar extensive bus systems (-3.63 in Washington, D.C. versus -3.65 in Baltimore).

More important, living in TOD has a significant impact on the overall amount of driving within households, even after controlling for other land use factors and transit accessibility. The TOD dummy variable captures the impact of TOD built-environment characteristics in addition to density, mixed use, and transit accessibly (e.g., urban design, activity types, connective, walkability). The results clearly show that people who live close to a major transit station tend to drive less, and therefore use transit or non-motorized modes of transportation more often. This effect is even more significant (almost tripled in the D.C. area) when the proximity to transit is accompanied by some specific land use characteristics (as the TOD variable indicates). In comparison, the amount of driving and households' VMT is significantly higher for those who live farther away from transit stations in low-density suburban areas, where the only convenient—or sometimes, the only accessible—mode of transportation is driving private automobiles.

From these results, one can also obtain the elasticity of VMT to TOD. It indicates that the VMT decreases by 37.7% in Washington, D.C. and 20.9% in Baltimore for people who live in TOD, compared to non-TOD areas, with all else being equal. These numbers show the elasticities without considering the potential self-selection effect, and may be biased toward overestimating the effect of living in TOD on VMT reduction. However, as argued in the body of literature, the effect of self-selection might be negligible; I believe that even after controlling self-selection, these numbers still prove the importance of pro-transit policies, like transit-oriented development, in reducing automobile travel. Implementation of such policies will eventually reduce automobile dependency and solve many transportation-related issues facing urban areas.

7.4.4. Mode Choice Models

In addition to trip generation, length, and the amount of driving (VMT) of TOD residents, it is crucial to understand travel mode choice patterns of the households and individuals living and/or working in TOD area. This is accomplished by developing discrete choice models in order to better understand mode choice distribution and patterns in TOD zones for the two case study areas of Washington, D.C. and Baltimore, MD.

Many Researchers believe that the built environment pattern at both trip origin and trip destination plays a role in changing travel pattern by influencing travel attributes such as travel time, distance, and mode of travel. Usually, in typical discrete mode choice models based on utility maximization theory (Domencich and McFadden, 1975), variables included are mostly the traveler’s socio-demographic characteristics, and the mode-specific attributes of travel, such as time, cost, and level of comfort; the effect of urban form setting at trip origin and destination is usually neglected in such models. This results in these models being under-specified and unable to fully explain the mode choice decision process, or the contributing factors (Cervero 2002). This study tries to overcome this limitation by constructing a multinomial logit model for mode choice for the two metropolitan areas of Washington, DC and Baltimore, using a wide range of built environment characteristics at both trip origin and destination. More specifically, by investigating the effect of TOD as either trip origin or destination on travel mode choice, and to see whether trips originated/ended in TOD areas have higher probabilities of transit mode choice.

As the first step, Table 7-2 provided descriptive statistics of mode choice of trips by purpose (work versus non-work) in TOD versus non-TOD areas, as well as a summary of car ownership among households who live in TOD versus non-TOD zones(see section 7.4.1). In general, the study shows that auto ownership in TOD zones is lower than that in the non-TOD zones, and people who live in TOD zones make more transit trips and less auto trips.

To test the hypothesis that trips that originate and/or end in TOD areas have a higher probability of being made by transit or non-motorized modes, the mode choice model was developed with three primary modes—auto, transit, and walk/bike—for the two metropolitan areas of Washington, D.C. and Baltimore.

In this process, a random utility model is designed to predict the choice of an individual *n* among a discrete set of alternatives C_n. It is assumed that each individual associates a utility to each available alternative, and eventually chooses the alternative with the highest utility. The utility associated by individual *n* to alternative *i*, denoted by U_{in} is a random variable so that:

$$U_{in} = V_{in} + \varepsilon_{in}$$

The probability that individual *n* chooses alternative *i* is given by:

$$P(\mathrm{i}|C_n) = \mathrm{P}(U_{in} \geq U_{in}\ \forall j \in C_n$$

Three classes of explanatory variables were used in the model: (1) the ratio of travel time by transit to the travel time by auto (as a measure of utility of travel), (2) the trip-maker's socioeconomic characteristics such as age, income, gender, household size, car ownership, the number of workers in the household, and number of bikes available, and (3) land use characteristics of both trip origin and destination location. Land use variables used in the model include residential and employment densities, level of land use mix, and average block size at both trip origin and destination, as well as whether trip origin/destination was located in a TOD zone. Modes included in the model are transit, auto, walk/bike, and other (treated as base in the model specification). Travel time for auto and transit were calculated using the origin-destination skim matrices from the MWCOG, which includes the network-based time required to travel between centroids of each TAZ pairs in the area for auto and transit, separately. The travel times are calculated for peak and off-peak periods separately and replaced in the data based on when the trips were made (for trips made during peak/off-peak period, travel time for peak/off-peak hours is replaced). Also, to calculate transit travel time between each TAZ pairs, access time, initial waiting time, transfer waiting time, transfer walk time, and in-vehicle time are all considered. Walk travel time is also calculated based on travel distance and using the average walking speed (3.1 mph) and detour factor (1.4), although not included in the final model. For descriptive statistics of variables, see Table 7-8.

Table 6-8 Descriptive Statistics

	Washington, DC		Baltimore, MD	
	Mean	**Std.**	**Mean**	**Std.**
Travel Characteristics				
Zone-based auto travel time	21.67	21.20	23.53	22.94
Zone-based transit travel time*	34.29	26.33	31.41	25.63
Distance-based walk travel time	184.39	250.52	180.87	244.89
Travel distance	6.80	9.25	6.67	9.038
Actual trip time	22.88	21.15	23.44	21.54
Land Use Characteristics				
Residential density	7.61	11.00	6.66	8.78
Job density	13.18	53.06	9.04	39.95
Entropy	0.42	0.24	0.50	0.23
Average block size	0.17	0.26	0.13	0.18
Number of trips originated from TOD	8,571		2,871	
Number of trips destined in TOD	8,744		3,215	

* Zone pairs with no transit options were excluded

Table 7-9 summarizes the results of mode choice model for Washington, D.C. and Baltimore. As it indicates, the choice of travel mode is significantly influenced by both socio-demographic characteristics of travelers as well as the land use pattern, at both trip origin and destination. The ratio of transit travel time to auto travel time has a significant negative association with all modes (except for auto in Washington, D.C. and transit in Baltimore, which are not statistically significant). However, the coefficients for walk/bike mode are larger in comparison, in both case study areas. It implies that the higher the ratio of time it takes to travel from one point to another by transit to that by auto, the lower the probability of choosing transit and walk/bike modes for that specific trip.

Age of the traveler also has significant positive effect on all modes, with the coefficient of auto being slightly larger than the other two modes, meaning that the older the traveler, the higher the chance of driving, as opposed to taking transit or walking to reach destinations. Income does not show to be a significant factor in transit mode choice in either of the cities, while car ownership has a significant positive impact on auto and a negative impact on transit and walk/bike mode choice. On the other hand, bike ownership (the number of bikes available in the household) does significantly influence mode choice, by reducing the probability of choosing auto and transit, and increasing the probability of choosing walk/bike mode. These results are all expected intuitively, and were found in a variety of previous research. Comparing the coefficients for the two case study areas, it is observed that although they show a consistent pattern in terms of sign and the level of statistical significance, Baltimore's coefficients are, in general, slightly smaller than those of the D.C. area (except for the car ownership and the number of workers in the household).

Table 6-9 MNL Results for Mode Choice

	Washington, DC		**Baltimore, MD**	
Variable (mode/s)	Coef.	p-value	Coef.	p-value
Constant (auto)	.91	0.000	.73	0.000
Constant (transit)	.49	0.001	.047	0.747
Constant (walk/bike)	.038	0.785	.401	0.004
Travel Characteristics				
Transit/Auto travel time ratio (auto)	-.0038	0.665	-.035	0.005
Transit/Auto travel time ratio (transit)	-.18	0.000	-.0089	0.570
Transit/Auto travel time ratio (walk/bike)	-.28	0.000	-.23	0.000
Traveler socioeconomic characteristics				
Age (auto)	.056	0.000	.049	0.000
Age (transit)	.054	0.000	.045	0.000

Age (walk/bike)	.041	0.000	.033	0.000
Household size (auto)	-.15	0.000	-.098	0.000
Household size (transit)	-.20	0.000	-.11	0.000
Household size (walk/bike)	-.106	0.000	-.099	0.000
Household income (auto)	.062	0.000	.042	0.000
Household income (transit)	-.016	0.142	.0098	0.379
Household income (walk/bike)	.047	0.000	.077	0.000
Household car ownership (auto)	.18	0.000	.26	0.000
Household car ownership (transit)	-.76	0.000	-.95	0.000
Household car ownership (walk/bike)	-.54	0.000	-.66	0.000
Household no. of workers (auto)	.059	0.041	.105	0.001
Household no. of workers (transit)	.56	0.000	.57	0.000
Household no. of workers (walk/bike)	.12	0.000	.13	0.001
Household no. of bikes (auto)	-.049	0.000	-.048	0.000
Household no. of bikes (transit)	-.073	0.000	-.066	0.000
Household no. of bikes (walkBike)	.076	0.000	.077	0.000
Land use characteristics				
Trips from TOD (auto)	-.100	0.241	-.32	0.008
Trips from TOD (transit)	.29	0.002	-.83	0.000
Trips from TOD (walk/bike)	.305	0.001	-.55	0.000
Trips to TOD (auto)	-.17	0.046	-.24	0.044
Trips to TOD (transit)	.17	0.069	-.28	0.040
Trips to TOD (walk/bike)	.18	0.044	-.601	0.000
Residential density at origin (auto)	-.000062	0.979	.0012	0.683
Residential density at origin (transit)	.0095	0.000	.00028	0.932
Residential density at origin (walk/bike)	.013	0.000	-.0034	0.273
Job density at origin (auto)	-.0037	0.000	-.0041	0.000
Job density at origin (transit)	.0019	0.000	.0025	0.000
Job density at origin (walk/bike)	.0019	0.000	.0022	0.000
Land use mix at origin (auto)	.44	0.000	.44	0.000
Land use mix at origin (transit)	-.11	0.325	.28	0.035
Land use mix at origin (walk/bike)	.69	0.000	.87	0.000
Avg. block size at origin (auto)	-.55	0.000	-.53	0.000
Avg. block size at origin (transit)	-3.22	0.000	-6.18	0.000
Avg. block size at origin (walk/bike)	-3.50	0.000	-5.36	0.000
Residential density at destination (auto)	.0022	0.350	-.00084	0.754
Residential density at destination (transit)	.0101	0.000	.0051	0.092
Residential density at destination (walk/bike)	.015	0.000	-.0101	0.001
Job density at destination (auto)	-.0027	0.000	-.0037	0.000

Job density at destination (transit)	.0026	0.000	.0024	0.000
Job density at destination (walk/bike)	.0025	0.000	.0031	0.000
Land use mix at destination (auto)	.31	0.001	.43	0.000
Land use mix at destination (transit)	-.15	0.190	.35	0.008
Land use mix at destination (walk/bike)	.51	0.000	.75	0.000
Avg. block size at destination (auto)	-.54	0.000	-.56	0.000
Avg. block size at destination (transit)	-3.75	0.000	-2.35	0.000
Avg. block size at destination (walk/bike)	-3.11	0.000	-6.46	0.000
Model output statistics				
No. observations	86,824		72,005	
Log-likelihood ratio	-46357.863		-41887.587.587	
LR Chi-squared (51)	27867.72		22375.62	
Prob > chi-squared	0.0000		0.00000	
Pseudo Rho-square	0.23		0.21	

In the D.C. area, trips originated and/or destined in TOD zones show to have lower probability of auto and higher probability of transit and walk/bike modes, while in Baltimore, it is not the case. This is similar to what was found in the VMT model, and is most likely because the TODs in Baltimore are not as efficient as they are in D.C. area; a lot of people who live in Baltimore—either in TOD or non-TOD zones—have to travel to D.C. for work or other trip purposes.

Other land use factors have significant association with travel mode choice. Higher residential and employment densities at the trip origin and destination reduce the chance of driving and increase the probability of using transit and walk/bike modes (although the coefficient of residential density at destination is positive for auto, it is not statistically significant).

A lower level of street connectivity (larger block size) at both trip origin and destination would reduce the probability of transit and walk/bike modes (although the coefficient for auto is also negative, its magnitude is much smaller than that of transit and walk/bike coefficients). Entropy—or level of land use mix—at both trip origin and destination has a significant positive correlation with auto and walk/bike probability and an insignificant negative correlation with transit mode choice probability. This implies that the choice of transit is minimally influenced by the level of land use mix. In reality, this is expected, since people who want to group their trips into more complex tours do not tend to use transit, as auto is a more convenient mode for complex tours. On the other hand, living in neighborhoods with a high ratio of land use mix—where many destinations can be reached within walking distance—encourages residents to complete some non-work trips on foot, thus increasing the probability of choosing walk/bike mode.

Although the effects of land use on mode choice are very promising and consistent with the previous research findings, the results from the Baltimore area do not follow similar trends, except for the effect of employment density and average block size (at both origin and destination). A higher level of land use mix at origin and destination increases the probability of walk/bike mode more than it does for the other two modes (larger coefficient). The effect of residential density at trip origin on mode choice is not statistically significant, and at the trip end, it is positively associated with transit and negatively associated with walk/bike mode. In Baltimore, TOD status of trip origin/destination is significantly correlated with all modes in an opposite direction. This, as stated before, might be because the TODs in Baltimore are not as efficient as they are in the D.C. area.

In summary, the mode choice model suggests that land use pattern at both trip ends play an important role in determining the mode for travel in the two study areas. However, these effects differ in magnitude, and sometimes in the direction of influence. From the D.C. model, it can be clearly concluded that effective TOD policy and design significantly reduces the probability of driving and encourages transit ridership. However, the Baltimore model does not fully support this conclusion, and further investigation is required to understand the potential reasons behind why. Thus, to further investigate the effects of built environment and transit accessibility on travel mode choice, additional evidence from other areas is helpful. Toward this goal, an aggregate-level analysis was performed for commute mode choice around transit stations all around the nation, which will be discussed in detail in the following section.

7.5. Nationwide Analysis of Rail Transit Stations and Their Commuting Mode Choice Effects

7.5.1. Introduction

According to the NHTS 2009, of all trips made by the surveyed American households, only 22% was commuting trips (Santos *et al.* 2011). Among all commuting trips, 89% were made by private automobile, 5% by public transit, and only 3% by walking. However, these statistics represent the national population, regardless of where commuters live, or their level of access to transit and walk/bike facilities. The number of studies that investigated the relationship among built environment, job accessibility via transit system, and the commute mode share is very limited; those who studied this relationship are limited in geographic scope as well as the way they measured the built environment.

This chapter represents the concepts, methodology, and results of a study which tries to fill in this gap, by looking at the commute mode share for residents who live in close proximity to major rail transit stations in 35 metropolitan areas across the U.S. (around 4,000 stations). It explores how the urban form and accessibility patterns at the neighborhood level (i.e., half-mile buffer around station areas and the census block group where the station is located), as well as the higher geographical levels (i.e., the entire region-metropolitan area), influences the commuting travel behavior and mode share.

Data is obtained for all fixed-guideway transit stations (i.e., rail, light rail, subway, and BRT) across the country from the National TOD Database (NTOD) and the SLD database, and is spatially processed using ArcGIS software package in order to calculate and then link the land use measures to the station areas. This is one of the first studies that analyzes mode share at a national scale, where the built environment at multiple levels of measurement is included.

Several studies done is the past suggest that high-density, mixed use urban development is a significant factor in influencing how people travel to/from work, and what mode of transportation they choose (Ewing and Cervero 2001). More specifically, it is stated that in areas where streets are more connected and efficient transit and non-motorized facilities are provided (leading to enhanced transit/non-motorized accessibility), residents tend to drive less and use transit more.

To date, many studies investigating the relationship between the built environment and mode choice fail to address all aspects of the relationship, either because of their scope of analysis—which is usually limited to one or a few cities—or because of data limitations, resulting in the neglect of several significant urban form measures, as well as their limited geographical scale of measurement. In terms of methodology used to construct a systematic cause-effect relationship between the two, significant progress has been made using advanced econometric models, such as structural equations models and advanced discrete choice models. While the overall share of transit for commuting in the United States is relatively low (about 5%), in transit-friendly neighborhoods, it is expected to see a higher share of transit and non-motorized modes for both commuting and non-commuting trips. However, to date, there is a limited number of studies trying to investigate this pattern and explore the contributing factors of the commuting mode share in transit station areas, especially at a national scope.

Theoretically, mode choice is largely influenced by the number of alternative modes that are available to the traveler, and he/she chooses the mode that has the highest utility—meaning the lowest travel time and cost, and highest availability and comfort—based on how that particular traveler defines utility of travel. Therefore, the level of transit accessibility and the number of jobs that are accessible via transit network within a reasonable period, can play a significant role in whether a traveler chooses transit to travel (Cervero 2002).

Using data from Montgomery County, Maryland, Cervero (2002) constructed a mode choice model which included measures of the three core "D" variables of density, diversity, and design, all measured at the TAZ level. He found that, in order to better estimate mode choice, it is crucial to include both travel attributes such as travel time and cost, and the built environment characteristics of trip origin and destination. Another study by Zhang (2004) investigated the role of land use—at both trip origin and destination—on travel mode choice for the two case study areas of Boston and Hong Kong. He modeled the mode choice for four modes—drive alone, transit, shared ride, and walk/bike—and found that the inclusion of land use variables significantly improved the explanatory power of the mode choice models in both cities. He also found that increased density and connectivity influences transit and non-motorized modes in a positive way, and drive alone and shared ride modes in a negative way.

However, in most of the mode choice analyses that included land use as part of their model specification, the number of land use variables used is very limited (only density and transit accessibility), and thus not capable of representing the overall built environment pattern of the area. Moreover, most of these studies focused only on land use at the neighborhood level, ignoring the fact that regional land use pattern and accessibility to destinations at larger scales could potentially influence the mode choice, especially if there exists a strong regional transit network in an area. The effect of the built environment at different geographical scales on commuting mode choice—a focus of the work presented in this section—is analyzed in very few studies in the previous literature. Renne, Ewing, and Hamidi (2015) examined the transit mode share for commuting trips in a national-level research study. They used a multi-level modeling technique and modeled the transit commuting mode share as a function of built environment, at both neighborhood and regional levels. Their findings suggest that boosting residential and employment densities within the station areas' precinct will eventually result in residents using transit more for commute trips. Although their study is robust in its nature, and they provide useful insight to the topic, there is still room for improvement. First, their study only looks at transit mode, as opposed to other modes such as auto and non-motorized modes; this prevents one from making comparisons of the effects of built environment on various competing modes. The second limitation of their study is the way they measured urban form at the regional level. They used a limited number of variables at the regional/metropolitan level, namely overall share of population living within ½ mile transit stations, overall share of employment located within ½ mile transit stations, jobs plus population share, sprawl level, and the metro area's congestion index. In the present study, several more urban form variables measured at the regional level were used in order to better understand and investigate the relationship between regional level land use and commuting pattern across the transit-accessible neighborhoods.

The present study expands the Renne, Ewing, and Hamidi (2015) analysis by modeling commuting mode share within station areas' precinct as a function of built environment at multiple levels, by including three modes of auto, transit, and walk/bike. The hypothesis is that higher density areas with good transit accessibility have a smaller share of auto, and a higher share of transit and non-motorized modes for various trip purposes (Frank and Pivo 1994; Newman and Kenworthy 1989). Specifically, it suggests that the commute mode share in the station areas is influenced by the land use characteristics at both the station area precinct (the local-level effect), where the trip is originated, and the overall land use pattern at the metropolitan area (regional-level effect), to represent the urban form at various destination locations (unknown work locations).

This study tries to test this hypothesis by including various measures of land use characteristics at multiple levels; the methodology used here (seemingly unrelated regression) allows for the error terms of the three regression equations to be correlated, so that it is easier to make comparisons of the effects of BE on various modes. The findings provide immediate guidance to planners and stakeholders to set transit-oriented policies across the existing stations areas, in order to promote transit mode share and decrease auto commuting.

7.5.2. Data and Methodology

The national TOD database was used to analyze the commuting mode choice pattern for about 4,000 existing stations located in 35 metropolitan areas across the nation. The data is available for proposed and planned transit stations as well, but in this study we only looked at existing stations in order to produce more viable results. The built environment variables used in the study, categorized by the level of measurement, are listed in Table 7-10, along with a brief description and their data sources.

Table 6-10 Variables and Data Sources

Variables	Description	Data source
Variables measured across the ½ mile station area		
T_popdens	Population density (acre)	NTOD
T_empdens	Employment density (acre)	
T_blksize	Average block size- sq. mi	
T_Hcost	Regional typical housing cost as % of income	
T_Walkscore	Walk score rating/walkability at the station point	Walk Score Inc.
Variables measured at the neighborhood level (CBG)		
BG_Popdens	Gross population density (people/acre)	SLD
BG_Empdens	Gross employment density (jobs/acre)	
BG_avgblksize	Average block size- sq. mi	
BG_Retdens	Gross retail density	
BG_entropy	Level of employment type mixture	
BG_JOBHH	Jobs per household in the CBG	
BG_Rdntwrk	Road network density in the CBG	
BG_intrsctdens	Intersection density in the CBG	
BG_45Transit	Jobs within 45-minute transit commute	
BG_45Auto	Jobs within 45-minute auto commute	
BG_TransitEmp	Proportion of CBG employment within ½ mile of transit stop	
Variables measured at the metropolitan level		
EmpTot	Total 2010 employment	SLD
PopTot	Total 2010 population	
%StationAreaEmp	% employment within ½ mile rail station areas	
M_Avg_Popdens	Average population density	
M_Avg_Empdens	Average employment density	
M_Entropy_avg	Average mixed use	
M_jobHH_avg	Average job-housing balance	
M_Pop_Resonly	% population living in residential-only zones	
M_blksize	Average block size	
M_smallblks	% blocks smaller than 0.01 sq. mi.	
M_rdntwrkdens	Road network density in the entire metro area	
%TransitServedPop	% population living within ½ mile rail station areas	NTOD
M_HH_Hcosts_2009	Average housing cost as % of income	NTOD
M_walkscore	Walk score rating of the entire metro area	Walk Score Inc.
Congestion_index	A score representing average roadway congestion level for each metro area	TTI

As shown in the table above, most of the variables are obtained either from the national TOD database or from the Smart Location database (SLD). However, some data included in the dataset was obtained from other sources. As mentioned in the data chapter, both the SLD and NTOD data are provide at the disaggregated levels of census block group, or half mile around transit stations. The Geographic Information System (GIS) was employed to spatially process the data and get the final measures at the regional level, as well as joining the data obtained from other sources to the dataset. The dependent variables in this study are the mode share for commuting trips for each of the existing fixed-guideway transit station's precinct in the United States. The independent variables are measured at three levels of station area precinct (half-mile buffer around the station), the census block group where the station is located, and the metropolitan area where the station is located. In addition to the built environment variables, socioeconomic and demographic variables such as age, race, income, education level, and auto ownership are also measured at all three levels. These variables have been calculated for 4,300 transit stations across the country. After the observations with missing values were deleted, the dataset includes 3,950 observations (transit stations).

Seemingly unrelated regression equations (SUR) model was applied in order to estimate the commute mode share for each of the three modes of auto, transit, and walk/bike simultaneously, each with its own error term and with contemporaneous correlation between the error terms. SUR is a system of linear equations with errors that are correlated across equations for a given observation, but uncorrelated across observations. This modeling technique has been applied in many studies seeking to address spatial autocorrelation (Rey and Montouri 1999; Gallo and Dall'erba 2003; Lundberg 2006), and especially in transportation and travel behavior analysis field in recent years (Noland 2001; Cao, Mokhtarian, and Handy 2009; Plaut 2006).

Our model specification allows for the error terms associated with equations estimated for auto, transit, and walk/bike mode share, to be correlated with one another, allowing for a more efficient estimation for the coefficients to be derived. This approach is based on generalized least squares (GLS) and assumes that:

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \end{pmatrix} = \begin{pmatrix} X_1 & 0 & 0 \\ 0 & X_2 & 0 \\ 0 & 0 & X_3 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix}$$

Where Y_i and ε_i are n×1 vectors; β_i is a $p_i \times 1$ vector; X_i is an $n \times p_i$ matrix; Y and ε are 3n×1 vectors; β is a $(p_1 + p_2 + p_3) \times 1$ vector; X is a 3n× $(p_1 + p_2 + p_3)$ matrix $(Greene\ 2003)$. The error term ε_j will satisfy the following assumptions:

- Mean of error term: $E(\varepsilon_j | X) = 0$
- Variance of error term in equation *j*: $E(\varepsilon_j \varepsilon_j' | X) = \sigma_{ij} I_N$
- Covariance of error terms across equations *j* and *j'*: $E(\varepsilon_j \varepsilon_{j'}' | X) = \sigma_{ij'} I_N$ where j≠j'
- Overall variance-covariance matrix: $\Omega = E(\varepsilon \varepsilon') = \Sigma \otimes I_N$

In the SUR models, the independent variables (regressors) can vary from equation to equation, depending on the model specification. In this model, most of the independent variables are the same across the three equations, except for those built environment variables specifically related to one mode (such as multi-modal road network density for transit, and pedestrian-oriented road network density for walk/bike mode), or those that are omitted in the walk/bike equation. It was assumed there are no relationships constructed among those variables and the dependent (percent walk/bike mode share) in the model specification (such as housing cost, congestion level, and gasoline price).

7.5.3. Results and Discussions

SUR results for three mode—auto, transit, and walk/bike—has been presented in Table 7-11, below. The proportion of trips for each mode were regressed against socio-demographic variables and built environment characteristics at three levels. As shown in Table 7-11, socio-demographic characteristics are significantly associated with the commute mode share, especially at the station area level, indicating individuals' taste differences and distributional effects. At the station area, the larger the average household size, the percentage of high-educated people and the median income, the lower the auto mode share, and the higher the share of transit and non-motorized modes. Age has a negative effect on auto and walk/bike mode share, probably due to physical limitations that people over 60 years of age, which restricts their ability to drive on a daily basis (for commuting trips). Their health conditions might also have an impact on their ability to walk and bike to work; therefore, the percentage of people over 60 only has a positive relationship with the transit mode share.

The percentage of low-wage workers has a negative impact on auto mode share. The higher the percentage of low-wage workers at the neighborhood scale, the lower the share of auto, and the higher the share of transit and walk/bike modes. This is also expected, because lower income influences car ownership, restricting the availability of auto mode and thus reducing the auto share as a chosen commute mode.

As expected, average car ownership has a statistically significant correlation with the commute mode share, with a positive direction for auto and a negative direction for transit and non-motorized modes. Similarly, as the percentage of households with no automobile increases, the transit and walk/bike mode share also increases, decreasing the auto mode share in the station area. It is also expected because the choice of travel mode largely depends on availability of a specific mode, and households' car ownership increases the availability of auto mode, thus encouraging auto use for commuting trips (Pucher and Renne, 2003).

Housing cost at the station area has a positive relationship with the transit mode share and a negative relationship with the auto mode share, meaning the higher cost of housing would decrease auto mode share. This is probably because households with higher housing cost would reduce transportation cost and drive less to compensate for the high cost of housing.

In terms of the effect of built environment at the small scale, results suggest that both population and employment densities significantly influence the commute mode share. Higher population density is associated with lower auto and non-motorized mode share, and a higher transit mode share. Employment density, however, follows an opposite trend. Results show that higher employment density at the station area precinct significantly reduces transit mode share and increases the walk/bike mode share for commuting trips. The coefficient of a station area's employment density is not statistically significant for the auto mode share equation.

The walk score coefficient suggests that the more walkable the station areas, the lower the share of auto and the higher the share of transit and walk/bike. However, the effect of walk score is not statistically significant for the transit mode share equation. This is a very important finding from a planning and policy perspective, as it suggests that promoting walkability, street connectivity and activities that could be done within walking distance of transit stations can significantly affect mode share of commuting trips, although it is generally thought that commuting trips are not very sensitive to the built environment and urban design. The coefficients of network and intersection densities also oppose this general belief. Auto-oriented intersection density positively influences auto mode share, as it increases the auto-oriented street connectivity. The intersection density of non-auto oriented intersections is also significantly and positively associated with walk/bike mode share. Higher intersection density, which implies smaller blocks and higher street connectivity, increases the non-motorized mode share. However, it is associated with transit mode share with an opposite direction. It might be because, what refers to transit here, is mainly rail transit (i.e., does not include bus) and rail transit is not really related to intersection density (either auto- or non-auto oriented intersections).

Table 6-11 SUR Model Results

	Auto		**Transit**		**Walk/Bike**	
	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
Constant	80.061	0.000	-50.81	0.000	3.084	0.783
Neighborhood effect- Variables measured across the ½ mile station area						
MedianHHinc	-.000065	0.000	-.000024	0.001	.000082	0.000
AvgCarOwnership	24.73	0.000	-16.60	0.000	-13.90	0.000
T_Hcost	-.11	0.062	.088	0.007	N/A	
P_grad	-.101	0.016	.098	0.000	.00083	0.965
AvgHHSize	-.095	0.916	2.09	0.000	1.13	0.020
P_WhiteAlone	.076	0.000	-.062	0.000	.014	0.072
P_age0_17	.15	0.011	.14	0.000	-.38	0.000
P_age_60+	-.0031	0.945	.068	0.008	-.040	0.097
T_popdens	-.081	0.000	.12	0.000	-.043	0.000

T_empdens	.0015	0.669	-.0087	0.000	.0053	0.003
T_Walkscore	-.048	0.003	.011	0.257	.039	0.000
Neighborhood effect- Variables measured at the CBG level						
P_autoown0	-1.29	0.462	3.22	0.002	5.09	0.000
P_lowwagewk	-15.36	0.000	5.05	0.032	5.24	0.020
BG_Retdens	.022	0.389	-.059	0.000	.017	0.229
BG_Rdntwrk	-.068	0.039	N/A		N/A	
BG_Rdntwrk_Ped	N/A		N/A		-.012	0.652
BG_MultiModalntwrk	N/A		-.054	0.096	N/A	
BG_intrsctdens_auto	.047	0.099	N/A		N/A	
BG_intrsctdens_nonauto	N/A		-.0034	0.049	.011	0.000
BG_45Transit	N/A		.000032	0.000	N/A	
BG_45Auto	-9.13e-06	0.000	N/A		N/A	
BG_TransitEmp	N/A		7.18	0.000	-3.91	0.000
Regional/metropolitan effect- Variables measured at the metropolitan level						
P_autoown0	-1.35	0.010	1.66	0.000	.42	0.117
P_WhiteAlone	-.30	0.000	.13	0.006	.068	0.044
P_age_60+	1.63	0.000	-.59	0.001	-.33	0.035
Avg_HHSize	6.41	0.404	16.71	0.000	-6.95	0.064
Median_HH_income	.00014	0.500	.00013	0.280	-.00035	0.000
Avg_autoownership_HH	-1.41	0.880	-12.22	0.024	23.48	0.000
GasPrice_2010	-9.15	0.040	8.58	0.001	N/A	
Congestion_Index	-8.96	0.116	6.049	0.057	N/A	
%StationAreaEmp	-.018	0.833	.014	0.765	.011	0.001
M_Avg_Popdens	.96	0.008	-1.69	0.000	.13	0.494
M_Avg_Empdens	-1.26	0.048	3.09	0.000	-1.13	0.001
M_blksize	5.42	0.158	-6.73	0.002	3.57	0.086
M_rdntwrkdens	.018	0.398	-.027	0.025	N/A	
M_HH_Hcosts_2009	-.38	0.455	.14	0.631	.50	0.005
M_walkscore	-.11	0.020	-.00034	0.990	.049	0.052
Overall Model's Goodness of Fit						
R-Squared	0.58		0.78		0.49	

Job accessibility is also an important factor in commute mode share. The proportion of CBG employment located within a station area precinct (1/2 mile buffer), and the percentage of jobs within 45 minutes of transit, both increases the transit mode share.

At the regional/metropolitan level, again, auto ownership is a significant factor influencing the households' mode choice. The overall percentage of households who do not have private cars in the metro area significantly reduces the auto mode share and increases transit and non-motorized mode share (although the walk/bike coefficient is not statistically significant).

Race proves to be a significant factor, both at the local level and at the regional levels. The percentage of the white population at a station area is positively correlated with auto and walk/bike modes and negatively correlated with transit mode share, indicating that whites tend to use transit for commuting less, compared to the other race groups. At the regional level, however, this relationship is opposite, meaning the higher the percentage of the white population in the metro area, the higher the share of transit and walk/bike modes and the lower the auto mode share for commuting trips. The same trend is observed for the effect of age on mode share. At the neighborhood level, age has a positive effect on transit while at the metropolitan level, results show that the higher the percentage of people 60 years or older, the higher the share of auto and the lower the share of transit and non-motorized modes.

Built environment at the regional level also shows to significantly influence the commute mode share. The average employment density in the metro area is negatively correlated with auto and walk/bike modes, and positively correlated with transit mode share. In addition, the higher regional population density increases the auto mode share for commute trips, while the higher employment density reduces the auto mode share and increases transit mode share. This is expected, since the model is only for the commuting trips and does not include non-work travel. Also, this result is probably because transit systems are mostly built with response to the concentration of jobs, rather than population. In most transit-friendly cities, the transit system is designed to cover the major employment centers; when a new transit system or route is being planned or built, the concentration of jobs is considered more important than the concentration of population.

However, once the transit system is in place, the concentration of population becomes important. Looking at the coefficients of population and employment density at the neighborhood level, it is observed that higher population density at the station area increases transit mode share, while higher employment density at the station area decreases it. This implies that in order to promote transit ridership, especially for work trips, it is important to change land use pattern not only around the station areas—by increasing population density and providing pedestrian-friendly facilities—but also at the regional level, by increasing the overall employment density and street connectivity (smaller block size) throughout the entire region.

Average block size throughout the entire metro area is positively associated with auto mode share. The larger the block size, the smaller the street connectivity, making the entire region a less walkable place and encouraging auto use. As the overall road network density increases, the share of auto increases as well, while transit mode share declines.

Walkability in the entire region shows a somewhat similar trend to the smaller scale. As the region’s walkability increases, the auto mode share decreases and the walk/bike mode share increases. However, for transit, the walk score coefficient is not statistically significant.

On the other hand, the coefficient of the total percentage of a region's employment located within transit stations shows a positive relationship with transit and walk/bike mode share. The higher this percentage, the higher the overall job accessibility by transit in the region, and the higher the share of transit and non-motorized modes for commuting trips.

As mentioned earlier, the model allows the residuals to be correlated, and estimates the full variance-covariance matrix of the coefficients. The correlation matrix for the three equations is displayed in Table 7-12, below. As shown, the correlations between the three modes are not zero, so we can reject the hypothesis that this correlation is zero and thus this model is a better fit than estimating the equations separately with a simple regression model.

Table 6-12 Correlation Matrix of Residuals

	Auto	**Transit**	**Walk/Bike**
Auto	1.000		
Transit	-0.2906	1.000	
Walk/Bike	-0.2518	-0.3534	1.000
Breusch-Pagan test of independence: Chi-squared = 1077.421, Pr = 0.0000			

7.6. Summary and Conclusions

In this chapter, advanced modeling methods were employed to explore the impacts of living in TODs on several travel behavior indicators, in order to provide a viable answer to the question, how effective are policies such as TOD in coping with traffic congestion, auto dependency, and environmental air pollution? In addition, how is promoting compact, mixed-use development in pedestrian-friendly neighborhoods with good transit and job accessibility able to influence mode choice, especially for commute trips, and will it potentially increase the share of transit and non-motorized modes?

I first proposed a unique and mathematically rigorous definition to quantitatively measure TODs and their boundaries based on the level of transit accessibility, as well as considering some important land use features required in TOD planning and design. The proposed methodology is a dynamic one, as it is sensitive to the value of the preset thresholds for densities and other land use factors.

Next, I modeled trip generation, trip length, household VMT, and mode choice, based on observed data from Washington, D.C. and Baltimore metropolitan areas. The results offer some insight to the travel behavior of people who live in TOD areas, and allows for comparison between two major metropolitan areas in the country. It shows that transit-oriented planning is generally associated with an overall higher level of trip generation (with a lower rate of auto trips), lower household VMT, increased transit ridership, and shorter trip length.

Statistical models indicate that TOD residents make about 4-6% more trips, which implies that TODs provide more active lifestyles and a higher quality of life, resulting in more vibrant and livable communities. TOD residents proved to have, on average, 38% and 21% (in Washington, D.C. and Baltimore, respectively) less VMT, and take transit more often than residents of non-TOD zones. In addition, trips made by TOD residents are roughly 25-40% shorter in length. However, the average duration of trips is higher in some cases, probably because of higher share of transit, bike, and walk modes. Taking transit requires longer access, transfer, and waiting time. Combining these results, one can understand how and to what extent factors like transit proximity, residential density and employment density would encourage non-auto trips and transit ridership.

In comparing the results from the two case studies, some differences are observed in terms of the effect of TOD on travel patterns. In Washington, D.C., the effect of TOD on promoting transit is much higher and leads to less driving, compared to TODs in Baltimore. Descriptive statistics and models developed for trip length also indicate TOD residents in Washington, D.C. make shorter trips. Results obtained from this analysis indicate that living in areas with good transit accessibility, along with other land use characteristics such as high density development and mix of land use types, encourages people toward a more sustainable and healthy life, with more transit use and less driving. This can eventually change urban neighborhoods into more pedestrian and transit-friendly areas.

However, as much of the current research has emphasized, providing additional information such as parking availability and price, as well as affordable housing near transit in TOD areas could be very helpful in gaining a better and more reliable understanding of the potential impacts of TOD and/or other pro-transit policies on travel behavior and, more specifically, on VMT. It is also crucial to provide a more efficient transit service. This includes facilities that offer higher travel speeds than auto travel, which can provide higher reliability in travel times through better scheduling and real-time information service for transit riders. Factors for a successful TOD include implementing restrictive policies on automobile use and parking supply, in addition to requiring good transit service frequency during both peak and off-peak periods, and promoting walking/biking conditions (Arrington & Cervero, 2008; WMATA 2008).

This study opens the opportunity for future research, by applying the proposed definition and modeling framework to other cities across the country, and improving the methodology by addressing the effect of residential location choice (aka self-selection effect), using more detailed data on socio-demographic characteristics, attitudes, and tastes, as well as longitudinal data with information such as length of residence, etc.

Findings from the disaggregate-level analysis clearly confirm the hypothesis proposed by TOD advocates, who claim that living within walking distance of transit, and specifically in TOD areas, will change people's travel behavior towards a more sustainable manner, with less driving and more transit use, thus eventually leading to decreasing traffic congestion and pollution. Findings show that, although proximity to transit alone encourages people to drive less and use transit more often, the additional attributes of TOD make it more influential on reducing the household VMT, especially in cities with a more efficient transit system.

From the aggregate-level analysis of commute mode choice across the country, findings suggest that urban form does significantly influence commuting at both station area (local effect) and at the entire metropolitan area (regional effect). At the small scale (station area), higher population density and walkability are associated with both lower auto and non-motorized mode share, and higher transit mode share. In addition, the more cities are facilitated toward auto-oriented design (higher auto-oriented intersection density and street connectivity), the more people tend to commute by automobiles. Job accessibility by transit is also an important factor at both local and regional levels. A higher proportion of jobs located within transit station-area precincts, and the percentage of jobs within 45 minutes of transit travel time, both positively influence the number of people who commute by transit. Auto accessibility (as indicated by households' car ownership) is, as expected, another significant factor in determining whether people commute by private cars. Results confirm that the higher the percentage of households who do not have private cars in the entire region, the lower the auto mode share and the higher transit and non-motorized mode share. This is potentially a very important factor, emphasizing the importance of car ownership restriction policies and gas tax/ parking cost increase policies, which are designed to discourage auto ownership by increasing the cost of owning and maintaining private automobiles.

In summary, the various models developed in this study provide strong statistical evidence that efforts in reducing VMT and encouraging transit ridership in TOD areas have been successful. Thus, programs and policies such as TOD, which are effective in reducing VMT, encouraging transit use, and promoting non-motorized transportation in TOD areas should be pursued and strengthened by the policymakers. Auto-oriented design policies should be avoided or reconsidered. However, future research should be conducted in order to quantify these effects in a more comprehensive way, with consideration of various other contributing factors. With an improved understanding on the relative effectiveness of different policy tools in improving transit ridership and reducing congestion and emissions, policy and decision-makers will be able to allocate resources more appropriately and efficiently toward the ultimate goal of making urban areas more sustainable and livable for all residents.

Chapter 8: Summary and Conclusions

This chapter provides a summary of what was done in this research as well as a brief review of the major findings, the policy implications and how they can be used by professionals and policy-makers, and concluding remarks. It highlights a set of policy recommendations made in this study for a more sustainable transportation and city design plan, developed based on the research findings obtained in various modeling steps and procedures. The set of policy recommendations provided here incorporate a more active lifestyle and eventually aim to solve many transportation and environmental issues currently faced in most urban areas. They are developed in such a way to be easily implemented in different metropolitan areas across the country or even internationally. It also discusses various limitations of the present study and provides suggestions for future research to overcome these limitations.

8.1. Summary of Findings

Thoroughly understanding and analyzing the complex relationships between built environment and travel behavior is a key factor in sustainable planning and the main goal of the present study. A comprehensive understanding of these relationships would help researchers and planners propose and implement the types of changes in land use that would eventually result in lower rates of automobile travel and shorter trips, and thus, less traffic congestion and environmental pollution.

This research developed a comprehensive, consistent, and efficient methodology for quantifying the built environment at various geographical scales, especially at the macro–metropolitan scale. It also shed light on various aspects of the built environment that influence travel behavior—specifically the amount of driving and the choice of automobile ownership—in American urban areas. It is done by developing advanced, spatial-statistical models that capture causality and have the ability to address endogeneity and self-selection issue as well.

Moreover, the comprehensive policy analysis done in this research for transit-oriented development policy could serve as a guideline for planners and policy makers, demonstrating that changing land use pattern to a compact, mixed-use, infill pattern with a pedestrian-friendly design and well-connected streets around major transit stations, is an effective policy that encourages transit ridership and reduces the VMT per person in urban areas. It also suggests that improving accessibility through transit network (by increasing the number of jobs located near transit stops, and reducing the transit travel time between home and work locations) in the entire metropolitan area would also help reduce auto travel and promote transit ridership, especially for commuting trips.

Findings clearly confirm that policies such as TOD will change people's travel behavior towards a more sustainable manner with less driving and more transit use, eventually leading to decreasing traffic congestion and pollution. They also show that although proximity to transit alone encourages people to drive less and use transit more often, the additional attributes of TOD make it more influential on reducing the household's VMT, especially in cities with more efficient transit system.

7.2. Concluding Remarks

The research findings suggest that:

1. Promoting a compact, mixed-use built environment with well-connected street networks and lower concentration of employment in the central business district (CBD) is very effective in reducing VMT and encouraging the use of modes other than private cars.

2. In general, residents of cities with better job-housing balance, overall higher densities, and transit accessibility produce lower VMT and own fewer private cars.

3. Larger households who have higher annual incomes and more commuters exhibit higher VMT and own more private cars.

4. The effect of urban form on short-term (VMT) and long-term (car ownership) travel behavior shows that, as expected, the built environment at larger scale is more influential in changing short-term travel behavior than long-term decisions such as car ownership, which are more influenced by neighborhood characteristics and parking/maintenance cost restrictions, and which are highly associated with the households' income.

5. There is a two-way relationship between the endogenous variables of VMT and car ownership and, as hypothesized, the results show that these two variables positively affect each other; higher VMT encourages vehicle ownership and automobile availability encourages households to drive more.

6. Higher residential density in the entire metropolitan area is associated with

higher households' VMT. It implies that as cities become denser in terms of the overall metropolitan-wide residential areas, the overall form of cities requires/forces the residents to drive more to reach various destinations.

7. There is a significant positive direction of influence of employment density at smaller scales and a negative direction at higher levels in both VMT and car ownership equations.

8. Similar to several other studies, this study found that both built environment characteristics and residential self-selection influence travel behavior and car ownership jointly, and reinforce the effects of each other. The performed self-selection effect analysis indicates a small but statistically significant influence of households' taste on residential location choice, which proves that the important effect of the built environment on travel could not be negligible.

9. The indirect effects of the built environment variables on travel behavior are weak and in most cases, statistically insignificant; thus, they are negligible. This also implies that although statistical models prove the existence of a statistically significant self-selection effect, or household's taste, as an indirect effect, it is not so high as to frustrate the true effect of the built environment on travel behavior.

10. Findings also suggest that urban design policies should definitely be considered as part of the solution to current highly debated transportation and environmental problems, and can potentially provide guidelines for decision-makers to evaluate and improve these land use and urban design policies for more sustainable neighborhoods.

Overall, the findings of this dissertation provide insights to both policy- and decision-makers, as well as academia. First, the findings suggest that urban form at various hierarchical levels does have significant effects on short- and long-term travel behavior indicators (i.e., VMT, car ownership, and mode choice), and the built environment at larger scales and the overall form of urban areas as a whole, play an important role in determining people's travel patterns. At the neighborhood level, results show that compact development patterns, higher employment opportunities, and better mixed neighborhoods encourage less driving. However, the effect of land use on a regional scale is larger and more significant, according to modeling results. Residents of metropolitan areas with smaller city centers, more regional employment subcenters, and higher transit accessibility will drive less and own fewer automobiles. This finding is consistent with those of other researchers who claim that changing land use patterns results in significant reduction of a households' VMT, and could eventually help reduce traffic congestion and environmental emissions (Krizek 2003; Shen 2000; Ewing and Cervero 2001 & 2010).

Second, the findings presented in this research can potentially provide guidelines for decision-makers to set or evaluate various land use-transportation policies and improve them for more sustainable neighborhoods, and suggest that new land use policies should definitely be considered as part of the solution to current, highly-debated transportation and environmental problems. The results provide detailed guidance as to how to effectively and efficiently change land use policies in order to get better outcomes, in terms of reduced automobile use and energy consumption. Policies that increase density alone would not be as effective as promoting mixed-use development and increasing job accessibility through transit network. This is explained in TOD policy analysis, and the findings show that policies which support development and pedestrian-oriented design around transit stations are very much successful in terms of reducing automobile use and encouraging transit ridership (especially for commute trips).

For the analyses, rich datasets were built in the present study, which includes several urban areas across the country as case studies. The models developed based on these datasets provide very useful information to potentially help planners and policy-makers develop a more thorough understanding of how various land use policies work in different urban structure settings, and how similar urban areas can benefit from similar land use transportation policies. Three groups of urban areas were identified in this study based on the overall built environment pattern, and the statistics show that urban areas with similar urban form pattern have similar travel patterns as well. Compact, well-connected and accessible urban areas have lower levels of per capita VMT and auto mode share for commuting trips, as well as higher level of transit and non-motorized mode share. In contrast, urban areas with lower levels of density, street connectivity, and destination accessibility observe higher automobile use (per capita VMT and percentage auto mode share), and a lower level of transit use. These findings suggest that, in order to reduce automobile dependency among American families and change the suburban lifestyle (as explained in previous chapters), it would be very effective to plan for more compact cities and invest in transit network development and expansion.

A comprehensive analysis of TOD as a popular planning and policy strategy was then performed, in order to verify and test how the findings in the previous chapters are applied in a real-world example of smart growth policy. This analysis also examined how TODs are changing people's travel behavior by reducing their amount of driving, and changing their mode choice pattern towards less automobile use and more transit ridership and walk/bike trips. The findings from TOD policy analysis in Washington, D.C. and Baltimore showed that TOD residents make about 4-6% more trips, while, on average, having 38% and 21% (in Washington, D.C. and Baltimore, respectively) less VMT. Also, trips made by TOD residents are on average 25-40% shorter in length.

8.3. Limitations and Future Research Opportunities

While this research has made significant contributions to the area of land use and travel behavior research, it also revealed several challenges and limitations. This section lists and briefly explains these limitations as well as directions for expansion of the present study in future research. Data limitation is probably the first and most important limitation of this research. Cross-sectional data was used in various parts of this study, which is not strong enough to fully investigate a causal relationship. An analysis based on longitudinal data would potentially offer more reliable evidence of the causal relationship between the built environment and travel behavior, with the clear establishment of temporal precedence (Finkel, 1995; Cao et al., 2007; Bagley & Mokhtarian, 2002). Also, traditional travel survey data was used in this study, which only contains information for the trip origin and trip destination and is not capable of recording point-to-point data for each single trip, like many GPS-based surveys. Therefore, it is hard to know the route choice and the effect of the built environment along the entire trip path and its effect on travel characteristics, such as trip length, number of stops (i.e., tour complexity), mode choice, and trip duration.

Second, due to the lack of attitudinal survey data for all case study areas, the impact of self-selection was not captured thoroughly. Other methods were used instead, such as inclusion of socio-demographic variables to the models and the latent variable approach, assuming that households' socio-demographic factors to some extent represent households' tastes, and thus influence their residential location choices. This is one of the advanced methods used by researchers so far to address the issue of self-selection (Cao, Mokhtarian, and Handy 2009). However, using attitudinal survey data in the future could potentially be very helpful to fully address this issue and separate the effect of land use on travel behavior from the residential location choice effect.

Also, in future research efforts, longitudinal data could be employed in order to fully capture the causal relationships among land use factors, travel behavior, and residential location choice.

Third, several factors influencing travel behavior at the metropolitan and regional levels have not been included in the present research, due to data limitation and the scope of the study. For instance, the overall safety and historical crime rate in a neighborhood and through the entire metropolitan area could potentially affect travel behavior—especially the use of transit and non-motorized modes for both work and non-work trips–thus indirectly influencing the VMT and car ownership (Bento et al., 2005). On the other hand, to investigate the multiple ways in which urban form influences car ownership and use in urban areas, it is required to know the level of accessibility of each mode. This has been partially addressed in the current research by including variables such as the percentage of jobs within ½ mile of transit, household's vehicle ownership, the overall walkability of the metro area, and transportation road network (lane mile density). However, data on parking availability and price, and the overall quality and coverage of transit service (such as frequency and the level of comfort), as well as the availability of affordable housing near transit, would provide a more detailed estimation of automobile vs. transit mode availability for various trip purposes.

These possible effects are neglected in the present study due to data limitation as well as measurement complexity. Future research is needed with such data in use, to gain a better and more reliable understanding of the potential impacts of various land use policies, such as TOD and the overall urban form on travel patterns and, more specifically, on the amount of driving.

Another major challenge of the present study is the lack of detailed information on mode choice accessibility. In the mode choice models developed in the present dissertation, information on travel time and cost for alternative modes is very limited.

In almost all the discrete choice models for mode choice, substitute variables, such as the ratio of transit travel time to auto travel time, have been used due to lack of actual data on travel time and cost—and other utility-based factors—for each mode. This limitation forces researchers and planners to interpret the results with more caution. The results from these models should only be used to assess the effect of land use characteristics at various geographical levels of measurement on mode choice, and understand and consider this limitation in all stages of interpretation of the results.

In terms of policy recommendations, the various models developed in this dissertation provide strong statistical evidence that land use change efforts in reducing VMT and encouraging transit ridership are effective in different urban areas with different sizes, population and geographical locations. Thus, programs and policies, such as TOD, should be pursued and strengthened by policymakers, and auto-oriented design policies should be avoided or reconsidered.

Future research should be conducted in order to quantify these effects in a more comprehensive way, with consideration of various other contributing factors. An improved understanding on the relative effectiveness of different policy tools will allow policy and decision-makers to allocate resources more appropriately and efficiently toward the ultimate goal of making urban areas more sustainable and livable for all residents.

Finally, this study presents several valuable measures of urban form that can be used in many, multi-disciplinary research projects, in addition to the field of transportation and travel behavior research. It opens the door for future research by applying the proposed measures of urban form on more advanced travel survey data (such as GPS-based data), to improve the models investigating the complex relationship between built environment and travel patterns. Some other potential topics for future research include investigating the effect of urban form at multiple scales on health condition and the level of physical activities, incorporating the impact of weather conditions—in addition to the urban form—on travel behavior by using longitudinal surveys for various weather conditions/ seasons of the year, and analysis of the effect of topography and urban morphology, land use, and weather condition jointly on travel pattern.

Appendices

Appendix A: Detailed Results- Neighborhood-Level Analysis

	Seattle						**Virginia**					
Variable	Mean	SD	95% interval		90% interval		Mean	SD	95% interval		90% interval	
Intercept	3.065	0.046	2.977	3.153	2.989	3.142	2.756	0.045	2.663	2.844	2.678	2.830
Socio-demographic Characteristics												
Age of householder	1.221	0.137	0.935	1.487	0.992	1.434	0.935	0.153	0.638	1.255	0.699	1.188
Age_sq	-1.313	0.142	-1.590	-1.022	-1.537	-1.080	-1.042	0.156	-1.362	-0.749	-1.296	-0.800
Education (H.S.)	-0.184	0.040	-0.263	-0.105	-0.247	-0.116	-0.141	0.041	-0.221	-0.058	-0.207	-0.072
Education (college)	-0.012	0.030	-0.066	0.047	-0.058	0.039	0.007	0.034	-0.059	0.075	-0.047	0.064
Gender of householder	0.151	0.023	0.107	0.196	0.113	0.190	0.213	0.025	0.164	0.263	0.172	0.254
Household size	-0.230	0.029	-0.288	-0.173	-0.277	-0.182	-0.224	0.032	-0.291	-0.165	-0.278	-0.174
Number of vehicles	0.346	0.030	0.287	0.403	0.296	0.394	0.255	0.03	0.195	0.316	0.206	0.306
Household income	0.158	0.029	0.097	0.217	0.111	0.207	0.203	0.03	0.142	0.260	0.154	0.253
Worker 1	0.240	0.042	0.156	0.316	0.170	0.305	0.015	0.039	-0.059	0.097	-0.050	0.082
Worker 2+	0.294	0.045	0.208	0.381	0.220	0.367	0.088	0.042	0.006	0.167	0.016	0.158
Land Use Characteristics												
Distance to bus stop	0.036	0.032	-0.026	0.098	-0.017	0.088	N/A	N/A	N/A	N/A	N/A	N/A
Residential density	-0.308	0.035	-0.375	-0.236	-0.364	-0.252	-0.262	0.060	-0.380	-0.149	-0.361	-0.163
Employment density	-0.071	0.039	-0.146	0.005	-0.135	-0.010	0.034	0.093	-0.150	0.215	-0.116	0.191
Entropy	-0.149	0.033	-0.211	-0.086	-0.202	-0.095	-0.003	0.049	-0.100	0.094	-0.087	0.076
Avg. block size	0.153	0.040	0.073	0.239	0.087	0.221	0.220	0.051	0.119	0.317	0.140	0.305
Distance from CBD	0.331	0.037	0.257	0.402	0.271	0.391	-0.043	0.043	-0.128	0.039	-0.112	0.027
sigma.a	0.196	0.019	0.157	0.234	0.164	0.226	0.169	0.022	0.129	0.216	0.134	0.207
sigma.y	0.948	0.009	0.930	0.965	0.933	0.961	1.063	0.009	1.046	1.080	1.049	1.078

R^2(person level)	0.238	0.112
R^2(group level)	0.768	0.585

	Baltimore						Washington, D.C.					
Variable	Mean	SD	95% interval		90% interval		Mean	SD	95% interval		90% interval	
Intercept	2.285	0.050	2.180	2.381	2.204	2.365	2.192	0.038	2.116	2.265	2.130	2.251
Socio-demographic Characteristics												
Age of householder	1.459	0.150	1.176	1.740	1.216	1.704	1.631	0.113	1.415	1.855	1.447	1.824
Age_sq	-1.521	0.156	-1.830	-1.213	-1.774	-1.269	-1.576	0.116	-1.808	-1.362	-1.770	-1.387
Gender of householder	0.242	0.028	0.187	0.301	0.195	0.291	0.198	0.021	0.158	0.242	0.165	0.233
Household size	-0.472	0.035	-0.543	-0.402	-0.531	-0.413	-0.325	0.027	-0.375	-0.272	-0.368	-0.281
# of Vehicles	0.365	0.038	0.292	0.438	0.303	0.428	0.581	0.029	0.524	0.638	0.534	0.629
Household income	0.381	0.036	0.310	0.455	0.320	0.440	0.184	0.025	0.133	0.235	0.142	0.225
Worker 1	0.343	0.053	0.236	0.450	0.253	0.427	0.159	0.039	0.083	0.238	0.095	0.226
Worker 2+	0.395	0.059	0.280	0.507	0.296	0.489	0.129	0.043	0.045	0.215	0.060	0.201
Land Use Characteristics												
Residential density	-0.344	0.047	-0.438	-0.250	-0.422	-0.268	-0.444	0.030	-0.503	-0.387	-0.496	-0.396
Employment density	-0.085	0.049	-0.181	0.008	-0.165	-0.002	-0.010	0.036	-0.079	0.058	-0.069	0.051
Entropy	-0.074	0.038	-0.148	0.001	-0.134	-0.012	-0.195	0.031	-0.257	-0.138	-0.248	-0.146
Avg. block size	0.089	0.048	-0.004	0.180	0.010	0.167	0.021	0.029	-0.037	0.077	-0.027	0.068
Distance from CBD	0.264	0.048	0.168	0.355	0.184	0.341	0.456	0.032	0.398	0.518	0.404	0.509
sigma.a	0.256	0.026	0.201	0.308	0.212	0.296	0.282	0.016	0.252	0.313	0.256	0.307
sigma.y	1.098	0.011	1.078	1.120	1.081	1.116	1.174	0.007	1.159	1.188	1.161	1.185
R^2(person level)	0.264						0.278					
R^2(group level)	0.596						0.685					

Appendix B: Metropolitan-Level Land Use Characteristics Summary

	Observed General G	Expected General G	Variance	z-score	p-value	Pattern
Atlanta-Sandy Springs-Marietta, GA						
Population	0.043352	0.054825	0.000001	-12.757648	0.000000	Low-clusters
Employment	0.092865	0.054825	0.000019	8.769448	0.000000	High-clusters
Austin-Round Rock-San Marcos, TX						
Population	0.198297	0.223896	0.000030	-4.670204	0.000003	Low-clusters
Employment	0.444485	0.223896	0.001594	5.525286	0.000000	High-clusters
Baltimore-Towson, MD						
Population	0.100937	0.146659	0.000008	-15.884939	0.000000	Low-clusters
Employment	0.127556	0.146659	0.000312	-1.080829	0.279773	Random
Birmingham-Hoover, AL						
Population	0.111548	0.143908	0.000019	-7.366430	0.000000	Low-clusters
Employment	0.284802	0.143908	0.000544	6.042594	0.000000	High-clusters
Boston-Cambridge-Quincy, MA-NH						
Population	0.066898	0.081936	0.000001	-12.386409	0.000000	Low-clusters
Employment	0.108177	0.081936	0.000048	3.778919	0.000158	High-clusters
Buffalo-Niagara Falls, NY						
Population	0.350630	0.405703	0.000055	-7.421869	0.000000	Low-clusters
Employment	0.432174	0.405703	0.001719	0.638375	0.523230	Random
Charlotte-Gastonia-Rock Hill, NC-SC						
Population	0.113828	0.125605	0.000007	-4.484750	0.000007	Low-clusters
Employment	0.208957	0.125605	0.000130	7.321284	0.000000	High-clusters
Chicago-Joliet-Naperville, IL-IN-WI						
Population	0.392410	0.446429	0.000008	-18.963141	0.000000	Low-clusters
Employment	0.458820	0.446429	0.000688	0.472460	0.636599	Random
Cincinnati-Middletown, OH-KY-IN						
Population	0.068756	0.088299	0.000003	-10.873752	0.000000	Low-clusters
Employment	0.130920	0.088299	0.000075	4.906829	0.000001	High-clusters
Columbus, OH						
Population	0.145817	0.188848	0.000018	-10.094788	0.000000	Low-clusters
Employment	0.221786	0.188848	0.000460	1.536356	0.124451	Random
Cleveland-Elyria-Mentor, OH						
Population	0.357192	0.415050	0.000027	-11.104386	0.000000	Low-clusters
Employment	0.441584	0.415050	0.001055	0.817084	0.413881	Random
Dallas-Fort Worth-Arlington, TX						
Population	0.054498	0.063316	0.000000	-15.050484	0.000000	Low-clusters
Employment	0.103270	0.063316	0.000017	9.658812	0.000000	High-clusters
Detroit-Warren-Livonia, MI						
Population	0.057683	0.074597	0.000001	-20.670568	0.000000	Low-clusters
Employment	0.070426	0.074597	0.000025	-0.838739	0.401616	Random

Denver-Aurora-Broomfield, CO						
Population	0.646795	0.682618	0.000025	-7.230720	0.000000	Low-clusters
Employment	0.766083	0.682618	0.000855	2.853877	0.004319	High-clusters
Hartford-West Hartford-East Hartford, CT						
Population	0.139267	0.153715	0.000011	-4.418038	0.000010	Low-clusters
Employment	0.214591	0.153715	0.000254	3.820610	0.000133	High-clusters
Houston-Sugar Land-Baytown, TX						
Population	0.089977	0.106394	0.000005	-7.735900	0.000000	Low-clusters
Employment	0.185640	0.106394	0.000085	8.574400	0.000000	High-clusters
Indianapolis-Carmel, IN						
Population	0.122548	0.161819	0.000029	-7.252561	0.000000	Low-clusters
Employment	0.195644	0.161819	0.000478	1.547128	0.121832	Random
Jacksonville, FL						
Population	0.329465	0.390160	0.000130	-5.317035	0.000000	Low-clusters
Employment	0.492223	0.390160	0.001393	2.734952	0.006239	High-clusters
Kansas City, MO-KS						
Population	0.173648	0.211442	0.000014	-9.988555	0.000000	Low-clusters
Employment	0.282668	0.211442	0.000337	3.881840	0.000104	High-clusters
Las Vegas-Paradise, NV						
Population	0.907892	0.901738	0.000027	1.192007	0.233258	Random
Employment	0.933705	0.901738	0.002459	0.644641	0.519160	Random
Los Angeles-Long Beach-Santa Ana, CA						
Population	0.650711	0.677340	0.000004	-12.687283	0.000000	Low-clusters
Employment	0.662204	0.677340	0.000299	-0.875831	0.381122	Random
Louisville/Jefferson County, KY-IN						
Population	0.145972	0.180324	0.000015	-8.935042	0.000000	Low-clusters
Employment	0.293809	0.180324	0.000685	4.334691	0.000015	High-clusters
Memphis, TN-MS-AR						
Population	0.258190	0.303870	0.000065	-5.659517	0.000000	Low-clusters
Employment	0.404946	0.303870	0.001608	2.520774	0.011710	High-clusters
Miami-Fort Lauderdale-Pompano Beach, FL						
Population	0.270542	0.269736	0.000004	0.414525	0.678490	Random
Employment	0.295881	0.269736	0.000145	2.172278	0.029835	High-clusters
Milwaukee-Waukesha-West Allis, WI						
Population	0.747122	0.777385	0.000026	-5.987191	0.000000	Low-clusters
Employment	0.821687	0.777385	0.001395	1.186125	0.235573	Random
Minneapolis-St. Paul-Bloomington, MN-WI						
Population	0.085036	0.116849	0.000004	-16.201087	0.000000	Low-clusters
Employment	0.149878	0.116849	0.000123	2.981111	0.002872	High-clusters
Nashville-Davidson-Murfreesboro-Franklin, TN						
Population	0.121157	0.161018	0.000025	-8.036547	0.000000	Low-clusters
Employment	0.302100	0.161018	0.000604	5.741189	0.000000	High-clusters
New Orleans-Metairie-Kenner, LA						
Population	0.647484	0.745994	0.000096	-10.029069	0.000000	Low-clusters
Employment	0.702041	0.745994	0.002364	-0.903965	0.366014	Random
New York-Northern New Jersey-Long Island, NY-NJ-PA						
Population	0.242846	0.259568	0.000002	-12.138797	0.000000	Low-clusters

Employment	0.285085	0.259568	0.000142	2.145069	0.031947	High-clusters
Oklahoma City, OK						
Population	0.230765	0.279405	0.000035	-8.232001	0.000000	Low-clusters
Employment	0.426685	0.279405	0.000761	5.337444	0.000000	High-clusters
Orlando-Kissimmee-Sanford, FL						
Population	0.284517	0.337450	0.000172	-4.034041	0.000055	Low-clusters
Employment	0.423179	0.337450	0.001531	2.191099	0.028445	High-clusters
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD						
Population	0.173807	0.222252	0.000006	-20.132772	0.000000	Low-clusters
Employment	0.179127	0.222252	0.000204	-3.020189	0.002526	Low-clusters
Phoenix-Mesa-Glendale, AZ						
Population	0.617384	0.650603	0.000013	-9.350335	0.000000	Low-clusters
Employment	0.856142	0.650603	0.000644	8.099806	0.000000	High-clusters
Pittsburgh, PA						
Population	0.072387	0.097672	0.000004	-13.165431	0.000000	Low-clusters
Employment	0.123880	0.097672	0.000113	2.469676	0.013524	High-clusters
Portland-Vancouver-Hillsboro, OR-WA						
Population	0.568772	0.594242	0.000033	-4.415965	0.000010	Low-clusters
Employment	0.727690	0.594242	0.000908	4.428707	0.000009	High-clusters
Providence-New Bedford-Fall River, RI-MA						
Population	0.063467	0.076001	0.000003	-7.296290	0.000000	Low-clusters
Employment	0.082714	0.076001	0.000048	0.970360	0.331867	Random
Raleigh-Cary, NC						
Population	0.101973	0.123363	0.000018	-5.024917	0.000001	Low-clusters
Employment	0.233440	0.123363	0.001009	3.465535	0.000529	High-clusters
Richmond, VA						
Population	0.220993	0.240822	0.000034	-3.416623	0.000634	Low-clusters
Employment	0.364225	0.240822	0.000951	4.001098	0.000063	High-clusters
Riverside-San Bernardino-Ontario, CA						
Population	0.738019	0.735048	0.000033	0.514997	0.606555	Random
Employment	0.742095	0.735048	0.000917	0.232788	0.815926	Random
Sacramento--Arden-Arcade--Roseville, CA						
Population	0.352586	0.361673	0.000030	-1.652308	0.098472	Low-clusters
Employment	0.428286	0.361673	0.001418	1.768652	0.076952	High-clusters
Salt Lake City, UT						
Population	0.987357	0.974227	0.000018	3.058656	0.002223	High-clusters
Employment	0.993922	0.974227	0.000526	0.859052	0.390312	Random
San Antonio-New Braunfels, TX						
Population	0.382105	0.436365	0.000047	-7.880343	0.000000	Low-clusters
Employment	0.613447	0.436365	0.001268	4.972909	0.000001	High-clusters
San Diego-Carlsbad-San Marcos, CA						
Population	0.407439	0.435958	0.000045	-4.262449	0.000020	Low-clusters
Employment	0.496344	0.435958	0.000951	1.958413	0.050182	High-clusters
San Francisco-Oakland-Fremont, CA						
Population	0.596500	0.638511	0.000011	-12.440897	0.000000	Low-clusters
Employment	0.657582	0.638511	0.000651	0.747362	0.454845	Random
San Jose-Sunnyvale-Santa Clara, CA						

Population	0.886049	0.884593	0.000029	0.272410	0.785307	Random
Employment	0.913580	0.884593	0.001481	0.753237	0.451307	Random
Seattle-Tacoma-Bellevue, WA						
Population	0.353834	0.362007	0.000004	-4.101440	0.000041	Low-clusters
Employment	0.506575	0.362007	0.000535	6.247542	0.000000	High-clusters
St. Louis, MO-IL						
Population	0.154267	0.202597	0.000015	-12.390960	0.000000	Low-clusters
Employment	0.252549	0.202597	0.000328	2.759619	0.005787	High-clusters
Tampa-St. Petersburg-Clearwater, FL						
Population	0.086579	0.097320	0.000002	-8.359228	0.000000	Low-clusters
Employment	0.148391	0.097320	0.000065	6.330017	0.000000	High-clusters
Virginia Beach-Norfolk-Newport News, VA-NC						
Population	0.128790	0.135687	0.000009	-2.338423	0.019365	Low-clusters
Employment	0.166080	0.135687	0.000221	2.045852	0.040771	High-clusters
Washington-Arlington-Alexandria, DC-VA-MD-WV						
Population	0.067910	0.078509	0.000001	-11.2833	0.000000	Low-clusters
Employment	0.132097	0.078509	0.000058	7.041931	0.000000	High-clusters

Appendix C: List of Counties and Travel Behavior Summary for the 50 Metropolitan Areas

CBSA	Counties
Atlanta-Sandy Springs-Marietta, GA	Barrow County, GA (13013); Bartow County, GA (13015); Butts County, GA (13035); Carroll County, GA (13045); Cherokee County, GA (13057); Clayton County, GA (13063); Cobb County, GA (13067); Coweta County, GA (13077); Dawson County, GA (13085); DeKalb County, GA (13089); Douglas County, GA (13097); Fayette County, GA (13113); Forsyth County, GA (13117); Fulton County, GA (13121); Gwinnett County, GA (13135); Haralson County, GA (13143); Heard County, GA (13149); Henry County, GA (13151); Jasper County, GA (13159); Lamar County, GA (13171); Meriwether County, GA (13199); Newton County, GA (13217); Paulding County, GA (13223); Pickens County, GA (13227); Pike County, GA (13231); Rockdale County, GA (13247); Spalding County, GA (13255); Walton County, GA (13297)
Austin-Round Rock-San Marcos, TX	Bastrop County, TX (48021); Caldwell County, TX (48055); Hays County, TX (48209); Travis County, TX (48453); Williamson County, TX (48491)
Baltimore-Towson, MD	Anne Arundel County, MD (24003); Baltimore County, MD (24005); Carroll County, MD (24013); Harford County, MD (24025); Howard County, MD (24027); Queen Anne's County, MD (24035); Baltimore city, MD (24510)
Birmingham-Hoover, AL	Bibb County, AL (01007); Blount County, AL (01009); Chilton County, AL (01021); Jefferson County, AL (01073); St. Clair County, AL (01115); Shelby County, AL (01117); Walker County, AL (01127)
Boston-Cambridge-Quincy, MA-NH	Essex County, MA (25009); Middlesex County, MA (25017); Norfolk County, MA (25021); Plymouth County, MA (25023); Suffolk County, MA (25025); Rockingham County, NH (33015); Strafford County, NH (33017)
Buffalo-Niagara Falls, NY	Erie County, NY (36029); Niagara County, NY (36063)
Charlotte-Gastonia-Rock Hill, NC-SC	Anson County, NC (37007); Cabarrus County, NC (37025); Gaston County, NC (37071); Mecklenburg County, NC (37119); Union County, NC (37179); York County, SC (45091)
Chicago-Joliet-Naperville, IL-IN-WI	Cook County, IL (17031); DeKalb County, IL (17037); DuPage County, IL (17043); Grundy County, IL (17063); Kane County, IL (17089); Kendall County, IL (17093); Lake County, IL (17097); McHenry County, IL (17111); Will County, IL (17197); Jasper County, IN (18073); Lake County, IN (18089); Newton County, IN (18111); Porter County, IN (18127); Kenosha County, WI (55059)
Cincinnati-Middletown, OH-KY-IN	Dearborn County, IN (18029); Franklin County, IN (18047); Ohio County, IN (18115); Boone County, KY (21015); Bracken County, KY (21023); Campbell County, KY (21037); Gallatin County, KY (21077); Grant County, KY (21081); Kenton County, KY (21117); Pendleton County, KY (21191); Brown County, OH (39015); Butler County, OH (39017); Clermont County, OH (39025); Hamilton County, OH (39061); Warren County, OH (39165)
Cleveland-Elyria-Mentor, OH	Cuyahoga County, OH (39035); Geauga County, OH (39055); Lake County, OH (39085); Lorain County, OH (39093); Medina County, OH (39103)
Columbus, OH	Delaware County, OH (39041); Fairfield County, OH (39045); Franklin County, OH (39049); Licking County, OH (39089); Madison County, OH (39097); Morrow County, OH (39117); Pickaway County, OH (39129); Union County, OH (39159)
Dallas-Fort Worth-Arlington, TX	Collin County, TX (48085); Dallas County, TX (48113); Delta County, TX (48119); Denton County, TX (48121); Ellis County, TX (48139); Hunt County, TX (48231); Johnson County, TX (48251); Kaufman County, TX (48257); Parker County, TX (48367); Rockwall County, TX (48397); Tarrant County, TX (48439); Wise County, TX (48497)
Denver-Aurora-Broomfield, CO	Adams County, CO (08001); Arapahoe County, CO (08005); Broomfield County, CO (08014); Clear Creek County, CO (08019); Denver County, CO (08031); Douglas County, CO (08035); Elbert County, CO (08039); Gilpin County, CO (08047); Jefferson County, CO (08059); Park County, CO (08093)
Detroit-Warren-Livonia, MI	Lapeer County, MI (26087); Livingston County, MI (26093); Macomb County, MI (26099); Oakland County, MI (26125); St. Clair County, MI (26147); Wayne County, MI (26163)

Hartford-West Hartford-East Hartford, CT	Hartford County, CT (09003); Middlesex County, CT (09007); Tolland County, CT (09013)
Houston-Sugar Land-Baytown, TX	Austin County, TX (48015); Brazoria County, TX (48039); Chambers County, TX (48071); Fort Bend County, TX (48157); Galveston County, TX (48167); Harris County, TX (48201); Liberty County, TX (48291); Montgomery County, TX (48339); San Jacinto County, TX (48407); Waller County, TX (48473)
Indianapolis-Carmel, IN	Boone County, IN (18011); Brown County, IN (18013); Hamilton County, IN (18057); Hancock County, IN (18059); Hendricks County, IN (18063); Johnson County, IN (18081); Marion County, IN (18097); Morgan County, IN (18109); Putnam County, IN (18133); Shelby County, IN (18145)
Jacksonville, FL	Baker County, FL (12003); Clay County, FL (12019); Duval County, FL (12031); Nassau County, FL (12089); St. Johns County, FL (12109)
Kansas City, MO-KS	Franklin County, KS (20059); Johnson County, KS (20091); Leavenworth County, KS (20103); Linn County, KS (20107); Miami County, KS (20121); Wyandotte County, KS (20209); Bates County, MO (29013); Caldwell County, MO (29025); Cass County, MO (29037); Clay County, MO (29047); Clinton County, MO (29049); Jackson County, MO (29095); Lafayette County, MO (29107); Platte County, MO (29165); Ray County, MO (29177)
Las Vegas-Paradise, NV	Clark County, NV (32003)
Los Angeles-Long Beach-Santa Ana, CA	Los Angeles County, CA (06037); Orange County, CA (06059)
Louisville/Jefferson County, KY-IN	Clark County, IN (18019); Floyd County, IN (18043); Harrison County, IN (18061); Washington County, IN (18175); Bullitt County, KY (21029); Henry County, KY (21103); Jefferson County, KY (21111); Meade County, KY (21163); Nelson County, KY (21179); Oldham County, KY (21185); Shelby County, KY (21211); Spencer County, KY (21215); Trimble County, KY (21223)
Memphis, TN-MS-AR	Crittenden County, AR (05035); DeSoto County, MS (28033); Marshall County, MS (28093); Tate County, MS (28137); Tunica County, MS (28143); Fayette County, TN (47047); Shelby County, TN (47157); Tipton County, TN (47167)
Miami-Fort Lauderdale-Pompano Beach, FL	Broward County, FL (12011); Miami-Dade County, FL (12086); Palm Beach County, FL (12099)
Milwaukee-Waukesha-West Allis, WI	Milwaukee County, WI (55079); Ozaukee County, WI (55089); Washington County, WI (55131); Waukesha County, WI (55133)
Minneapolis-St. Paul-Bloomington, MN-WI	Anoka County, MN (27003); Carver County, MN (27019); Chisago County, MN (27025); Dakota County, MN (27037); Hennepin County, MN (27053); Isanti County, MN (27059); Ramsey County, MN (27123); Scott County, MN (27139); Sherburne County, MN (27141); Washington County, MN (27163); Wright County, MN (27171); Pierce County, WI (55093); St. Croix County, WI (55109)
Nashville-Davidson--Murfreesboro--Franklin, TN	Cannon County, TN (47015); Cheatham County, TN (47021); Davidson County, TN (47037); Dickson County, TN (47043); Hickman County, TN (47081); Macon County, TN (47111); Robertson County, TN (47147); Rutherford County, TN (47149); Smith County, TN (47159); Sumner County, TN (47165); Trousdale County, TN (47169); Williamson County, TN (47187); Wilson County, TN (47189)
New Orleans-Metairie-Kenner, LA	Jefferson Parish, LA (22051); Orleans Parish, LA (22071); Plaquemines Parish, LA (22075); St. Bernard Parish, LA (22087); St. Charles Parish, LA (22089); St. John the Baptist Parish, LA (22095); St. Tammany Parish, LA (22103)
New York-Northern New Jersey-Long Island, NY-NJ-PA	Bergen County, NJ (34003); Essex County, NJ (34013); Hudson County, NJ (34017); Hunterdon County, NJ (34019); Middlesex County, NJ (34023); Monmouth County, NJ (34025); Morris County, NJ (34027); Ocean County, NJ (34029); Passaic County, NJ (34031); Somerset County, NJ (34035); Sussex County, NJ (34037); Union County, NJ (34039); Bronx County, NY (36005); Kings County, NY (36047); Nassau County, NY (36059); New York County, NY (36061); Putnam County, NY (36079); Queens County, NY (36081); Richmond County, NY (36085); Rockland County, NY (36087); Suffolk County, NY (36103); Westchester County, NY (36119); Pike County, PA (42103)
Oklahoma City, OK	Canadian County, OK (40017); Cleveland County, OK (40027); Grady County, OK (40051); Lincoln County, OK (40081); Logan County, OK (40083); McClain County, OK (40087); Oklahoma County, OK (40109)
Orlando-Kissimmee-Sanford, FL	Lake County, FL (12069); Orange County, FL (12095); Osceola County, FL (12097); Seminole County, FL (12117)
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	New Castle County, DE (10003); Cecil County, MD (24015); Burlington County, NJ (34005); Camden County, NJ (34007); Gloucester County, NJ (34015); Salem County, NJ (34033); Bucks County, PA (42017); Chester County, PA (42029); Delaware County, PA (42045); Montgomery County, PA (42091); Philadelphia County, PA (42101)

Phoenix-Mesa-Glendale, AZ	Maricopa County, AZ (04013); Pinal County, AZ (04021)
Pittsburgh, PA	Allegheny County, PA (42003); Armstrong County, PA (42005); Beaver County, PA (42007); Butler County, PA (42019); Fayette County, PA (42051); Washington County, PA (42125); Westmoreland County, PA (42129)
Portland-Vancouver-Hillsboro, OR-WA	Clackamas County, OR (41005); Columbia County, OR (41009); Multnomah County, OR (41051); Washington County, OR (41067); Yamhill County, OR (41071); Clark County, WA (53011); Skamania County, WA (53059)
Providence-New Bedford-Fall River, RI-MA	Bristol County, MA (25005); Bristol County, RI (44001); Kent County, RI (44003); Newport County, RI (44005); Providence County, RI (44007); Washington County, RI (44009)
Raleigh-Cary, NC	Franklin County, NC (37069); Johnston County, NC (37101); Wake County, NC (37183)
Richmond, VA	Amelia County, VA (51007); Caroline County, VA (51033); Charles City County, VA (51036); Chesterfield County, VA (51041); Cumberland County, VA (51049); Dinwiddie County, VA (51053); Goochland County, VA (51075); Hanover County, VA (51085); Henrico County, VA (51087); King and Queen County, VA (51097); King William County, VA (51101); Louisa County, VA (51109); New Kent County, VA (51127); Powhatan County, VA (51145); Prince George County, VA (51149); Sussex County, VA (51183); Colonial Heights city, VA (51570); Hopewell city, VA (51670); Petersburg city, VA (51730); Richmond city, VA (51760)
Riverside-San Bernardino-Ontario, CA	Riverside County, CA (06065); San Bernardino County, CA (06071)
Sacramento--Arden-Arcade--Roseville, CA	El Dorado County, CA (06017); Placer County, CA (06061); Sacramento County, CA (06067); Yolo County, CA (06113)
St. Louis, MO-IL	Bond County, IL (17005); Calhoun County, IL (17013); Clinton County, IL (17027); Jersey County, IL (17083); Macoupin County, IL (17117); Madison County, IL (17119); Monroe County, IL (17133); St. Clair County, IL (17163); Franklin County, MO (29071); Jefferson County, MO (29099); Lincoln County, MO (29113); St. Charles County, MO (29183); St. Louis County, MO (29189); Warren County, MO (29219); Washington County, MO (29221); St. Louis city, MO (29510)
Salt Lake City, UT	Salt Lake County, UT (49035); Summit County, UT (49043); Tooele County, UT (49045)
San Antonio-New Braunfels, TX	Atascosa County, TX (48013); Bandera County, TX (48019); Bexar County, TX (48029); Comal County, TX (48091); Guadalupe County, TX (48187); Kendall County, TX (48259); Medina County, TX (48325); Wilson County, TX (48493)
San Diego-Carlsbad-San Marcos, CA	San Diego County, CA (06073)
San Francisco-Oakland-Fremont, CA	Alameda County, CA (06001); Contra Costa County, CA (06013); Marin County, CA (06041); San Francisco County, CA (06075); San Mateo County, CA (06081)
San Jose-Sunnyvale-Santa Clara, CA	San Benito County, CA (06069); Santa Clara County, CA (06085)
Seattle-Tacoma-Bellevue, WA	King County, WA (53033); Pierce County, WA (53053); Snohomish County, WA (53061)
Tampa-St. Petersburg-Clearwater, FL	Hernando County, FL (12053); Hillsborough County, FL (12057); Pasco County, FL (12101); Pinellas County, FL (12103)
Virginia Beach-Norfolk-Newport News, VA-NC	Currituck County, NC (37053); Gloucester County, VA (51073); Isle of Wight County, VA (51093); James City County, VA (51095); Mathews County, VA (51115); Surry County, VA (51181); York County, VA (51199); Chesapeake city, VA (51550); Hampton city, VA (51650); Newport News city, VA (51700); Norfolk city, VA (51710); Poquoson city, VA (51735); Portsmouth city, VA (51740); Suffolk city, VA (51800); Virginia Beach city, VA (51810); Williamsburg city, VA (51830)

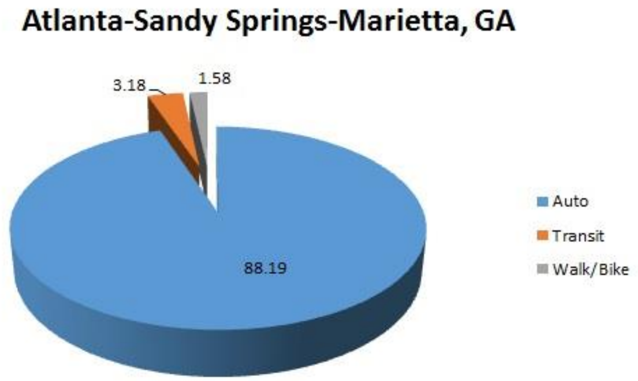
Washington-Arlington-Alexandria, DC-VA-MD-WV	District of Columbia, DC (11001); Calvert County, MD (24009); Charles County, MD (24017); Frederick County, MD (24021); Montgomery County, MD (24031); Prince George's County, MD (24033); Arlington County, VA (51013); Clarke County, VA (51043); Fairfax County, VA (51059); Fauquier County, VA (51061); Loudoun County, VA (51107); Prince William County, VA (51153); Spotsylvania County, VA (51177); Stafford County, VA (51179); Warren County, VA (51187); Alexandria city, VA (51510); Fairfax city, VA (51600); Falls Church city, VA (51610); Fredericksburg city, VA (51630); Manassas city, VA (51683); Manassas Park city, VA (51685); Jefferson County, WV (54037)

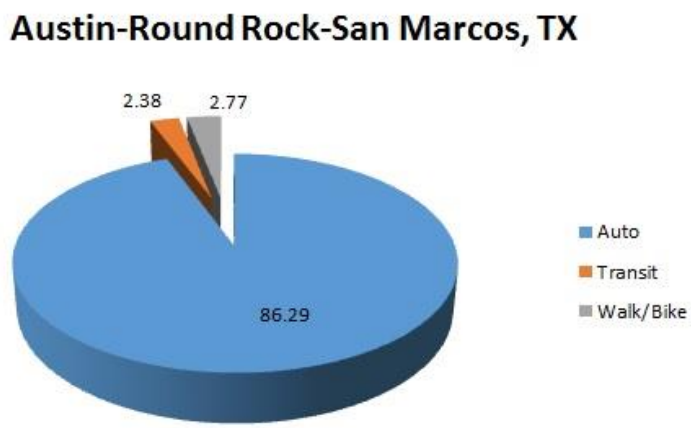
Metropolitan area	**Annual VMT***	**Commute mode share: auto**	**Commute mode share: transit**	**Commute mode share: walk/bike**
Atlanta-Sandy Springs-Marietta, GA	42,654.19	88.19	3.18	1.58
Austin-Round Rock-San Marcos, TX	13,678.43	86.30	2.38	2.77
Baltimore-Towson, MD	23,989.49	85.87	6.21	2.87
Birmingham-Hoover, AL	10,736.11	94.71	0.58	1.13
Boston-Cambridge-Quincy, MA-NH	31,606.20	76.49	11.88	6.20
Buffalo-Niagara Falls, NY	7,228.61	89.80	3.49	3.38
Charlotte-Gastonia-Rock Hill, NC-SC	13,504.76	89.87	2.15	1.67
Chicago-Joliet-Naperville, IL-IN-WI	44,849.84	79.50	11.34	3.81
Cincinnati-Middletown, OH-KY-IN	16,602.39	91.47	2.01	2.25
Cleveland-Elyria-Mentor, OH	14,669.29	89.87	3.33	2.47
Columbus, OH	15,354.00	90.45	1.68	2.60
Dallas-Fort Worth-Arlington, TX	53,624.35	91.27	1.43	2.60
Denver-Aurora-Broomfield, CO	20,236.95	85.53	4.35	3.06
Detroit-Warren-Livonia, MI	38,759.41	92.85	1.59	1.55
Hartford-West Hartford-East Hartford, CT	10,147.96	88.91	3.35	3.13
Houston-Sugar Land-Baytown, TX	46,944.70	90.96	2.42	1.64
Indianapolis-Carmel, IN	18,412.29	92.41	1.13	2.04
Jacksonville, FL	12,517.89	91.03	1.23	1.82
Kansas City, MO-KS	15,588.99	92.26	1.16	1.47
Las Vegas-Paradise, NV	11,466.45	89.52	3.82	2.20
Los Angeles-Long Beach-Santa Ana, CA	99,744.23	84.17	6.11	3.55
Louisville/Jefferson County, KY-IN	11,925.79	92.22	1.93	1.84
Memphis, TN-MS-AR	12,649.92	93.68	1.28	1.40

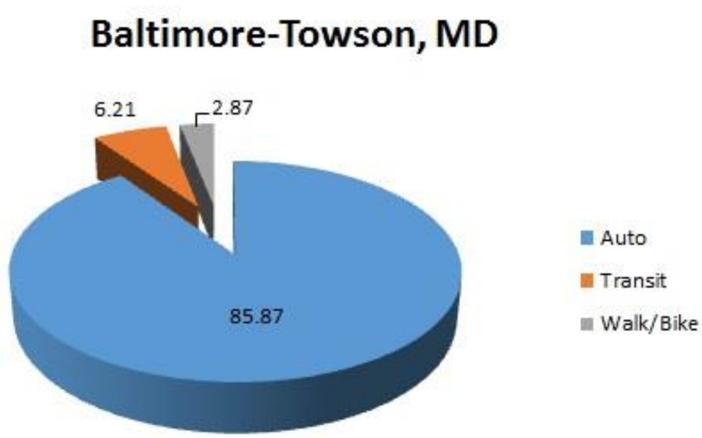
Miami-Fort Lauderdale-Pompano Beach, FL	39,922.64	87.82	3.82	2.39
Milwaukee-Waukesha-West Allis, WI	11,621.95	89.01	3.67	3.24
Minneapolis-St. Paul-Bloomington, MN	28,237.96	86.70	4.58	3.05
Nashville-Davidson--Murfreesboro--Franklin, TN	15,688.74	91.88	1.18	1.46
New Orleans-Metairie-Kenner, LA	8,234.13	89.42	2.85	3.56
New York-Northern New Jersey-Long Island, NY-NJ-PA	87,282.84	56.85	30.94	6.65
Oklahoma City, OK	12,348.89	93.18	0.46	1.99
Orlando-Kissimmee-Sanford, FL	18,662.50	90.38	2.02	1.64
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	42,273.58	81.60	9.38	4.27
Phoenix-Mesa-Glendale, AZ	31,716.24	88.12	2.09	2.30
Pittsburgh, PA	19,621.58	86.15	5.56	3.73
Portland-Vancouver-Hillsboro, OR-WA	14,279.44	80.60	6.22	5.85
Providence-New Bedford-Fall River, RI	11,746.71	89.47	2.74	3.51
Raleigh-Cary, NC	8,607.91	90.26	1.00078	1.46
Richmond, VA	13,184.01	90.98	1.70	2.14
Riverside-San Bernardino-Ontario, CA	38,249.35	90.91	1.60	2.01
Sacramento--Arden-Arcade--Roseville, CA	17,002.31	86.58	2.63	3.98
Salt Lake City, UT	8,064.15	90.87	2.48	2.01
San Antonio-New Braunfels, TX	17,305.82	87.91	3.44	3.01
San Diego-Carlsbad-San Marcos, CA	26,567.26	90.55	2.23	2.05
San Francisco-Oakland-Fremont, CA	32,782.14	86.28	3.02	3.44
San Jose-Sunnyvale-Santa Clara, CA	14,542.63	71.36	14.98	6.06
Seattle-Tacoma-Bellevue, WA	24,395.21	87.11	3.23	3.69
St. Louis, MO-IL	18,686.90	80.54	8.29	4.69
Tampa-St. Petersburg-Clearwater, FL	20,990.71	89.78	1.36	2.32
Virginia Beach-Norfolk-Newport News, VA	12,916.53	89.23	1.94	3.32
Washington-Arlington-Alexandria, DC-VA-MD-WV	42,473.80	76.04	14.31	3.94

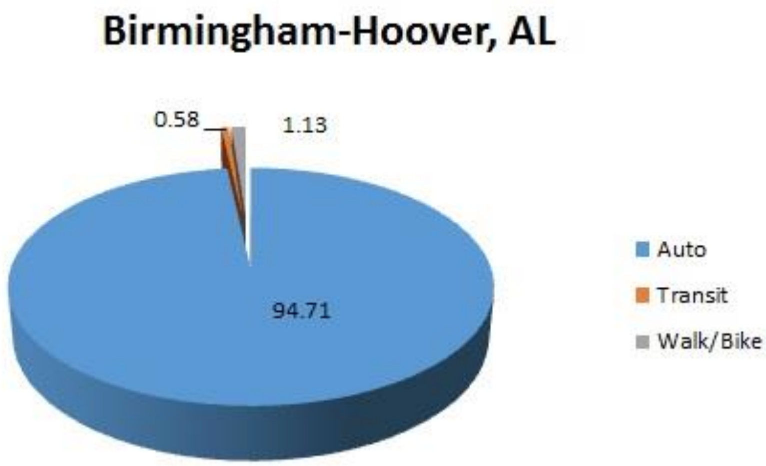
* VMT is measured in million miles

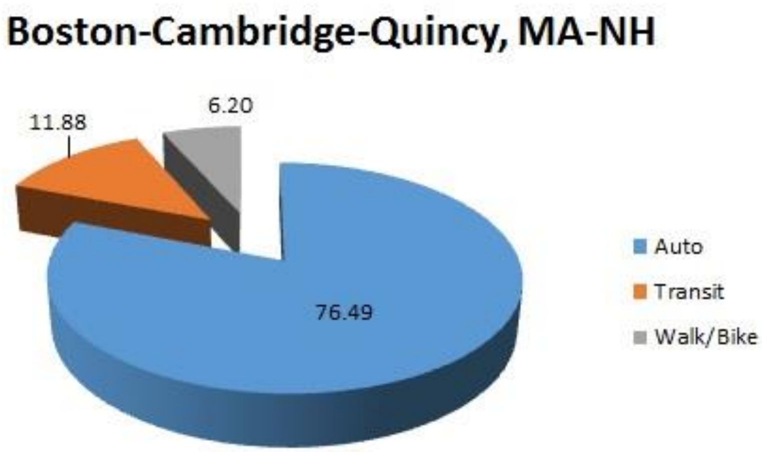
Appendix D: Commute Mode Share Charts

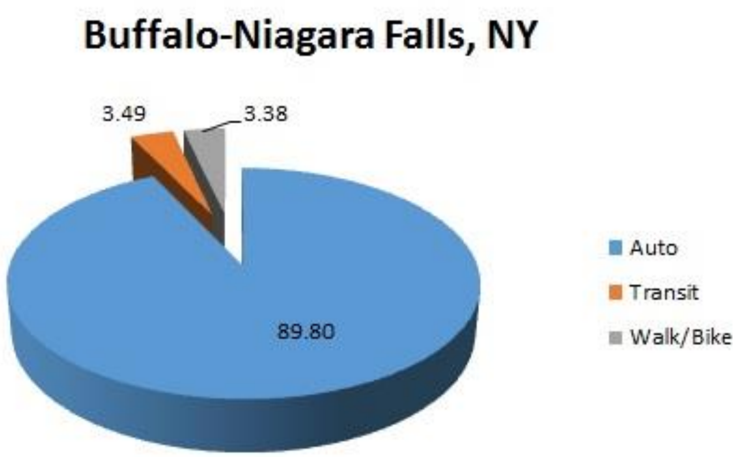




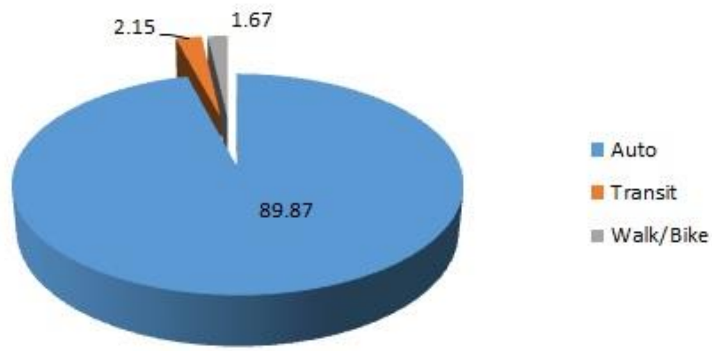



Birmingham-Hoover, AL
0.58
1.13
94.71
Auto
Transit
Walk/Bike

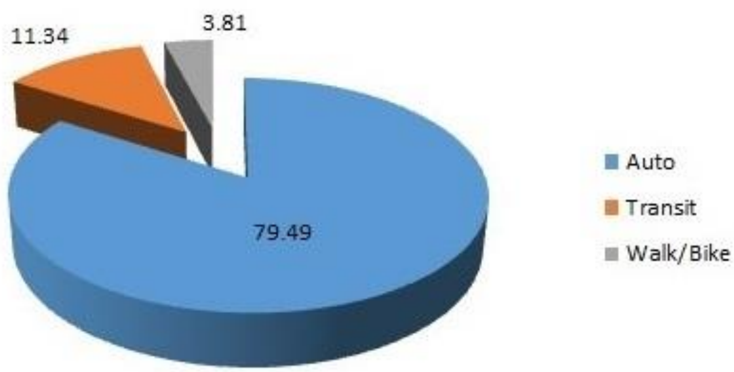

Boston-Cambridge-Quincy, MA-NH
11.88
6.20
76.49
Auto
Transit
Walk/Bike


Buffalo-Niagara Falls, NY
3.49
3.38
89.80
Auto
Transit
Walk/Bike

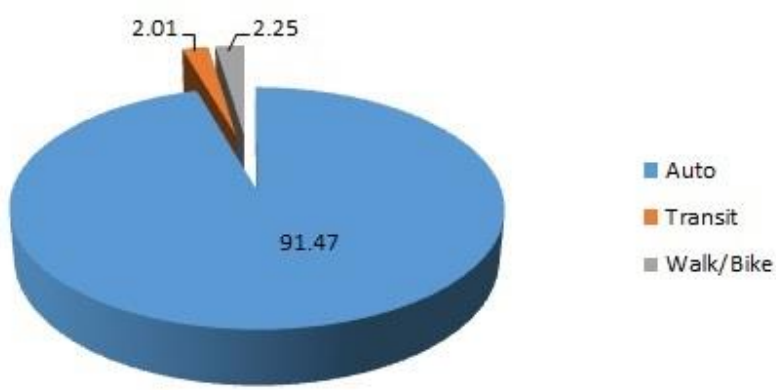
Charlotte-Gastonia-Rock Hill, NC-SC



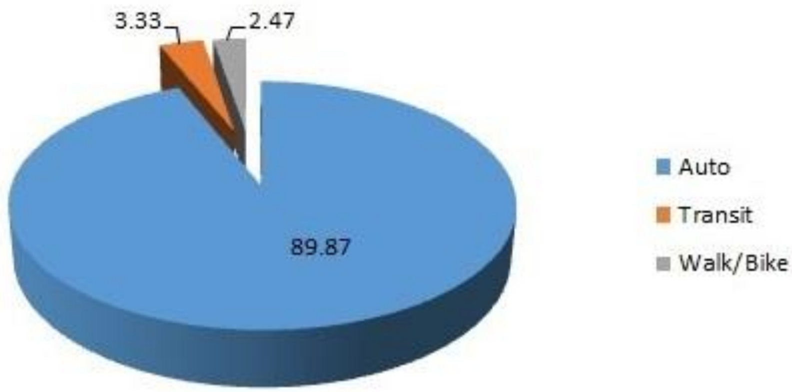
Chicago-Joliet-Naperville, IL-IN-WI



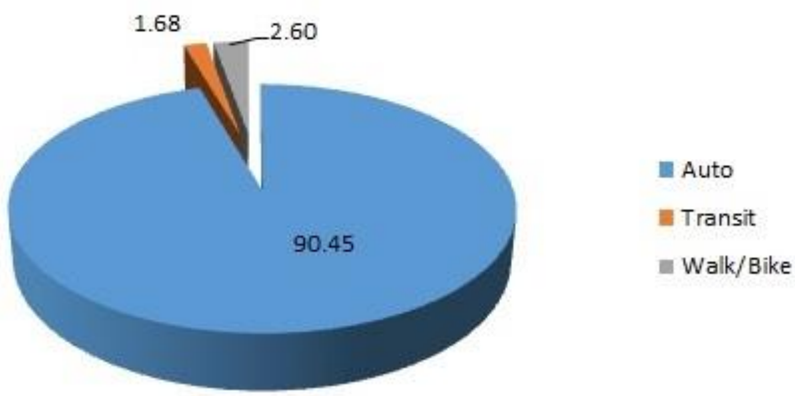
Cincinnati-Middletown, OH-KY-IN



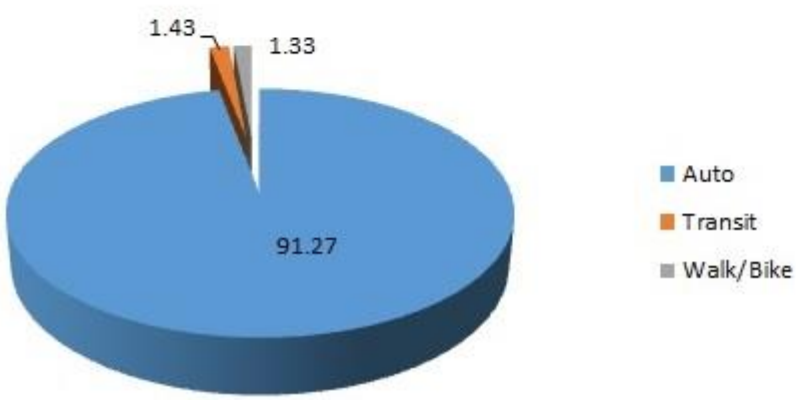
Cleveland-Elyria-Mentor, OH

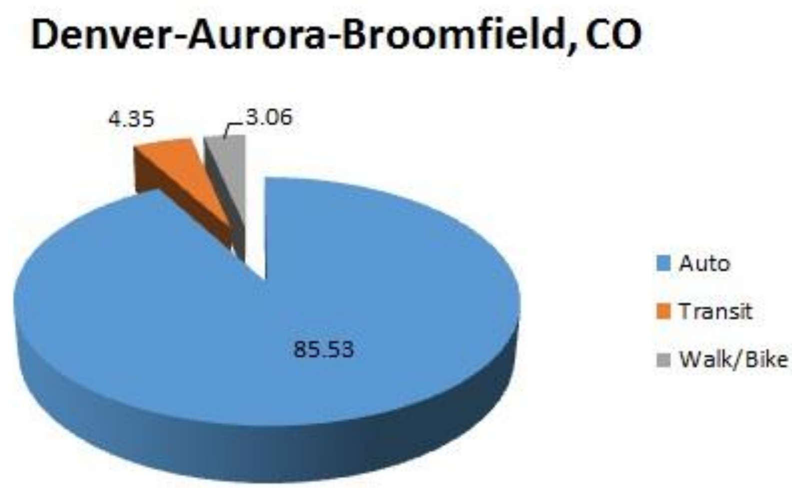


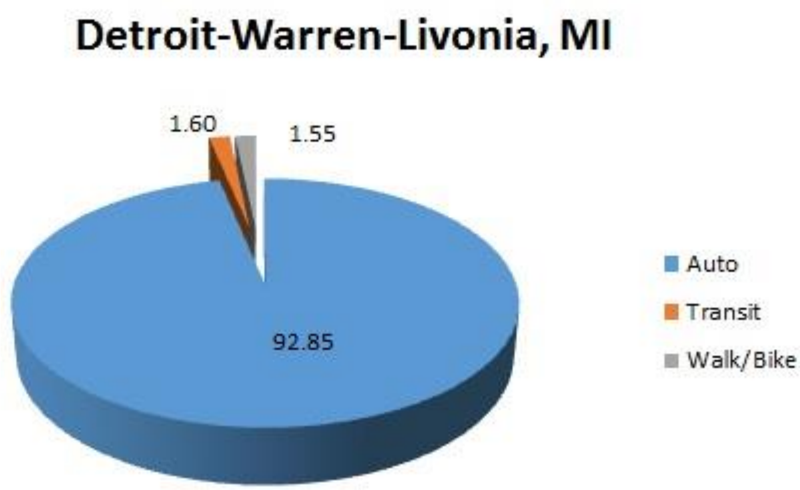
Columbus, OH

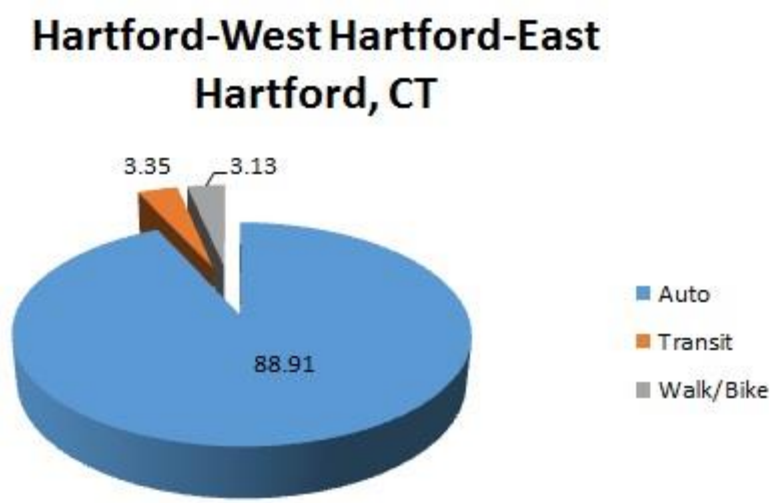


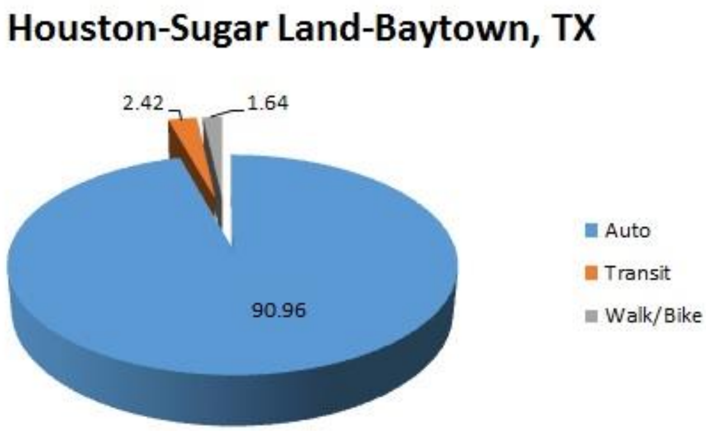
Dallas-Fort Worth-Arlington, TX

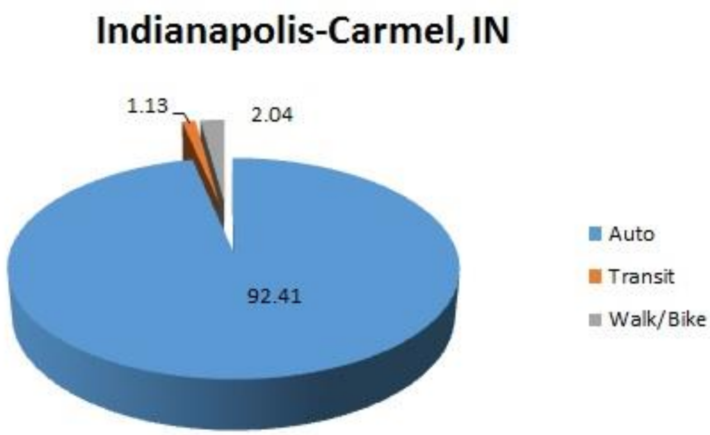


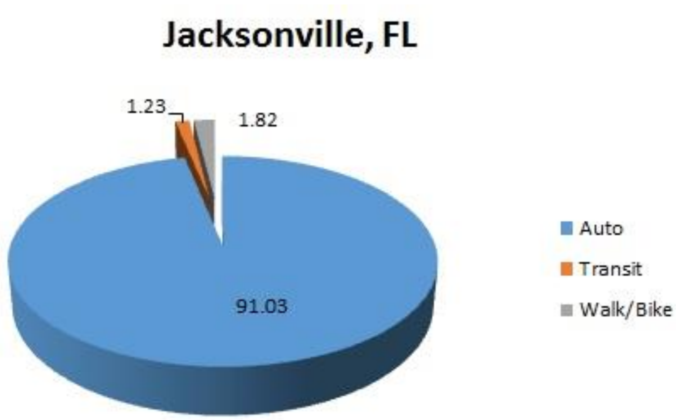

Denver-Aurora-Broomfield, CO
4.35
3.06
85.53
Auto
Transit
Walk/Bike

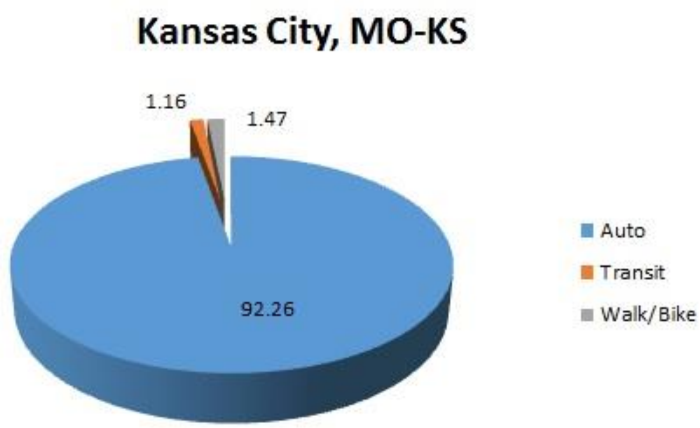

Detroit-Warren-Livonia, MI
1.60
1.55
92.85
Auto
Transit
Walk/Bike

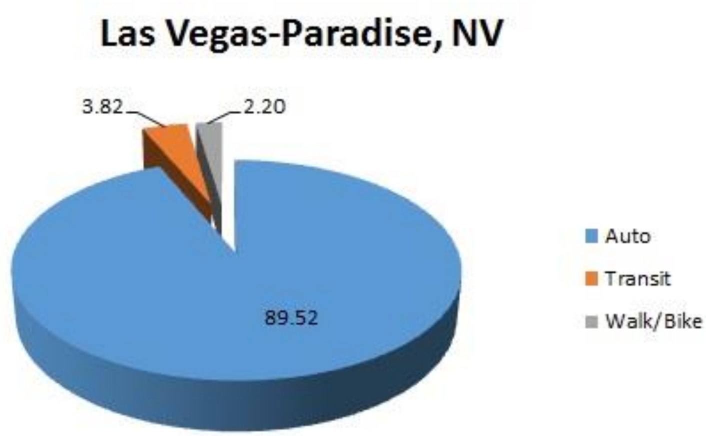

Hartford-West Hartford-East Hartford, CT
3.35
3.13
88.91
Auto
Transit
Walk/Bike


Houston-Sugar Land-Baytown, TX
2.42
1.64
90.96
Auto
Transit
Walk/Bike

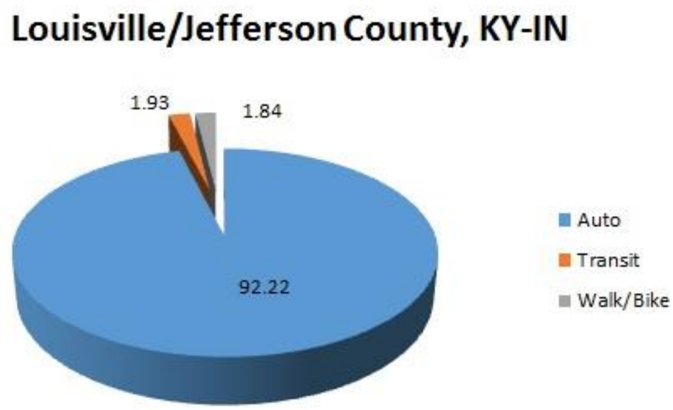

Indianapolis-Carmel, IN
1.13
2.04
92.41
Auto
Transit
Walk/Bike

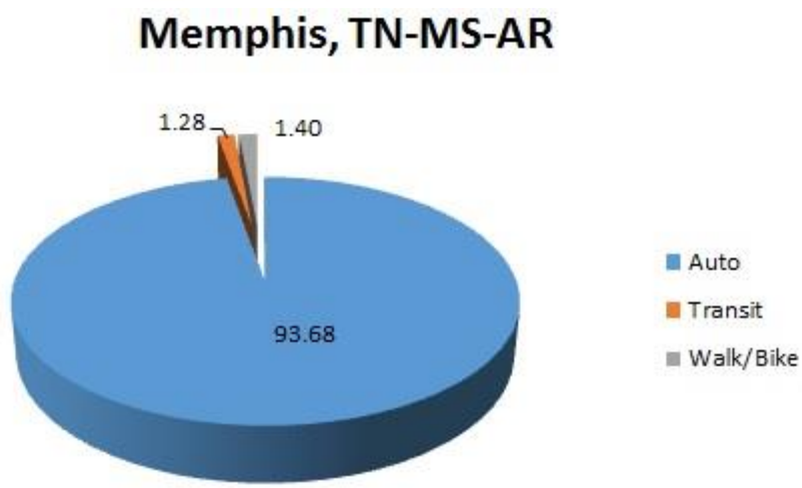

Jacksonville, FL
1.23
1.82
91.03
Auto
Transit
Walk/Bike

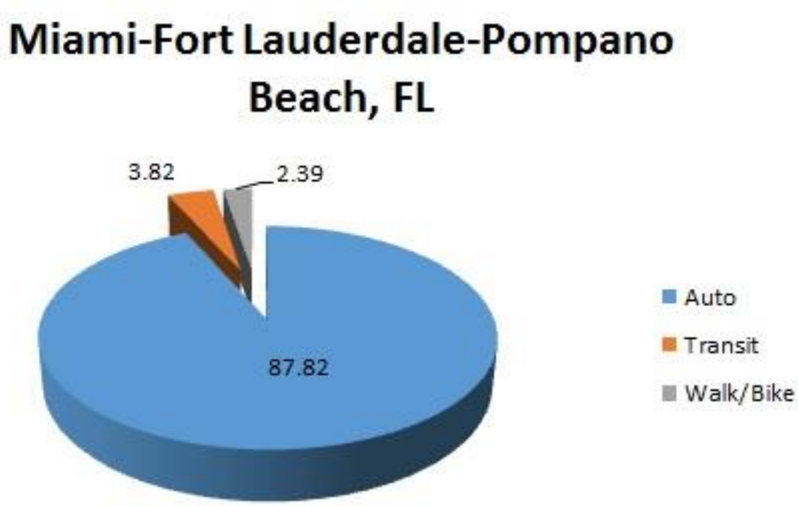

Kansas City, MO-KS
1.16
1.47
92.26
Auto
Transit
Walk/Bike

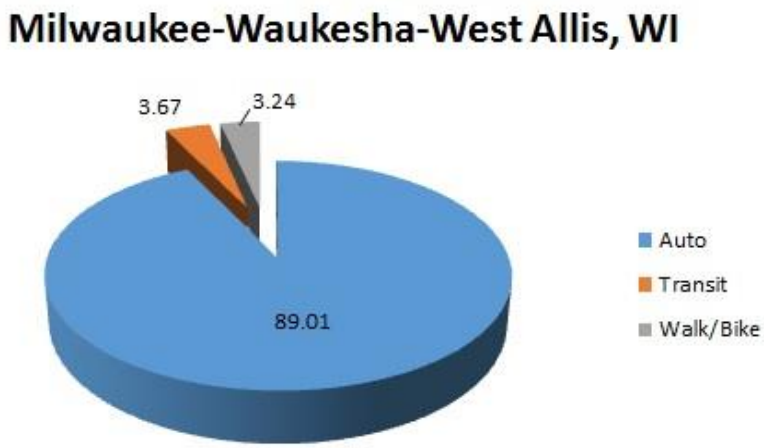

Las Vegas-Paradise, NV
3.82
2.20
89.52
Auto
Transit
Walk/Bike

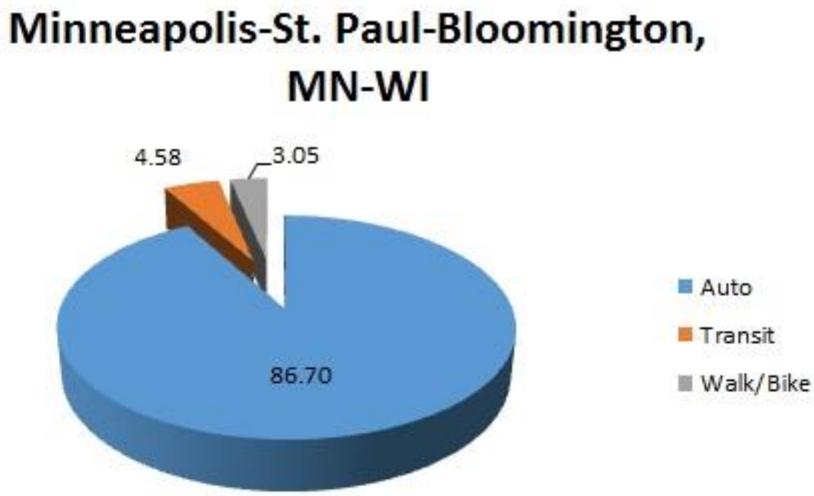

Los Angeles-Long Beach-Santa Ana, CA
6.11
3.55
84.17
Auto
Transit
Walk/Bike

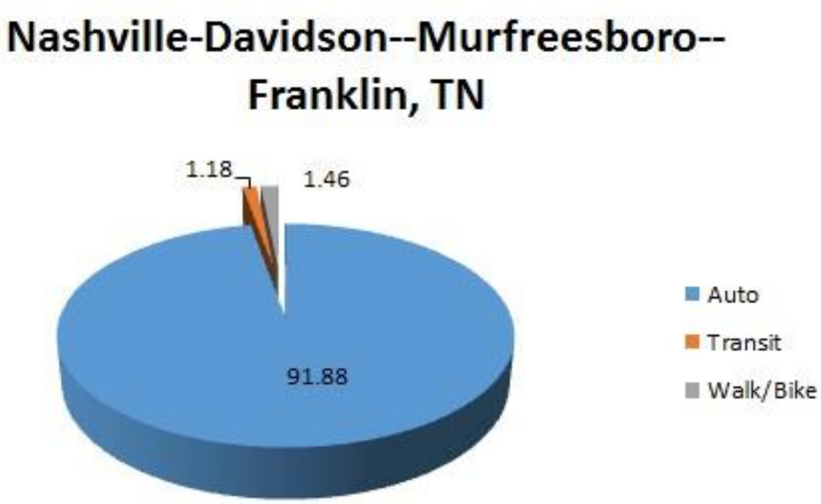

Louisville/Jefferson County, KY-IN
1.93
1.84
92.22
Auto
Transit
Walk/Bike


Memphis, TN-MS-AR
1.28
1.40
93.68
Auto
Transit
Walk/Bike

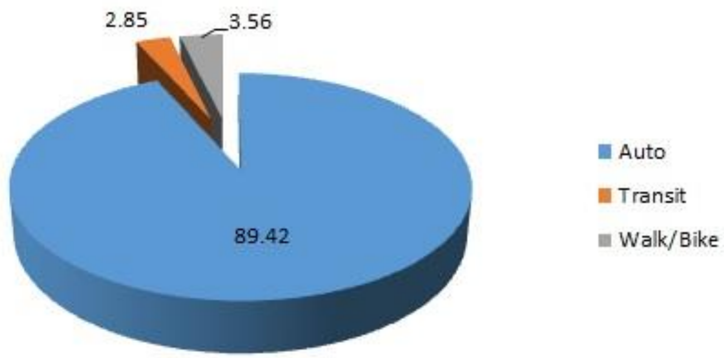

Miami-Fort Lauderdale-Pompano Beach, FL
3.82
2.39
87.82
Auto
Transit
Walk/Bike


Milwaukee-Waukesha-West Allis, WI
3.67
3.24
89.01
Auto
Transit
Walk/Bike

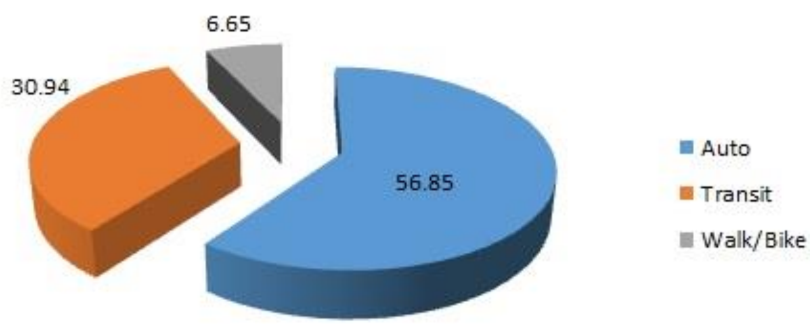

Minneapolis-St. Paul-Bloomington, MN-WI
4.58
3.05
86.70
Auto
Transit
Walk/Bike


Nashville-Davidson--Murfreesboro--Franklin, TN
1.18
1.46
91.88
Auto
Transit
Walk/Bike

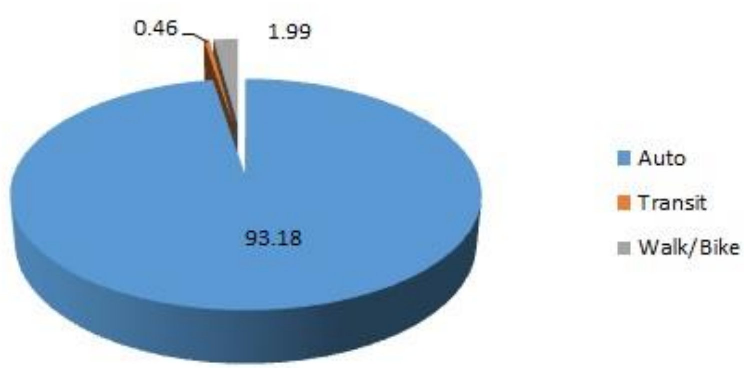
New Orleans-Metairie-Kenner, LA

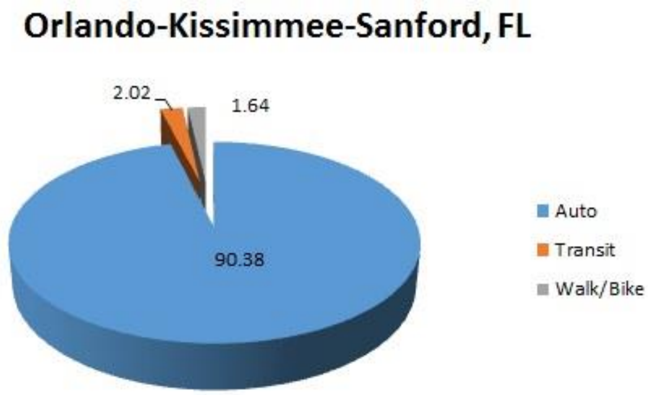


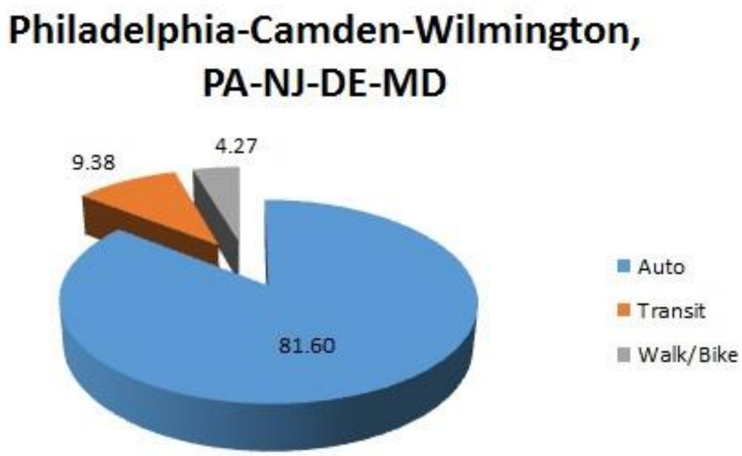
New York-Northern New Jersey-Long Island, NY-NJ-PA



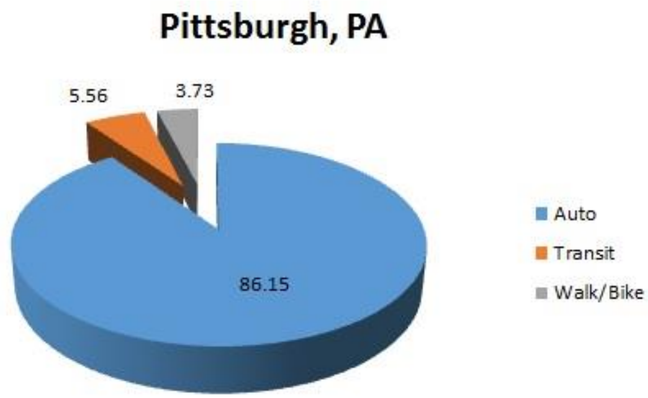
Oklahoma City, OK

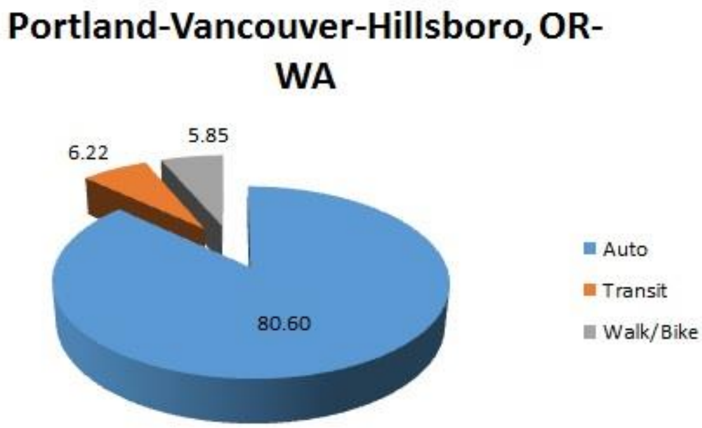


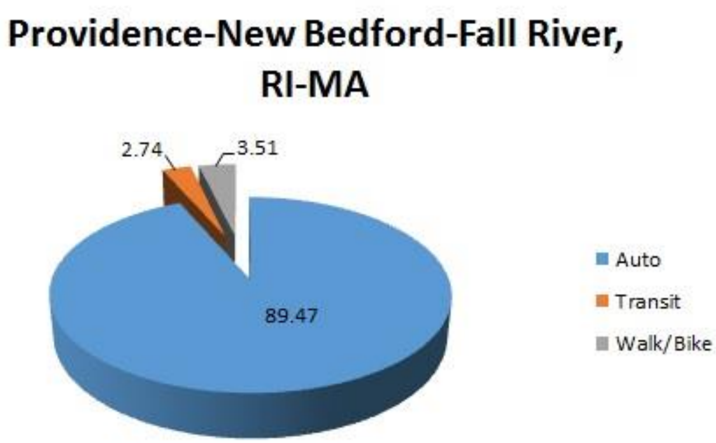

Orlando-Kissimmee-Sanford, FL
2.02
1.64
90.38
Auto
Transit
Walk/Bike

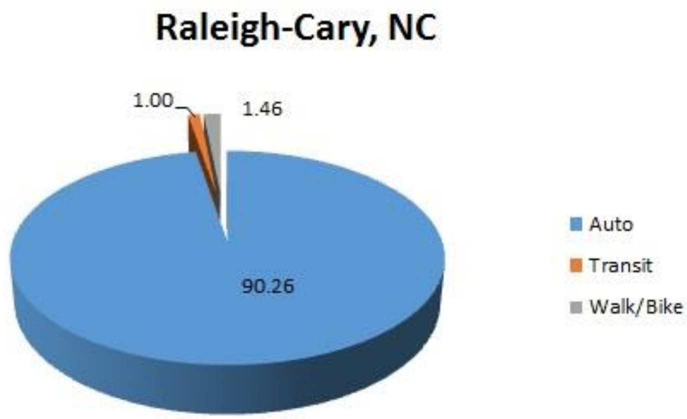

Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
9.38
4.27
81.60
Auto
Transit
Walk/Bike

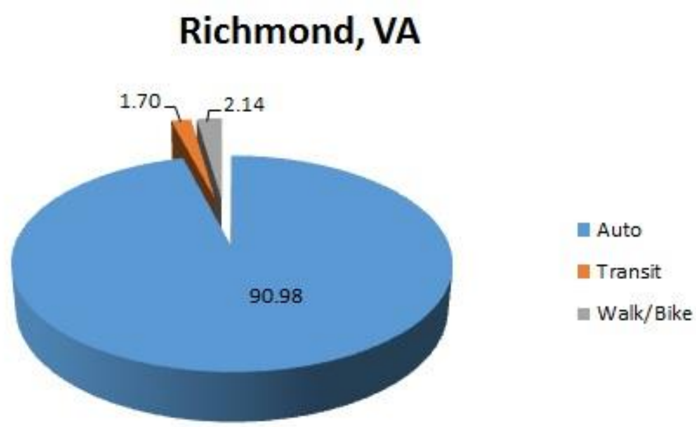

Phoenix-Mesa-Glendale, AZ
2.09
2.29
88.12
Auto
Transit
Walk/Bike

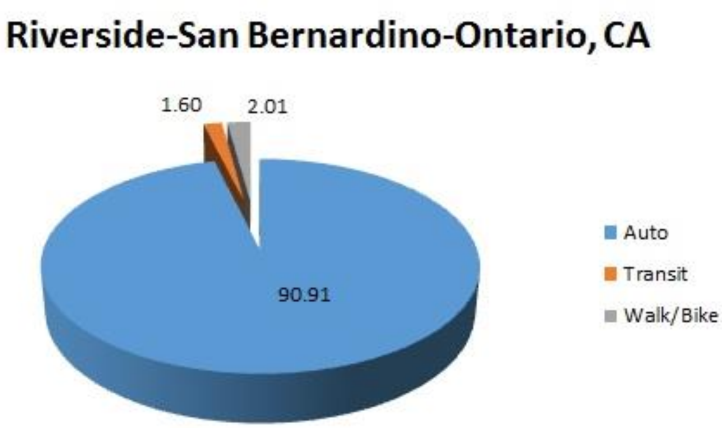

Pittsburgh, PA
5.56
3.73
86.15
Auto
Transit
Walk/Bike

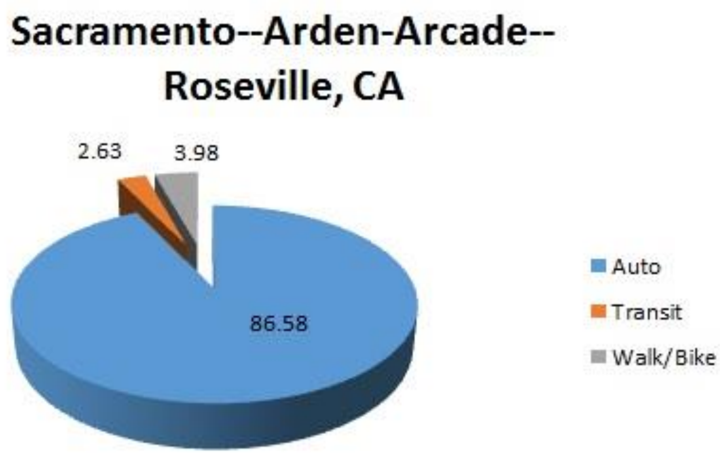

Portland-Vancouver-Hillsboro, OR-WA
6.22
5.85
80.60
Auto
Transit
Walk/Bike

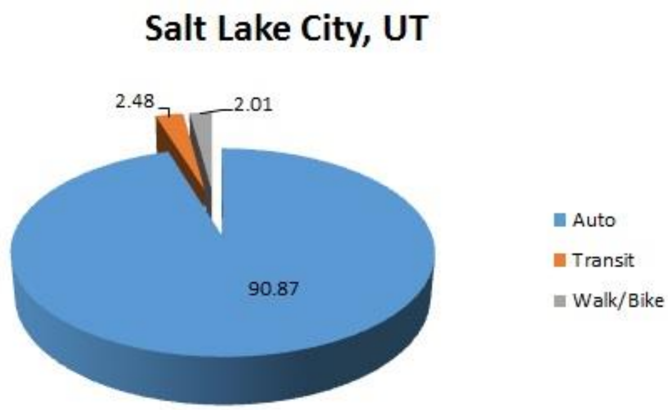

Providence-New Bedford-Fall River, RI-MA
2.74
3.51
89.47
Auto
Transit
Walk/Bike

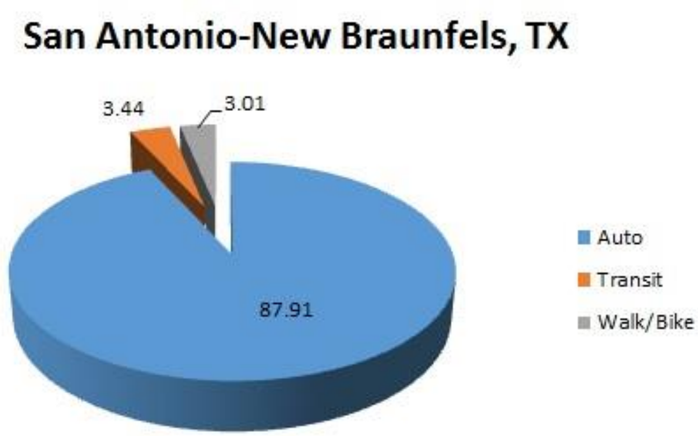

Raleigh-Cary, NC
1.00
1.46
90.26
Auto
Transit
Walk/Bike


Richmond, VA
1.70
2.14
90.98
Auto
Transit
Walk/Bike

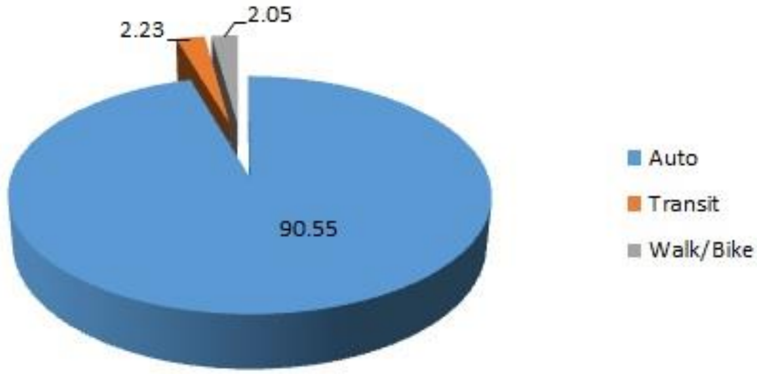

Riverside-San Bernardino-Ontario, CA
1.60
2.01
90.91
Auto
Transit
Walk/Bike


Sacramento--Arden-Arcade--Roseville, CA
2.63
3.98
86.58
Auto
Transit
Walk/Bike

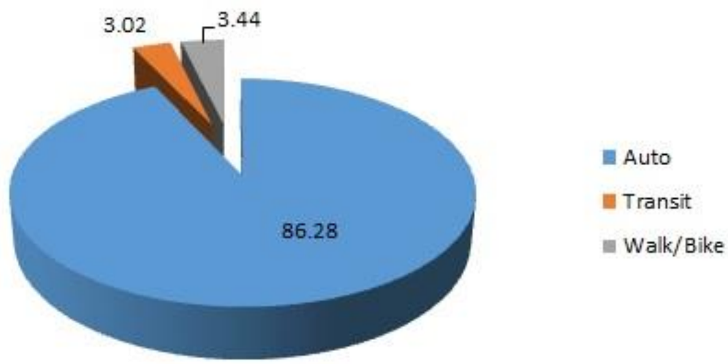

Salt Lake City, UT
2.48
2.01
90.87
Auto
Transit
Walk/Bike


San Antonio-New Braunfels, TX
3.44
3.01
87.91
Auto
Transit
Walk/Bike

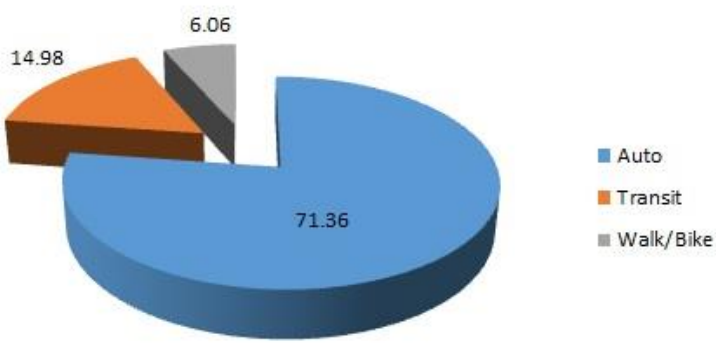
San Diego-Carlsbad-San Marcos, CA



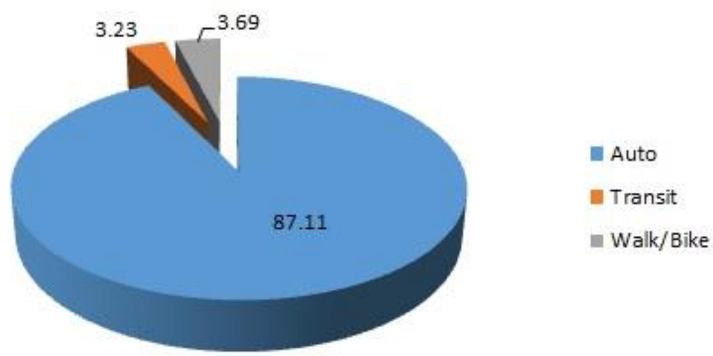
San Francisco-Oakland-Fremont, CA



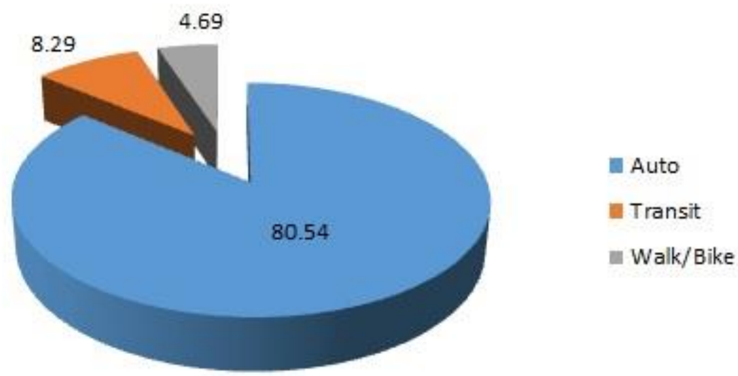
San Jose-Sunnyvale-Santa Clara, CA



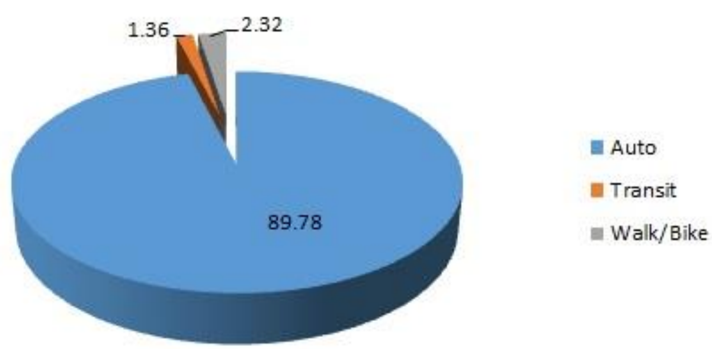
Seattle-Tacoma-Bellevue, WA

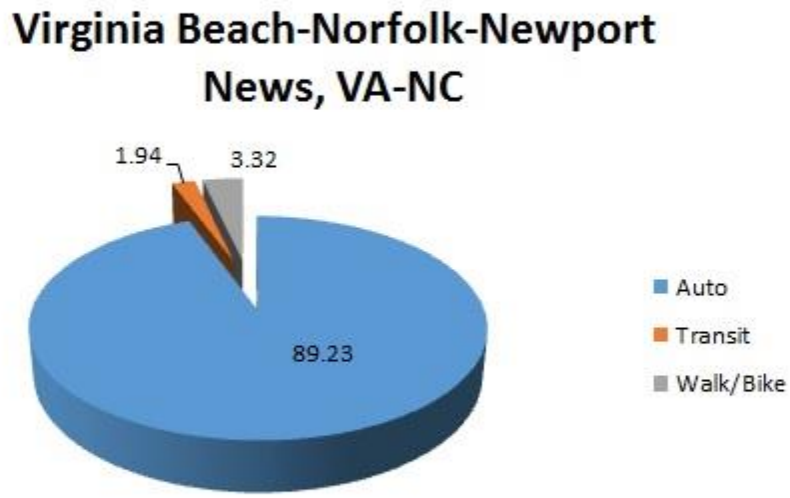


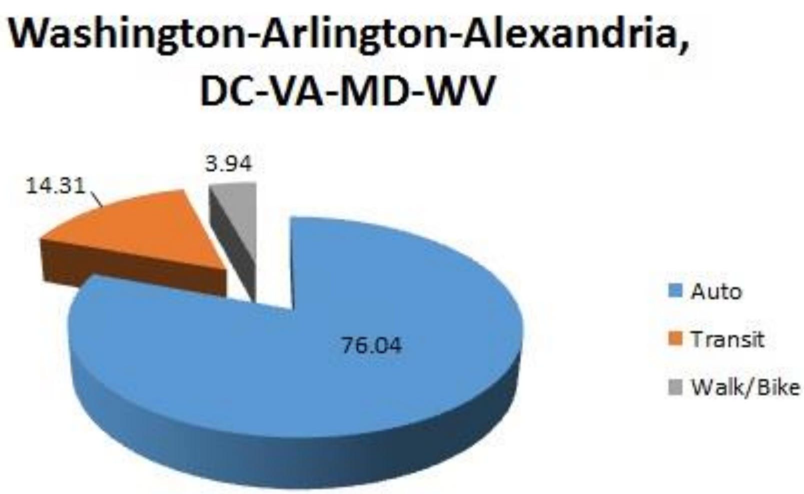
St. Louis, MO-IL



Tampa-St. Petersburg-Clearwater, FL




Virginia Beach-Norfolk-Newport News, VA-NC
1.94
3.32
89.23
Auto
Transit
Walk/Bike


Washington-Arlington-Alexandria, DC-VA-MD-WV
14.31
3.94
76.04
Auto
Transit
Walk/Bike

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