The Built Environment, Activity Space, and Time Allocation

An activity-based framework for modeling the land use and travel connection

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ABSTRACT

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(Under the direction of Asad J. Khattak)

Cities and metropolitan regions face several challenges including rising urban populations, sprawled land use patterns, and related auto dependence, energy consumption, greenhouse emissions, and human health effects. An important aspect of addressing these challenges involves understanding the connection between urban environments and spatial and temporal characteristics of individual activity-travel behavior. Advances in the research arena can inform the development of land use and transportation policies that facilitate access to local opportunities, reduce auto dependence, promote healthy travel behavior such as walking and bicycling, and generate travel time savings. Further, research efforts on this subject can help to measure the successes of existing transportation and land use planning tools in terms of their "secondary" effects on individuals' spatial accessibility, time allocation, and quality of life.

My dissertation systematically tests the connection between land use and activity-travel behavior by presenting three perspectives: one that focuses on the census block group level; another that focuses on the individual level; and one that focuses on the trip level. The analysis at the census block group level, named as the census block group level activity pattern analysis in this research, examines how the built environment of a census block-group

is associated with the aggregated distribution of activities and trips occurring within the census block-group. The individual-level analysis, named as the individual activity space and time allocation analysis, links individuals' spatial and temporal footprints to the built environment at the home location, traffic conditions at the home location, weather conditions, and individual/household characteristics. The trip-level analysis, named as the trip distance and duration analysis, demonstrates how environmental factors at the trip origin and destination and activity/trip characteristics are associated with the distance and duration of each trip.

The census block group level activity pattern analysis indicates that dense developments are not necessarily positively associated with diversity in activity categories or demographic diversity of the individuals who were involved with activities in the area. Greater land use diversity is associated with higher activity density and greater activity diversity but lower alternative mode share. Grid street patterns and the presence of sidewalks are both associated with higher activity density and more alternative mode share.

The individual activity space and time allocation analysis shows that small activity area size—less spatially dispersed daily activity locations—are related to dense developments, more retail stores, the presence of sidewalks, and the presence of heavy traffic in the residential neighborhood and are related to cold weather and precipitation. Most of the built environment factors show no association with time allocations to out-of-home activities or leisure activities, while they do show various associations with travel time allocations depending on the travel mode. Besides the built environment at the home location, weather conditions and traffic conditions also play an important role in both the individual spatial footprint and time allocation.

The trip distance and duration analysis suggests that shorter distance of non-work related trips is related to more retail stores, fewer industrial firms, and heavy traffic near the trip origin. After controlling for trip distance, the duration of driving trips is positively related to street grids, the presence of sidewalks, and dense developments at the trip origin and/or destination while the duration of walking trips is not. The analysis also suggests different activity/travel categories show dramatic differences in the sensitivity to environmental factors such as the built environment, traffic conditions, and weather. Not only do trips with different modes respond to these environmental factors in different ways, but trips related to different activity categories also show differences in the environmental sensitivity. Walking trips are more vulnerable to weather conditions than are driving trips.

This research took an activity-based and time use approach to study the land use-travel connection, which fills the gap between activity modeling and land use-travel modeling in the existing literature. Evidence found in this research supports the notion that transportation problems can be ameliorated through the use of land use strategies. The research also points out that the strength of the land use-travel connection is conditional on other environmental factors such as traffic and weather conditions, as well as activity context such as activity type and time of day.

Dedicated to my mother, Jiannan, and to my father, Zenan

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CHAPTER I: Introduction

Problem Definition

Over the past two decades, land development and energy consumption in the United States have been rising entirely out of scale with population growth. The amount of developed land increased 47% from 1980 to 2000—twice as much as the population growth rate (24%). In the same period, household annual vehicle miles traveled (VMT) increased 108% and average time spent in traffic increased about 238% (Bureau of Transportation Statistics 2001). The recent trends not only place mounting pressures on natural resources, the environment and the climate but also have the potential to impact on the social environment and human well-being in a variety of negative ways (Song, Gee et al. 2007).

Environmental, health and social problems arise from complex processes involving many factors such as planning and zoning practices, technology developments, governmental interventions, etc. However, the extensive use of automobiles has played a critical, if not the most important, role in recent trends.

On the one hand, on-road motor vehicles account for a significant proportion of air pollution and energy use. On the other hand, with the close connection between transportation and land use, extensive auto usage results in more auto-oriented land development patterns which in turn present significant obstacles to alternative transportation modes and physical activity. In addition, although advanced technology development has been improving the performance of vehicles and overall transportation systems, the improvements do not necessarily mean less traffic congestion, better accessibility to places and more time savings. In 2003, Americans on average spent about 70 minutes per capita on driving every day (Fan and Khattak 2006), which is about twice as much as twenty years ago. The increased time spent in traffic has negative impacts on economic productivity and overall quality of life. Therefore, given the harmful effects of auto travel on the environment, public health, and economy, it is essential for us to seek policy and planning solutions that are able to reduce driving time.

In recent years, one of the most popular planning ideas has been the use of urban design to solve traffic and social problems. The presumption that auto travel will decrease in more compact and gridlike land-use development is so appealing that it has been reported as a virtual fact on this subject (Boarnet and Crane 2001). Notions like active living by design and place-making have been gaining currency in both academic and public discourses. Researchers in relevant fields have made substantial progress in exploring land use and travel interactions. Much existing research has documented the negative correlation between compact development patterns and car travel. However, simple correlation cannot confirm a real connection, establish the casual theory, or provide sufficient robustness for policy development. For instance, the negative relationship between density and auto use might be due to heavy traffic and lower speed limits associated with dense developments, high levels of land use mix associated with high building density, and/or the fact that density shortens travel distance. Without knowing the underlying mechanisms explaining the land use and travel connection, we cannot safely propose any urban design solutions to achieve transportation benefits.

The challenge lies in the complexity of decision-making and the enormous interactions between urban form and travel. Travelers in urban environments make numerous daily decisions including what activities to pursue, how much time to allocate to each activity, when, where and with whom to participate in the activities, how to travel to the selected activity locations, and so on. Interactions exist within these daily decisions and further contribute to the intricate maze of human decision-making. As cities, transportation networks, and communication systems exist to alter space and time (Miller 2004), individuals' daily decisions are influenced by urban environments in many ways at various spatial-temporal scales. The relationship between urban planning and activity patterns is especially relevant in the context of processes such as urban sprawl and the decentralization of economic activities, which impact individuals' option for activities and trip-making. With the assumption that urban planning can allow individuals to engage in all their required activities with shorter travel distances and possibly by non-motorized modes, a better understanding of the relationship between the built environment and activity and travel patterns can help to propose the solutions to global warming, climate change, and peak oil.

In addition, urban planning and human activity and travel patterns are mutually related phenomena. As Chapin (1974) pointed out, studying aggregate distributions of activities in time and space sheds light on the impacts of different policy scenarios. Examining the spatial and temporal characteristics of daily individual activity-travel behavior can demonstrate the kind of environment that concentrates individuals' activities within and around highly accessible mixed-use centers and hold important implications for understanding and addressing urban problems.

Therefore, it is essential to sketch out an activity-based framework about how the built environment may influence the spatial and temporal patterns of travel and systematically empirically test the mechanisms behind the land use and travel connection. This dissertation research makes a significant step towards that aim.

Research Objectives

The main research question to be examined in this research is: How are built environment factors, including land use patterns, street patterns, and pedestrian facilities, associated with individuals' space and time use?

The subsequent question is: If compact development patterns in the built environment (e.g., high land use density, mixed land uses, street grids, and presence of sidewalks) are associated with less spatially dispersed activity patterns and less daily time spent on car travel, what are the underlying mechanisms?

Specifically, this research tests the following two sets of mechanisms:

- Dense developments, street grids, and mixed land uses are associated with shorter distance of non-work travel.
- After controlling for trip distance, land use density, street patterns, and sidewalks are associated with driving trip duration and walking trip duration with different significance, magnitude, and directions.

Three Analyses

To investigate how land use patterns relate to space and time use, the research examines the land use-activity/travel connection at three analysis levels: the census block group, the individual, and the trip.

- At the census block group level, the research links built environment factors to human activity and travel patterns. The census block group level analysis explains the aggregate distributions of activities in time and space.

- The individual-level analysis examines how the built environment at individuals' residences relate to individuals' daily activity spaces and daily time allocations to various activities and travel modes. This space and time use approach at the individual level not only can incorporate the fullness of the space and time dimensions but also can further address the complexity of daily decision-making. In addition to built environment factors, traffic and weather conditions were included as another important set of environmental factors in this analysis.

- The trip-level analysis takes a closer look at how the built environment at the trip origin and/or the destination may influence the distance and duration of each trip. In addition to controlling for household factors, personal socio-demographics, and individual attitudes and preference, the analysis further incorporates activity characteristics (such as activity type and activity time of day) and trip characteristics (such as mode, distance, and home-based indicator) into modeling the connection between the built environment and trip distance and duration. By disaggregating the elements of travel such as distance and duration and specifying the travel mode and the activity context, this trip-level analysis is dedicated to testing the mechanisms underlying the land use and travel connection.

Contribution

When compared with similar literature, this study is unique in several ways. In terms of theoretical contributions, this research explicitly derives a theoretical model of land use and travel connection from the economic theory of demand and the psychological theory of environment-behavior interactions. The theoretical framework provides mechanisms by which land use influences aggregate urban traffic and individual travel behavior. A key modeling strategy is to treat trip distance and duration as choice variables rather than parameters of mode choice.

In terms of empirical contributions, this research systematically tests the connection between land use and activity-travel behavior from three angles—the block group, the individual, and the trip. It echoes three different film-making styles: one focuses on a physical space, one focuses on an actor—the individual, while yet another focuses on a journey. The census block group level activity and travel pattern analysis examines how the built environment of a census block group is associated with the aggregated distribution of activities and trips occurring within the census block group. The individual activity space and time allocation analysis links individuals' spatial and temporal footprints to the built environment at the home location, traffic conditions at the home location, weather conditions, and individual/household characteristics. The trip-level distance and duration analysis investigates how environmental factors at the trip origin and destination and activity/trip characteristics are associated with the distance and duration of each trip.

To the author's knowledge, this is the first activity-based study that investigates the land use and travel connection using three analysis units from both the spatial and temporal perspectives. By offering activity and travel analyses at the aggregate level and disaggregate levels, this dissertation is able to give more explicit and more meaningful attention to environmental contingencies as well as to provide insights into the environment effects on activity and travel decision-making.

The treatment of urban form and land use in this research is extensive, incorporating the following measures for the Triangle area in North Carolina: residential density, employment density, accessibility to commercial uses or retail stores, presence of industrial uses or companies, connected node ratio, and presence of sidewalks. In addition to these direct measures, a transect—a typology of neighborhood types—was developed and used to analyze how individual activity spaces and time allocations vary across neighborhood types. The use of direct measures improves the transferability of the results to other regions and helps to make more practical and more specific planning recommendations. The use of neighborhood clusters provides an intuitive spatial representation of urban environments and captures the collective and interactive effects involving multiple environmental features on activities and travel. In addition, the geo-coded behavior data in the Triangle survey make it possible to generate and focus on measures not only at the home locations but also at the trip origins and destinations.

In addition to built environment factors at the home location and the trip origin and destination, the research considered traffic conditions and weather conditions as another important set of variables. The inclusion of traffic and weather conditions not only improves the estimates of built environment factors, but also helps us propose more practical policy implications.

Activity-travel pattern measurement includes approaches drawn from spatial statistics and computational geometry. Kernel density estimation was used to generalize driving destinations to the entire study area and generate driving destination density—a proxy measure of urban traffic conditions. Individual activity space, defined as the minimum convex polygon containing an individual's activity locations, was developed to describe the spatial activity patterns at the individual level. The research also develops entropy measures to describe diversity in the types and the times of activities occurring within the census block group, and the race, income, and age mix in the individuals who accomplished activities within the census block group.

Furthermore, while considerable evidence has suggested that compact development patterns are associated with auto travel reduction, little existing research explains the mechanisms by which compact land use patterns achieve this reduction. By disaggregating the elements of travel such as distance and duration and specifying the travel mode and the activity context, the research disentangles the land use and travel connection into several testable hypotheses and examines them systematically. Thus, the research proposes, isolates and separately tests potential channels through which the built environment may influence travel. This goes beyond the conventional individual-level cross-sectional studies in the field.

Research investigating the land use-travel connection rarely focuses on the time dimension. Very little is known regarding how the built environment relates to activity and travel time use. This research focuses on daily activity and travel time allocations that incorporate the fullness of the time dimension, and the trip duration that has implications for the time cost of traveling. With the individual-level time allocation models, this research provides insights into how time allocations to various activities and travel modes change with built environment factors at individuals' residences. With the trip-level duration models, the research findings help us better understand to what degree the built environment changes the time cost of travel.

Earlier studies largely examined the land use-travel connection outside of the activity contexts, which may generate inconsistent estimates. Trips of different types may respond differently to environmental factors (Meurs and Haaijer 2001). This research incorporates activity contexts (activity type and time of day) and trip characteristics (home-based indicator and travel mode) into the models of the built environment and trip distance and duration. By developing activity-specific models and mode-specific models of the built environment and travel behavior, this research predicts travel behavior more accurately. Further, time use and activity-based approaches are theoretically appealing and make it possible to account for the interconnectivity among trips, the interplay between activity and travel, and the role of the time-space continuum in modeling travel demand (Pendyala and Goulias 2002).

In terms of contributions to policy and practice, the research findings contribute to such emerging movements as active living by design and place-making. As the research findings are intended to disentangle the mechanisms behind the land use-travel connection, the results will help policy-makers make more informed and more specific decisions to create supportive places that encourage healthy travel behavior and improve individual quality of life.

The research findings also contribute to the ongoing policy debates regarding travel demand management. More specifically, as this research focuses on the effect of the built environment on trip distance and duration that closely relate to trip price/cost, the research findings are comparable to the earlier findings about transportation pricing policies. Findings from this travel time research can be used to shed light on how well direct regulatory policies such as pricing compare with more indirect planning interventions such as urban design. In addition, the research findings enable travelers to make more informed decisions regarding which transportation mode can free up more time resources.

Chapter Structure

Chapter II presents a synthesis of the literature relevant to activity engagement and travel decision-making in urban environments. Two key areas are identified: activity studies, and studies about the built environment and activity/travel decision making.

In Chapter III, I first discuss the theoretical foundations for this work drawing on the environment-behavior model in social physiology and the theory of demand in microeconomics. Based on the theoretical foundations, I further provide a framework for how factors in urban environments including the built environment, urban activity patterns, and weather conditions may influence activity engagement and travel behavior.

Chapter IV describes the research design and methodology used in this study. The chapter details the study site, data collection and manipulation, and models.

In Chapter V, I analyze how built environment factors relate to activity/travel patterns at the census block group level. Activity patterns were measured using density and diversity indicators. Alternative mode share in all the trips attracted to each block group is used to describe the travel pattern in the block group. This analysis tests whether great density and diversity in physical land uses is associated with high activity density and greater diversity in activity types and population groups (e.g., race, income, and age). This chapter also tests whether grid street patterns and pedestrian facilities attract more trips using alternative transportation modes.

In Chapter VI, I analyze how built environment factors at the home location combined with traffic and weather conditions relate to individual daily activity space and time allocation. The analysis controls for individual/household socio-demographics, location choice factors, and traffic information usage.

In Chapter VII, I develop a neighborhood typology in the study area and identify six neighborhood clusters. A mean comparison analysis was conducted to describe how individuals' daily activity spaces and activity/travel time allocations differ across the six neighborhood clusters. The neighborhood clusters were further used to model the collective effects involving multiple environmental features on individual daily activity space and time allocation.

In Chapter VIII, I analyze how the environmental factors at the trip origin and destination are associated with the distance of non-work trips, and how theses factors are further associated with trip duration. The analysis was carried out at the single activity/trip level. Activity-specific distance models and mode-specific duration models were developed to understand how the direction and/or strength of the relationship between the built environment and travel vary by activity type and travel mode.

The findings were reviewed in Chapter IX as they relate to the hypotheses and *a priori* expectations. Based on the findings, I further draw conclusions from the findings, discuss policy relevance, and describe implications for future research on land use and travel.

CHAPTER II: Review of Relevant Literature

As this dissertation aims at developing an integrated activity-based land use-travel modeling system, the purpose of this literature review is mainly to analyze and synthesize what past research can tell us about the interrelationships among the built environment, activity engagement, and travel behavior. This review identifies the remaining gaps between activity-based modeling and the modeling of land use and travel demand. I also explain gaps within those two areas, the reasons why studies in each area did not reach consistent results, and future directions suggested by the existing work.

The first section in this chapter focuses on studies along the line of an activity-based framework and discusses the concept development in spatially and/or temporally describing activity-travel patterns. The second section reviews studies on the connection between land use and travel. In the summary section, I identify the remaining gaps and disagreements in those two areas and discuss the synergy potential of these two areas.

Activity-Travel Pattern Studies

According to Chapin (1974), urban planning should be based on the study of individuals' needs for activity engagement. Since the early 1970s, researchers on the subject have been seeking comprehensive treatments of the space and time dimensions in studying human behavior (Hagerstrand 1970; Chapin 1974).

Hägerstrand (1970) first formulated a time-geographic framework to describe how urban activity systems set limitations on individuals' options for being engaged in activities. He modeled individuals as paths or trajectories in time-space, experiencing capability constraints, coupling constraints, and authority constraints. The time-geographic model takes a disaggregate view of human activity and provides a complete contextual base for interpreting individual activities and travel in urban environments. The usefulness of the time geography approach was soon recognized in many fields (Pred 1977). Such fields include historical geography (Hagerstand 1978), social equity (Palm and Pred 1978), urban transportation (Lenntorp 1978), and regional differences (Martensson 1978).

To date, multiple spatial concepts have been developed based on the time-geographic approach to describe the actual and potential individual activity engagement. Example concepts include space-time path/prism (Burns 1979 ; Kim and Kwan 2003), potential path area (Miller 1991; Kwan 1999), travel probability fields (Beckmann, Golob et al. 1983), action/activity standard ellipse/circle (Zahavi 1979; Schonfelder and Axhausen 2003), and minimum convex polygon containing activity locations (Buliung and Kanaroglou 2006; Buliung and Kanaroglou 2006).

Another important research theme in activity studies is synoptic studies at the spatially aggregate level. As Chapin (1974) argued, studying aggregate distributions of activities in time and space can shed light on the impacts of different policy scenarios, as it is the users of space that the planning and policy decisions intend to serve. With the explicit recognition of cities as places or spatial events (Lynch 1976; Goodchild and Janelle 1984; Batty 2003), researchers in the planning field have been increasingly considering the temporal and spatial activity patterns as the basis of the urban ecological structure. Rather than documenting all the individual interactions in time-space, the synoptic analysis of spatiotemporal activity patterns uses a ‘census-like’ methodology (measures of central tendency, frequency distribution, etc.) to describe population activity patterns at any time of day at any level of spatial aggregation.

Chapin (1974) began with the individual-level choice model to study the human activity patterns of the population aggregates, including the patterns of activity choice (what kind of activities), the temporal patterns (when these activities take place), and the spatial patterns (where these activities take place). Temporal patterns were examined using the percentage of people engaging in each activity category by hour of the day. Spatial patterns were examined using “mean locus,” which was defined as the sum of the linear distances from a person’s home to every out-of-home activity location visited during a 24-hour period. Many early studies (Hemmens 1970; Cullen 1975; Shapcott and Steadman 1978; Hanson and Hanson 1980; Hanson and Hanson 1981) used similar methods to explore the temporal and spatial patterns of daily activities and travel behavior. However, this early generation of activity pattern analysis uses simple distance and duration measure that can not really capture or visualize the complexity of human activity patterns in cities.

An important breakthrough in the synoptic analysis of spatiotemporal time activity patterns was achieved by Taylor and Parkes (1975) who proposed a factorial-ecology experiment using space-time units (STUs). They artificially created the activity location and timing data of a typical working day in summer in a medium-sized British city. In terms of activity space, the city was divided into ten districts based on the locational and socio-economic variations. The 24 hours of the typical working day were divided up into eight periods to reflect predominant activity bundles such as sleep time, commuting time, work time, lunch time, and so on. Each of the ten geographic units was treated separated through each of the eight periods, yielding a total of eighty STUs. A total of 22 census-like variables were used to describe the urban ecology in each STU, including land use variables, social and demographic characteristics of the population, and count measures of travel behavior in each STU. Common factor analysis reduced the 22 variables to seven factors. The factor scores of those seven factors in 80 STUs were then interpreted to better understand the dynamic social geography in the hypothetical city through the day.

Taylor and Parkes' hypothetical experiment has strongly motivated the subsequent research design and empirical documentation of urban activity patterns using factorial analysis. Goodchild and Janelle (1984) replicated and extended the factorial-ecology experiment using the actual data based on the daily activity space-time survey in the metropolitan area of Halifax, Canada. Besides using the factorial-ecology method to explore the Halifax data, Janelle and Goodchild (1983) conducted another study which incorporated the temporal dimension into simple spatial statistics. They calculated the location quotient, the index of dissimilarity and the density gradient to monitor the geographical concentration, segregation, and mobility for selected subpopulations and role groups in each spatial unit at different times of the day.

Using advanced geo-visualization and geo-computation techniques, Kwan and Lee (2004) explored the use of 3D activity density surfaces for representing and comparing activity patterns of different population groups in the Portland metropolitan region. The three dimensions of activity density surfaces are the time of day (X-axis), the distance of an activity from home (Y-axis), and the activity density value (Z-axis). Activity density values were generated using kernel density estimation. Kwan and Lee's (2004) method reveals the intensity of activities in space and time simultaneously, which facilitates the analysis of space-time interactions. It also avoids the interpretative difficulties of conventional quantitative methods in synoptically describing the spatiotemporal activity patterns.

The approach offered by the time-geographic model—coupled with recent advances in GIS technologies and the available micro-level data, makes it more feasible than eve to measure human activity patterns in space and time at both the individual level and the aggregate levels. However, very few studies have incorporated activity patterns in examining the land use effects on travel demand.

Early contributors in studying urban activity patterns (Chapin 1974) made limited implications about the environment effects on human activity patterns by linking census characteristics of sub-metropolitan communities with surveyed activity patterns in those communities. The spatial factors included in recent activity studies are often simple measures such as population/job density, metropolitan status, distance to CBD, number of shores within certain distance (Bhat and Misra 1999; Yamamoto and Kitamura 1999; Ettema 2005; Fan and Khattak 2006; Ye and Ram M. Pendyala 2006). At the individual level, the role of the built environment in activity engagement has rarely been examined in a systematic way and from both the spatial and temporal perspectives. In addition, recent advances in synoptic activity pattern analysis have been focusing on visually presenting urban activity systems and generalizing a totalizing master vision. At the spatially aggregate levels, few studies have explored the linkages between the physical urban systems and the human activity systems.

This dissertation investigates the connection between the built environment and activity patterns at both the spatially aggregate level and the individual level. Several concepts in the literature were used, including the 3D activity density estimation at the spatially aggregate level and the daily activity space measurement at the individual level. New concepts of activity patterns were developed as well, including entropy measures of diversity in activity types and activity population. To the author's knowledge, the diversity concepts in activity population have rarely been measured using entropy measures. However, entropy measures are commonly used in many similar concept measurements (e.g. land use diversity) (Cervero 2002; Song and Knaap 2004), which ensures the robustness of the diversity measures of human activity patterns.

The Built Environment and Travel Behavior

Extensive research has demonstrated an association between the built environment and travel behavior. However, very little is known regarding the causal links between the built environment and travel behavior, and there is little agreement on how to reliably learn more (Boarnet and Crane 2001). The remaining challenges involve the lack of a coherent environment-behavior theory, the difficulty in measuring the built environment, and data and methodology issues in modeling the linked choices such as where to live, where to travel, when to travel, and how to travel. This section introduces supportive theories of the built environment and travel connection, and provides a summary of the existing empirical evidence.

Theoretical foundations

The theoretical bases of the environment-behavior interactions come from a variety of fields and disciplines. The established theories include the spatial interaction theory, the theory of demand, expected utility theory, prospect theory, and the theory of planned behavior.

The spatial interaction theory (Lakshmanan and Hansen 1965), mostly developed based on 'law of gravitation,' explains the spatial interaction between two locations by the attractiveness of those two locations and the distance between them. The theory indicates that the choice of visiting a particular shopping center is determined by travel distance and the attractiveness of the shopping center, which suggests a connection between urban environments and activity engagement.

The theory of demand assumes that individuals make choices based on their preferences over the goods in the consumption set, the relative costs of those goods and available resources (Parkin 2004). As the travel cost of a certain mode decreases, the demand for the mode will increase. As Boarnet and Crane (2001) argued, street grids, mixed land uses, and inviting pedestrian neighborhoods are intended to change either the time cost of traveling (e.g., by placing origins and destinations in more direct proximity) or the relative cost across modes (e.g., by slowing auto travel and facilitating non-automobile alternatives). Thus, the theory of demand suggests a connection between land use and travel.

Expected utility theory takes a different view from the theory of demand and suggests that each choice offers a certain "utility" or value to the individual who seeks to maximize his/her utility (Baron 2000). Anything that increases or decreases the utility of trip-making will have impacts on travel behavior. For example, attractive neighborhood design and better transit accessibility can increase the utility of walking and taking local bus.

At an operational level, discrete choice models (Domencich and McFadden 1976; Ben-Akiva and Lerman 1985; Train 2003) have been developed to apply the utility maximization framework to model travel behavior. However, there are limitations in using utility maximization to represent underlying behavior processes that shape travel behavior (Garling 1998). Utility maximization is concerned with identifying the best decision to take, assuming a rational decision taker who is fully informed and able to compute with perfect accuracy. In reality such ideal situations assumed by this model do not exist. People may use principles other than utilities, and may use different principles in different circumstances. Furthermore, personal values and preferences may changes over time and across different situations. Recent research projects have seen more diversity in identifying decision making factors. Examples include personal habits, preferences, neighborhood norms, etc.

While the models in economics are often normative models suggesting certain similarity and homogeneity in decision making such as utility maximization, models in psychology emphasize individual differences and behavior changes. For example, the theory of planned behavior, developed by Icek Ajzen (1991) based on the traditional mainline of social psychology, suggests three determinant factors of behavior as attitudes, subjective norms, and perceived behavioral controls. Individual behavior tends to be consistent with individual attitudes. Better perceived behavior control leads to higher behavioral performing rate. The notion of "perceived control" is defined as "one's perception of how easy or difficult it is to perform their behavior" (Eagly and Chaiken 1993). This variable is determined by personal beliefs about the likelihood that one has the necessary resources and opportunities to perform his/her behavior. The inclusion of the perceived control in this behavior model suggests the linkage between urban environments and individual travel decisions. For example, pedestrian-friendly design and places with many pedestrians both can increase the perceived control of walking.

Although theories in psychology explains the role of individual attitudes/values and social norms in decision-making process, at an operational level, it is difficult to generate reliable measures for those constructs. Further, the revealed psychological connections are complex and there has not yet been an operational model that can be implemented by practicing planners and engineering. This research incorporates both theories in social psychology and economic theories into developing the conceptual framework for the land use and travel connection.

Empirical studies

Despite the fact that there has not yet been a coherent theory explaining the connections between the built environment and travel decision-making, a tremendous amount of empirical research on the subject has been developed and presented. The most common means used to examining the land use-travel connections are simulations, descriptions, and multivariate statistical analysis (Boarnet and Crane 2001). Several extensive literature surveys are already available in the field of the built environment and travel behavior (Crane 1999; Badoe and Miller 2000; Ewing and Cervero 2001) as well as in the field of the built environment and physical activity (Frank and Engelke 2001; Handy, Boarnet et al. 2002). Four key dimensions can be derived from the existing research evidence and studies, including transportation systems, land development patterns, micro-scale urban design and regional structure.

In terms of transportation systems, gridlike and well-connected street networks with smaller blocks and more intersections were found to be associated with decreased trip length, increased route options, and increased mode options (Badoe and Miller 2000; Ewing and

Cervero 2001; Handy, Boarnet et al. 2002; Handy 2005). Sample measures of transportation infrastructure include street connectivity (ratio of intersections or cul-de-sacs), directness of routing, block size, transit performance, transit accessibility, and sidewalk continuity (Ewing and Cervero 2001; Handy, Boarnet et al. 2002). Non-motorized travel and auto travel were found to be related to different sets of environmental attributes. Street patterns have more impacts on auto travel than alternative modes, while street design features such as block size, intersection density, and street width have more effects on alternative mode travel such as walking and biking.

In terms of land patterns, compact developments and mixed land use were found to be associated with high walking and transit trip rates (Cervero and Radisch 1996; Handy and Clifton 2001; Krizek 2003; Shay, Fan et al. 2006; Shay and Khattak 2007). Several studies also show that the relationship between land use and mode choice may be non-linear (Frank and Pivo 1994) and different land use elements have different effect size. Cervero (1996) found that commercial services within neighborhoods better predict non-motorized trips than residential uses.

Trip length (e.g., time or distance) is generally shorter at locations that are more accessible, have higher densities, and have mixed land uses (Cervero and Wu 1997; Cervero and Wu 1998). Existing evidence also shows that land use patterns, especially accessibilities to activity centers, are significantly associated with mode choice and trip frequency (Ewing and Cervero 2001; Shay, Fan et al. 2006; Khattak and Rodriguez 2005). Sample measures of land use patterns include residential density, employment density, land use mix, accessibility to shopping and employment centers, and so on.

In terms of micro-scale urban design variables, pedestrian amenities such as sidewalks, street trees, lightings, and benches in the neighborhood were found to promote walking behavior (Handy, Boarnet et al. 2002). Parking spaces were found to create access problems for pedestrians and transit users. In general, pedestrians and bicyclists are more sensitive to micro-scale urban design features than are motorists.

Regional structure variables describe the overall structure of the metropolitan area, such as centralization vs. decentralization and monocentric vs. polycentric. This regional structure dimension closely relates to vehicle miles traveled (VMT), while it is much less sensitive to walking and biking (Handy 1993; Ewing, Haliyur et al. 1994).

In terms of measurement techniques, recent research has been making progress in applying statistical methods to describing the built environment, especially factor analysis and cluster analysis. Factor analysis is increasingly used to combine all the underlying environmental features into composite measures (Srinisvasan and Ferreira 1999; Rodriguez, Young et al. 2006). Cluster analysis is able to reduce the multiple quantitative measures into a neighborhood typology (Song and Knaap 2006). The distinctive neighborhood types identified using cluster analysis can be used to examine the neighborhood effects on daily activities and travel. The downside of factor analysis and cluster analysis is that the derived factor scores and neighborhood clusters are much more difficult to interpret than direct measures, which creates more difficulties in producing practical policy implications.

Both direct measures and composite measures of the built environment were used in this dissertation. Direct measures include measures on the dimensions of land use density, land use diversity, street patterns, and pedestrian facilities. Results on direct measures help policy makers make more informed and more specific decisions regarding creating supportive places that encourage sustainable behavior. Composite measures were a set of neighborhood cluster variables, which captures the collective effects involving multiple environmental features on activities and travel.

Literature review also shows that few studies have taken an activity-based approach to study the land use-travel connection. Most research did not distinguish trips of different types or only focused on the journey to work. As commuting trips and non-work related trips may respond differently to environmental factors (Frank and Pivo 1994; Meurs and Haaijer 2001), this dissertation incorporates the activity/trip context into modeling the land use and travel connection and develops activity-specific models as well as mode-specific models

Summary

Large gap between activity modeling and land use-travel modeling

My review of the literature in activity pattern research and travel behavior research shows a large gap between the activity modeling and the land use-travel modeling, which suggests a justification for developing an activity-based framework in modeling the land use-travel connection and linking systematic environmental measures to activity pattern measures at both the census block group level and the 0.25-mile buffer area level at the home location. Activity pattern measures include census block-level activity density and diversity measures and individual-level daily activity space and daily time allocation.

Inconsistent environmental measures and limited geographic detail

There is little consensus in the operational definitions of the environmental concepts (density, land use mix, etc), which make it difficult to generalize consistent results about the effects of the built environment on travel behavior. Further, we do not know whether alternative mode travel promoted by mixed uses, street grids, and compact developments complement or substitute for existing trip that rely on motorized modes (Ewing and Cervero, 2001; Handy, 2006). On one hand, compact development patterns shorten trip distance and make walking trips more appealing. On the other hand, compact development patterns may increase auto mobility as well by providing better connected street systems.

In measuring the built environment and travel connection, scale does matter. Each environmental feature can be measured in different ways at different scales. The same environmental measure may generate different magnitudes of environment effects. Further, most travel diary data are limited in their geographic detail and have no information on the exact locations of trip destinations. The limited geographic information has restricted most research from investigating the impact of land use patterns near trip origins and destinations. The existing literature on land use and travel lays stress on residential environments. Those issues above suggest that further research on the relationship between the built environment and travel behavior is needed.

Few studies on other factors in urban environments than the built environment

Urban environments contain much more than the built environment. Many other environmental elements relate to activity and travel decision making. Rodriguez and Joo (2004) found local topography to be significantly associated with the attractiveness of non-motorized modes. Theoretically, traffic congestion and adverse weather conditions suppress travel demand. However, those environmental factors were rarely explored in the context of land use and travel. This research incorporates variables of traffic conditions and weather conditions into modeling the built environment and travel connection. Driving destination density was used as the proxy measure of traffic conditions. Indicators of weather conditions include daily lowest temperature and precipitation.

CHAPTER III: Conceptual Framework

This chapter presents a conceptual framework for understanding how factors in urban environments including the built environment may influence activity engagement and travel. The conceptual framework is derived from two branches of theory: the body of literature on environment-behavior interactions and the body of literature on individual decision-making. The first section introduces a general environment-behavior model, which outlines possible effects of urban environments on daily activity/travel decision making. The first section picks the environment end of the interactions and detects all the possible decisions with which urban environments can interfere. The second section takes a different perspective. It begins with a subject-specific level and applies the theory of demand to investigate the built environment-travel connection within a consumer demand framework. Built upon the discussion in the previous sections, the final section offers a detailed conceptual framework about how the built environment may influence travel. The final section also details the hypotheses to be tested in the research and the expected results.

A General Environment-Behavior Model

In urban environments, places and people are two sides of the same coin: people create, select, and transform places to perform their various activities, and at the same time urban places influence human behavior. The theoretical base of the connections between the urban environments and human behavior includes both micro-level decision-making theories and ecological models.

Figure 3-1 is a representation of the interplay between the urban environments and human behavior. This model was developed based on Ajzen's theory of planned behavior (1991) and Chapin's activity choice model in urban environments (1977). The individual decision-making process positioned in the circle in Figure 3-1 is embedded within the macro-level ecological model of environmental impacts.

Individuals make a series of decisions at different temporal scales, which are categorized into three levels: strategic decisions, tactical decisions and routine decisions. Strategic decisions are decisions that are most influential and important to an individual's life, and often come with radical changes such as job changing, family restructuring and pursuit of education or training. Tactical decisions are the set of decisions subsequent to strategic decisions. They are more frequent than strategic decisions and are directly influenced by them. Examples of tactical decisions include changing home location, buying a car, installing phone services, joining a club or group, etc. The purpose of tactical decisions often involves facilitating daily living functions. The lowest level of individual decisions is routine decisions such as shopping, commuting, meeting with friends, and so on. While decisions at higher levels constrain decisions at lower levels, lower-level decisions may affect higher-level decisions as well, but to a relatively small degree. Individual decisions at all levels create the traffic flow and drive urban growth, which in turn have direct impacts on both the built and social dimensions in urban environments.

In this general ecological model, variables of the built and other environments influence individual decisions at all levels. The built environment provides opportunities and constraints for individuals to perform their activity decisions. Traffic conditions and natural environments act as another set of environmental constraints. Demographic and social environments facilitate human interactions, as people gather, request, receive and exchange information, which not only affects the human knowledge about choice sets but also shape individual attitudes and preferences. Demographic and social environments impacts individual decisions at multiple levels, including individual, interpersonal and community. Interactions exist between the built environment and other environments.

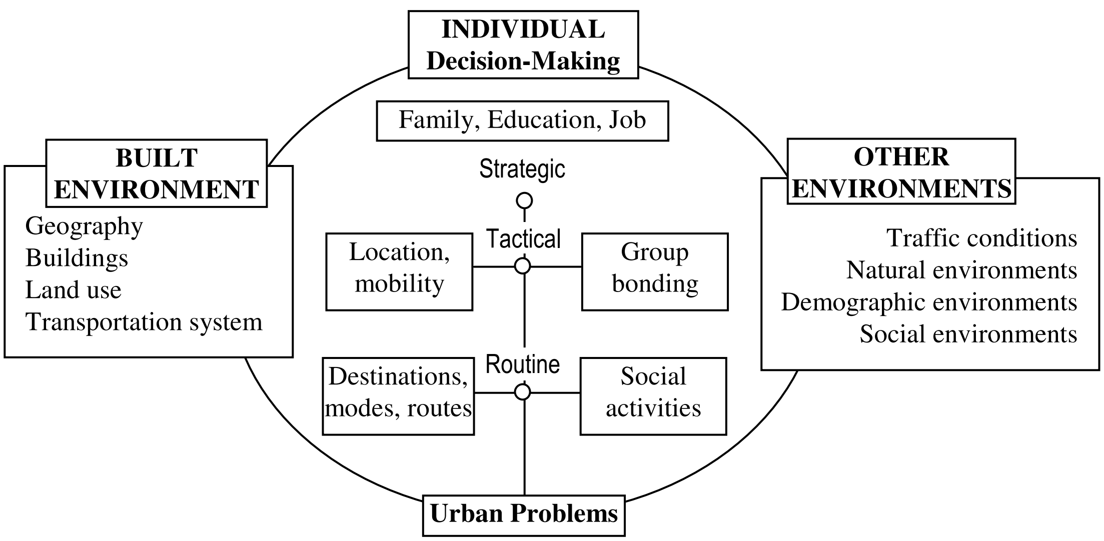

Figure 3-1 A general environment-behavior model

The Theory of Demand

Boarnet and Crane (2001) presented a theory of consumer demand for travel behavior. It holds that urban design strategies can change the absolute cost of trips as well as the relative cost of traveling on different modes. Figure 3-2 illustrates how travel distance—a determinant of the absolute trip cost—changes as land use patterns become more compact. Compact development patterns often mean high density, better accessibility, better street connectivity and fewer cul-de-sacs. By putting uses in close proximity to one another and creating better street connectivity, compact development patterns shrink the distances between potential trip origins and destinations. The relationship is often non-linear as the amount of decrease in trip distance decreases as the travel environment becomes more compact.

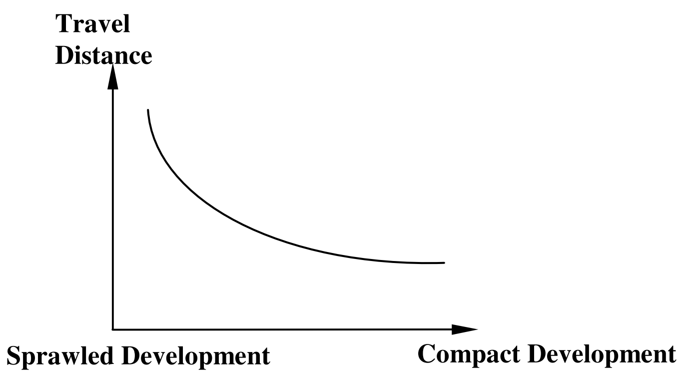

Figure 3-2 Changes in travel distance by land use patterns

As discussed by Boarnet and Crane (2001), urban design not only may reduce the distance of traveling by all modes, but also may change the relative cost of traveling across modes. For example, while heavy traffic, low speed limits, and more intersections associated with compact development patterns often have strongly negative impact on auto travel speed, travel speeds of alternative transportation modes such as walking, bicycling, and transit may not change much across different land use patterns. In addition to influencing the time cost of traveling differently depending on the travel mode, land use patterns can also alter the relative psychological cost of travel. With more aesthetically oriented design elements, such as plazas and streetscapes, compact development pattern can make walking trips more pleasing.

Thus, if we hold travel distance constant, we would expect that trip cost changes with the built environment. Compact development patterns are expected to lower walking trip cost, and to increase driving trip cost. Figure 3-3 illustrates when trip distance is held constant, how land use patterns can change the relative attractiveness of driving versus walking by influencing trip cost.

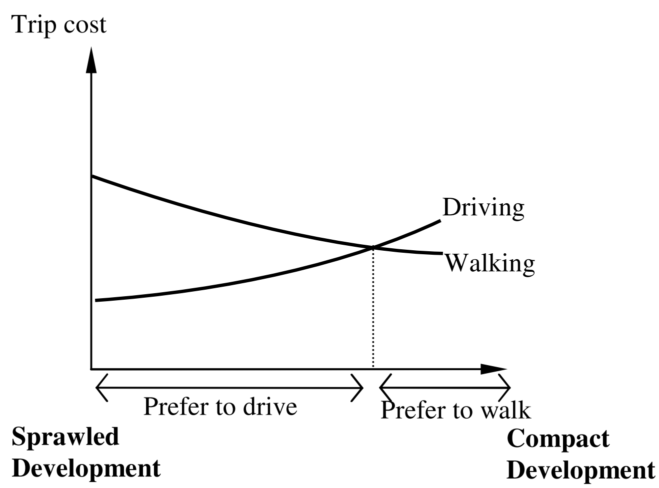

Figure 3-3 Changes in driving and walking trip cost by land use patterns

Based on the discussion above, two mechanisms underlying the land use-travel connection can be identified. One is that compact development patterns that incorporate dense developments, mixed land uses, and street grids may shorten the distance of non-work related trips. Another is that compact development may decrease the cost of walking trips but may increase the cost of driving trips after controlling for trip distance. Among the many elements of travel cost, this dissertation places emphasis on the time cost of travel. Travel distance and duration are outcome variables in this dissertation.

How the Built Environment May Influence Activity Engagement and Travel

Based on the theoretical bases offered by the previous two sections, Figure 3-4 portrays how the built environment can influence human activity patterns in urban spaces (Link 1a), how factors in urban environments including the built environment, weather conditions, and traffic conditions influence activity engagement and travel at the individual level (Links 2a and 2b), and how factors in urban environments coupled with activity contexts influence trip distance and duration at the trip level (Links 2a, 2b, and 2c).

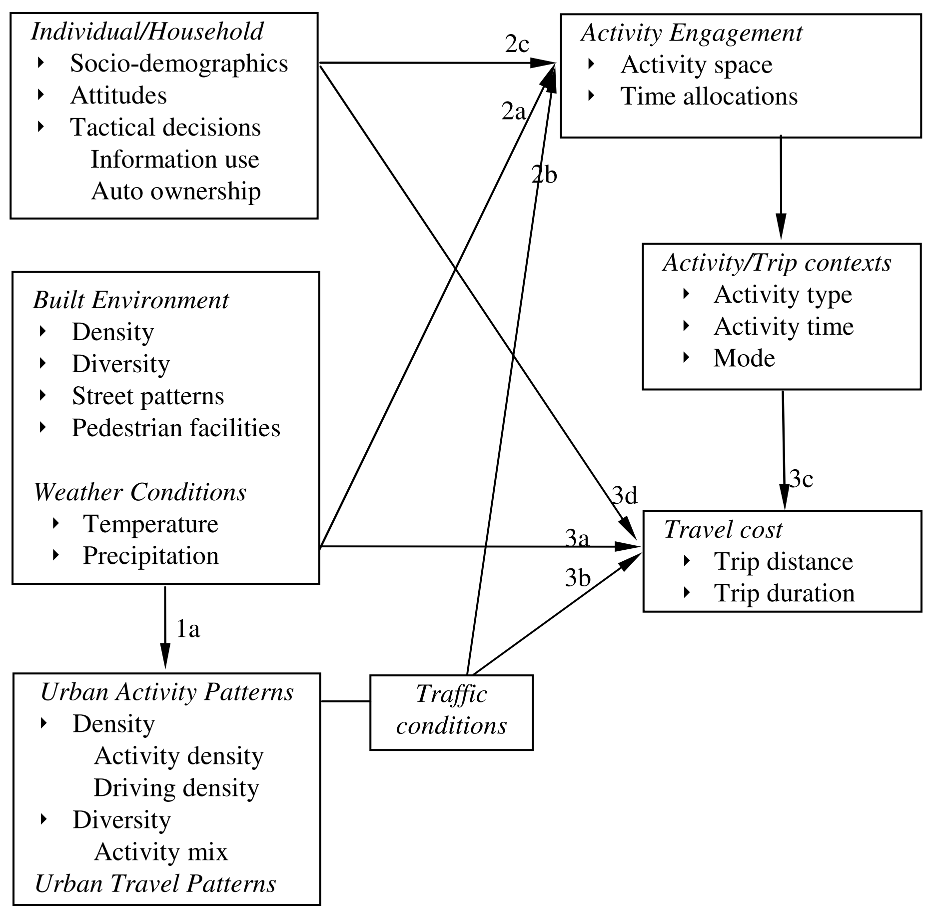

Figure 3-4 How the built environment may influence activity engagement and travel

Links 1a in the Figure 3-4 shows that the built environment may influence human activity patterns at the spatially aggregate level. This link was examined by the census block group level activity pattern analysis in Chapter V.

Links 2a, 2b, and 2c in Figure 3-4 display the personal and situational factors of daily activity engagement at the individual level. Links 2a and 2b show that the built environment, urban activity patterns, and weather conditions may have effects on daily activity engagement, as those environments form a backcloth against which people live their daily lives and make various activity decisions. For link 2b, driving activity density, an activity pattern indicator, captures the effect of traffic conditions on daily activity and travel time allocations. Link 2c indicates that daily activity engagement is influence by individual and household socio-demographics, attitudes and values, and tactical decisions that the individual made to facilitate his/her daily living functions. This research utilizes the socio-demographic factors (gender, income, household size, etc.) as proxy variables of individual biological needs. Mobility tools such as auto ownership and information access were included to represent individuals' tactical decisions. Factors considered in individuals' home location choices (such as length of commute and access to transit) were used as the proxy variables of travel preferences and attitudes. Links 2a, 2b, and 2c were examined by the individual-level activity space and time allocation analysis in Chapter VI.

Links 3a, 3b, 3c, and 3d respectively show that the four explanatory factors of trip distance and duration in this research are the built environment at the trip origin and destination, urban activity patterns (mainly traffic conditions measured by driving activity density), activity/trip characteristics, and individual/household factors. Through link 3c, this research incorporates daily decisions into modeling travel distance and duration. The daily decisions include in what activities to engage, when to participate, and how to travel. The strength of the environment effects on trip distance and duration may vary by activity and trip characteristics. This research will investigate links 3a-3d at the trip level in Chapter VII.

The discussion above suggests three sets of key hypotheses to be tested at different geographic levels using different units of analysis. The first set of hypotheses is about the relationship between the built environment and human activity patterns at the census block group level. The second set of hypotheses is about how environmental factors including the built environment near the residential location, traffic conditions near the residential location, and weather conditions are associated with daily activity engagement at the individual level. The third set of hypotheses is about how environmental factors at the trip origin and/or the destination are associated with trip distance and duration at the trip level. In the following text, I detail each set of hypotheses to be tested in this research.

Hypothesis set # 1(shown in Table 3-1)

At the block group level, built environment factors are significantly associated with human activity patterns in urban spaces. The planning and design of the built environment are concerned with organizing people in space by making physical representations of social relations (Herbert and Thomas 1997). The concept of urban planning itself, with its concerns about the production of urban places and the reflection of social values, offers a link between the built environment and the patterns of urban activity systems. In addition, spatial models of human behavior provide additional theoretical foundations to the relationship between the systems of urban services and the spatial patterns of human behavior. For example, central place theory regards cities and towns as markets providing goods and services. It assumes that people minimize their movements and consume goods and services at the nearest center. Other supportive theories include spatial interaction models such as gravity models. Prior theories and research suggest that higher density and diversity in the built environment lead to higher activity density and greater diversity in urban places. See table 3-1 for my hypotheses in the census block group level activity pattern analysis.

Table 3-1 Hypotheses in the census block group level activity pattern analysis

Activity patterns	**Travel patterns**
The Built environment	
Land use density:	Land use density:
Both residential density and employment density are positively associated with high density and diversity in urban activity systems.	Density is positively associated with alternative mode share and traffic conditions.
	Residential density has a stronger effect on alternative mode share than employment density.
The effect of employment density on activity patterns is stronger than that of residential density.	Employment density has a stronger effect on traffic conditions than residential density.
Land use diversity:	Land use diversity:
Commercial uses positively relate to density and diversity of human activities in urban spaces.	Commercial uses positively relate to alternative mode share and traffic conditions.
Industrial uses negatively relate to lower density and diversity of activities in urban spaces.	Industrial uses negatively relate to alternative mode share but positively relate to urban traffic.
Street patterns:	Street patterns:
Street grids positively relate to density and diversity in urban activity systems.	Street grids are positively associated with alternative mode share and traffic conditions.
Pedestrian facilities:	Pedestrian facilities:
Presence of sidewalks positively relates to density and diversity in urban activity systems.	Presence of sidewalks is positively associated with alternative mode share and shows no association with traffic conditions.

I hypothesize that both residential density and employment density are positively associated with higher activity density and diversity, but with different magnitude. Employment density has a stronger effect on human activity patterns, especially the diversity patterns, than residential density. This is because residential neighborhoods are often homogenous in nature while employment density may bring diverse population to the area.

Alternative mode share and traffic conditions are expected to be positively related to both residential density and employment density. However, residential density has a stronger effect on alternative mode share than employment density in that commuting trips are more temporally constrained and in favor of auto modes. For the same reason, employment density has a stronger effect on traffic conditions than residential density.

More commercial uses and fewer industrial uses are associated with higher density and diversity in urban activity systems in that commercial uses bring local activity opportunities to the area while industrial uses do not. Likewise, more commercial uses and fewer commercial uses are associated with more alternative mode share and more urban traffic.

Street grids positively relate to activity density and activity diversity in urban spaces in that better connected street systems promote activity and travel demand. For the same reason and the reason that better connected street systems are more walkable, street grids are positively associated with alternative mode share and traffic conditions.

Pedestrian facilities are expected to be associated with high activity density and great activity diversity in urban spaces. As we build more sidewalks, we expect that pedestrian facilities are able to accommodate dense developments and serve diverse population groups. Presence of sidewalks is expected to be associated with alternative mode share in that it makes walking safer and more comfortable. We do not expect any association between pedestrian facilities and traffic conditions.

Hypothesis set #2(shown in Table 3-2)

At the individual level, the built environment at the home location, urban traffic conditions, and weather conditions provide opportunities and constraints to individuals' options for being engaging in activities and further affect travel behavior. Thus, environmental factors in the residential neighborhood relate to individual daily activity space and daily time allocations to various activities including travel. Individual activity space represents the spatial distribution of daily activity locations. Individual activity space changes with residential environments in that some residential environments allow residents to be engaged in all their daily activities at less spatially dispersed locations while others do not.

In terms of individual time allocation, not all the activity time allocations are theoretically related to factors in urban environments. In a general sense, changes in residential environments or relocations may not result in changes in daily time spent on subsistence activities (such as work and school) and maintenance activities (such as shopping). Time allocations to subsistence activities or maintenance activities are mainly and directly determined by basic human needs and the time dimension, which are mainly related to individual characteristics such as gender, employment status, household size, and so on. In this research, I expect that daily time allocations to out-of-home activities, leisure activities, and travel are related to the environment factors including the built environment at the residential location, traffic conditions at the residential location, and weather conditions. See Table 3-2 for a list of hypotheses in the individual activity space and time allocation analysis.

Table 3-2 Hypotheses in the individual activity space and time allocation analysis

Activity space and daily miles traveled	Activity and travel time allocations
The built environment at the home location	
Dense developments, more commercial uses, fewer industrial uses, and street grids in the residential neighborhood are associated with smaller daily activity space in that such particular planning paradigms make activity locations less spatially dispersed. Dense developments, more commercial uses and fewer industrial uses, street grids have mixed effects on daily miles traveled. Compact development patterns lead to shorter distance of each trip, but at the same time, compact development patterns may increase travel demand and further relate to increased daily miles traveled.	E: Dense developments, more commercial uses and fewer industrial uses, street grids, and presence of sidewalks in the residential neighborhood are associated with a high probability of engaging in out-of-home activities (especially leisure activities) and are expected to be associated with more use of alternative modes. T/E: Dense developments, more commercial uses and fewer industrial uses, street grids, and presence of sidewalks positively relate to the actual time spent on out-of-home activities and leisure activities, but have mixed effects on actual travel time.
Urban traffic conditions	
Heavy traffic in the residential neighborhood is associated with smaller daily activity space and fewer daily miles traveled in that traffic congestion suppresses travel and out-of-home activity demand and reduces the probability of long-distance travel.	E: Heavy traffic in the residential neighborhood negatively relates to out-of-home activity engagement, but positively relates to the use of alternative modes in that heavy traffic suppresses auto travel demand and further decreases the chance of being engaged in out-of-home activities. T/E: Heavy traffic negatively relates to the actual out-of-home activity time, but has mixed effects on actual travel time.
Weather conditions	
Adverse weather conditions such as extremely cold or hot weather and precipitation are associated with smaller daily activity space and fewer daily miles traveled in that such weather conditions suppresses travel and out-of-home activity demand and reduces the probability of long-distance travel. A non-linear relationship between weather and activity space or daily miles traveled is expected.	E: Extremely cold or hot weather and precipitation are associated with less out-of-home activity participation, more auto use, and less use of alternative modes. T/E: Extremely cold or hot weather and precipitation are associated with less actual out-of-home activity time, but have mixed effects on travel time.

Note: Time allocation contains two sub-decisions, as an individual must decide whether to engage in a certain type of activities or travel, and if so, how much time he/she would like to allocate. In this table, “E” represents the engagement decision, and “T/E” represents the conditional decision about the time spent on the activity category.

Individual daily activity space is expected to be negatively related to dense developments, more commercial uses, fewer industrial uses, and street grids. Such particular planning paradigms encourage the use of local opportunities, spatially concentrate residents’ activities, and potentially lead to shorter travel distance of each trip. Given this phenomenon, the spatial distribution of individual activities in compact development settings is less dispersed than that of sprawled settings. However, compact development patterns may not necessarily relate to reduction in daily miles traveled. On one hand, compact development patterns reduce distances of daily trips. On the other hand, compact development patterns may increase travel demand and lead to a higher number of daily trips. Thus, the land use effect on daily miles traveled is mixed.

Heavy traffic and adverse weather conditions are expected to be associated with smaller daily activity space and fewer daily miles traveled in that such conditions suppresses travel demand and decrease the probability of long-distance travel at the same time. More specifically, I expect daily activity space and daily miles traveled have a non-linear relationship with temperature, in that either extremely cold or hot weather may result in travel reduction.

Out-of-home activity engagement (including all the daily activities conducted outside the home but excluding travel) is expected to be related to the built environment, in that different residential environments provide different amount of activity and interaction opportunities. People who live in a compact development setting with better accessibility and higher density may spend more time outside their homes than residents living in a sprawled development setting. Leisure activities are a subset of the out-of-home activity category and are discretionary activities that are relatively less constrained by the time dimension. Compact development patterns are expected to be associated with more leisure activities. Note that time allocation contains two sub-decisions, as an individual must decide whether to conduct an activity or trip (selection/engagement decision), and if so, how much time he/she would like to allocate (duration decision). In terms of activity time allocations, factors positively associated with activity engagement, in general, positively relate to the actual activity time. If a person decides to participate in certain type of activities, he/she has to allocate more time on that activity category.

Daily travel constitutes human movements in the space dimension, which is directly influenced by spatial factors. However, in terms of travel time allocations, factors positively associated with the use of certain modes (mode selection) are not necessarily positively associated with the actual time spent on the selected modes (duration). Compact development patterns are expected to be associated with more use of alternative transportation modes in that this kind of environment is friendlier to transit users, pedestrians, and bicyclists. As time is considered a valuable resource, a traveler may choose the travel mode that minimizes their travel time. In addition, travel time allocation to each mode per day per individual is an aggregate value reflecting travel demand, travel distance and travel speed. Urban environments influence the demand, distance, and speed of daily travel in different ways. People who choose to make more pedestrian trips may not spend more time on walking. Therefore, I expect that compact development patterns are associated with more use of alternative transportation modes, but it is unclear whether compact development patterns are associated with more or less actual time allocated to alternative transportation modes.

Urban traffic conditions relate to activity and travel time allocations as well. Heavy traffic is expected to be negatively associated with out-of-home activities and leisure activities, in that it prolongs travel time and suppresses out-of-home activity demand. For mode-specific travel time allocations, traffic congestion is expected to be negatively related to the use of auto modes. As daily driving time allocation is an aggregated value of the number of daily driving trips and the duration of each trip, we are not sure whether traffic conditions are negatively or positively associated with the actual time spent on driving.

For weather conditions, I expect a nonlinear relationship between temperature and activity and travel time allocations. Extremely cold or hot weather is associated with less time spent on out-of-home activities and leisure activities. Precipitation relates to less time spent on out-of home activities and leisure activities as well. Weather conditions have a mixed effect on travel time. On the one hand, low temperature and precipitation may suppress some travel demand. On the other hand, adverse weather conditions have a strongly negative impact on travel speed.

Hypothesis set #3 (shown in Table 3-3)

At the trip level, the built environment at the trip origin and destination can influence trip distance and duration. As I discussed in the previous section, daily travel time allocations integrate several elements in travel behavior including demand, distance and speed. Analyzing time allocation indicators at the personal level may provide mixed results and may not be able to provide insights into the mechanisms behind the built environment and travel connection. This set of hypotheses was developed at the trip level. By considering trip distance and trip duration separately and incorporating activity/trip characteristics, the hypotheses in Table 3-3 specify multiple underlying mechanisms of the land use-travel connection.

Table 3-3 Hypotheses in the trip distance and duration analysis

Trip distance of non-work travel	Trip duration [a]
The Built environment at the trip origin/destination	
Dense developments, more commercial uses, fewer industrial uses, and street grids at the trip origin are associated with shorter trip distance, in that high density, greater diversity, and street grids put potential origins and destinations in closer proximity.	Dense developments and grid street patterns at the trip origin and destination are associated with more driving trip duration, as density and street grids slow down auto travel and intersections often mean more stops for automobiles. More sidewalk coverage at the trip origin and destination relates to shorter walking trip duration, in that it improves pedestrian safety and thus increases walking speed.
Urban traffic conditions	
Driving density is negatively associated with trip distance in that heavy traffic suppresses long-distance travel more than short-distance travel.	Driving density is positively associated with trip duration, in that heavy traffic slows down travel speed and thus increases trip duration.
Weather conditions	
Adverse weather conditions such hot or cold weather and precipitation are associated with shorter trip distance in that adverse weather conditions reduce the chance of long-distance travel. The relationship between temperature and trip distance is non-linear.	Precipitation is associated with longer driving trip duration in that it slows down auto travel speed. Temperature is positively associated with walking trip duration in that pedestrians walk slower in warm weather.

NOTE: [a] Longer distance implies longer trip duration; hypotheses in this column are about additional factors that may influence trip duration after controlling for trip distance.

Compact development patterns are expected to be associated with shorter distance of non-work travel, in that non-work travel has flexible destination choices and high density, greater diversity, and street grids put potential origins and destinations in more direct proximity. After controlling for trip distance, I do not expect that mixed land uses in the built environment are associated with trip duration. However, dense developments and street grids are expected to be positively associated with more driving trip duration, but are not necessarily associated with walking trip duration. More specifically, dense developments and street grids slow down driving speed and often mean more stops for automobiles. Sidewalk coverage is expected to be associated with less walking trip duration in that it improves pedestrian safety and thus increases walking speed. Sidewalk coverage may show no association with driving trip duration.

In terms of traffic conditions, higher driving density is expected to be associated with shorter trip distance but longer trip duration. Driving density is a measure of urban traffic. Intense driving activities are associated with heavy traffic and further suppress long-distance travel more than short-distance travel. Thus, driving density is negatively associated with trip distance. From the perspective of trip duration, intense driving activities slow down travel speed and thus increase trip duration.

In terms of weather conditions, adverse weather conditions are expected to be associated with decreased trip distance in that a chill or sweating temperature or heavy rain/thunder reduces the chance of long-distance travel and further lead to shorter distance of travel. Temperature has a non-linear relationship with trip distance. Precipitation is expected to be associated with increased driving duration in that it often slows down auto travel speed and further leads to longer driving trip duration. Warm weather is expected to be associated with increased walking duration in that pedestrians walk slower in warm weather than in hot or cold weather.

CHAPTER IV. Research Design and Methods

The research design centers around two questions. Are built environment factors, coupled with other environmental factors such as traffic and weather conditions, associated with activity and travel at both the aggregate level and the disaggregate level? And if yes, what are the underlying mechanisms of the association? The research approach is to use a cross-sectional behavior dataset to regress activity and travel variables on factors that include the environmental factors mentioned above at different levels. The regression models were developed based on the conceptual model presented in the previous chapter.

The research uses secondary travel data from the 2006 Greater Triangle Travel Study (N=5,107 households). The land use data comes from local government agencies in Orange, Durham, and Wake Counties. More than twenty environmental measures were generated using ArcGIS. Land use measures include indictors at both the census block group level and the location-based buffer level. The land use variables used in the analyses in the following chapters were selected from the originally created measures.

Three analyses were conducted in this study. The first analysis presents census block group level models that link the built environment measures at the census block group level to human activity patterns within the census block group. The second analysis presents individual-based models that examine how daily activity space and daily time allocations to various activities and travel modes are related to the built environment and traffic conditions at the residential location, weather conditions, and other control factors.

The third analysis was undertaken at the trip level, which makes it possible to investigate trip distance and duration separately and examine how the two trip variables are related to various environmental factors at the trip origin and/or at the trip destination. To model trip distance, multiple models were developed for different activity categories. By comparing regression coefficients across the activity-specific distance models, we can have a sense about differences in the environmental sensitivity of different activity categories. Likewise, mode-specific models were developed in modeling trip duration to examine how the relationship between environment factors and trip duration varies across transportation modes.

Data Sources and Study Area

The research uses an existing activity-based travel survey dataset in the Triangle area of North Carolina—the Greater Triangle Travel Study conducted in 2006. This survey was sponsored by the Capital Area Metropolitan Planning Organization, the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization, the Triangle Transit Authority, and the North Carolina Department of Transportation. The sampled households were surveyed on different dates from January 31 to May 26, which provides great variation in weather conditions. Data on weather conditions were collected from NCDC. The weather station used in the data collection is the Raleigh-Durham International Airport weather station.

The Triangle travel survey was conducted using state-of-the-art travel survey methods and computer-aided telephone interviewing (CATI) technology. It entailed the collection of activity and travel information for all household members during a specific 24-hour period. The survey relied on the willingness of regional households to 1) provide demographic information about the household, its members and its vehicles and 2) have all household members record all travel-related details for a specific 24-hour period, including address information for all locations visited, trip purpose, mode, and travel times. Due to variances in response rates, incentives were offered to select households (such as those with no vehicles, those living in the outlying counties who were of African American descent, and those consisting of university students). This was accompanied by an extensive public information campaign that was designed to emphasize the importance of and benefits from participating. The response rate of this survey is 25%.

Out of the 12 counties in the greater Triangle region, only Durham, Wake and Orange Counties are able to provide land use GIS data at the parcel level. Those three counties are the study area of this research. See Figure 4-1 for a general view of the study area.

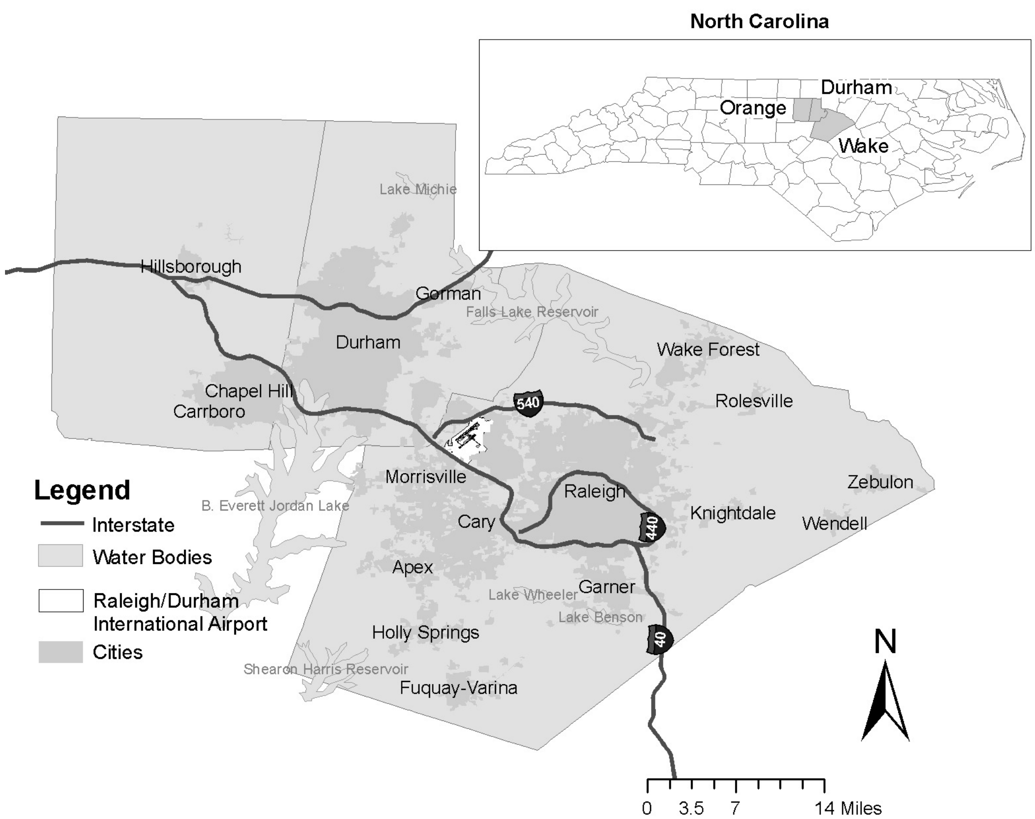

Figure 4-1 Study area (Orange, Durham, and Wake Counties, NC)

One of the advantages of the Triangle survey lies in its sample design which included minimum sample sizes for the following population subgroups: low-income households, transit-using households, college students, and households with members who walk or bike to work/school. This ensures adequate statistical power in studying travel behavior of alternative modes (transit, bicycling, and walking).

The total of 3,480 survey households including 7,422 residents in Durham, Orange and Wake Counties, North Carolina, comprise the final dataset for model estimation. The attributes for describing those households include personal/household information, geo-referenced activity and travel data, and the built environment measures. The survey dataset includes a weight variable that was developed to adjust the over-sampling of particular population segments. This weight was used in the descriptive analyses in the research. There also is an expansion weight that expands the survey data to represent total households in the Durham, Orange and Wake Counties. The expansion weight allows us to magnify the results of the 3,480 surveyed households to those of the 376,918 regional households. The expansion weight was used to generate measures of urban activity patterns in the region.

Measuring the Built Environment

To address the multi-dimensionality of the built environment, four sets of the built environment variables were created at both the census block group level and the location-based buffer level, including measures of density, diversity, street patterns, and alternative transportation infrastructure.

The census block group level

To avoid problems of multi-collinearity, to isolate the key dimensions, and to keep the model size manageable, six measures were selected to measure the built environment at the census block group level. The measures were chosen based on their relevance as key components of the built environment dimensions and their familiarity to researchers in the field of the built environment and travel.[1]

Residential density – the number of residents per acre with the block group
Employment density – the number of employees per acre within the block group
Commercial use ratio – the percentage of area in commercial uses within the block group (including retail and service uses)
Industrial use ratio – the percentage of area in industrial uses within the block group
Connected node ratio – the percentage of intersections that are not dead ends within the block group
Sidewalk coverage – the ratio of sidewalk length to total street length within the block group

Among the indicators above, residential density and employment density are indicators of the density dimension; commercial use ratio and industrial use ratio are indicators of the diversity dimension; connected node ratio is the indicator of grid street patterns; and sidewalk coverage is the indicator of alternative transportation infrastructure. Bus stop density was not included in the transportation infrastructure measures since it is highly correlated with sidewalk coverage (Pearson correlation index >0.8). The multiple density and diversity measures allow us to isolate different density and diversity effects, such as residential vs. employment and commercial vs. industrial. It is important to measure residential density and employment density separately since most of the new developments at the urban fringe have been gaining density in residential density but still lack job-housing

[1] We originally created more than twenty built environment measures based on prior theories and research, the built environment measures used in this research are selected from those measures to make sure that the selected independent variables are not highly correlated with each other and are able to represent the four key dimensions of the built environment in study travel behavior. The four key dimensions are density, diversity, street patterns, and alternative transportation facilities.

balance (Gober and Burns 2002). Recent literature also shows that the effect of retail and service uses on human spatial behavior is different from that of industrial uses or residential uses in terms of the effect size and direction (Cervero 1996).

The location-based buffer level

The measurement at the location-based buffer level places a straight line or airline buffer around a location (such as home locations, trip origins, and trip destinations). The radius of the buffer was set to 0.25 miles, chosen for its policy relevance and its consistency with the existing research in the field. A total of five measures were created at this geographic scale to capture the dimensions of density, diversity, street patterns, and pedestrian infrastructure.

Land parcel count – the number of parcels within the buffer area
Retail count – the number of retail stores within the buffer area
Industrial count – the number of industrial firms within the buffer area
Connected node ratio – the percentage of intersections that are not dead ends within the buffer area
Sidewalk length – miles of sidewalks within the buffer area

Rather than population density and employment density, land parcel count was used to capture the density dimension at the buffer level. This is because the population data are not available at the location-based buffer level.

Measuring Human Activity Patterns

Patterns of urban activity systems are also multi-dimensional in nature. Measures of urban activity patterns in this research mainly summarize the density patterns and the diversity patterns. Multiple diversity measures were generated for measuring diversity in activity categories as well as demographic diversity in activity population.

Activity density patterns

By definition, activity density in urban spaces is the amount of the activities in a given area. The density can be simply measured by dividing the activity amount by the area of the spatial unit or can be estimated by a more sophisticated kernel density function. In this research, simple density measures were developed at the census block group level, while kernel estimation was used to develop activity density measures at the location-based buffer area. Two activity density measures were created in this research.

Activity density – the number of activities per acre occurring within the census block group (the simple measure)

Driving density – the number of driving trip destinations per acre within the 0.25-mile buffer area (the kernel density estimation; a proxy measure of urban traffic)

The calculation of the simple activity density measure is straightforward - dividing the number of activities occurring within the census block group by the area size in acres. However, due to the fact that the activity data were collected from 3,480 Triangle households that were sampled as representative of the total population in the Triangle area (376,918 regional households), using weighted activity data may generate biased spatial density measures. The reliability of the simple density measures decreases as the measurement geographic scale becomes more disaggregate and smaller. Given this situation, kernel density estimation is more appropriate for developing small-scale density measures in that it generalizes all the surveyed activities to the entire region. In particular, kernel density estimation can provide density values at any location and can be displayed by either surface maps or contour maps.

CrimeStat 3.0, used for the kernel density estimation of driving activities in urban spaces, was developed by Ned Levine & Associates (Levine 2004). CrimeStat is specifically designed for analyzing spatial patterns of incident/activity locations. Detail procedure of kernel density interpolation can be found in Chapter 8, the CrimeStat 3.0 manual. In this research, I used the quadratic kernel function with the bandwidth of 0.25 mile to estimate the crash density surface for the Triangle area. Figure 4-2 illustrates the estimated driving destination density and presents the spatial distribution of driving activities in the Triangle area. The density estimates were scaled by color. Darker tones represent higher densities while lighter tones represent lower densities.

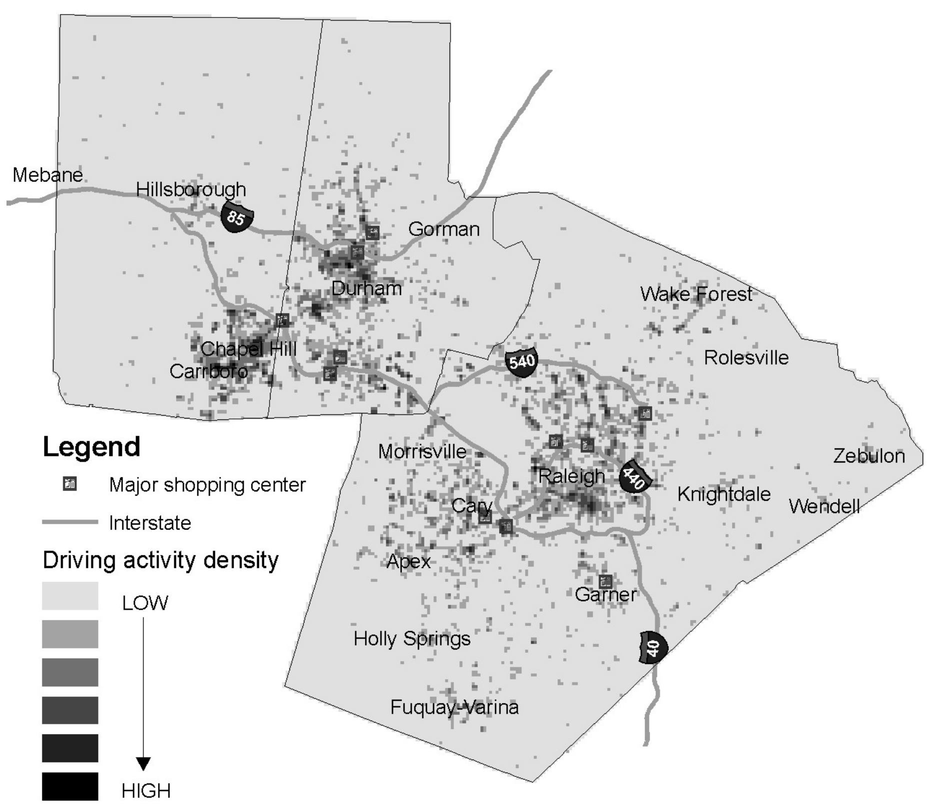

Figure 4-2 Driving destination density in the Triangle region

Note: Driving destination density is a proxy measure of traffic conditions in urban spaces, which is used in modeling daily activity spaces, daily time allocations, and trip distance and duration.

The spatial analysis of driving destination locations cannot only illustrate the spatial patterns of driving trips, but can also generate crash density at the land cell/grid level. In this research, the triangle region was divided into 42,628 0.2mile*0.2mile cells. Each cell has an estimated density value. Those cells were further aggregated to the 0.25-mile buffer area. For each buffer area, I use the median value of the density estimates as a proxy measure of traffic conditions. This urban traffic measure was used in the subsequent individual time allocation analysis and trip duration analysis to explore the relationships among urban traffic, activity engagement, and trip distance and duration.

Activity diversity patterns

The activity diversity indicators include measures on activity type mix, activity time mix, race mix in activity population, income mix in activity population, and age mix in activity population.

Activity type mix – entropy measure of mix in a total of eight activity types (0-1 scale)
Activity time mix – entropy measure of mix in a total of six time periods (0-1 scale)
Race mix in activity population – entropy measure of mix in a total of five race groups (0-1 scale)
Income mix in activity population – entropy measure of mix in a total of seven income groups (0-1 scale)
Age mix in activity population – entropy measure of mix in a total of six age groups (0-1 scale)

All the activity diversity indicators were measured at the census block group level. Note that all the activity diversity measures of each census block group were calculated from all the daily activities occurring within each census block group. The measures were not calculated from all the daily activities conducted by the residents who lived within each census block group. For instance, income diversity in urban activity systems is defined as the income diversity in the population who were involved with activities within each census block group. The research uses entropy measures to measure the diversity dimension in urban activity systems. The following equation shows the calculation of the entropy indicators.

$$Entropy = -1 * \sum_{1}^{K} (p(k) * \ln p(k)) / \ln K$$

Where k = Index of groups/categories

P (k) = Percentage of a specific group/category

Categories/groups of each diversity dimension are listed as below:

- Activity types: at-home activities, work-related activities, school-related activities, leisure activities, shopping activities, personal business, social activities, and other.
- Activity time periods: early morning (3:00am-9:29am), morning (9:30am-12:29pm), noon (12:30pm-2:29pm), afternoon (2:30pm-5:29pm), night (5:30pm-10.29pm), and late night (10:30pm-2:59am).
- Race groups: white, African American, Asian, Hispanic, and other.
- Income groups: low than $15,000, $15,000 -$24,999, $25,000-$34,999, $35,999-$49,999, $50,000-$74,999, $75,000-99,999, and higher than $100,000.
- Age groups: younger than 16, 16-24, 25-34, 35-54, 55-64, and older than 65.

To the author's knowledge, entropy is a brand new concept for measuring activity patterns. However, entropy measures are commonly used in many similar concept measurements (e.g. land use patterns) to describe patterns of diversity or evenness. In the existing literature, a variety of land use diversity/evenness measures exist (Cervero 2002; Song and Knaap, 2004). Besides entropy measures, examples include the job/housing balance index (Cervero 2002), the Herfindahl-Hirschman index, dissimilarity indices (Sakoda 1981; Wong 2003), Gini Index (Brown 1994), and the Atkinson index. Entropy measures were chosen in this research due to their simplicity and their capability of handling multiple groups or categories.

Measuring Individual Activity-Travel Behavior

Two set of indicators were developed to measure individual activity-travel behavior: one depicts the spatial dimension and another describes the time dimension.

From a spatial perspective, individual activity-travel behavior can be modeled as the distribution of daily activity locations. The spatial statistics and computational geometry literature provides several measures that can be used to describe the spatial patterns of point events. The three most commonly used measures in describing the spatial dispersion of daily or weekly activities are standard distance circles, standard deviation ellipses(Yuill 1971; Ebdon 1985; Levine 2004), and minimum convex polygons (Beyer 2002; Buliung and Kanaroglou 2006). This research uses the minimum convex polygon as an area-based geometry for describing the geographical extent of daily individual activity patterns. Hawth's Analysis Tools for ArcGIS were used to calculate the minimum convex polygon containing all the activity locations visited by an individual. Figure 4-3 illustrates two individuals' daily activity spaces. For individual #1, he/she has three activity locations including home, workplace and his/her kids' school location. For individual #2, he/she also has three activity locations on the survey day, including home, workplace and a shopping center. Another spatial measure of individual activity-travel behavior used in this research is daily miles traveled. For each individual, trip distances between successive activity locations are calculated using ArcGIS's shortest path method. Individual daily miles traveled were then calculated by summing up all the distances of his/her daily trips.

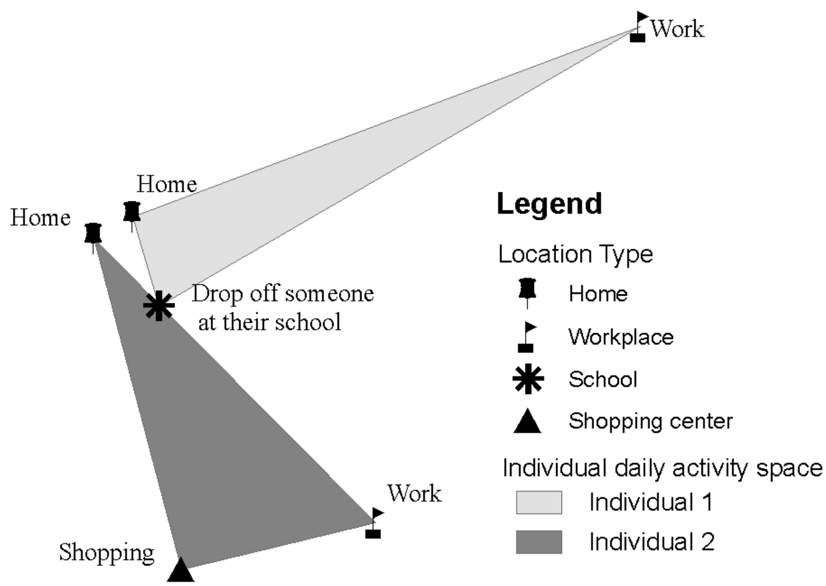

Figure 4-3 Two individuals' daily activity spaces

From a temporal perspective, individual activity-travel behavior can be modeled as daily time spent on various activity categories and travel modes. In this research, activity and travel time allocation is measured by the number of minutes that individuals allocate to activities of different types and travel using different modes.

Variables and Models

Three sets of analyses were undertaken to examine how environmental factors are associated with human activities and travel at different levels. The three analyses are: 1) the analysis of urban activity/travel patterns at the census block group level, 2) the analysis of individual activity space and time allocations at the personal level; and 3) the analysis of trip distance and duration at the trip level. This section details the variables used in each analysis and the model development of each analysis.

Analysis of urban activity/travel patterns (hypothesis set #1)

This analysis focuses on testing whether compact development patterns (high density, great diversity, street grids, and more pedestrian facilities) are associated with high activity density and great diversity in activity categories and activity population at the spatially aggregate level. The unit of analysis is the census block group level. Table 4-1 lists all the variables used in this research.

Table 4-1 Variables used in the census block group level activity pattern analysis

Activity density and diversity pattern analysis	**Travel pattern analysis**
Negative binomial model and OLS model	Logit model for grouped data and negative binomial model
DVs (activity density and diversity patterns): Number of activities; mix of activity types; mix of activity time; race mix in activity population; income mix in activity population; and age mix in activity population	DVs: Alternative transportation mode share; Driving density
IVs (the built environment): Population density; employment density; % of retail uses; % of industrial uses; connected node ratio; sidewalk coverage	IVs: same as the left cell
CVs (demographic environments): % of white population; mean household size; median income	CVs: same as the left cell

Note: DVs-dependent variables; IVs-independent variables; and CVs- control variables.

Negative binomial regression was used to model activity density in urban spaces. Such a model is appropriate because activity density can be obtained by dividing the number of activities by the area size. The number of activities within each census block group is a discrete and positive count variable and the area size of the census block group is specified as the exposure variable. The model specification is show below.

$$\log(\frac{Y_N}{X_{AS}}) = \beta_0 + \beta_{BE} * X_{BE} + \beta_{DE} * X_{DE}$$

Where,

Y_N – the number of activities within the census block group or the number driving trip destinations within the census block group.

X_{AS} – area size in acres of the census block group, the exposure variable in negative binomial regression..

X_{BE} – the built environment variables, including population density, employment density, percentage of retail uses, percentage of industrial uses, connected node ratio, and sidewalk coverage ratio. See the Measuring the Built Environment section for detailed definitions.

X_{DE} – the variables of demographic environments at the census block group level, including percentage of white population, average household size, and percentage of renter-occupation housing. These variables are control factors in this analysis.

OLS regression was used to model activity diversity patterns. See the model specifications below.

$$Y_{ADIV} = \beta_0 + \beta_{BE} * X_{BE} + \beta_{DE} * X_{DE}$$

Where,

Y_{ADIV} – diversity measures of activity patterns. See the left column in Table 4-1 for the list of dependent variables and see the Measuring Human Activity Patterns for detailed variable definitions.

X_{BE} – the built environment variables.

X_{DE} – the variables of demographic environments.

In addition to the activity density and diversity models, a model of travel patterns was developed at the census block group level as well. Percentage of alternative-mode trips (including pedestrian, bicycle and transit trips) was used as the indicator of travel patterns in this analysis. Logit regression for grouped data was used to model the mode share (proportion) of alternative transportation in urban spaces. Such a logit model is appropriate because the dependent variable (alternative transportation mode share) is a grouped binary outcome- the proportion of alternative-mode trips in the census group. See the model specification below.

$$Y_{ATMS} = \frac{e^{\beta_0+\beta_{BE}*X_{BE}+\beta_{DE}*X_{DE}}}{1+e^{\beta_0+\beta_{BE}*X_{BE}+\beta_{DE}*X_{DE}}}$$

Where,

Y_{ATMS} – alternative transportation mode (walk, bike, and transit use) share;

X_{BE} – the set of the built environment measures at the census block group level.

X_{DE} – the indicators of demographic environments, which are the same control factors in the activity density and diversity models above.

Analysis of individual activity space and time allocation (hypothesis set #2)

The analysis of individual activity engagement also contains two set of models: models of activity space, and models of time allocation. See Table 4-2 for a list of variables used in this analysis.

Table 4-2 Variables used in the individual time allocation analysis

Activity space analysis	**Time allocation analysis**
Untransformed OLS and semi-log transformed OLS models	The Tobit model and the Heckman selection model
DVs: Individual daily activity space in acres Individual daily miles traveled in miles	DVs (activity/travel time allocations in minutes): Out-of-home activity time allocation; leisure activity time allocation; drive time allocation; walk time allocation; and transit time allocation
IVs: The built environment at the home location – land parcel count; retail count; industrial count; connected node ratio; and sidewalk coverage Traffic conditions at the home location – driving activity density Weather conditions –daily lowest temperature and precipitation	Ivs: Same as the left cell
CVs (individual and household factors): socio-demographics; tactical decisions; and attitudes	CVs: Same as the left cell

Note: DVs-dependent variables; IVs-independent variables; and CVs- control variables.

Dependent variables in the activity space analysis (the left column in Table 4-2) are two variables describing the spatial patterns of individual daily activities: daily activity space and daily miles traveled. See the pervious sections for detail definitions of the two variables. Dependent variables in the time allocation analysis (the right column in Table 4-2) are all time allocation variables measured in minutes. The key independent variables in this analysis include three sets of variables: the built environment variables at the home location, the traffic condition variables at the home location, and the weather condition variables. The built environment variables at the home location were measured at the 0.25-mile buffer level. The buffer was placed around the home location. See the Measuring the Built Environment section for detail definitions of the built environment variables. The variable representing traffic conditions at the home location is driving activity density measured at the 0.25-mile buffer level. See the Measuring Human Activity Patterns section for the detail definition of the driving density variable.

The sampled households were surveyed on different dates from January 31 to May 26, which provides great variation in weather conditions. Daily lowest temperature and precipitation are used to describe weather conditions.

The control variables used in this analysis can be categorized into three groups: socio-demographics, tactical decisions, and attitudes. Socio-demographic variables include household size, household income, residential tenure, gender, age, race, and employment. Variables of tactical decisions include auto ownership and travel information usage. Household location choice factors were used in this analysis as proxy measures of individual attitudes towards travel. See detail definitions of the control variables in this analysis below.

HH size – the number of persons per household
HH income – ordinal variable scaled from 1 to 7: 1-houshold income <15,000; 7-household income>100,000
Residential tenure – the number of years lived in a same house
Female – dummy variable: 1-Female; 0-Male
Children – dummy variable: 1 if the person is 14 years old or younger; 0 otherwise
Young – dummy variable: 1 if age is in the range from 15 to 24; 0 otherwise
Adult – dummy variable: 1 if age is in the range from 25 to 64; 0 otherwise
Old – dummy variable: 1 if the person is 65 years old or older; 0 otherwise
White – dummy variable: 1-white; 0-non-white
Employed – dummy variable: 1-employed; 0-unemployed
Multiple jobholder – dummy variable: 1 if the person has multiple jobs; 0 otherwise
Auto ownership – the number of vehicles owned per household
Travel information – dummy variable: 1-seeks traffic information more than once a week; 0-never seek traffic info
Commute attitude – dummy variable: 1-residential choice made with considering length of commute, 0-otherwise
Transit attitude – dummy variable: 1-residential choice made with considering access to transit, 0-otherwise

Both untransformed OLS regression and semi-log transformed regression were used in the activity space analysis. Theoretically, semi-log transformed regression is better as the distributions of the daily activity space measure and the daily miles traveled measure are positively skewed. See detailed model specifications below.

$$Y_{DAS} = \beta_0 + \beta_{BEH} * X_{BEH} + \beta_{TCH} * X_{TCH} + \beta_{WC} * X_{WC} + \beta_{IH} * X_{IH}$$

$$\log(Y_{DAS}) = \beta_0 + \beta_{BEH} * X_{BEH} + \beta_{TCH} * X_{TCH} + \beta_{WC} * X_{WC} + \beta_{IH} * X_{IH}$$

$$Y_{DMT} = \beta_0 + \beta_{BEH} * X_{BEH} + \beta_{TCH} * X_{TCH} + \beta_{WC} * X_{WC} + \beta_{IH} * X_{IH}$$

$$\log(Y_{DMT}) = \beta_0 + \beta_{BEH} * X_{BEH} + \beta_{TCH} * X_{TCH} + \beta_{WC} * X_{WC} + \beta_{IH} * X_{IH}$$

Where,

Y_{DAS} – the daily activity space in acres. It is defined as the minimum convex polygon containing all the activity locations visited by an individual per day.
Y_{DMT} – daily miles traveled by an individual per day.
X_{BEH} – the set of built environment variables at the 0.25-mile buffer area around the home location, including land parcel count , retail count, and connected node ratio.
X_{TCH} – driving activity density at the 0.25-mile buffer area around the home location.

X_{WC} – the set of weather variables, including daily lowest temperature and precipitation.
X_{IH} – the set of individual and household factors.

Activity and travel time allocations are only observable when the individual choose to be engaged in activities and travel. Both the Tobit model and the Heckman selection model are appropriate to model time allocation variables since the two kind of models are meant to address the missing data bias and dependent variables with many zero values. In the following text, the Tobit model and the Heckman selection model are presented and compared.

The Tobit model is an econometric model proposed by James Tobin (1958) to describe the relationship between variables when the dependent variable cannot take on values smaller than zero. The Tobit model can be presented as a discrete/continuous model that first makes a discrete choice of passing the zero threshold, and second – if it is passed – a continuous choice regarding the value above the zero threshold. This approach is appropriate for activity/travel time allocation, as an individual must decide whether to engage in the activity, and if so, how much time he/she would like to allocate. The standard Tobit model's form is presented in the following equation:

$$y = \begin{cases} y^* = \beta \cdot x + \varepsilon & if \quad y^* > 0 \\ \\ 0 & if \quad y^* \le 0 \end{cases}$$

where, y^* is a latent unobservable variable that linearly depends on a vector of independent variables x via a parameter (vector) β. ε is a normally distributed error term that captures random influences on the relationship between y^* and x. y is the observable variable which is defined to be equal to the latent variable whenever the latent variable is above zero, and zero otherwise.

Although the Tobit model has been designed specifically for addressing the two-step decision-making procedure in activity/travel time allocations, the model structure assumes that the same variables affect both the engagement decision and the conditional decision about the actual activity/travel time. This assumption may be too restrictive. For instance, the probability of traveling by auto modes may not depend on traffic information usage, while the actual travel time may do so. See Table 3-2 for more examples. From this angle, the Heckman selection model has the advantage since it includes a classical regression and a binary probit selection criterion model (Greene 2002). The Heckman selection model is presented in the following equation:

$$y = \beta \cdot x + \varepsilon$$

$$z = \begin{cases} 1 & if \quad z^* = \alpha \cdot w + u > 0 \\ 0 & if \quad z^* = \alpha \cdot w + u <= 0 \end{cases}$$

with $Corr[\varepsilon, \mu] = \rho$ and $[y, x]$ only observed when $z = 1$.

The Heckman selection model consists of two equations – the classical regression equation and the probit selection equation. The selection model is based on a latent continuous variable z^*, reflecting the propensity that the individual chooses a given category of activities or a given mode of transportation. The propensity is a function of a set of independent variables w (some or all of which may overlap with x), associated parameters α, and unobserved factors summarized by the error term μ. The correlation between the unobserved variables in the two equations is given by ρ. A statistically significant estimate for ρ indicates that modeling the decisions on activity/travel engagement and activity/travel time allocation simultaneously is superior to modeling them separately (Bhat, 1997; Schwanen and Mokhtarian, 2005). A positive sign on ρ suggests that unobserved factors are associated with the engagement decision and the time allocation decision in the same direction. A negative sign on ρ implies that unobserved factors are associated with the engagement decision and the time allocation decision in opposite directions.

In the activity time allocation analysis, y represents the two activity time allocation indicators: daily time allocated to out-of-home activities, and daily time allocated to leisure activities. x and w are explanatory variables including the built environment at the home location, traffic conditions at the home location, weather conditions and the control variables. See Table 4-2 the full list of independent variables and control factors.

In the travel time allocation analysis, y represents the four mode-specific travel time allocation variables: daily time allocated to driving, daily time allocated to walking, daily time allocated to transit use, and daily time allocated to bicycle use. x and w are explanatory variables in Table 4-2.

Analysis of trip distance and duration (hypothesis set #3)

An advantage of investigating travel behavior at the single activity/trip level is that the research specifies certain components of travel decisions and creates segmented models for different activity or trip categories. Models in this analysis include a set of activity-specific trip distance models and a set of mode-specific trip duration models. See Table 4-3 for the list of variables used in the trip distance and duration analysis.

Table 4-3 Variables used in the trip distance and duration analysis

Trip distance analysis	Trip duration analysis
Untransformed OLS and semi-log transformed OLS models	Untransformed OLS and semi-log transformed OLS models
DVs (Shortest path distance from the origin to the destination in miles): Daytime shopping distance; night shopping distance; daytime leisure trip distance; and night leisure trip distance	DVs (Trip duration in minutes): Driving trip duration; walking trip duration; and bicycling trip duration
Ivs: The built environment at the trip origin –land parcel count; retail count; industrial count; and connected node ratio Traffic conditions at the trip origin – driving activity density Weather conditions –daily lowest temperature and precipitation Activity contexts –*activity type; and activity time Trip characteristics – home-based indicator and travel mode	Ivs: The built environment at the trip origin and destination –sidewalk coverage Traffic conditions at the trip origin and destination – driving activity density Weather conditions –daily lowest temperature and precipitation Activity contexts – activity time Trip characteristics – *travel mode; and trip distance
CVs (individual and household factors): Socio-demographics, Attitudes, Tactical decisions	CVs: Same as the left cell

Note: * As each of the three trip distance models specified one activity category and the categories were defined based on activity type , activity type was not included as an independent variable in the specification of each distance model. For the same reason, travel mode was not included as an independent variable in the specification of each duration model.
DVs-dependent variables; IVs-independent variables; and CVs- control variables.

The dependent variables in the trip distance models are the shortest path distance from the trip origin to the trip destination, measured in miles. Note that the Triangle survey did not ask respondents to report trip distance and this distance variable was calculated using the locational information of activities in the Triangle dataset and the street network GIS layer. The Network Analyst Tool in ArcGIS 9.1 was used to calculated the shortest path distance from each trip origin to each trip destination. The shortest path distance from the trip origin to the trip destination is not a precise measure of trip distance, since the real trip distance within urban transportation networks is often longer than the shortest path distance between the origin and destination. This measurement error is further discussed in the analysis chapter-Chapter VII. Independent variables in this analysis include measures of the built environment and traffic conditions at the trip origin, weather conditions, and trip characteristics. Control variables are the individual and household factors defined in the pervious section. Compared to the time allocation analysis at the individual level, this analysis takes activity contexts and trip characteristics into account. Descriptions and definitions of the activity and trip variables are shown blow.

Activity type – categorical variable: 1- shopping; 2-lesure activities; 3- other non-work related activities; 4-work-related activities.
Night activity – dummy variable: 1-night activities (6:31pm -3:00am); 0-daytime activities (3:01 am – 6:30pm)
Home-based – dummy variable: 1, if the trip is home-based; 0, otherwise
Driving mode – dummy variable: 1, if the trip uses driving mode; 0, otherwise
Walking mode – dummy variable: 1, if the trip uses walking mode; 0, otherwise –

There are a total of three activity-specific models on trip distance, respectively focusing on the trips related to three activity categories: shopping trips, leisure trips, and other non-work related trips. Commuting trips were not examined in this analysis because work-related trips tend to have fixed destinations. And the commuting distance is more reflected in home location choices than is influenced by the built environment around trip origins. Semi-log transformed regression was used in this distance analysis because the distribution of non-work trip length is positively skewed. The three activity-specific trip distance models have the same model specifications shown below.

$$Y_{DS} = \beta_0 + \beta_{BEO} * X_{BEO} + \beta_{TCO} * X_{TCO} + \beta_{WC} * X_{WC} + \beta_{TR} * X_{TR} + \beta_{IH} * X_{IH}$$

$$\log(Y_{DS}) = \beta_0 + \beta_{BEO} * X_{BEO} + \beta_{TCO} * X_{TCO} + \beta_{WC} * X_{WC} + \beta_{TR} * X_{TR} + \beta_{IH} * X_{IH}$$

Where,

Y_{DS} – the shortest path distance from the trip origin to the trip destination.

X_{BEO} – the set of built environment variables at the 0.25-mile buffer area around the trip origin, including land parcel count , retail count, and connected node ratio. See the Measuring the Built Environment section in this chapter for detailed descriptions and definitions of the built environment variables.

X_{TCO} – driving activity density at the 0.25-mile buffer area around the trip origin. See the Measuring Human Activity Patterns section for the detailed definition of driving activity density.

X_{WC} – the set of weather variables, including daily lowest temperature and precipitation.

X_{TR} – the set of variables of activity and trip characteristics, including the night activity indicator, the activity the home-based indicator, the driving mode indicator, and the walking mode indicator.

X_{IH} – the set of individual and household factors. The previous section offers detailed definitions of these factors.

In terms of the trip duration analysis, two mode-specific models were developed to respectively focus on the driving mode and the walking mode. The transit trips and bicycle trips were excluded from this analysis due to the small number of observations. In this duration analysis, both work-related trips and non-work related trips were included since this analysis focuses on travel time rather than destination choice. Trips longer than 2 miles were excluded from this duration analysis because for long-distance trips, the effect of the environmental factors at the origin and the destination on trip duration may not be testable. The dependent variables in trip duration models are the reported trip duration in minutes. The dependent variables may also have some measurement error since people perceive duration nonlinearly. The model specifications are shown below.

$$Y_{DR} = \beta_0 + \beta_{BEO} * X_{BEO} + \beta_{BED} * X_{BED} + \beta_{TCO} * X_{TCO} + \beta_{TCD} * X_{TCD} + \beta_{WC} * X_{WC} + \beta_{DS} * X_{DS} + \beta_{IH} * X_{IH}$$

$$\log(Y_{DR}) = \beta_0 + \beta_{BEO} * X_{BEO} + \beta_{BED} * X_{BED} + \beta_{TCO} * X_{TCO} + \beta_{TCD} * X_{TCD} + \beta_{WC} * X_{WC} + \beta_{DS} * X_{DS} + \beta_{IH} * X_{IH}$$

Where,

Y_{DR} – the reported trip duration in minutes
X_{BEO} – the set of built environment variables at the 0.25-mile buffer area around the trip origin, including connected node ratio and sidewalk coverage[2].
X_{BED} – the set of built environment variables at the 0.25-mile buffer area around the trip destination, including connected node ratio and sidewalk coverage.
X_{TCO} – driving activity density at the 0.25-mile buffer area around the trip origin.
X_{TCD} – driving activity density at the 0.25-mile buffer area around the trip destination.
X_{WC} – the set of weather variables, including daily lowest temperature and precipitation.
X_{DS} – the shortest path distance from the trip origin to the trip destination.
X_{IH} – the set of individual and household factors.

Threats to Validity

Cross-sectional analyses like this research do not allow us to make inference about changes. Although the land use changes and other changes in the built environment are much slower and may not be immediately affected by changes in activity engagement and travel behavior, the environment-behavior relationship is bidirectional. In the real world, planning and policy decisions about land use, transportation and urban design are made based on human activity/travel patterns. This issue poses potential threats to the inferences regarding the causality between the built environment and activity/travel decision-making.

The self-selection issue is another major threat to the internal validity of this research. To alleviate this cause for concern, I included two household location choice factors (length of commute and access to transit) in the models. If the household considered length of commute or job locations when they moved to the current location, the household has an attitude of minimizing the travel time and distance. If the household considered access to transit in the home location choice, the household may be assumed to have a preference of using alternative transportation modes.

[2] Variables of mixed land uses were not included in the trip duration models because theoretically mixed land uses show no association with trip duration after controlling for trip distance.

Sampling bias and non-response bias are possible given the use of a telephone survey and high non-response rate (75%). Comparison was made between the descriptive statistics of the final sample and the census statistics of the study area, and did not suggest significant differences. Omitted variable bias exists in this research since it does not include factors on community values and neighborhood norms. This creates potential threats to internal validity.

External validity is limited at the geographical level, given the single study location (the Triangle region). Randomization, the sample size, and the comparison between the final sample and census data guaranteed the external validity within the study area.

In terms of construct validity, the variables of urban activity patterns is more open to question as there is little theoretical guidance for operationalizing those concepts. Indeed, the diversity concepts in activity population have rarely been measured using entropy measures. However, entropy measures are commonly used in many similar concept measurements (e.g. land use diversity), which may ensure the robustness of the diversity measures of human activity patterns.

Several weaknesses may arise from data imperfections. The activity data were collected from an activity-based travel survey which only recorded the activities that relate to movements. For example, the survey did not ask questions about the activity participation at home. To obtain activity start time and stop time, I assume that the trip arrival time is the activity start time and the next trip departure time is the activity stop time. In addition, the collected activity information is limited, which does not include information about the company context (with whom) of the activity. Using time-use survey data may be able to overcome those problems. However, I did not have access to any time-use survey with geo-referenced activity location information.

Measurement error bias is another cause for concern in this research. In the activity-specific trip distance models, the dependent variables contain measurement error. The trip distance variable used in this research is the shortest path distance between the trip origin and the trip destination. This distance measure tends to underestimate trip distance. The amount of underestimation is larger for trips made in congested areas than for trips made in uncongested areas. Therefore, this measurement error may overestimate the effect of traffic conditions on trip distance. If the estimated coefficients of traffic conditions are large, this measurement error in trip distance becomes less of a concern.

In the mode-specific trip duration models, the dependent variables are reported trip duration in minutes. This variable has some measurement error as well since people perceive duration nonlinearly. In addition, the trip distance variable becomes explanatory variables in trip duration models. The measurement error in trip distance may create more complicated problem as measurement error in explanatory variables may generate biased estimates as well as influence the consistency of OLS regression. However, as trips longer than 2 miles were excluded from the sample of the duration analysis, I assume the extent of measurement error may become relatively small.

The transferability of findings for the Triangle area in North Carolina to other urban regions is somewhat limited. The Triangle area in North Carolina, one of the most rapidly growing areas in U.S., is home to three research universities and the largest research park in the world (the Research Triangle Park). According to Census data, the 2005 population in Orange, Durham, and Wake Counties is 1,120,277. In the last decade, population in the three counties increased about 50% (Hartgen 2003). The Triangle's population is the most educated in the United States, with the highest number of Ph.D.s per capita. Anchored by leading technology firms, government and world-class universities and medical centers, the area's economy has performed exceptionally well.

Travel in the Triangle has risen substantially during the past decade. However, the Triangle also has increased the capacity of the freeways to carry traffic, which has improved traffic conditions and led to only modest growth in congestion. The growth rates of traffic per lane in Raleigh and Durham urban area was about 1 percent per year from 1990 to 2001 (Hartgen 2003). Commuting from Wake County to Durham County, at 43,400 daily commuters, is the highest inter-county commuting in the State. Compared to other metro areas in U.S. with similar population density, the Triangle area has a much higher percentage of transit trips and non-motorized trips. The 2006 travel survey data suggest that, in Orange County, about three percent of trips were made by transit and about 18% of trips were made by non-motorized modes (walking and biking). This is partly due to good public transportation systems in the Triangle. Raleigh is served by the Capital Area Transit (CAT) municipal transit system, while Durham has the Durham Area Transit Authority (DATA) system. Chapel Hill is served by Chapel Hill Transit, and Cary also is served by its own public transit systems. In addition, the Triangle Transit Authority (TTA) works in cooperation with all area transit systems by offering transfers between its own routes and those of the other systems.

Given the uniqueness of the Triangle Area described above, the results of this study may not be able to be generalized to high congested regions, regions with poor transit services, and regions depending on heavy industry sectors such as manufacturing and mining. In addition, the travel survey data were collected during January 31 to May 26, 2006—the winter and spring seasons, which does not contain travel data in either extremely cold weather or in hot weather. Therefore, I cannot generalize the research results to the coldest regions up north and the hottest regions down south. Likewise, I may not be able to detect the non-linearity between temperature and activity-travel behavior.

CHAPTER V: Census Block Group Level Activity Pattern Analysis

The analysis in this chapter tests whether compact development patterns are associated with high activity density and great diversity in activity categories and activity population, suggested by Link 1a in Figure 3-4. The unit of analysis is the census block group. Dependent variables include activity density, activity type mix, activity time mix, race mix in activity population, income mix in activity population, age mix in activity population, and alternative mode share. The key independent variables are indicators of compact development patterns including population density, employment density, industrial use share, commercial land share, connected node ratio, and sidewalk coverage. Control variables are indicators of demographic environments including average household size, median household income, and percentage of white population.

The first part of this chapter describes the built environment, demographic environments, and urban activity patterns across the Triangle region – Orange, Durham, and Wake counties. Following the descriptive statistics, this chapter examines the relationship between the built environment and activity density and diversity patterns using negative binomial regression and OLS regression. Further, the logit model for grouped data is used to estimate how alternative transportation mode share in urban spaces is related to built environment factors, after controlling for demographic environments.

Descriptive analysis

To gain a general idea about urban environments of the study area, I conducted a descriptive comparison of the environmental measures among Orange, Durham, and Wake counties in North Carolina. Table 5-1 shows the descriptive statistics of all the variables measured at the census block group level, including measures of the built environment, measures of demographic environments, and measures of urban activity systems.

As shown in Table 5-1, Orange County has the highest employment density. Durham County has the highest residential density and highest connected node ratio in the region. High connected node ratio indicates more gird street patterns. Wake County has the highest percentage of commercial uses and industrial uses, which indicates its great land use diversity. Wake County is the most urbanized county in the Triangle region, and it has the best sidewalk coverage.

In terms of urban activity patterns, Orange County has not only the greatest diversity in activity type, activity time, age groups and travel modes, but also the highest activity density of about 18 activities per acre. The population who were involved with daily activities in Durham County has the greatest race and income diversity. Comparing to the US average, all three counties have relatively good percentage of non-auto mode share ranging from 8% to 14%.

The descriptive statistics are in line with our expectation for the three counties. However, the descriptive comparison of the three counties does not show consistency between the built environment and urban activity systems in terms of density and diversity. For example, although Wake County has the highest sidewalk coverage, Orange County has the highest non-auto mode share. The highest activity density was found in the county with the least dense population – Orange County.

Results from the descriptive analysis indicate that the spatial variation in the built environment indicators does not match the variation in urban activity patterns. To further examine how the built environment indicators are associated with the activity pattern indicators, regression models were used in the next section.

Table 5-1 Descriptive statistics of the built environment, demographic environments, and human activity patterns in the Triangle area

Variables	**Orange (56 census block groups)**		**Durham (129 census block groups)**		**Wake (263 census block groups)**		**Total (448 census block group)**	
	Mean	Dev.	Mean	Dev.	Mean	Dev.	Mean	Dev.
Built Environment								
Residential density	3.224	4.932	4.511	3.758	3.994	3.204	4.047	3.634
Employment density	2.707	6.727	2.275	5.036	2.400	5.791	2.403	5.701
Commercial use share (%)	0.031	0.066	0.070	0.100	0.080	0.093	0.071	0.094
Industrial use share (%)	0.007	0.017	0.027	0.059	0.029	0.065	0.026	0.059
Connected node ratio	0.640	0.09	0.729	0.125	0.688	0.127	0.694	0.125
Sidewalk coverage	0.247	0.373	0.395	0.358	0.451	0.411	0.409	0.396
Demographic Environments								
% of white population	0.776	0.130	0.501	0.297	0.705	0.247	0.655	0.271
Average household size	2.387	0.287	2.423	0.342	2.474	0.384	2.450	0.359
Median Income	5.609	1.103	4.642	1.529	5.261	1.346	5.132	1.409
Activity Patterns								
Activity density	18.333	33.103	14.767	23.194	10.958	15.128	12.962	20.818
Activity type mix	0.647	0.206	0.597	0.221	0.618	0.234	0.615	0.227
Activity time mix	0.798	0.177	0.790	0.161	0.782	0.180	0.786	0.174
Race mix in activity pop.	0.238	0.149	0.365	0.208	0.275	0.198	0.296	0.200
Income mix in activity pop.	0.682	0.199	0.693	0.220	0.645	0.203	0.664	0.208
Age mix in activity pop.	0.764	0.187	0.752	0.194	0.734	0.177	0.743	0.183
Travel Patterns								
Alternative mode share	0.138	0.145	0.094	0.107	0.076	0.126	0.089	0.125
Driving activity density	9.034	17.092	7.521	11.130	6.280	8.464	6.981	10.692

Activity Pattern Models

Activity density, diversity in activity categories, and demographic diversity in activity population in urban spaces relate to the sense of place, the community attractiveness, and the equity and segregation of the social dimension in urban places. To understand how built environment factors relate to activity density and diversity patterns, five regression models were applied to link the five measures of urban activity systems to built environment factors and demographic environments. Among them, negative binomial regression was used to estimate the activity density model since the dependent variable—the number of activities—is a count variable (see Figure 5-1 for the frequency distribution). OLS regression was used to estimate the activity diversity models. See Chapter III for the relevant *a priori* expectations and see Chapter IV for detailed model specifications.

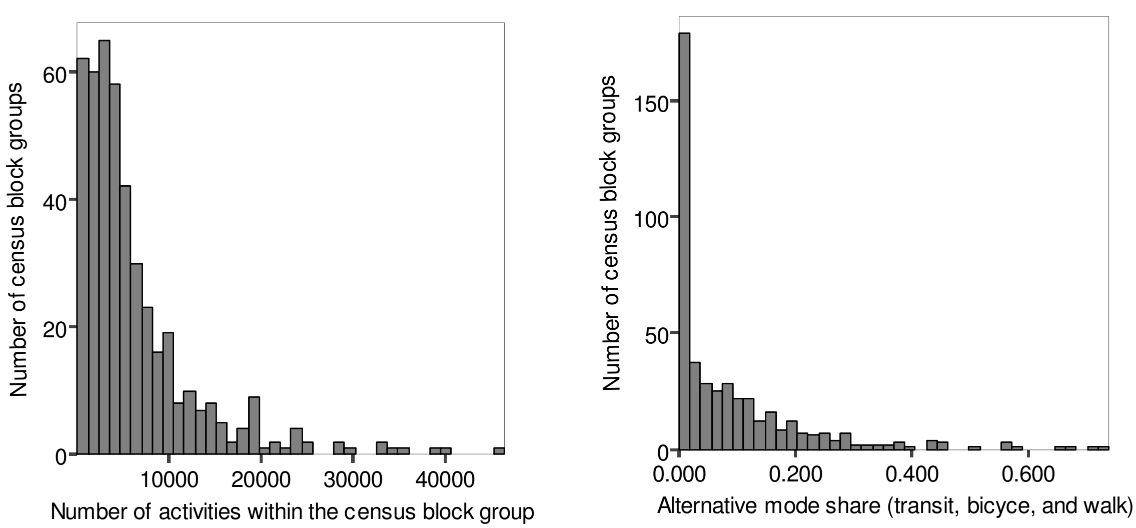

Figure 5-1 Distributions of activity frequency and alternative mode share at the census block group level

Table 5-2 shows the regression results including the estimated coefficients and their significance. For the activity density model, incident rate ratios (IRRs) rather than coefficients were reported in Table 5-2. Both the activity density model and the activity diversity models performed well, given that the lowest R-square of the models is about 0.1.

Table 5-2 Negative binomial regression and OLS regression results of activity patterns

Variables	Activity Density (Negative binomial IRRs)	Activity Diversity (OLS coefficients)				
		Activity Type Mix	Activity Time Mix	Race Mix	Income Mix	Age Mix
Constant	1.126	0.649***	0.979***	0.684***	1.172***	0.838***
The built environment						
Residential density	1.207***	-0.007*	0.001	-0.008**	-0.003	-0.003
Employment density	1.030**	0.003	0.002	0.005***	0.005***	0.003
Commercial use (%)	12.511***	0.598***	0.099	0.095	0.274**	0.086
Industrial use (%)	1.220	0.098	0.141	0.477***	0.269*	0.149
Connected node ratio	6.193***	-0.141	-0.318***	-0.108	-0.265***	-0.184**
Sidewalk coverage	1.851***	0.073**	0.101***	0.043	0.064**	0.112***
Demographic environments						
% of white pop.	1.617**	0.103**	0.135***	-0.183***	0.082*	0.104**
Average HH size	0.632***	-0.061*	-0.052**	-0.060**	-0.141***	-0.029
Median income	1.025	0.018**	0.001	-0.012	-0.017**	-0.002
Summary Statistics						
N	448	448	448	448	448	448
R^2	0.047[a]	0.171	0.138	0.157	0.171	0.089
Adjusted R^2		0.154	0.121	0.140	0.070	0.154
Prob > F	0.000[a]	0.000	0.000	0.000	0.000	0.000
Alpha	0.830*					

Note: [a]Pseudo R^2 and Prob>Chi^2 were reported for the activity density model; * p<.1; ** p<.05, *** p<.01. The range of the number of activities occurring within the census block group is from 0 to 46,563 activities. The range of the activity diversity indicators are from 0 to 1. See Table 5-1 for means and standard deviations of the dependent variables.

Results show that activity density is significantly and positively related to land use density, land use diversity, grid street patterns, and pedestrian facilities. High degree of activity type mix is associated with high percentage of commercial uses and presence of sidewalks. Activity time mix is positively related to sidewalk coverage but is negatively related to connected node ratio. Race mix in activity population is positively related to the ratio of industrial uses and employment density. Income mix in activity population is positively related to employment density, industrial uses, commercial uses, and presence of sidewalks. Age mix in activity population is positively related to sidewalk coverage. In the following text, I describe how each of the four sub-dimensions in the built environment is associated with activity density and diversity patterns in turn.

Land use density and activity patterns

Results in Table 5-2 show that high land use density is associated with high activity density, but high land use density is not necessarily associated with high activity diversity or high diversity in activity population. With the area size and all other variables held constant, a one-unit increase in residential density (residents per acre) is associated with a 21% increase in the number of activities occurring within the census block group. A one-unit increase in employment density is associated with a 3% increase in the number of activities. However, at the 0.05 significance level, residential density and employment density are only significant in predicting race diversity and income diversity in activity population. Residential density shows a negative association with race diversity in activity population. A one-unit increase in residential density is associated with a 0.008 decrease in the entropy measure of race mix in activity population. Employment density, however, shows a positive association with race diversity and income diversity in activity population. A one-unit increase in employment density is associated with a 0.005 increase in the entropy measures of race mix and income mix in activity population. This indicates that high employment density in a census block group is associated with diverse race and income groups in the population who were involved with activities within the census block group.

In other words, more jobs in the area are associated with higher activity density and greater race and income diversity within the people who accomplished activities in the area. More residents in the area are associated with higher activity density but lower race diversity in activity population. The results are not consistent with our general expectation that higher land use density is associated with greater activity diversity. However, the results may confirm an existing problem in the Triangle region – the job-housing balance problem. The Triangle region offers greater diversity in its labor market than its housing market. There are many low-wage employments but few affordable houses in Orange, Durham and Wake Counties.

Land use diversity and activity patterns

Results show that more commercial uses and industrial uses in the census block group are associated with higher activity density, greater activity type diversity, greater race diversity in activity population, and greater income diversity in activity population.

The percentage of commercial uses in the census block group has a much stronger relationship with activity density than industrial uses. Ten percent additional commercial uses within the census block group (a 0.1-unit increase in commercial use ratio) are associated with a 28.7%[3] increase in the number of activities occurring within the census block group. Industrial uses show no association with the number of activities within the census block group.

In terms of activity diversity, ten percent additional commercial uses (a 0.1-unit increase in commercial use ratio) within a census block group is associated with a 0.06 increase in the entropy measure of activity type mix at the census block group. This is a

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[3] A one-unit increase in the percentage of commercial uses is often not possible since the maximum value of the percentage of commercial uses is 100%. Thus, instead of interpreting a one-unit change here, we interpret a 0.1-unit change. The percentage change in the dependent variable associated with the 0.1-unit change in commercial use share (ten percent additional commercial uses) can be obtained through the equation: $(12.511^{0.1}-1)*100\% = (1.287-1)*100\% = 28.7\%$.

relatively large increase since the entropy measure is scaled from 0 to 1. However, more industrial uses are not associated with higher degree of activity type mix.

More commercial uses show an association with greater income mix in activity population, but do not relate to greater race mix. More industrial uses, however, are associated with greater race mix in activity population, but do not show an association with income mix in activity population at the 0.05 significance level. Ten percent additional commercial uses in a census block group is associated with a 0.03 increase in the entropy measure of income mix within the population who engaged in activities in the census block group. Ten percent additional industrial uses are associated with a 0.05 increase in the entropy measure of race mix in activity population. These are interesting results, which may point out the social equity problem in the Triangle area. That is, the minority's activity spaces in the Triangle area often contain industrial uses.

Transportation infrastructure and activity patterns

Connected node ratio, the indicator of grid street patterns, is positively associated with activity density, but is negatively associated with activity time mix, income mix in activity population, and age mix in activity population. A 0.1-unit increase in connected node ratio (ten percent additional intersections that are not dead ends) is associated with a 20% increase in the number of activities in the census block group. In terms of activity diversity, ten percent additional intersection share is associated with a 0.03 decrease in the entropy measure of activity time mix, a 0.03 decrease in the entropy measure of income mix in activity population, and a 0.02 decrease in the entropy measure of age mix in activity population.

The positive relationship between connected node ratio and activity density is what I expected. However, I did not expect that grid street patterns would show an association with low activity diversity. A possible explanation is that the decentralization trend has moved certain activity categories out of the city centers. For example, after 9:00pm, it is difficult to find a shopping place in the downtown areas since stores open 24 hours are mostly highway retail stores and suburban shopping malls.

Presence of sidewalks shows a positive and significant association with activity density as well as activity diversity indicators. Ten percent additional sidewalks to street length (a 0.1-unit increase in sidewalk coverage ratio) is associated with a six percent increase in the number of activities in the census block group, a 0.007 increase in the entropy measure of activity type mix, a 0.01 increase in the entropy measure of activity time mix, a 0.006 increase in the entropy measure of income mix in activity population, and a 0.01 increase in the entropy measure of age mix in activity population. The estimated positive relationship between sidewalk coverage and activity density and diversity patterns coincides with the general planning expectation. As we build more sidewalks, we expect that pedestrian facilities are able to accommodate dense developments and serve diverse population groups.

Demographic environments and activity patterns

The control factors in the activity pattern analysis, indicators of demographic environments, are mostly significant in predicting human activity patterns. The percentage of white population negatively relates to activity density and race diversity in activity population, but is positively associated with activity type mix, activity time mix, and income diversity and age diversity in activity population. Average household size negatively relates to all the activity density and diversity indicators. Median household income shows a positive association with activity density and activity type mix, but is negatively associated with income diversity in activity population.

Travel Pattern Models

This section focuses on human travel patterns in urban spaces and its association with the built environment, after controlling for demographic environments. Two models were estimated, one is an alternative mode share model and another is a driving activity frequency model. Alternative transportation mode share is defined as the percentage of transit, walking, and bicycling trips within the census block group (see Figure 5-1 for the distribution). Logit model for group data was used in predicting alternative mode share. Chapter IV specifies the model and justifies the use of such logit model. Driving activity frequency in a census block group is defined as the number of driving trips ending in the census block group. Negative binomial regression was used to model this variable. The area size of the census block group is specified as the exposure variable. See Chapter IV for the model specification. Table 5-3 presents the estimated regression results.

Table 5-3 Regression results on alternative mode share and driving activity frequency

Variable	Alternative mode share (Logit model for grouped data)		Driving activity frequency (Negative binomial model)	
	Coefficients	Odds ratio	Coefficients	IRR
Constant	-1.383*	0.251*	-0.150	0.861
The built environment				
Residential density	0.073***	1.076***	0.169***	1.184***
Employment density	0.023***	1.023***	0.022*	1.023*
Commercial use (%)	-2.005***	0.135***	3.377***	29.297***
Industrial use (%)	-1.385*	0.250*	0.240	1.272
Connected node ratio	1.421**	4.140**	1.595***	4.929***
Sidewalk coverage	0.222	1.249	0.515***	1.674***
Demographic environments				
% of white pop.	0.291	1.338	0.495**	1.641**
Average HH size	-0.446***	0.640***	-0.624***	0.536***
Median income	-0.239***	0.787***	0.093**	1.097**
Summary Statistics				
N	448		448	
Pseudo R^2	0.094		0.047	
Log-likelihood	-875774.55		-4083.73	
alpha			-0.227***	
Chi-square test	0.000		0.000	

Note: * p<.1; ** p<.05; *** p<.01. Standard errors were adjusted for intra-census block group autocorrelation.

The logit model of alternative mode share performs well with a pseudo R-square of 0.094. The negative binomial model of driving activity frequency has a pseudo R-square of 0.047. Both models are statistically significant, as suggested by chi-square tests. In the alternative mode share model, standard errors were adjusted for the intra-census block group autocorrelation because the logit model for grouped data uses total population in the study area rather than the number of census block groups to calculate the degrees of freedom.

As I expected, high land use density and grid street patterns are associated with high alternative mode share and more driving activities. Table 5-3 shows that a one-unit increase in residential density in a census block group is associated with a 7.6% increase in the odds of using alternative transportation modes and an 18% increase in the number of driving activities occurring within the census block group. For people engaged in activities within a census block group, a one-unit increase in employment density of the census block group is associated with a 2.3% increase in their odds of using alternative transportation modes. A one-unit increase in employment density is associated with 2.3% increase in the number driving trips ending in the census block group. The results show that residential density has a stronger relationship with alternative mode share and driving activity frequency than employment density.

Surprisingly, more commercial uses are associated with less alternative mode share, which is contradictory to the general expectation of the positive relationship between commercial use mix and the use of alternative transportation modes. Ten percent additional commercial uses within a census block group is associated with an 18%[4] decrease in the odds of using alternative modes. The measurement of commercial use share may lead to this surprising result. Large-scale commercial uses are often suburban malls rather than local retail stores. It might be better to use the number of retail stores rather than the percentage of commercial area within the total area of the census block group. In addition, this analysis was undertaken at the aggregate level, assuming that all the individuals within a census block group exhibit characteristics of the census block group at large. This might lead to the unexpected signs of some coefficients.

As I expected, more industrial uses are associated with a lower alternative mode share. Ten percent additional industrial uses within a census bock group are associated with a 13% decrease in the odds of using alternative modes.

Connected node ratio, as the indicator of street grids, shows a positive association with alternative mode share. A 0.1-unit increase in connected node ratio (ten percent

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[4] A one-unit increase in the percentage of commercial uses, which is a 100% increase, is associated with a 76.5% decrease in the odds of using alternative modes. 76.5% is obtained subtracting 0.135 from 1 and then multiplying 100%. However, a one-unit increase in the percentage of commercial uses is not possible since the maximum value of the percentage of commercial uses is 100%. Thus, instead of interpreting a one-unit change here, we interpret a 0.1-unit change. The percentage change in the dependent variable associated with the 0.1-unit change in the percentage of commercial uses can be obtained through the equation: $(1-0.135^{0.1})*100\% = (1-0.8185)*100\% = 18.15\%$

additional intersections that are not dead ends) is associated with a 15% increase in the odds of using alternative transportation modes.

Results show that alternative mode share is not significantly related to sidewalk coverage ratio. This may be because alternative mode share is an aggregate value of pedestrians, bicyclists, and transit users. Connected node ratio shows a stronger association with high alternative mode share than sidewalk coverage.

All the control variables in Table 5-3 show expected signs. The percentage of white population positively relates to alternative mode share, but the relationship is insignificant in the model. Average household size and median household incomer show significant and positive associations with alternative mode share.

Key Findings and Limitations

Table 5-4 summarizes the empirical evidence on the relevant hypotheses about the built environment and human activity patterns. As shown in Table 5-4, land use density positively relates to activity density and alternative mode share, but land use density in an area may not positively relate to diversity in activity categories or demographic diversity in the population who were involved with activities in the area. More specifically, residential density has a stronger association with activity density and alternative mode share than employment density. Employment density mainly has a moderate and positive relationship with activity diversity, but residential density may have negative relationship with activity diversity.

Greater land use diversity, indicated by more commercial and industrial uses in the area, is associated with higher activity density and greater activity diversity but lower alternative mode share. Grid street patterns and presence of sidewalks are both associated with high activity density and more alternative mode share.

Table 5-4 Evidence found in the census block group level activity pattern analysis

Changes in built environment factors	**Changes in dependent variables**							
	Number of activities	Entropy measures					Odds of using alternative modes	Number of driving activities
		Activity type mix	Activity time mix	Race mix	Income mix	Age mix		
The built environment								
+1 resident/acre	21%	-0.007		-0.001			8%	18%
+1 employee/ acre	3%			0.001	0.001		2%	2%
+10% commercial use share	29%	0.060			0.027		-18%	40%
+10% industrial use share				0.048	0.027		-13%	
+0.1 connected node ratio	20%		-0.032		-0.027	-0.018	15%	17%
+0.1 sidewalk ratio	6%	0.007	0.010		0.006	0.011		5%

Note: Results reported in this table are all significant at the 0.1 level.

Several limitations exist in this analysis. First, this is an activity pattern analysis at the spatially aggregate level, which is subjected to the ecological fallacy[5] (Robinson 1950). In real-world situations, activity and travel decisions are made at the individual level. However, the aggregate models presented in this chapter assume that all the individuals within a census block group exhibit characteristics of the census block group at large. This is part of the reason some estimated coefficients show unexpected signs. For example, as shown in Table 5-4, ten percent additional commercial uses within the census block group are associated with an 18% decrease in the odds of using alternative transportation modes.

Although activity and travel analysis at the disaggregate level is theoretically more appealing, aggregate models have their strength in urban planning. Given inherently aggregate nature of urban services and facilities in serving the general public, it is not sufficient to explore activity and travel decision at the individual level. In urban planning,

[5] The ecological fallacy is a widely recognized error in the interpretation of statistical data, whereby inferences about the nature of individuals are based solely upon aggregate statistics collected for the group to which those individuals belong.

human activities as behavioral phenomena must eventually be juxtaposed with another set of phenomena concerned with the development process (Chapin, 1974). By offering activity and travel analyses at the aggregate level and the disaggregate levels, this dissertation is able to give more explicit and more meaningful attention to environmental contingencies as well as to provide insights into the environment effects on activity and travel decision-making. It is reminiscent of three different film-making styles: one focuses on a physical space, one focuses on an actor—the individual, while yet another focuses on a trip.

In this analysis, I used OLS models to estimate the activity diversity indicators. Since the activity diversity indicators are all entropy measures with a 0-1 scale, OLS regression may not be able to generate efficient estimates. After checking the distribution of the entropy measures, I found out that all the activity diversity indicators follow the beta distribution, which is a family of continuous probability distributions defined on the interval [0, 1](Evans, Hastings et al. 2000). Unfortunately, the beta distribution is hard to model and the parameter estimation for the beta distribution is outside the scope of this dissertation.

CHAPTER VI: Individual Activity Space and Time Allocation Analysis

The previous chapter examined how the built environment is associated with human activity and travel patterns at the neighborhood level. This chapter aims at examining the role of residential environments in daily activity spaces and daily activity/travel time allocations at the individual level, suggested by Links 2a, 2b, and 2c in Figure 3-4. The built environment factors included in this individual activity space and time allocation analysis were measured at the 0.25-mile buffer level around the home location, including indicators of land use density, retail uses, industrial uses, street grids, and pedestrian facilities. In addition to built environment factors, I included traffic conditions at the home location and weather conditions as another set of important environmental factors in this analysis. Control factors are individual and household variables including socio-demographic indicators, household location choice factors, auto ownership, and traffic information usage.

The structure of this chapter is as follows. First, descriptive analysis was conducted to provide a general picture about the demographics of the surveyed Triangle residents, their residential environments, their daily activity spaces, and their daily time allocations to various activities and travel modes. Further, how environment factors (including the built environment at home location, traffic conditions, and weather conditions) are associated with daily activity space and daily miles traveled were quantified using untransformed OLS and semi-log transformed OLS regressions. Following the analysis of individual spatial activity patterns, individual time allocation was analyzed. Out-of-home activity time allocation and leisure activity time allocation were estimated using the Tobit model and the Heckman selection model. Following the activity time allocation models, mode-specific travel time allocation models were presented. And finally, the key findings from this individual activity space and time allocation analysis were summarized and limitations were pointed out.

Descriptive Analysis

Table 6-1 presents the descriptive statistics of daily activity-travel indicators. Spatial measures of individual activity-travel behavior include individual activity space and daily miles traveled. Temporal measures of individual activity-travel behavior include individual daily time allocations to various activities categories and travel modes.

In terms of activity space, 4,937 respondents' daily activity spaces were generated. Since no polygon can be created with less than three input points, I was not able to generate activity space for residents who did not travel on the survey day (472 out of the total 7,422 respondents) or those who only visited two locations on that day (2,012 out of the total 7,422 respondents). Respondents who visited more than two locations on the survey day on average have a daily activity space of 9,130 acres. The total 7,422 respondents on average traveled 15.7 miles on the survey day.

Figure 6-1 illustrates the activity spaces of several central city residents and several suburban residents. I selected two census block groups in the Chapel Hill and Carrboro downtown area and three census block groups in the Orange County suburban area. Activity spaces of residents living in the two areas were displayed. As shown in Figure 6-1, the activity spaces of downtown residents are much smaller than that of suburban residents.

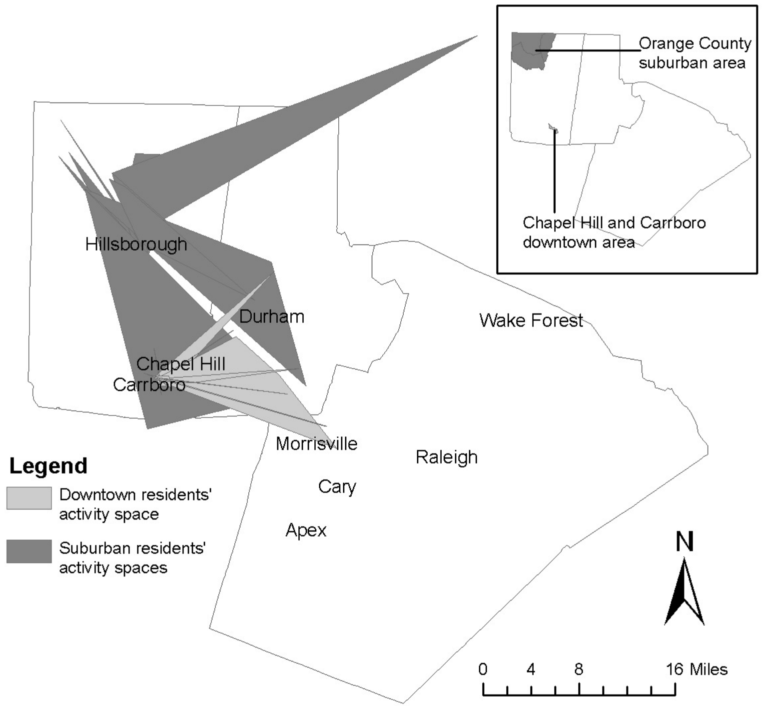


Figure 6-1 Individual activity spaces and home locations

Table 6-1 Descriptive statistics of activity space and time allocation indicators (N=7,422)

Category	**Variable**	**Mean**	**Std. Dev.**	**Min**	**Max**
Spatial indicators	Activity space (acres)	9129.51	18062.95	0.0014	304511
	Daily miles traveled	15.71	16.75	0	185
Time allocation indicators (minutes)	At-home activities	952.84	284.29	0	1439
	[a] Out-of-home activities	410.19	262.11	0	1439
	Work-related activities	215.49	281.87	0	1439
	School-related activities	102.38	191.65	0	1439
	Shopping activities	13.13	37.58	0	1439
	Leisure activities	44.61	120.80	0	1439
	Total daily travel	74.98	63.17	0	1224
	Driving	45.98	60.69	0	1224
	Carpooling	16.83	37.41	0	822
	Walking	4.20	15.97	0	692
	Transit	1.99	14.22	0	294
	Bicycling	0.54	6.72	0	207

Note:
[a] Out-of-home activities include all the activities outside of the home but exclude travel.

In terms of time allocation, the 7,422 respondents on average spent about 15.8 hours at home, 3.6 hours on work-related activities, about 1.7 hours on school-related activities, about 13 minutes on shopping, about 45 minutes on leisure activities (including social, entertainment, recreation, and civic activities), and about 75 minutes (1.25 hours) on traveling. Out of the 75-minute travel time, about 50 minutes were spent on driving, 17 minutes on carpooling, 4 minutes on walking, 2 minutes on taking transit trips, and only one minute on bicycling. There is substantial variation in daily time allocations to various activities and travel modes, as indicated by the large values of standard deviations and the wide ranges. Results show that the mean travel time allocations in the 2006 Greater Triangle Survey is very similar to the mean travel time allocations in the 2003 American Time Use Survey (ATUS). Individuals in the 2003 ATUS sample on average allocated about 76 minutes to daily travel, 52 minutes to driving, and 2.4 minutes on walking (Fan and Khattak, 2007). This indicates that time allocations to daily travel and driving in the Triangle area are about the same as the US averages, while daily walking time allocation in the Triangle area is higher than the US average (4 minutes >2.4 minutes).

Table 6-2 shows descriptive statistics of independent variables and control factors in this analysis, including built environment factors and a traffic condition measure at the home location, weather variables, and individual and household factors.

Table 6-2 Descriptive statistics of environment factors and control factors (N = 7,422)

Variable	Mean	Std. Dev.	Min	Max
The built environment at the home location				
Parcel Count	355.337	291.864	4	2294
Retail Count	2.504	6.014	0	73
Industrial count	1.347	2.556	0	36
Connected node ratio	0.665	0.170	0	1
Sidewalk length (miles)	1.075	1.489	0	12.337
Traffic conditions at the home location				
Driving activity density	0.075	0.113	0	1.687
Weather conditions				
Daily lowest temperature	42.668	11.543	21	66
Precipitation	0.318	0.466	0	1
Control factors				
HH size	2.958	1.318	1	8
HH income	6*	1.645	1	7
Residential tenure	4*	1.289	1	5
Female	0.521	0.500	0	1
Children	0.198	0.399	0	1
Young adult	0.073	0.261	0	1
Adult	0.608	0.488	0	1
Old	0.120	0.325	0	1
White	0.818	0.386	0	1
Employed	0.587	0.492	0	1
Multiple jobholders	0.088	0.284	0	1
Auto ownership	2.127	0.940	0	8
Traffic information usage	0.561	0.496	0	1
Commute attitude	0.560	0.496	0	1
Transit attitude	0.127	0.333	0	1
Single-family detached	0.827	0.378	0	1

* Category 6 ($75,000 to $99,999) is the median value of the household income variable. Category 4 (5-10 years) is the median value of the residential tenure variable.

On average, the households in the sample have 355 parcels, 2.5 retail stores, 1.35 industrial firms, and 1.08 miles of sidewalks within the 0.25-mile buffer area at their home locations. The average percentage of intersections that are not dead ends within the 0.25-mile buffer area is 66.5%. There is substantial variation in residential environments of the sampled households, as indicated by the large standard deviations and the wide ranges of the built environment indicators.

The indicator of traffic conditions – driving activity density – has its average value at 0.075 driving activities per acre. Note that this is a kernel density estimate and is not the absolute value of the number of activities divided by the area size. See the Measuring Human Activity Patterns in Chapter IV for detailed calculation procedure of this driving density indicator.

Since sampled households were surveyed on different dates from January 31 to May 26, the data have great variation in weather conditions. The average daily lowest temperature in the survey period is 43 in Fahrenheit degrees. The lowest value in daily lowest temperature is 21°F and the highest value is 66 °F, according to the downloaded records from the National Climatic Data Center (NCDC). Among the travel dates in the 2006 Triangle Travel Survey, about 33% of the dates were recorded with precipitation at the Raleigh Durham International Airport weather station.

In terms of individual and household socio-demographics, the average household size of the surveyed respondents is 2.96 persons per household, which is higher than the average value of 2.5 for the greater Triangle region (including a total of 12 counties) and the average value of 2.6 for the U.S. (US Census, 2000). The median category of household income is from $75,000 to $99,999, which indicates that more than half of the surveyed households earn more than $75,000 per year, which is much higher than the state average and the national average.

The average auto ownership is about two cars per household among the surveyed respondents in Orange, Durham, and Wake Counties. More than half of the respondents (56.1%) sought information about traffic and general travel in the region. More than half of the residents have lived at the current address more than 5 years. In terms of individual preferences and attitudes, about 56% of the respondents considered job location (length of commute) as an important factor when they moved to their current home locations. About 13% of the respondents considered access to transit as an important factor in their household location choices. 52% of the respondents are female. In terms of age groups, 20% of the sample are children that are 14 year old or younger; 7% are young adult (15-24 years old); 61% are adult (25-64 years old); and 12% are people who are older than 65. About 59% of the respondents had a job at the time of survey and about 9% had multiple jobs. 83% of the respondents lived in single-family detached housing.

Activity Space Models

Models in this section investigate the spatial patterns of individual activity-travel behavior. Using a multivariate approach, the effect of the built environment, traffic conditions, and weather conditions on activity space and daily miles traveled was evaluated while controlling for socio-demographics, tactical decisions, and attitudes. OLS regression and semi-log transformed regression were used in this analysis. See Chapter IV for detailed model specifications.

Figure 6-2 and Figure 6-3 shows frequency distributions of the two dependent variables in this activity space analysis—daily activity space and daily miles traveled. Distributions show that both of the two spatial activity-travel measures are positively skewed. The two measures have many small values but few large values.

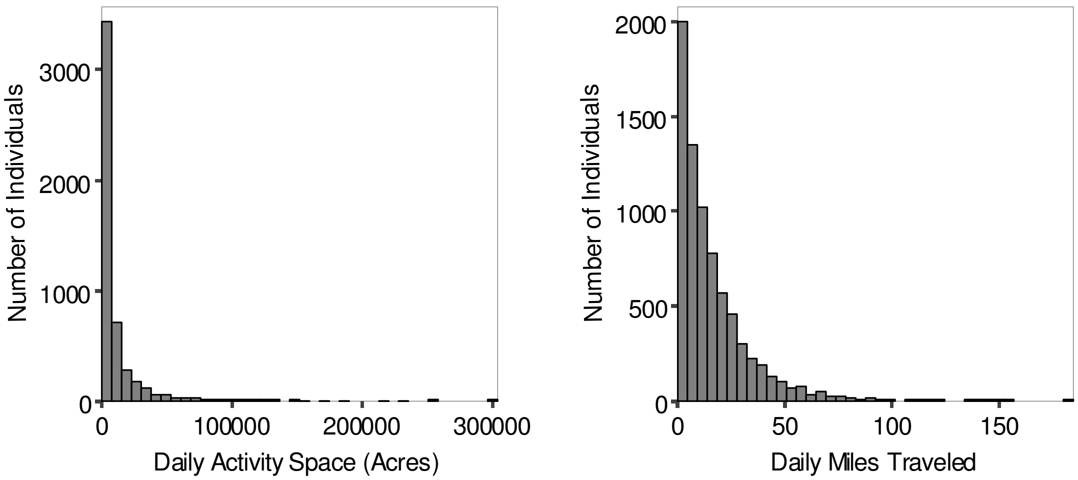


Figure 6-2 Frequency distribution of spatial activity-travel indicators

Table 6-3 and Table 6-4 present the modeling results on individual daily activity space and individual daily miles traveled. As shown in Table 6-3, all the activity space models are statistically significant. R-squares of the non-log transformed models are about 0.06, and R-squares of the semi-log transformed models are about 0.1. Although R-squares of semi-log transformed models and non-log transformed models are not comparable, semi-log transformed models are theoretically more appropriate in that the dependent variables in activity space models are positively skewed (see Figure 6-2). In the following text, the coefficients of the final semi-log transformed model are interpreted.

Results show that smaller daily activity spaces are related to more retail stores, more sidewalks, heavier traffic, and more parcels in the residential neighborhood. Cold temperature and precipitation are associated with smaller daily activity spaces.

Ten additional parcels in the 0.25-mile buffer area at an individual's home location are associated with a 0.35%[6] decrease in his/her daily activity space. One additional retail store in the residential neighborhood is associated with a 1.6% decrease in individual daily

[6] 10 unit increase in X associated with 100*(exp(b*10)-1) percent change in Y. Thus, ten additional parcels are associated with 100*exp((-0.00035*10)-1)=-0.35% percent change in daily activity space.

activity space. One additional mile of sidewalks within the buffer area is associated with a 9.8% decrease in individual daily activity space. The results support the hypothesis that presence of sidewalks, more retail uses and dense developments in the neighborhood are associated with smaller activity spaces—less spatially dispersed distribution of daily activity locations.

A one-unit increase in driving activity density is associated with a 79% (exp(-1.55)-1=-0.79) decrease in the area size of daily activity space. This result indicates that heavy traffic in the residential neighborhood relate to concentrated activity locations.

A 10- Fahrenheit degree increase in temperature is associated with a 6% increase in individuals' activity spaces. Precipitation is associated with a 13% decrease in individuals' activity spaces. The results indicate the strong association between weather conditions and daily activity patterns. The results also support the early hypothesis that adverse weather conditions are associated with smaller activity spaces. Note that the relationship between temperature and daily activity space would be non-linear if I have travel data in extremely cold or hot weather.

For control variables, high household income, male, adult (age 35-65), employment, single-family detached housing, and a negative attitude towards length of commute are associated with small activity spaces.

Table 6-3 Modeling results on individual daily activity space

Variable	Full Model		Final Model	
	Untransformed OLS	Semi-log transformed OLS	Untransformed OLS	Semi-log transformed OLS
Constant	7405.506***	7.580***	7301.668***	7.314***
The built environment at the home location				
Parcel Count	-3.264***	-0.00032*	-4.046***	-0.00035**
Retail Count	36.154	-0.016*		-0.016*
Industrial count	87.214	-0.002		
Connected node ratio	-1529.084	-0.195		
Sidewalk length	-279.859	-0.087***		-0.098***
Traffic conditions at the home location				
Driving activity density	-12254.790***	-1.395**	-11752.677***	-1.550**
Weather conditions				
Daily lowest temperature	36.435	0.005		0.006*
Precipitation	-325.579	-0.128		-0.137*
Control factors				
HH size	-398.223	-0.059		
HH income	-110.224	0.057*		0.081***
Residential tenure	-114.545	-0.042		
Female	-2215.569***	-0.098*	-2148.954***	-0.102*
Children	-4158.611***	-0.880***	-4779.874***	-0.951***
Young adult	-3537.778***	-0.506***	-3827.404***	-0.505***
Old	-51.168	-0.303**		-0.287**
White	791.503	0.119		
Employed	2548.690***	0.391***	2683.572***	0.402***
Multiple jobholders	1186.819	0.153*		0.149*
Auto ownership	1394.442***	0.095**	1217.797***	
Traffic information usage	2159.635***	0.210***	2102.483***	0.212***
Commute attitude	-1492.473**	-0.182**	-1617.444***	-0.196***
Transit attitude	307.438	-0.184		
Single-family detached	2183.918***	0.216*	1947.428***	0.199*
Summary statistics				
N	4,937	4,937	4,937	4,937
R^2	0.059	0.106	0.057	0.103
Adjust R^2	0.055	0.102	0.055	0.100
F	15.88	19.12	33.11	24.46
F-test	0.000	0.000	0.000	0.000

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01.

Table 6-4 presents the modeling results on daily miles traveled. The models for daily miles traveled used the full sample—7,422 respondents. Modeling results from the final semi-log transformed model are presented in the following text.

Table 6-4 Modeling results on daily miles traveled

Variable	Full Model		Final Model	
	Untransformed OLS	Semi-log transformed OLS	Untransformed OLS	Semi-log transformed OLS
Constant	12.604***	1.918***	12.226***	1.972***
The built environment at the home location				
Parcel Count	-0.004***	-0.00021***	-0.004***	-0.00020***
Retail Count	0.006	-0.002		
Industrial count	-0.061	-0.010		
Connected node ratio	-2.138	-0.170*		-0.185*
Sidewalk length	-0.207	-0.021*		-0.028**
Traffic conditions at the home location				
Driving activity density	-3.248	-0.108	-5.688*	-0.338*
Weather conditions				
Daily lowest temperature	0.037	0.002		
Precipitation	-0.868	-0.074**		-0.056*
Control factors				
HH size	-0.029	-0.017		
HH income	0.094	0.027**		0.032***
Residential tenure	-0.037	-0.004		
Female	-1.496***	-0.060***	-1.498***	-0.059***
Children	-5.107***	-0.215***	-5.076***	-0.234***
Young adult	-3.908***	-0.133***	-3.957***	-0.132***
Old	-1.962**	-0.188***	-2.048***	-0.181***
White	1.703***	0.120***	1.957***	0.129***
Employed	5.225***	0.526***	5.271***	0.531***
Multiple jobholders	1.740**	0.119***	1.714**	0.116***
Auto ownership	0.526	0.023	0.625**	
Traffic information usage	2.011***	0.130***	2.008***	0.130***
Commute attitude	-2.062***	-0.096***	-2.091***	-0.100***
Transit attitude	-0.143	-0.025		
Single-family detached	1.853***	0.126***	2.099***	0.129***
Summary statistics				
N	7,422	7,422	7,422	7,422
R^2	0.103	0.139	0.101	0.137
Adjust R^2	0.100	0.136	0.099	0.136
F	40.80	48.78	66.62	64.17
F-test	0.000	0.000	0.000	0.000

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01.

Table 6-4 shows that daily miles traveled are negatively related to parcel count, connected node ratio, sidewalk length, driving density, and precipitation. Ten additional parcels within the 0.25-mile buffer area at the home location are associated with a 0.2% decrease in daily miles traveled. Ten percent additional intersections that are not dead ends are associated with 1.8% decrease in daily miles traveled. One additional mile of sidewalks within the buffer area is associated with a 2.8% decrease in daily miles traveled.

Heavy traffic in the residential neighborhood is associated with decreased daily miles traveled. A one-unit increase in driving activity density is associated with a 28.7% (exp(-0.338)-1=-0.287) decrease in daily miles traveled. As I expected, precipitation is associated with a 5.5% decrease in daily miles traveled.

When compared with activity space models, in models of daily miles traveled, connected node ratio becomes significant and the number of retail stores becomes insignificant. This does not mean inconsistent results between those two sets of models. Instead, modeling results from the two model sets indicate similar things after taking the different dependent variables into account. Daily activity space was defined as the minimum convex polygon containing daily activity locations, which does not reflect the shapes of paths (linear versus curvilinear) between activity locations. Thus, the daily activity space models may not be able to detect the effect of street connectivity on travel.

As I discussed in Chapter III (Table 3-2), built environment factors may have mixed effects on daily miles traveled. On one hand, compact development patterns shorten travel distance of each trip. On the other hand, compact development patterns may be associated with additional miles traveled because of their positive impact on travel demand. Therefore, an explanation that the number of retail stores shows significance in predicting daily activity space while not in predicting daily miles traveled is that the positive impact of retail stores on travel demand is so strong that it offsets the negative impact of retail stores on travel distance.

Activity Time Allocation Models

Two sets of activity time allocation models were developed to answer questions about how activity time allocation is related to residential environments and whether compact development patterns at the home location are associated with more time allocated to out-of-home activities and leisure activities. The dependent variables are respectively the number of minutes spent on out-of-home activities (excluding travel) by the individual per day, and the number of minutes spent on leisure activities by the individual per day. See Figure 6-3 for frequency distributions of the two dependent variables.

The key independent variables include indicators of the built environment at home location, traffic conditions at the home location, and weather conditions. Both the Tobit model and the Heckman selection model were used in this analysis. See Chapter IV for detailed model specifications.

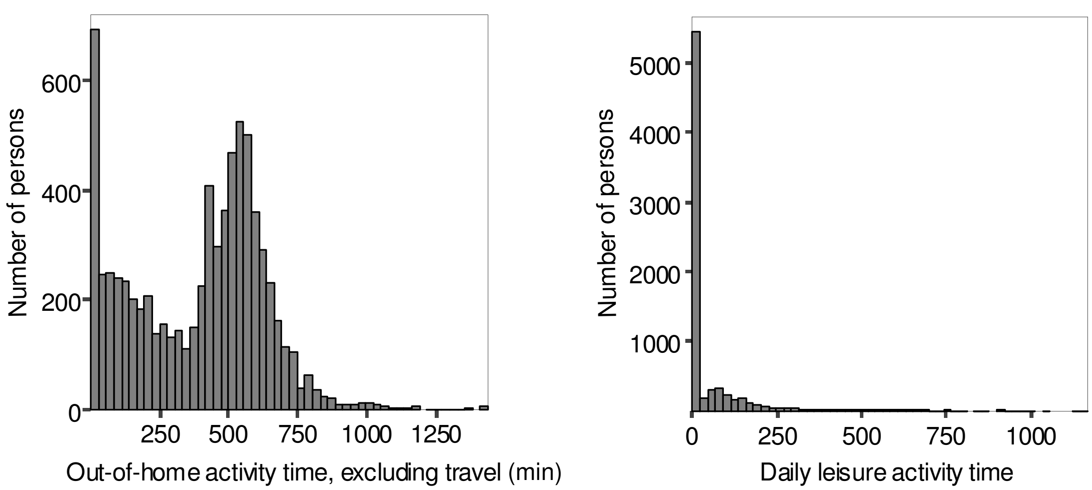


Figure 6-3 Frequency distributions of the activity time allocation variables

Out-of-home activities include all the daily activities conducted outside of the home but excluding travel. Leisure activities are a subset of the out-of-home activity category. This study defines leisure activities as activities related to social interaction, entertainment, recreation, and civic/religious purposes. Out of the 7,422 surveyed respondents, 6,936 respondents spent time outside their homes, and only 2,130 residents were engaged in out-of-home leisure activities on the survey day. Table 6-5 presents the Tobit modeling results. Table 6-6 and Table 6-7 present the Heckman selection modeling results.

The chi-square tests reported in Table 6-5 shows that all the Tobit models are statistically significant. The modeling results in Table 6-5 include estimated coefficients, marginal effects, and their significance. Unlike traditional regression coefficients, the Tobit coefficients cannot be interpreted directly as estimates of the marginal effects of changes in the explanatory variables on the expected value of the dependent variable. In a Tobit equation, each marginal effect includes both the influence of the explanatory variable on the probability of engagement as well as on the intensity of engagement. Model estimation software Stata/SE 8.0 provides a ‘dtobit2’ command for calculating the marginal effects of the estimated Tobit model. The marginal effects of our three Tobit models are presented in Table 6-5 as well, which translate the Tobit coefficients into OLS regression equivalents.

Table 6-5 Activity time allocation models using the Tobit model

Variable	Out-of-home activities			Leisure activities		
	Full model		Final	Full model		Final
	Coefficient	Marginal	Marginal	Coefficient	Marginal	Marginal
Constant	160.453***			-223.452***		
The built environment at the home location						
Parcel Count	0.003	0.003		-0.015	-0.004	
Retail Count	-0.656	-0.617		-1.927*	-0.559	-0.506
Industrial count	1.780	1.673		0.033	0.010	
Connected node ratio	24.030	22.595		-61.351**	-17.807	-16.586
Sidewalk length	-3.693	-3.472		2.373	0.689	
Traffic conditions at the home location						
Driving activity density	110.518**	103.918	86.742	234.259***	67.992	
Weather conditions						
Daily lowest temperature	0.588**	0.553	0.416	0.840**	0.244	0.169
Precipitation	-8.759	-8.236		-14.857	-4.312	
Control factors						
HH size	-13.338***	-12.541	-12.428	-11.308***	-3.282	-3.353
HH income	11.269***	10.596	10.043	-0.707	-0.205	
Residential tenure	4.502*	4.233	4.793	9.308***	2.702	2.655
Female	-31.812***	-29.913	-29.956	17.716**	5.142	5.097
Children	168.599***	158.531	158.509	-1.359	-0.394	
Young adult	164.473***	154.650	152.661	16.381	4.754	
Old	-114.677***	-107.828	-107.647	47.633***	13.825	12.755
White	-9.309	-8.753		54.472***	15.810	15.669
Employed	229.656***	215.941	215.135	-64.100***	-18.605	-18.744
Multiple jobholders	-31.186***	-29.323	-29.837	60.462***	17.549	17.419
Auto ownership	-2.822	-2.654		-1.890	-0.549	
Traffic information usage	25.682***	24.148	23.597	5.409	1.570	
Commute attitude	10.597*	9.964	9.617	7.420	2.154	
Transit attitude	1.317	1.238		11.962	3.472	
Single-family detached	11.322	10.645		28.412**	8.246	7.080
Summary statistics						
N=7,422 persons	6,936 uncensored observations			2,130 uncensored observations		
LL (convergence)	-53644.7		-53649.4	-19379.2		-19382.4
Std. error of residuals	249.088			293.283		
Pseudo R^2	0.0152		0.0151	0.0044		0.0042
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01.

Results show that daily time allocated to out-of-home activities (excluding travel time) is not sensitive to built environment factors in residential environments. All the built environment indicators are insignificant in the out-of-home activity model. Thus, the results do not support the hypothesis that compact development patterns are associated with more out-of-home activities. However, the variables of traffic conditions and weather conditions are significant in modeling out-of-home activity time allocation. Warm weather shows a positive association with time allocated to out-of-home activities. A 10- Fahrenheit degree increase in temperature is associated with 4.16 additional minutes allocated to out-of-home activities. Heavy traffic in the residential neighborhood is associated with more time allocated to out-of-home activities. A one-unit increase in driving activity density is associated with 86 additional minutes allocated to out-of-home activities. Note that this traffic condition indicator is the median value of driving activity density estimated using kernel function within the 0.25-mile buffer area around the home allocation, and the range of this indicator is from 0-1.687.

In the leisure activity time allocation model, two built environment factors are significant. One additional retail store within the 0.25-mile buffer area around a respondent's home location is associated with 0.51 less minutes allocated to out-of-home leisure activities by the respondent per day. A 0.1-unit increase in connected node ratio is associated with a 1.66-minute decrease in time allocated to out-of-home leisure activities. Leisure activity time allocation is positively and significantly related to urban traffic and temperature. A one-unit increase in driving activity density at the residential allocation is associated with 62 additional minutes allocated to leisure activities outside the home. A 10- Fahrenheit degree increase in temperature is associated with 1.69 additional minutes allocated to leisure activities.

Results indicate that compact land use patterns (higher density, more mixed land uses, more street grids, and more pedestrian facilities) show no association with time allocated to out-of-home activities or leisure activities. This contradicts our expectation that compact development patterns often mean more activity opportunities nearby and may stimulate out-of-home activity demand. However, results show that traffic conditions at the home location and weather conditions do matter in time allocation. Heavy traffic at the residential location is associated with more time spent on out-of-home activities including leisure activities. Higher temperature is associated with more time spent on out-of-home activities and leisure activities.

The Tobit model estimation has several limitations. First, it assumes the same variables affect both the engagement decision and the conditional decision about the actual activity/travel time. This creates difficulties in interpreting separately the effects on the engagement decision and the conditional decision. Second, the Tobit model cannot address the cluster structure of datasets and does not take into account the intra-household autocorrelation in the analysis, which may generate higher significance estimates. The Heckman selection model can avoid the limitations above. Table 6-6 and Table 6-7 present the Heckman selection modeling results.

The chi-square tests in Table 6-6 and Table 6-7 show that all the Heckman selection models are statistically significant. Each table contains the full model and the final model. The full model includes all the environmental variables and the control factors. The final model only includes the variables that are significant in the full model.

Table 6-6 Out-of-home activity time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection coefficient	Odds ratio	OLS coefficient	Selection coefficient	Odds ratio	OLS coefficient
Constant	1.101***	3.007	219.430***	1.040***	2.829	233.866***
The built environment at the home location						
Parcel Count	-0.000	1.000	0.005			
Retail Count	0.002	1.002	-0.770			
Industrial count	-0.029**	0.971	4.117**			
Connected node ratio	-0.196	0.822	36.501**			41.218**
Sidewalk length	0.008	1.008	-4.701**			-2.199
Traffic conditions at the home location						
Driving activity density	1.082*	2.951	55.133	0.738*	2.092	
Weather conditions						
Daily lowest temperature	0.001	1.001	0.555**			0.443*
Precipitation	-0.039	0.962	-6.477			
Control factors						
HH size	-0.073***	0.930	-9.929***	-0.072***	0.931	-10.260***
HH income	0.038**	1.039	9.104***	0.048***	1.049	8.699***
Residential tenure	0.010	1.010	3.847			
Female	0.020	1.020	-34.538***			-34.572***
Children	0.463***	1.588	144.989***	0.459***	1.582	144.390***
Young adult	0.361***	1.435	150.682***	0.352***	1.422	149.015***
Old	-0.189**	0.828	-109.424***	-0.187**	0.829	-106.711***
White	0.024	1.024	-11.352			
Employed	0.745***	2.107	191.497***	0.737***	2.090	191.313***
Multiple jobholders	0.011	1.011	-32.907***			-32.656***
Auto ownership	-0.010	0.990	-2.396			
Traffic information	0.018	1.018	26.028***			25.211***
Commute attitude	-0.025	0.975	12.549**			12.276**
Transit attitude	0.142	1.153	-6.880			
Single-family detached	0.074	1.077	7.984			
Summary statistics						
N=7,422 persons	6,936 uncensored observations			6,936 uncensored observations		
LL(convergence)	-54036.77			-54056.09		
Rho	0.075**			-0.073**		
Std. error of residuals	226.320			226.618		
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Table 6-7 Leisure activity time allocation models using the Heckman selection with OLS model

Variable	Full model			Final model		
	Selection			Selection		
	coefficient	Odds ratio	OLS coefficient	coefficient	Odds ratio	OLS coefficient
Constant	-0.867***	0.420	214.470***	-0.858***	0.424	218.130***
The built environment at the home location						
Parcel Count	-0.000	1.000	-0.012			
Retail Count	-0.006	0.994	-1.383			
Industrial count	-0.007	0.993	4.054			
Connected node ratio	-0.201	0.818	-19.145			
Sidewalk length	0.013	1.013	-0.751			
Traffic conditions at the home location						
Driving activity density	1.016***	2.762	-50.525	0.594***	1.811	
Weather conditions						
Daily lowest temperature	0.003	1.003	0.202			
Precipitation	-0.069	0.933	5.935			
Control factors						
HH size	-0.033*	0.968	-5.992	-0.032*	0.969	
HH income	0.010	1.010	-7.577**			-9.453***
Residential tenure	0.032**	1.033	2.779	0.030*	1.030	
Female	0.083***	1.086	-5.556	0.080***	1.083	
Children	0.031	1.032	-17.816			
Young adult	0.012	1.013	27.994			
Old	0.154***	1.166	20.048	0.130**	1.139	
White	0.226***	1.254	-6.051	0.223***	1.250	
Employed	-0.181***	0.834	-36.509***	-0.198***	0.820	-27.570***
Multiple jobholders	0.254***	1.289	-3.274	0.255***	1.290	
Auto ownership	-0.030	0.971	12.548*			13.275**
Traffic information	0.012	1.012	5.434			
Commute attitude	0.016	1.016	9.158			
Transit attitude	0.087	1.091	-18.334*			-27.570***
Single-family detached	0.105*	1.110	2.050	0.109**	1.115	
Summary statistics						
N=7,422 persons	2,130 uncensored observations			2,130 uncensored observations		
LL(convergence)	-20478.97			-20507.88		
Rho	-0.022			-0.075*		
Std. error of residuals	183.69			185.37		
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Compared to the Tobit models in Table 6-5, the Heckman selection models in Table 6-6 and 6-7 provide more informative results, indicating the effects of environmental factors on both activity engagement/participation and time allocation.

Results show that, although built environment factors do not significantly relate to the probability of being engaged in out-of-home activities, connected node ratio are positively and significantly associated with the time spent on out-of-home activities after the engagement decision was made. A 0.1-unit increase in connected node ratio is associated with 0.4 additional minutes spent on out-of-home.

In the Heckman selection models, none of the built environment factors are significant in predicting time allocated to leisure activities, while the number of retail stores and connected node ratio are significant in the Tobit models. Besides the reason that the Tobit models did not account for autocorrelation among household members, this may be partly due to that the Tobit models present the aggregate effects on the engagement decision and the conditional decision about the actual activity time.

Results show that the propensity that an individual is engaged in out-of-home activities is related to driving activity density at the individual's home location, while the actual time spent on out-of-home activities is not. A one-unit increase in driving activity density is associated with a109% increase in the odds of being engaged in out-of-home activities, and is associated with an 81% increase in the odds of being engaged in leisure activities.

The propensity of being engaged in out-of-home activities and leisure activities is not significantly related to weather conditions. However, warm weather is associated with more actual out-of-home activity time. For those who engaged in out-of-home activities, a10-Fahrenheit degree increase in temperature is associated with 4.43 additional minutes spent on out-of-home activities.

For control variables, people with large household size, women, and old people are associated with less time allocated to out-of-home activities. High income, younger age, and employment are associated with more time allocated to out-of-home activities. Large household size and employment are associated with less leisure activities, while residential tenure, female, elderly, white racial category, and single-family detached housing are associated with more leisure activities.

In general, the built environment at the residential location shows no association with activity time allocation, while traffic conditions at the home location and weather conditions are significantly associated with activity time allocation. Heavy traffic at the residential location is associated with more out-of-home activities including leisure activities. Warm weather is associated with more time spent on out-of-home activities.

Travel Time Allocation Models

This section examines travel time allocations to various modes separately, including driving, walking, taking transit, and bicycling. See Figure 6-4 for frequency distributions of daily driving time, daily walking time, and daily transit time. Both the Tobit model and the Heckman selection model were applied to investigate the relationship between environment factors and mode-specific travel time allocations.

Results in the previous section show that the Heckman selection models provide more informative results and is more methodologically appealing. Therefore, the Tobit modeling results were presented in Table 6-8 and Table 6-9 but are not described in the text. The Heckman selection models were presented in Table 6-10, Table 6-11, and Table 6-12 were discussed in the following text.

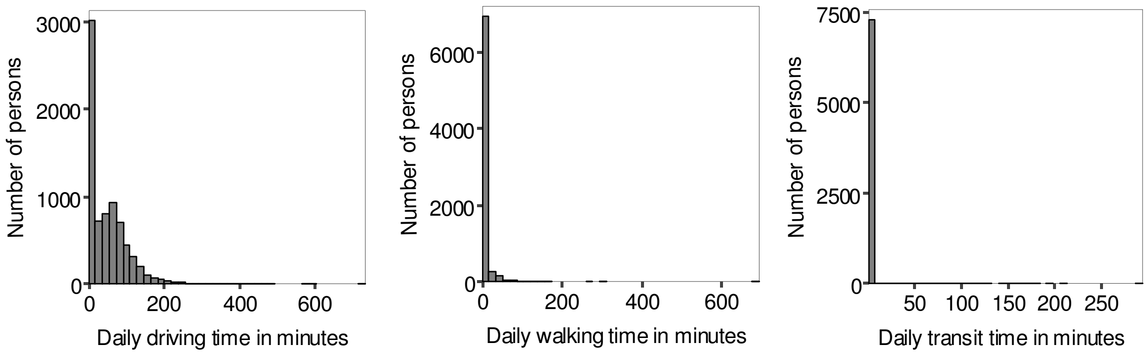


Figure 6-4 Frequency distributions of the travel time allocation variables

Table 6-8 Drive and walk time allocation models using the Tobit model

Variable	**Drive**			**Walk**		
	Coef.	Marg.	F. Marg.	Coef.	Marg.	F. Marg.
Constant	29.282***			-61.598***		
The built environment at the home location						
Parcel Count	-0.013***	-0.008	-0.009	0.007*	0.001	0.001
Retail Count	-0.198	-0.126		-0.198	-0.029	
Industrial count	-0.463	-0.294		-0.865*	-0.125	-0.172
Connected node ratio	-16.422***	-10.421	-11.986	17.588***	2.542	2.491
Sidewalk length	0.281	0.178		3.326***	0.481	0.497
Traffic conditions at the home location						
Driving activity density	1.633	1.036		82.567***	11.932	11.512
Weather conditions						
Daily lowest temperature	0.005	0.003		-0.135	-0.019	
Precipitation	-3.939*	-2.500	-2.510	-2.314	-0.3343	
Control factors						
HH size	-3.722***	-2.362	-2.191	-1.746*	-0.252	-0.314
HH income	2.176***	1.381	1.756	0.425	0.061	
Residential tenure	-1.914**	-1.215	-1.020	-0.444	-0.064	
Female	-6.954***	-4.413	-4.296	1.658	0.240	
Children	-512.581[1]	-325.260	-332.870	-3.239	-0.468	
Young adult	-42.328***	-26.859	-26.799	-0.104	-0.015	
Old	-2.849	-1.808		-13.397***	-1.936	-2.057
White	3.802	2.413		16.703***	2.414	2.506
Employed	35.837***	22.741	23.065	-0.735	-0.1062	
Multiple jobholders	9.814***	6.228	6.237	4.149	0.599	
Auto ownership	8.933***	5.668	5.858	-8.535***	-1.233	-1.157
Traffic information	9.596***	6.089	6.142	-8.784***	-1.269	-1.307
Commute attitude	-5.873***	-3.727	-3.556	3.223	0.466	
Transit attitude	-7.075**	-4.490	-4.681	16.386***	2.368	2.449
Single-family detached	4.150	2.634		-7.727***	-1.117	-1.124
Summary statistics						
N=7,422 persons		4,644 uncensored			988 uncensored	
LL(convergence)		-30601.441			-8250.8406	
Pseudo R^2		0.0706			0.0313	
Std. error of residuals		72.574			56.213	
Chi-square test		0.000			0.000	

Note: * p<0.10; ** p<0.05; *** p<0.01; F. Marg.: Marginal effects in the final model.

Out of 7,422 respondents in Orange, Durham, and Wake Counties, 4,644 made driving trips on the survey day. 989 of 7,422 respondents made walking trips. 154 respondents made transit trips and only 82 respondents reported bicycle trips. Results show that all the four Tobit models are statistically significant. The transit Tobit model has the highest pseudo R-square than other Tobit models.

Table 6-9 Transit and bicycle time allocation models using the Tobit model

Variable	**Transit**			**Bicycle**		
	Coef.	Marg.	F. Marg.	Coef.	Marg.	F. Marg.
Constant	-38.922			-341.833***		
The built environment at the home location						
Parcel Count	0.014	0.000		0.031*	0.000	0.000
Retail Count	-1.321*	-0.034	-0.041	-1.004	-0.012	
Industrial count	-0.914	-0.023		2.709	0.033	
Connected node ratio	31.856	0.814		-44.639	-0.538	
Sidewalk length	-0.323	-0.008		2.803	0.034	
Traffic conditions at the home location						
Driving activity density	146.250***	3.738	4.827	239.843***	2.888	2.308
Weather conditions						
Daily lowest temperature	-1.299***	-0.033	-0.029	1.047**	0.013	0.010
Precipitation	11.919	0.305		-15.522	-0.187	
Control factors						
HH size	-6.186*	-0.158	-0.183	4.387	0.053	
HH income	-7.408***	-0.189	-0.245	-12.533***	-0.151	-0.128
Residential tenure	-8.131***	-0.208	-0.255	-3.414	-0.041	
Female	0.032	0.001		-49.613***	-0.597	-0.616
Children	-74.053***	-1.893	-1.934	9.267	0.112	
Young adult	3.492	0.089		-11.542	-0.139	
Old	-29.205**	-0.746	-0.752	-57.669*	-0.694	-0.811
White	-32.432***	-0.829	-0.839	66.250***	0.798	0.755
Employed	19.712**	0.504	0.446	12.349	0.149	
Multiple jobholders	-14.232	-0.364		34.080**	0.410	0.434
Auto ownership	-23.476***	-0.600	-0.651	-4.867	-0.059	
Traffic information	-8.204	-0.210		3.702	0.045	
Commute attitude	-20.720***	-0.530	-0.490	41.260***	0.497	0.518
Transit attitude	77.585***	1.983	2.034	27.767**	0.334	0.330
Single-family detached	-20.567**	-0.526		18.447	0.222	
Summary statistics						
N=7,422 persons	154 uncensored			82 uncensored		
LL(convergence)	-1724.7607			-929.8682		
Pseudo R^2	0.1375			0.0721		
Std. error of residuals	104.331			120.610		
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; F. Marg.: Marginal effect in the final model.

Table 6-10, Table 6-11, and Table 6-12 respectively present drive time allocation models, walk time allocation models, and transit time allocation models using the Heckman selection model. Bicycle time allocation models were not presented because only 82 respondents from 70 households reported bicycle use and the small number of cases further led to unsuccessful and insignificant Heckman selection models.

Table 6-10 Drive time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection			Selection		
	Coefficient	Odds ratio	OLS coefficient	Coefficient	Odds ratio	OLS coefficient
Constant	0.371***	1.449	32.828***	0.350***	1.419	32.847***
The built environment at the home location						
Parcel Count	-0.00019***	1.000	-0.013***	-0.00018***	0.99982	-0.013***
Retail Count	-0.003	0.997	-0.184			
Industrial count	-0.009	0.991	-0.375			
Connected node ratio	-0.208**	0.813	-15.903***	-0.248***	0.780	-18.048***
Sidewalk length	0.002	1.002	0.359			
Traffic conditions at the home location						
Driving activity density	0.081	1.085	-0.827			
Weather conditions						
Daily lowest temperature	-0.000	1.000	0.012			
Precipitation	-0.046	0.955	-3.969**			-0.781*
Control factors						
HH size	-0.063***	0.939	-3.288***	-0.060***	0.941	-3.056***
HH income	0.030***	1.030	2.036***	0.039***	1.039	2.544***
Residential tenure	-0.030**	0.970	-1.769**	-0.027**	0.973	-1.475**
Female	-0.087***	0.916	-7.155***	-0.086***	0.918	-6.963***
Children	-8.146***	0.000		-8.111***	0.000	
Young adult	-0.577***	0.561	-40.194***	-0.577***	0.562	-39.884***
Old	-0.046	0.955	-2.543			
White	0.052	1.053	2.901			
Employed	0.488***	1.629	34.210***	0.493***	1.637	34.718***
Multiple jobholders	0.135***	1.144	9.631***	0.135***	1.145	9.552***
Auto ownership	0.139***	1.149	8.145***	0.144***	1.155	8.420***
Traffic information	0.122***	1.129	9.594***	0.122***	1.130	9.648***
Commute attitude	-0.072**	0.931	-6.303***	-0.067**	0.935	-6.029***
Transit attitude	-0.116***	0.891	-5.894*	-0.117***	0.889	-6.241**
Single-family detached	0.070*	1.073	3.795	0.017	1.018	
Summary statistics						
N=7,422 persons	4,644 uncensored			4,644 uncensored		
LL(convergence)	-26814.01			-26823.86		
Rho	0.999***			0.999***		
Std. error of residuals	71.093			71.090		
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Table 6-11 Walk time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection			Selection		
	coefficient	Odds ratio	OLS coefficient	coefficient	Odds ratio	OLS coefficient
Constant	-1.010***	0.364	18.595**	-1.020***	0.361	25.400***
The built environment at the home location						
Parcel Count	0.000	1.000	0.002			
Retail Count	-0.004	0.996	0.008			
Industrial count	-0.017*	0.983	-0.043	-0.024***	0.976	
Connected node ratio	0.235*	1.264	17.100***	0.238*	1.269	21.435***
Sidewalk length	0.059***	1.061	0.633	0.069***	1.072	
Traffic conditions at the home location						
Driving activity density	1.734***	5.660	-0.559	1.764***	5.837	
Weather conditions						
Daily lowest temperature	-0.004*	0.996	0.198	-0.005**	0.995	
Precipitation	-0.035	0.966	-1.078			
Control factors						
HH size	-0.030	0.971	-0.960			
HH income	0.006	1.006	0.306			
Residential tenure	-0.006	0.994	-0.831			
Female	0.057*	1.059	-3.359*	0.061*	1.062	-3.793**
Children	0.003	1.003	-9.929***			-10.942***
Young adult	0.059	1.061	-9.117***			-9.272***
Old	-0.237***	0.789	-3.370	-0.231***	0.793	
White	0.323***	1.382	-0.127	0.348***	1.416	
Employed	-0.023	0.977	1.237			
Multiple jobholders	0.101	1.106	-2.552			
Auto ownership	-0.145***	0.865	-2.585**	-0.153***	0.858	-2.334**
Traffic information	-0.168***	0.846	-0.027	-0.173***	0.841	
Commute attitude	0.038	1.039	3.156			
Transit attitude	0.326***	1.385	-0.247	0.326***	1.386	
Single-family detached	-0.151**	0.860	0.887	-0.159***	0.853	
Summary statistics						
N=7,422 persons	988 uncensored			988 uncensored		
LL(convergence)	-7578.292			-7590.814		
Rho	-.0438**			-0.0834*		
Std. error of residuals	32.088			32.355		
Chi-square test	0.000			0.000		

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Table 6-12 Transit time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection coefficient	Odds ratio	OLS coefficient	Selection coefficient	Odds ratio	OLS coefficient
Constant	-0.318	0.728	52.712**	-0.093	0.911	47.129***
The built environment at the home location						
Parcel Count	0.000	1.000	-0.012**			-0.019***
Retail Count	-0.013*	0.988	-0.356	-0.017***	0.983	
Industrial count	-0.008	0.992	-0.348			
Connected node ratio	0.342	1.408	-16.790			
Sidewalk length	-0.019	0.982	5.731**			5.926**
Traffic conditions at the home location						
Driving activity density	1.555***	4.737	5.961	1.924***	6.850	
Weather conditions						
Daily lowest temperature	-0.013***	0.987	0.587**	-0.012***	0.988	0.602**
Precipitation	0.120	1.128	-7.224			
Control factors						
HH size	-0.081**	0.922	9.499***	-0.076**	0.927	9.979***
HH income	-0.069***	0.934	-2.177	-0.080***	0.923	
Residential tenure	-0.086***	0.918	2.552	-0.080***	0.923	
Female	0.019	1.019	-6.799			
Children	-0.676***	0.509	-18.599*	-0.709***	0.492	-10.652*
Young adult	0.031	1.031	1.968			
Old	-0.330**	0.719	16.673	-0.287*	0.751	
White	-0.293***	0.746	-8.636	-0.300***	0.741	
Employed	0.185*	1.204	0.347	0.149	1.161	
Multiple jobholders	-0.183	0.832	21.718**			17.963*
Auto ownership	-0.215**	0.806	0.601	-0.220***	0.802	
Traffic information	-0.114	0.892	9.861			
Commute attitude	-0.203**	0.816	-2.230	-0.204***	0.815	
Transit attitude	0.753***	2.123	7.976	0.761***	2.141	
Single-family detached	-0.189**	0.828	-5.762	-0.181**	0.834	
Summary statistics						
N=7,422 persons		154 uncensored			154 uncensored	
LL(convergence)		-1755.473			-1769.574	
Rho		-0.387			-0.501*	
Std. error of residuals		41.633			45.538	
Chi-square test		0.000			0.000	

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

All the Heckman selection models in Table 6-10, Table 6-11, and Table 6-12 are statistically significant, shown by the chi-square test in the tables. Results show that the engagement of driving is negatively related to the number of parcels and connected node ratio at the home location. Traffic conditions at the home location and weather conditions show no association with either the engagement of driving or the actual driving time. More walking trip making was found to be related to less industrial firms, higher connected node ratio, more sidewalk coverage, and heavier traffic in the residential neighborhood, and lower temperature.

As shown in Table 6-10, ten additional parcels within the 0.25-mile buffer area around an individual's home location are associated with a 0.18% decrease in the odds of driving and a 0.13-minute decrease in the actual driving time. This supports our earlier hypothesis that land use density at the home location is negatively associated with driving time allocation. A 0.1-unit increase in connected node ratio (meaning ten percent additional intersections that are not dead ends) is associated with a 2.45% decrease in the odds of driving, and for those who are engaged in driving, it is also associated with a 1.80-minute decrease in the actual driving time.

As shown in Table 6-11, one additional industrial firm in an individual's residential neighborhood is associated with a 2.4% decrease in the individual's odds of making walking trips. This is consistent with our hypothesis that industrial uses are negatively associated with walking behavior. Ten percent additional intersections that are not dead ends (a 0.1-unit increase in connected node ratio) is associated with a 2.4% increase in the odds of walking, and is associated with 2.14 additional minutes in the actual walking time. This is consistent the earlier hypothesis that grid street patterns are associated with more walking. As I expected, sidewalk coverage is positively associated with walking. One additional mile of sidewalks is associated with 7.2% increase in the odds of walking.

Heavy traffic in the residential neighborhood is associated with high walking trip generation. A one-unit increase in driving activity density is associated with a 483% increase in the odds of walking. This indicates traffic congestion in central cities is associated with a substitution of walking trips for trips using motorized modes. In other words, the evidence shows that traffic congestion have an effect on travel more than just suppressing auto travel—it may encourage walking at the same time. Warm weather is associated with low probability of walking. A 10-Fahrenheit degree increase in temperature is associated with a 4.89% decrease in the odds of walking ($-4.89\%=0.995^{10}-1$).

As shown in Table 6-12, higher probability of transit use is associated with fewer retail stores and heavier traffic in the residential neighborhood, and is associated with lower temperature. One additional retail store in the residential neighborhood is associated with a 1.7% decrease in the odds of using transit. A one-unit increase in driving activity density at the home location is associated with a 585% increase in the odds of using transit. This result is consistent with the finding that heavy traffic is associated with increased odds of walking. It is additional supportive evidence that traffic congestion not only suppresses auto travel but may also encourage the use of alternative modes.

A 10-Fahrenheit degree increase in temperature is associated with an 11.4% decrease in the odds of using transit. The actual time spent on transit use is positively related to connected node ratio and temperature, and is negatively related to the number of parcels in the 0.25-mile buffer area at the home location. For those who choose to make transit trips, ten additional parcels in the neighborhood are associated 0.19 fewer minutes spent on transit use. One additional mile of sidewalks is associated with 5.9 additional minutes spent on transit use. A 10-Fahrenheit degree increase in temperature is associated with 6.02

additional minutes spent on transit use. Note that the range of daily lowest temperature in this dataset is from 21˚F to 66˚F, which does not contain extremely cold weather or extremely warm weather. This is part of the reason that I can not detect the non-linearity of temperature in predicting travel behavior.

In general, grid street patterns and presence of sidewalks are associated with more walking. Industrial uses are associated with less walking. High land use density and grid street patterns are associated with less driving. Traffic conditions at the home location and weather conditions do not have a significant relationship with driving. However, heavy traffic at home allocation and low temperature is significantly associated with high probability of walking or using transit.

Key Findings and Limitations

Table 6-13 summarizes the evidence found in the individual activity space and time allocation analysis. The analysis results show supportive evidence for our early hypothesis about the reduction effect of heavy traffic, adverse weather conditions, and compact development patterns on daily activity space. Supportive evidence was also found for the association between adverse weather conditions and less use of alternative modes, the association between heavy traffic and more use of alternative modes, and the association between compact development patterns and high walking trip generation and low driving trip generation.

Table 6-13 Evidence found in the individual activity space and time allocation analysis (direct measure models)

Changes in environmental factors	Daily activity space	Daily miles traveled	Changes in daily time allocation: Out-of-home activity (E)	Out-of-home activity (T)	Leisure activity (E)	Leisure activity (T)	Drive (E)	Drive (T)	Walk (E)	Walk (T)	Transit (E)	Transit (T)
The built environment												
+10 parcels	-0.35%	-0.20%					-0.18%	-0.13				-0.19
+1 retail store	-1.6%										-1.7%	
+1 industrial firm									-2.4%			
+0.1 connected ratio		-1.8%		4.12			-2.5%	-1.80	2.4%	2.14		
+1 mile sidewalks	-9.3%	-2.8%							7.2%			5.9
Traffic conditions												
+1 driving activity/acre	-79%	-29%	109%		81%				484%		585%	
Weather conditions												
+10 ˚F in temperature	6.2%			4.43					-4.9%		-11%	6.02
Precipitation	-12.8%	-5.5%						-0.78				

Note: E: the percent change in the odds of being engaged in the activity or travel category; T: the unit increase in the actual activity or travel time.

Less spatially dispersed daily activity locations are related to dense developments, more retail stores, presence of sidewalks, and presence of heavy traffic in the residential neighborhood and are related to cold weather and precipitation. The environment effect on daily miles traveled aggregates the environment effect on trip making and the environment effect on the distance of each trip. Even though the positive environment effect on trip making may offset the negative environment effect on trip distance, land use density, street grids, sidewalks, heavy traffic, and precipitation are associated with fewer daily miles traveled.

In terms of activity time allocation, most of the built environment factors at the home location are not significant in predicting time allocations to out-of-home activities or leisure activities, but are significant in predicting mode-specific travel time allocation. Both the probability of driving and the actual driving time are negatively related to the land use density indicator – the number of parcels within the 0.25-mile buffer area at the home location. The probability of walking is negatively related to industrial uses in the residential neighborhood. High connected node ratio is not only associated with less driving, but is also associated with more walking and longer walking time. This supports the hypothesis that better connected streets can encourage more walking to substitute auto use. The presence of sidewalks is positively associated with the engagement of walking.

Traffic conditions at the home location and weather conditions are significant in both the set of activity time allocation models and the set of travel time allocation models. Heavy traffic in the residential neighborhood is associated with high chances of being engaged in out-of-home activities and out-of-home leisure activities, and is associated with high probability of walking and using transit. Warm weather is associated with more time spent on out-of-home activities, and is associated with low probability of walking and using transit.

The Heckman selection models generally provide more informative results than the Tobit models. Variables relating to the engagement decision are different from variables relating to the conditional decisions about the actual activity or travel time. In addition, the Heckman selection model can take into account the intra-household autocorrelation while the Tobit model cannot (using existing software).

Although the Heckman model is more appealing the Tobit model in many ways, the Tobit model has its strengths. For example, the number of parcels is positively significant in the Tobit model of walking time allocation. In the Heckman selection model, the number of parcels positively relates to both the probability of walking and the actual walking time, but either of the positive relationships is significant. Thus, the Heckman selection model may underestimate the significance of the variables that may aggregately have a significant effect on time allocation (including both the engagement decision and the conditional decision of the actual activity or travel time). However, due to the fact that the Tobit model cannot adjust the intra-household autocorrelation, I cannot safely draw conclusions about the significance of effects.

Another limitation of this individual time allocation analysis is that the results can only show the quantitative associations between environmental factors and daily time allocation, but are not able to provide insights into the mechanisms behind the associations. As the models examine the time spent on each mode per day per individual, the dependent variables are aggregate values reflecting travel demand, travel distance and travel speed. Thus, the results do not tell us how factors in urban environments may be respectively associated with travel demand, travel distance, and travel speed of each mode, but only tell us the overall impact of the environment factors on daily time allocations to various activities and travel modes. For example, we can argue that the positive relationship between walking time and density may be due to that 1) high density is associated with low travel speed of pedestrians, 2) high density is associated with high walking demand, and/or 3) high density is associated with long travel distance. That is, we do not know in which way or ways higher density prolongs walking time. Disentangling those mixed effects would require a closer look into each trip. The next chapter takes this challenge and develops more disaggregate models of trip distance and trip duration at the single activity/trip level.

In addition, this analysis uses the built environment and traffic conditions at the home location to predict daily time allocation. However, theoretically, the built environment and traffic conditions within all the daily activity spaces (including the home location, the job location, other destinations, and places along travel routes) can influence individual time allocation. Thus, omitted variable bias may exist in this analysis.

CHAPTER VII: Neighborhood Clusters, Activity Space, and Time Allocation

The previous chapter focuses on specific elements in the built environment and isolates their effects on individual activity space and time allocation. In this chapter, I first identify neighborhood types using more than twenty environmental measures at the census block group level and the 0.25-mile residential location buffer level. A mean comparison analysis was then conducted to provide a general picture about how individuals' activity spaces and time allocations differ across different neighborhood types. To further quantify the relationship between neighborhood types and individual activity-travel behavior, the identified neighborhood clusters were included in a set of regression models to estimate their connections with individual activity space and time allocation. Untransformed OLS and semi-log transformed OLS were used to model the spatial measures of individual activity-travel behavior. The Heckman selection model was applied to estimate time allocation models.

Identification of Neighborhood Clusters

Developing a neighborhood typology based on more than twenty environmental measures involves two basic data reduction techniques. One is factor analysis and another is cluster analysis. Factor analysis reduces redundancy and condenses multiple variables into a more compact and efficient set of factors. Cluster analysis groups together neighborhoods that are most similar in terms of factors.

Using principal factor analysis, a total of five environmental factors were derived, respectively representing the following dimensions: 1) general density, 2) land use diversity, 3) access to the Interstate Highway System, 4) social diversity, and 5) neighborhood wealth. The extracted five factors capture about 65% of the total variation among the 25 environmental indicators. Factor scores were generated on each of these five factors for the 3,480 households using the default regression method (in Stata8.0) suggested by Thompson. Factors are scaled such that means and standard deviations equal zero and one, respectively.

Base on the five derived factors, this analysis further identifies neighborhood typologies using K-means cluster analysis. K-means cluster analysis uses Euclidean distance. Initial cluster centers are chosen in a first pass of the data. Then, each additional iteration categorizes observations based on nearest Euclidean distance to the mean of the cluster. Cluster centers change at each pass. The process continues until cluster means do not shift more than a given cut-off value or the iteration limit is reached.

To select the neighborhood typologies that make most sense, I performed a series of analyses by varying the number of clusters from 6 to 10. According to the local knowledge, the six-cluster scenario is the most appropriate and representative in describing neighborhood types within the Triangle region. Figure 7-1 displays the spatial distribution of the categorized households using six clusters – downtown neighborhoods, urban neighborhoods, suburban neighborhoods, industrial neighborhoods, “gated communities”, and exurban neighborhoods. The six identified neighborhood types are described below.

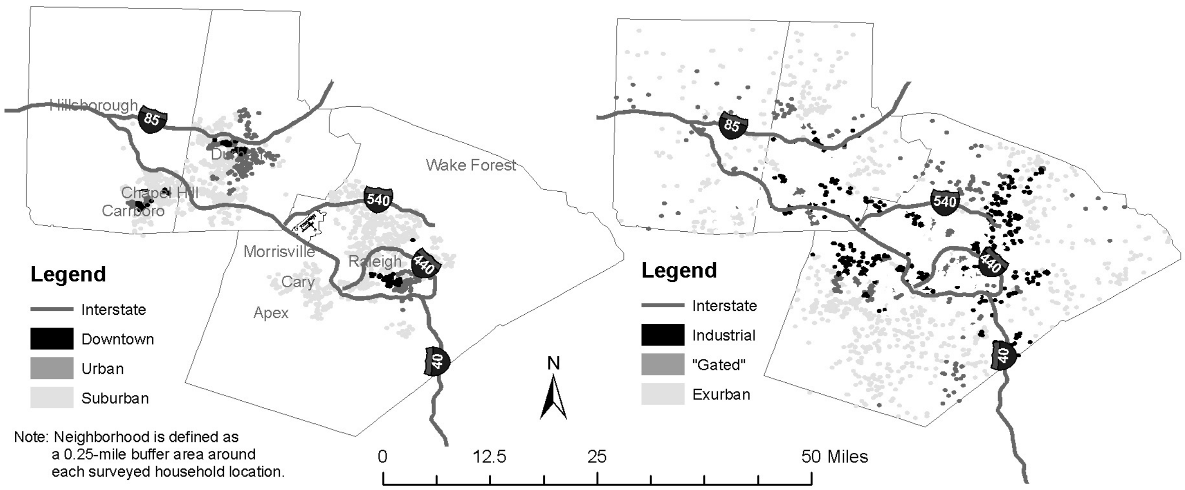


Figure 7-1 Identified clusters of survey households

Downtown neighborhoods, shown in black on the left side of Figure 7-1, are located in the central business districts in the Triangle region. They are the commercial hearts in the Triangle cities including Carrboro, Chapel Hill, Durham, and Raleigh. Downtown neighborhoods tend to have very high density, great diversity, and low access to the Interstate Highway System. In addition, the downtown area often has the best transit service and sidewalk coverage in the cities. 132 of the total 3,480 surveyed households lived in the downtown neighborhoods.

Urban neighborhoods, shown in dark gray on the left side of Figure 7-1, are located near the downtown districts. The density in the urban neighborhoods is high but not as high as the downtown area. Given the general development patterns in the Triangle area, urban neighborhoods do not have a good mix in various land uses. Urban neighborhoods have good transit service and sidewalk coverage, and have a high concentration of low-income residents. Urban neighborhoods do not have a good access to the Interstate Highway System. Out the 3,480 surveyed households, 284 households were identified as the urban neighborhood type.

Suburban neighborhoods, shown in light gray on the left side of Figure 7-1, are located on the outskirts of the cities. The neighborhoods have low density and diversity, and have a concentration of middle-class households. Most homes are owner-occupied and single-family houses. The neighborhoods have good access to the Interstate Highway System. Suburban neighborhoods are the most typical neighborhood type in the Triangle region. More than 40% of the surveyed households lived in suburban neighborhoods, including a total of 1,404 households.

Industrial neighborhoods, shown in black on the right side of Figure 7-1, are located further away from the city. The neighborhoods often contain intense industrial uses or highway retail uses. Therefore, the industrial neighborhoods have the best access to the Interstate Highway System in the region. The land value in the neighborhood is cheap and residential density is very low. Although those neighborhoods have great diversity in land uses, residential environments of the neighborhoods are not desirable. 434 out of 3,480 survey households lived in industrial neighborhoods.

"Gated communities", shown in dark gray on the right side of Figure 7-1, are often located at the urban fringe and close to natural amenities such as surface water and forest. Single-family homes with large lot sizes dominate the landscape of those neighborhoods. People living there have the highest income in the region. Less than 10% of the surveyed households belong to this category, including a total of 329 households.

Exurban neighborhoods, shown in light grey on the right side of Figure 7-1, are located in the outer suburbs of the urbanized area. The neighborhoods have large lot size and the lowest residential density in the region. Residents there are often farmers or long-distance commuters. 900 out of 3,480 surveyed households lived in exurban neighborhoods.

Mean Comparison

To gain a more comprehensive and explicit view of who lives in various neighborhood clusters and how the residents' daily activity spaces and daily time allocations differ across clusters, I conducted a mean comparison analysis by neighborhood type. Table 7-1 shows how individual and household characteristics vary by neighborhood type. Results show that the downtown neighborhoods have smaller family size (2.5) than other neighborhoods (3.0-3.3). Compared to other neighborhood clusters, urban neighborhoods have the poorest households in the Triangle area. The median income category for urban households is 2 ($15,000 - $24,999), which is much lower than the regional median value of 6 ($75,000 - $99,999).

Table 7-1 Socio-demographic mean comparison by neighborhood type

Variable	Downtown N=188	Urban N=528	Suburban N=2,857	Industrial N=949	Gated N=754	Exurban N=2,146
HH size	2.523	3.053	3.009	3.108	3.249	3.305
[a] HH Income	5	2	6	6	6	6
Residential tenure	3.245	3.107	3.683	3.250	3.845	3.568
Children	0.079	0.199	0.207	0.217	0.240	0.226
Young adult	0.084	0.083	0.068	0.081	0.058	0.082
Adult	0.684	0.554	0.586	0.609	0.622	0.569
Old	0.153	0.163	0.140	0.093	0.080	0.122
Female	0.507	0.546	0.527	0.544	0.511	0.503
White	0.766	0.217	0.827	0.732	0.877	0.883
Employed	0.645	0.420	0.573	0.549	0.556	0.530
Multiple jobholder	0.116	0.043	0.092	0.069	0.087	0.071
Auto ownership	1.392	0.963	2.011	1.935	2.120	2.237
Traffic information	0.277	0.501	0.537	0.567	0.611	0.640
Commute attitude	0.644	0.436	0.623	0.582	0.579	0.465
Transit attitude	0.326	0.437	0.165	0.098	0.073	0.061

Note: [a] Median values are shown for household income. 1 represents <$15,000; 2 represents $15,000 to $24,999; 3 represents $25, 000 to $34,999; 4 represents $35,000 to $49,999; 5 represents $50,000 to $74,999; 6 represents $75,000 to $99,999; and 7 represents $100,000 or more.

On average, downtown households own 1.4 cars per household, which is higher than urban households (0.96) but lower than other neighborhood clusters (from 1.9 to 2.2 cars per households). The percentage of households seeking traffic information increases towards the more rural clusters.

In terms of residential location choice, both downtown and suburban residents are most likely to consider their job locations or commuting length as an important factor, while urban and exurban residents are least likely to do that. Access to transit was considered as an important home location factor to 44% of the urban residents, which is much more than other neighborhood clusters.

Among personal demographics, female percentage is very similar across neighborhood clusters. Downtown neighborhoods have the lowest rate of children (14 years old or younger). Industrial neighborhoods and "gated communities" have a higher percentage of old people than other neighborhoods. The share of white population is lowest in urban neighborhoods, showing a strong association between race and income. The worker status is most common in downtown and suburban neighborhoods. The share of workers is lowest in urban neighborhoods. Most triangle residents are employed with one job. Downtown residents have the highest percentage of multiple jobholders in the region.

Figure 7-2 presents how individual activity space and individual daily miles traveled vary across neighborhood clusters. Figure 6-2 suggests that downtown and urban residents travel less than residents in other neighborhood types and have less spatially dispersed weekday activity patterns. Average daily miles traveled and the average size of activity spaces increase in the downtown –exurban direction: lowest in the downtown clusters and highest in the exurban clusters. The average daily miles traveled by downtown residents is

10.4 miles, which is about 7 miles fewer than that of exurban residents. The average area size of downtown residents' activity spaces is 3,500 acres, which is about 5,500 acres smaller than that of exurban residents. The results that central-city and urban residents have smaller activity space than suburban residents coincide with the existing evidence in the literature (Chapin 1974; Schonfelder and Axhausen 2003; Buliung and Kanaroglou 2006). Chapin (1974) found that urban residential have shorter *mean locus* (average distance of daily trips) than suburban residential. Schonfelder and Axhausen (2003) reported increasing individual activity spaces with distance between the place of residence and city center. Buliung and Kanaroglou (2006) found that residents in Portland CBD have smaller activity spaces than suburban residents.

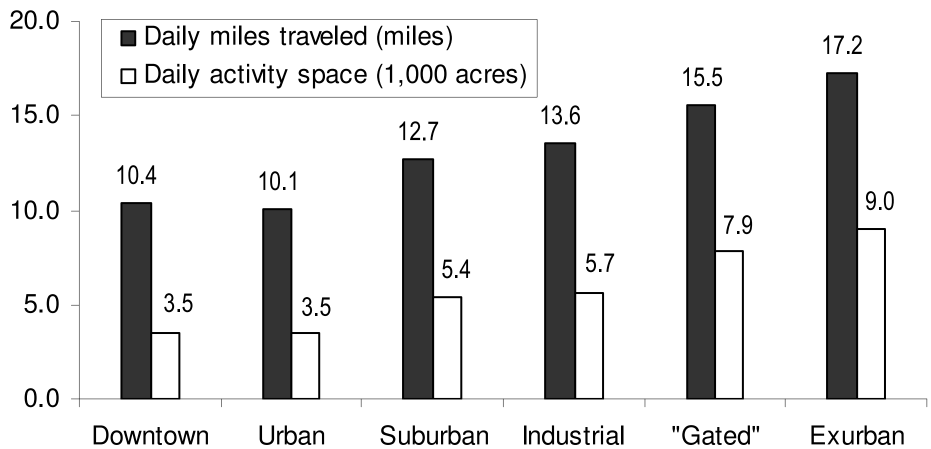


Figure 7-2 Spatial measures of individual activity-travel behavior by neighborhood type

Figure 7-3 shows how residents in different types of neighborhoods allocate their daily time to various activities. Surprisingly, residents in the identified urban neighborhoods spend less time outside their homes and spend more time on travel than suburban neighborhoods. This indicates that although urban residents have more activity destinations nearby, they do not spend more time outside their homes. An explanation is the high concentration of low-income households and unemployed individuals in the urban neighborhoods. Low-income and unemployment are associated with less time allocated to out-of-home activities

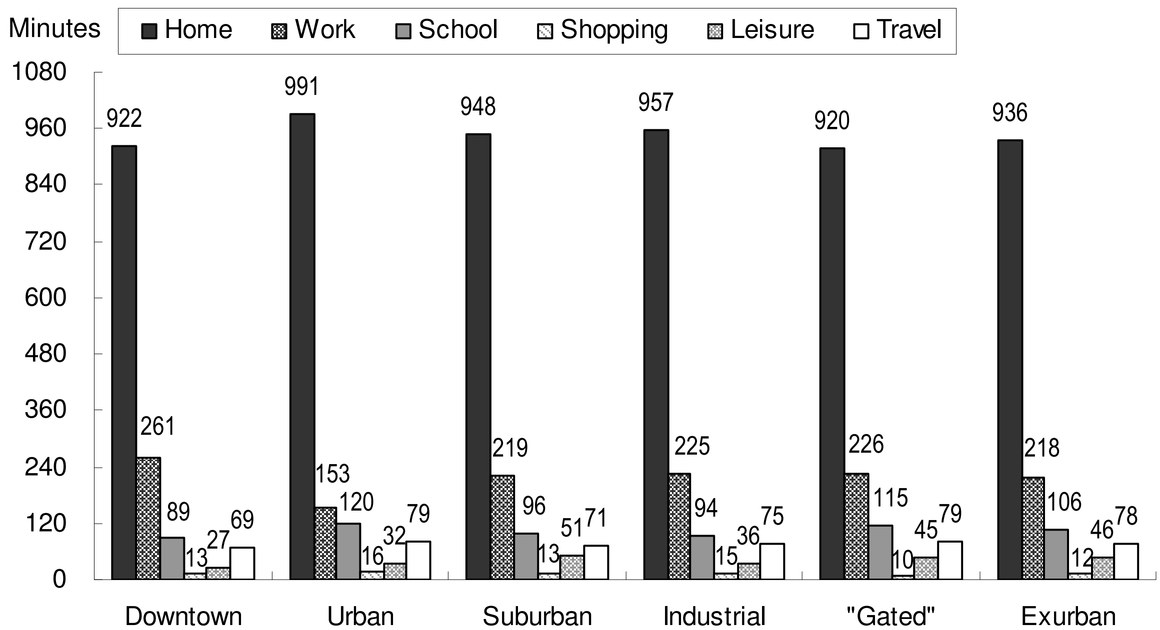


Figure 7-3 Activity time allocations by neighborhood type

Downtown residents and residents in "gated communities" have the highest out-of-home activity time allocation. However, the formation of the phenomena might have multiple underlying mechanisms. The fact that downtown residents spent more time outside may be due to their heavier workloads or their better environmental opportunities to participate outdoor activities. Residents in "gated communities" are rich and their more time allocation to out-of-home activities may be simply due to the fact that they are rich.

Suburban residents have the highest time allocation to leisure activities (51 minutes). A possible explanation is that the general decentralization of economic activity in the

Triangle region and the great access from suburban homes to the Interstate Highway System have made suburban residents have the best accessibility to leisure activity locations. Shopping time allocation does not change much across different neighborhood types.

As shown in Figure 7-3, downtown residents and suburban residents spend less time on travel than the residents in the other parts of the region. On average, people living in downtown area spend about 69 minutes on daily travel, which is about the same amount of time that suburban residents (71 minutes) allocate to daily travel. Urban residents, residents in "gated communities", and exurban residents averagely spent about 79 minutes per day on travel. Although urban residents have travel fewer miles and have smaller activity spaces than suburban residents (in Figure 7-2), urban residents have a higher travel time allocation than suburban resident. This is perhaps due to the fact that urban neighborhoods have a high concentration of low-income residents who are do not have access to high speed transportation means.

Figure 7-4 presents mean travel time allocations to different modes. Although downtown residents spent as much daily time on total travel as suburban residents, those two neighborhood clusters have distinct mode choice behavior. On average, out of the 71-minute daily travel conducted by downtown residents, only half of the time (36 minutes) was spent on driving. And more than twenty minutes were spent on non-automobile alternatives including bicycling, walking and taking transit. For suburban residents, about 66.7% of their daily travel time was allocated to driving. Out of their 72-minute daily travel, they only spent 6 minutes per day using alternative transportation modes (walking, bicycling and taking buses).

On average, urban residents allocate 12 minutes to transit use-much more than residents in other neighborhood types, reflecting not only urban residents' great access to transit system but also their relatively low income.

As shown in Figure 7-4, bicycling and walking modes are most likely to be used in downtown area than other neighborhood types. About 17% of the daily travel conducted by downtown residents is walking (12 out of 69 minutes).

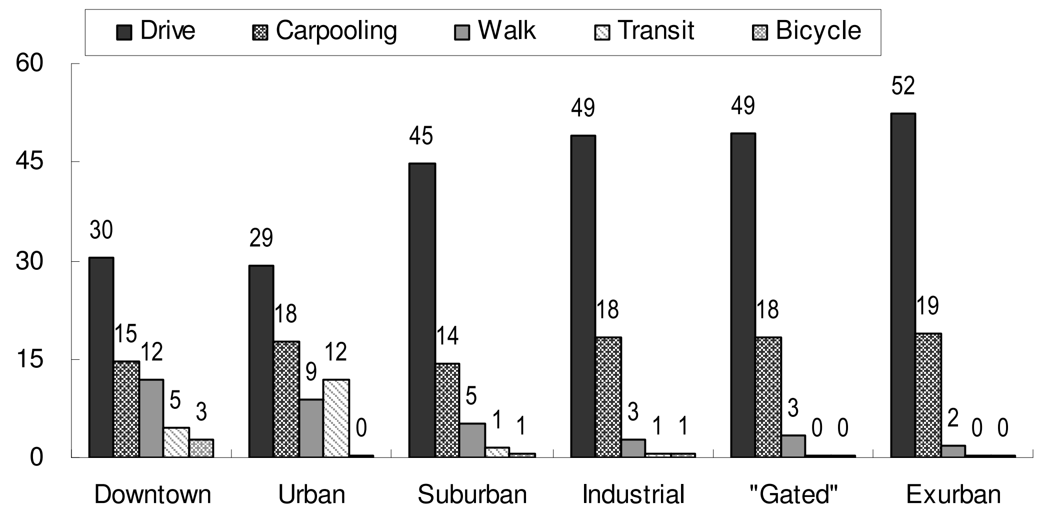


Figure 7-4 Travel time allocations by neighborhood type

Neighborhood Cluster Models

In order to answer questions about differences in individual activity-travel patterns across neighborhood clusters, the six neighborhood types were included in activity space and time allocation models as independent variables with exurban neighborhood serving as the reference category. Control variables in neighborhood cluster models include weather conditions and individual/household factors.

Table 7-2 presents results of the activity space models. Results show that both untransformed OLS models and semi-log transformed OLS models are statistically significant. The final semi-log transformed activity space model was interpreted in the following text because the semi-log transformed model is more appropriate for the positively skewed activity space variable (See Figure 6-2).

Table 7-2 Modeling results on daily activity space and neighborhood clusters

Variable	**Full Model**		**Final Model**	
	Untransformed OLS	Semi-log transformed OLS	Untransformed OLS	Semi-log transformed OLS
Constant	7597.580***	7.377***	8050.093***	7.223***
Neighborhood cluster (exurban is reference category)				
Downtown	-7190.891***	-1.333***	-7160.839***	-1.296***
Urban	-5502.398***	-0.684***	-5597.649***	-0.696***
Suburban	-5061.321***	-0.536***	-5030.939***	-0.499***
Industrial	-4103.535***	-0.336***	-4152.834***	-0.277***
"Gated"	-1938.363*	-0.199	-1919.005*	
Weather conditions				
Daily lowest temperature	42.087*	0.006**	38.219*	0.006**
Precipitation	-198.936	-0.107		-0.115
Control factors				
HH size	-470.408*	-0.049	-490.000**	
HH income	5.445	0.062**		0.062**
Residential tenure	12.226	-0.019		
Female	-2197.610***	-0.105*	-2147.158***	-0.107*
Children	-4338.209***	-0.883***	-4367.767***	-0.951***
Young adult	-3495.003***	-0.490***	-3545.053***	-0.520***
Old	176.787	-0.246**		-0.207*
White	152.295	0.057		
Employed	2399.219***	0.366***	2562.944***	0.365***
Multiple jobholders	1239.225	0.150*		0.143*
Auto ownership	1375.487***	0.094**	1365.229***	0.081*
Traffic information usage	2231.729***	0.225***	2210.356***	0.222***
Commute attitude	-1247.578**	-0.158**	-1253.748**	-0.175**
Transit attitude	323.357	-0.183		
Single-family detached	1447.957**	0.190*	1464.140**	0.166*
Summary statistics				
N	4,937	4,937	4,937	4,937
R^2	0.063	0.106	0.063	0.103
Adjust R^2	0.059	0.102	0.060	0.100
F	18.75	19.31	22.25	23.87
F-test	0.000	0.000	0.000	0.000

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

As shown in Table 7-2, the size of daily activity spaces declines from exurban to downtown. When all control variables are held constant, the downtown, urban, suburban, and industrial clusters are all negatively associated with daily activity space, with coefficients suggesting decreases in daily activity space of about 73%[7], 50%, 39%, and 24%, respectively, for people living in these clusters compared to exurban clusters. Residents in "gated communities" do not have a different size of daily activity space from residents in exurban clusters.

In other words, when all the control variables hold constant, the average size of activity spaces of exurban residents is about four times as large as that of downtown residents, twice as large as that of urban residents, 1.7 times as large as that of suburban residents, and 1.3 times as large as that of residents in industrial neighborhoods.

Despite certain substantive and methodological variations, the results are consistent with past studies about urban form and activity space. Buliung and Kanaroglou (2006) reported larger activity space for suburban households. Several studies found increasing activity spaces or ellipses with distance between the residential location and the city center or regional center (Schonfelder and Axhausen 2003; Beckmann, Golob et al. 1983).

When compared to the activity space models on direct measures in the previous chapter, the activity space models on neighborhood clusters have a similar model performance. This indicates that the direct environment measures and neighborhood clusters capture about a same amount of variation in activity-travel behavior. Models on direct measures and models on neighborhood cluster are complementary to each other. Direct measure models point out important environmental elements that explain individual activity-

[7] One-unit increase in X associated with exp(b) fold change in Y, OR one-unit increase in X associated with 100*(exp(b)-1) percent change in Y. Therefore, compared to exurban residents, downtown residents' activity spaces are about 100*(exp(-1.296)-1)=100*(0.27-1)=-73 percent smaller.

travel behavior, while neighborhood cluster models reflect the collective effects of environmental elements.

Table 7-3 presents results of the model of daily miles traveled and neighborhood clusters. Results show that individual daily miles traveled decline from exurban to downtown. When all control variables are held constant, compared to the exurban clusters, the downtown, urban, suburban, and industrial clusters are respectively associated with 39%[8], 27%, 21%, and 12% decreases in daily miles traveled.

Compared to the effect of neighborhood clusters on daily activity space, the effect of clusters on daily miles traveled is smaller. This is partly due to that higher activity frequencies lead to more daily miles traveled for downtown and urban residents.

The neighborhood cluster models marginally detected the positive effect of temperature on daily activity space and the negative effect of precipitation on daily miles traveled, showing consistency with results from the previous chapter.

[8] One-unit increase in X associated with exp(b) fold change in Y, OR one-unit increase in X associated with 100*(exp(b)-1) percent change in Y. Therefore, compared to exurban residents, downtown residents' activity spaces are about 100*(exp(-0.492)-1)=100*(0.61-1)=-39 percent smaller.

Table 7-3 Modeling results on daily miles traveled and neighborhood clusters

Variable	Full Model		Final Model	
	Untransformed OLS	Semi-log transformed OLS	Untransformed OLS	Semi-log transformed OLS
Constant	12.381***	1.843***	15.056***	1.890***
Neighborhood cluster (exurban is reference category)				
Downtown	-5.715***	-0.496***	-6.232***	-0.492***
Urban	-5.154***	-0.316***	-5.916***	-0.316***
Suburban	-4.535***	-0.249***	-4.598***	-0.236***
Industrial	-3.382***	-0.147***	-3.441***	-0.129***
"Gated"	-1.958**	-0.074	-1.920**	
Weather conditions				
Daily lowest temperature	0.034	0.002		
Precipitation	-0.747	-0.067*		-0.053*
Control factors				
HH size	-0.077	-0.020		
HH income	0.216	0.034***		0.036***
Residential tenure	0.055	0.003		
Female	-1.435***	-0.056**	-1.502***	-0.057**
Children	-5.100***	-0.216***	-5.090***	-0.241***
Young adult	-3.832***	-0.126**	-3.581***	-0.125***
Old	-1.761**	-0.176***	-1.912**	-0.161***
White	1.135*	0.091*	1.381**	0.100**
Employed	5.182***	0.524***	5.390***	0.529***
Multiple jobholders	1.788**	0.123***	1.708**	0.120***
Auto ownership	0.518	0.024		
Traffic information usage	1.983***	0.125***	2.104***	0.129***
Commute attitude	-1.872***	-0.086***	-1.850***	-0.093***
Transit attitude	-0.012	-0.014		
Single-family detached	1.216*	0.100**	1.830***	0.105**
Summary statistics				
N	7422	7422	7422	7422
R^2	0.107	0.140	0.106	0.139
Adjust R^2	0.105	0.138	0.104	0.137
F	45.04	51.61	55.84	66.09
F-test	0.000	0.000	0.000	0.000

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Table 7-4, Table 7-5, and Table 7-6 present results of the travel time allocation models using neighborhood clusters. The Heckman selection model was used in this analysis. Chapter IV details the model specifications and justifies the use of the Heckman selection model. The Tobit model was not reported, given that neither does it take intra-household autocorrelation into account, nor does it provided separate results for the engagement decision and the conditional decision about the actual travel time.

As shown in Table 7-4, the drive time allocation models on neighborhood clusters are statistically significant. The estimated coefficients show that, compared to the exurban clusters, the downtown, urban, and suburban clusters are associated with decreased chances of driving and a reduction in the actual driving time.

Compared to exurban residents, downtown residents are associated with a 43% (1-0.573 = 0.43 = 43%) decrease in the odds of driving and a 33-minute decrease in the actual driving time. Urban residents are associated with a 23% (1-0.772 = 0.23 = 23%) decrease in the odds of driving and an 11-minute decrease in the actual driving time. Suburban residents, when compared to exurban residents, are associated with a 14% (1-0.863 = 0.14 = 14%) decrease in the odds of driving and a 9-minute reduction in the actual driving time. Weather conditions (the temperature and precipitation indicators) show no association with either the propensity of driving or the actual daily driving time.

Table 7-4 Drive time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection coefficient	Odds ratio	OLS coefficient	Selection coefficient	Odds ratio	OLS coefficient
Constant	0.222**	1.249	20.363***	0.108	1.114	17.968***
Neighborhood cluster (exurban is reference category)						
Downtown	-0.562***	0.57	-34.186***	-0.556***	0.573	-32.681***
Urban	-0.237***	0.789	-10.367**	-0.259***	0.772	-11.402***
Suburban	-0.155***	0.857	-10.386***	-0.147***	0.863	-9.236***
Industrial	-0.032	0.969	-3.976			
"Gated"	-0.075	0.927	-3.433			
Weather conditions						
Daily lowest temperature	-0.001	0.999	-0.015			
Precipitation	-0.004	0.996	-1.375			
Control factors						
HH size	-0.054***	0.948	-2.008***	-0.053***	0.949	-1.983***
HH income	0.035***	1.035	1.799***	0.042***	1.043	2.093***
Residential tenure	-0.017	0.983	-0.832			
Female	-0.070**	0.932	-4.730***	-0.067**	0.935	-4.820***
Children	-8.265***			-8.016***		
Young adult	-0.665***	0.514	-37.978***	-0.658***	0.518	-37.705***
Old	-0.046	0.955	-1.266			
White	0.080	1.083	4.934*			
Employed	0.520***	1.683	32.583***	0.534***	1.706	32.804***
Multiple jobholders	0.135***	1.145	7.061***	0.114**	1.121	7.061***
Auto ownership	0.146***	1.157	7.025***	0.151***	1.163	7.068***
Traffic information	0.105***	1.111	7.378***	0.111***	1.117	7.251***
Commute attitude	-0.053*	0.948	-4.694***	-0.055*	0.947	-4.853***
Transit attitude	-0.071	0.931	-2.556			
Single-family detached	0.042	1.043	1.394			
Summary statistics						
N=7,422 persons		4,644 uncensored			4,644 uncensored	
LL (convergence)		-26800.27			-26810.68	
Rho		0.998***			0.998***	
Std. error of residuals		61.81			61.82	
Chi-square test		0.000			0.000	

Note: Adult is the reference category of age; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Table 7-5 presents the walk time allocation model on neighborhood clusters. Results show that, the downtown, urban, and suburban clusters are significant, with positive coefficients suggesting increases in the odds of walking of 85%, 22%, and 16% as well as increases in the actual walking time of 8.9 minutes, 8.8 minutes, and six minutes, respectively, for people living in these clusters compared to the exurban clusters.

Table 7-5 Walk time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection			Selection		
	coefficient	Odds ratio	OLS coefficient	coefficient	Odds ratio	OLS coefficient
Constant	-0.822***	0.439	20.960***	-0.720***	0.487	22.893***
Neighborhood cluster (exurban is reference category)						
Downtown	0.679***	1.971	9.477***	0.615***	1.850	8.930***
Urban	0.261**	1.298	11.797**	0.196*	1.216	8.809*
Suburban	0.200***	1.221	7.782***	0.150***	1.162	6.023**
Industrial	0.067	1.07	1.973			
"Gated"	0.146	1.158	[a]			
Weather conditions						
Daily lowest temperature	-0.005**	0.995	0.295**	-0.006***	0.994	0.292**
Precipitation	-0.073	0.93	-4.103*			-3.743*
Control factors						
HH size	-0.009	0.991	-0.684			
HH income	0.010	1.01	0.083			
Residential tenure	-0.003	0.997	-1.417			
Female	0.054	1.056	-2.560			
Children	0.033	1.034	-9.079***			-9.290***
Young adult	0.093	1.097	-9.516***			-9.271***
Old	-0.188**	0.828	-4.134	-0.201***	0.818	
White	0.291***	1.337	3.903	0.299***	1.348	
Employed	-0.051	0.95	1.498			
Multiple jobholders	0.106	1.112	-2.972			
Auto ownership	-0.164***	0.848	-3.078***	-0.165***	0.848	-2.131*
Traffic information	-0.149***	0.862	0.699	-0.149***	0.861	
Commute attitude	0.003	1.003	2.416			
Transit attitude	0.351***	1.421	-0.334	0.351***	1.420	
Single-family detached	-0.140**	0.869	2.485	-0.137**	0.872	
Summary statistics						
N=7,422 persons		988 uncensored			988 uncensored	
LL (convergence)		-7622.897			-7635.72	
Rho		0.028**			0.093**	
Std. error of residuals		33.31			33.60	
Chi-square test		0.000			0.000	

Note: [a] There are such few pedestrians in exurban neighborhoods that the Heckman selection model cannot be converged using exurban as reference category. In the full model, both gated communities and exurban neighborhoods serve as the reference category. * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

An interesting finding is that downtown residents have a much higher probability of walking than urban residents, but the actual daily walking time is about the same for the downtown and urban clusters. This indicates that, compared to urban residents, downtown residents make more frequent walking trips but with shorter distance of each walking trip.

In terms of weather conditions, a 10- Fahrenheit degree increase in temperature is associated with a 6% ($1-0.994^{10} = 0.058 = 6\%$) drop in the odds of walking, but a 3-minute increase in the actual walking time. Precipitation shows no association with the propensity of walking, but is marginally significantly associated with 3.7 less minutes of walking.

Table 7-6 presents results of the transit time allocation model. An interesting thing about the transit modeling results is that the neighborhood types having positive associations with transit use are negatively associated with the actual time spent using transit. As shown in Table 7-6, compared to the exurban clusters, the downtown clusters relate to an 80% (1.798-1 = 0.798 = 80%) increase in the odds of using transit. However, compared to the urban clusters or the exurban clusters, the downtown clusters relate to a 36-minute decrease in the actual time of using transit. This indicates that downtown residents consider public transit as a usable transportation option, but may not use the transit system to a substantial degree as they may have other appealing alternative transportation modes such as biking and walking. The transit use probability of suburban residents is higher than exurban residents and is lower than downtown and urban residents, which the actual transit use time of suburban residents is higher than downtown residents and is lower than other residents in urban, industrial, “gated”, or exurban neighborhoods.

Table 7-6 Transit time allocation models using the Heckman selection model with OLS

Variable	**Full model**			**Final model**		
	Selection			Selection		
	coefficient	Odds ratio	OLS coefficient	coefficient	Odds ratio	OLS coefficient
Constant	-0.612*	0.542	78.310***	-0.939***	0.391	101.488***
Neighborhood cluster (exurban is reference category)						
Downtown	0.663***	1.94	-46.410***	0.587***	1.798	-36.122***
Urban	0.490***	1.632	-13.900	0.401***	1.493	
Suburban	0.320**	1.377	-28.603**	0.214**	1.238	-17.348**
Industrial	0.033	1.034	-7.866			
“Gated”	0.288	1.334	-27.557			
Weather conditions						
Daily lowest temperature	-0.013***	0.987	0.745*	-0.011***	0.990	0.586*
Precipitation	0.112	1.119	-2.348			
Control factors						
HH size	-0.051	0.95	6.544			
HH income	-0.071**	0.932	-1.090	-0.069**	0.933	
Residential tenure	-0.052	0.95	2.016			
Female	-0.015	0.985	-5.444			
Children	-0.614***	0.541	-13.611	-0.633***	0.531	
Young adult	0.141	1.151	-4.422			
Old	-0.226	0.797	18.360			
White	-0.263**	0.769	-10.737	-0.299***	0.742	
Employed	0.192*	1.212	-2.159	0.210**	1.234	
Multiple jobholders	-0.250	0.779	23.853			
Auto ownership	-0.167*	0.846	3.034	-0.164**	0.848	
Traffic information	-0.046	0.955	9.872			
Commute attitude	-0.221**	0.802	8.029	-0.179**	0.836	
Transit attitude	0.761***	2.141	8.773	0.788***	2.199	
Single-family detached	-0.246**	0.782	-4.942	-0.315***	0.730	
Summary statistics						
N=7,422 persons		154 uncensored			154 uncensored	
LL (convergence)		-1336.047			-1350.617	
Rho		-0.543**			-0.565**	
Std. error of residuals		48.81			51.61	
Chi-square test		0.003			0.003	

Note: Adult is the reference age category; * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

The results are interesting but also reasonable. Given that transit is not favorable in terms of speed, convenience, reliability, and comfort, most people would like to distribute part of their travel needs to the transit mode, but they do not want to depend on public transit to fulfill their travel needs and desires. However, keep in mind that this is the Triangle case and this statement may not hold in those most congested metropolitan areas where transit is the primary mode.

In terms of weather conditions, a 10- Fahrenheit degree increase in temperature is associated with a 10% ($1-0.99^{10} = 1-0.904 = 0.096 = 10\%$) drop in the odds of making transit trips, but is associated with six additional minutes of using transit.

Key Findings and Limitations

Table 7-7 summarizes the evidence found in neighborhood cluster models. Daily activity space, daily miles traveled, and daily driving time allocation generally decrease from exurban to downtown. Walking time allocation and transit time allocation generally increase from exurban to downtown.

Table 7-7 Evidence found in the individual activity space and time allocation analysis (neighborhood cluster models)

Changes in environmental factors	**Changes in daily activity space and time allocation**				
	Daily activity space	Daily miles traveled	Time allocation: Drive (E ǀ T)	Time allocation: Walk (E ǀ T)	Time allocation: Transit (E ǀ T)
Neighborhood clusters					
Downtown	-75%	-39%	-43% ǀ -33	85% ǀ +9	80% ǀ -36
Urban	-50%	-27%	-23% ǀ -11	21% ǀ +9	49% ǀ
Suburban	-39%	-21%	-14% ǀ - 9	16% ǀ +6	24% ǀ -17
Industrial	-24%	-12%			
"Gated"					
Exurban					
Weather conditions					
+10 ˚F in temperature	+6%			-6% ǀ +0.3	-10%ǀ +6
Precipitation		-5%		ǀ -4	

Note: E: the percent change in the odds of being engaged in the travel category; T: the minute increase in the actual travel time.

When compared across models, the effect of clusters on daily miles traveled is smaller than on daily activity space. This is partly due to that higher activity frequencies lead to more daily miles traveled for downtown and urban residents and offset the reduction effect on distances of trips. The transit mode shows its uniqueness in that clusters with higher transit trip generation experience less actual time spent on transit use. This phenomenon indicates that people would like to distribute part of their travel needs to the transit mode, but they do not want to depend on public transit to fulfill their travel needs and desires.

In addition, compared to urban residents, downtown residents make more frequent walking trips but with shorter distance of each walking trip. Results on weather conditions are consistent with the previous chapter. The driving mode is not sensitive to weather conditions (as analyzed in this study) while pedestrians and transit users show their sensitivities to both temperature and precipitation (on a typical day), indicating the importance of taking weather into account when studying alternative modes.

The neighborhood cluster models are highly context sensitive and have limited geographic generalizability. Different datasets or geographical regions can result in different neighborhood typology. Another limitation is that neighborhood clusters reflect the collective effect of many environmental elements, which creates difficulties in interpreting the results and deriving policy implications.

CHAPTER VIII: Trip Distance and Duration Analysis

The previous chapter examines how daily time allocations to various activities and travel modes are related to environmental factors including the built environment at the home location, traffic conditions at the home location, and weather conditions. Suggested by Links 3a-3c, this chapter takes a closer look at trip distance and duration at the trip level, and specifically focuses on two questions: whether compact land use patterns at the trip origin are associated with short travel distance of non-work trips; and after controlling for trip distance, whether compact land use patterns at the trip origin and the destination are associated with long driving trip duration but short walking trip duration.

The structure of this chapter is as follows. First, descriptive statistics of trip characteristics were present. Then, two sets of models were introduced, including activity-specific trip distance models and mode-specific trip duration models. Activity-specific models were developed to test how non-work travel distance is related to environmental factors (the built environment, traffic conditions, and weather conditions) and how the relationship differs across activity types. Mode-specific trip duration models aim at examining how trip duration is related to environmental factors after controlling for trip distance and other control factors. Following the presented models, key findings and limitations were discussed.

Descriptive analysis

Table 8-1 shows descriptive statistics for measures of trip characteristics. Trips with missing locational information were excluded from this analysis because locational information was used to calculate trip distance. Trips that have destinations outside of Orange, Durham, and Wake Counties were also excluded from this analysis because I only obtained land use GIS information for locations within the three counties. The final trip dataset includes 22,952 trips, including 15,270 driving trips.

The three sets of models developed in this analysis have different focuses. Activity-specific trip distance models focus on non-work related trips, and mode-specific trip duration models focus on trips that are shorter than 2 miles. Reasons for the different focuses were explained in the following sections. Descriptive statistics presented in Table 8-1 included both of the two trip groups in distance models and duration models. Note that the trip distance variables used in this analysis is defined as the shortest path distance between the trip origin and the trip destination rather than Euclidean distance.

There are a total of 9,250 non-work related trips in the trip dataset, which comprises the final sample of the activity-specific trip distance analysis. About 22% of the non-work trips are shopping trips and about 25% are leisure trips. The mean duration of shopping trips is about 14 minutes, which is about the same as that of leisure trips. The mean distance of shopping trips (3.3 miles) also is about the same as that of leisure trips (3.2 miles). Shopping trips have a lower percentage of home-based trips and a lower percentage of night trips than leisure trips. About 30% of shopping trips were home-based, while leisure trips have about 47% home-based trips. 19% of shopping trips and 34% of leisure trips were made after 6:30pm. In terms of mode share, leisure trips have the highest percentage of walking trips –

about 9%, and have the lowest percentage of driving trips – about 59%. 73% of shopping trips were made by driving and only 4% of them were made by foot.

There are a total of 9,699 trips shorter than 2 miles, which comprises the final sample of the mode-specific trip duration analysis. About 58% of them were made by driving and 14.4% were made by foot. The remaining 27% include trips made by car passengers, transit users, bicyclists, and motorcyclists. Within the trips shorter than 2 miles, the mean distance of driving trips (1.42) is much higher than walking trips (0.37 miles). However, the mean duration of driving drips is 8.4 minutes, which is about 2 minutes fewer than that of walking trips. Walking trips have a higher percentage of home-based trips than driving drips.

Table 8-1 Descriptive statistics for measures of trip characteristics

	Non-work related trips N= 9,250			Trips<=2 mile N= 9,699			Total trips
	Shopping	Leisure	Other	Drive	Walk	Other	
N	2,092	2,318	4,840	5,660	1,398	2,641	22,952
Mean trip duration	13.95	13.99	14.51	8.40	10.44	11.02	15.96
Mean trip distance	4.00	3.96	4.44	1.42	0.37	1.47	5.01
% of home-based trips	30.4%	47.2%	48.2%	28.7%	36.6%	33.7%	33.0%
% of night trips	19.0%	34.4%	16.3%	22.5%	19.7%	24.0%	24.7%
% of driving trips	73.2%	59.1%	67.6%				66.5%
% of walking trips	3.7%	9.2%	6.9%				6.1%

Figure 8-1 and Figure 8-2 illustrate walking trips path and driving trip paths in the Triangle dataset. As shown in the two figures, walking trips are short and concentrate in central cities while driving trips spread all over the region.

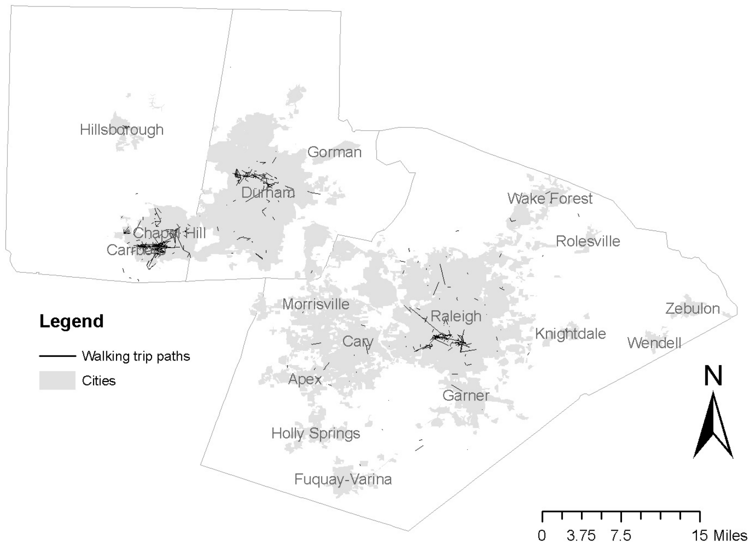


Figure 8-1 Walking trip paths in the Triangle area

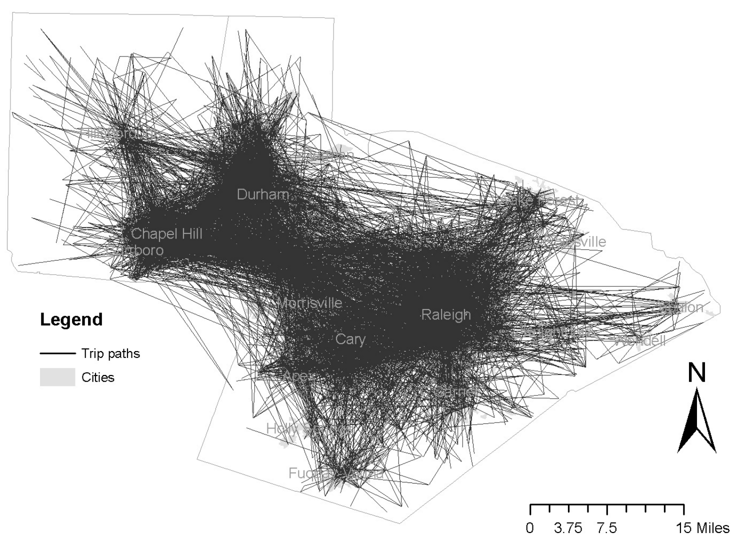


Figure 8-2 Driving trip paths in the Triangle area

Activity-Specific Distance Models

This analysis investigates the connection between environmental factors including the built environment at the trip origin, traffic conditions at the trip origin, and weather conditions and the distance of non-work trips. Commuting trips were excluded from this trip distance analysis because the distance of a commuting trip is often predetermined by residential location choice. Non-work trips, however, do not have fixed destinations and their distances are more likely to be influenced by environmental factors such as the built environment at the trip origin, traffic conditions at the trip origin, and weather conditions.

In this analysis, non-work trips were categorized into three groups: shopping trips, trips related to leisure activities, and other non-work related trips. See Figure 8-3 for frequency distributions of shopping, leisure, and other trip distances.

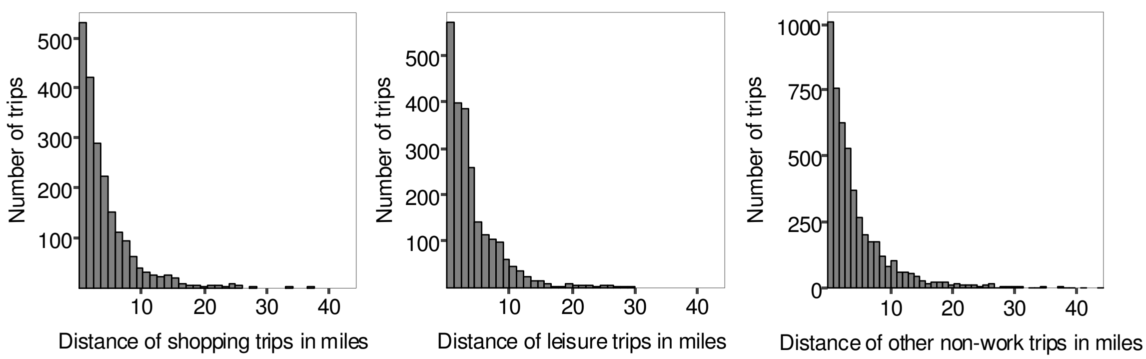


Figure 8-3 Frequency distributions of distances of shopping, leisure, and other trips

For each trip group, trip distance was modeled as a function of environment factors and control factors including trip characteristics and individual/household factors. The trip distance variable was measured as the shortest path distance between the trip origin and the destination. Given the strongly positive skewness in the trip distance variable, this dependent variable was semi-log transformed to make the data look normal and then OLS regression was used to estimate the activity-specific distance models. See Chapter IV for detailed specifications of the models.

Table 8-1 presents the semi-log transformed regression results of the three activity-specific models, including the estimated coefficients and their significance. F-tests suggest that all the travel distance models are statistically significant at the 0.001 level. R-squares in the models are not low, ranging from 0.19 to 0.34, which indicate good model performance. The leisure trip model has the highest R-square value.

Table 8-2 Semi-log transformed regression results on trip distance of non-work travel

Variable	**Shopping**		**Leisure**		**Other**	
	Full model	Final model	Full model	Final model	Full model	Final model
Constant	1.283***	1.032***	1.129***	1.081***	1.370***	1.541***
The built environment at the trip origin						
Parcel Count	-0.000		0.00029*	0.00028*	-0.000	
Retail Count	-0.004	-0.005*	-0.010*	-0.010*	-0.006**	-0.007**
Industrial count	0.034***	0.035***	0.018*	0.017	0.016**	0.015**
Connected node ratio	-0.483*	-0.449*	-0.285		-0.466***	-0.523***
Traffic conditions at the trip origin						
Driving density	-0.886***	-0.879***	-0.927**	-0.905**	-0.721***	-0.814***
Weather conditions						
Lowest temperature	-0.007		0.001		0.002	
Precipitation	0.060		-0.057		0.018	
Trip characteristics						
Home-based	0.335***	0.345***	0.303***	0.305***	0.052	
Night trip	-0.496***	-0.496***	0.163*	0.179**	0.041	
Auto trip	0.206		0.073		-0.070	
Pedestrian trip	-3.543***	-3.693***	-3.166***	-3.217***	-2.630***	-2.610***
Control factors						
HH size	0.070*	0.064*	-0.060		-0.008	
HH income	-0.003		0.026		-0.007	
Residential tenure	-0.056*	-0.056*	-0.073**	-0.075**	0.002	
Female	-0.148**	-0.181***	0.011		-0.044	
Children	0.353*		0.162		-0.198**	-0.180***
Young adult	0.283		0.041		0.107	0.132*
Old	0.103		-0.047		-0.144**	-0.154**
White	-0.177		-0.097		0.054	
Employed	0.353***	0.292***	0.109		0.037	
Multiple jobholders	0.001		0.077		-0.021	
Auto ownership	-0.036		0.002		0.026	
Traffic information	0.004		0.002		0.012	
Commute attitude	0.238**	0.232***	0.115		0.044	
Transit attitude	-0.196		0.057		-0.059	
Summary statistics						
N	2092	2092	2318	2318	4840	4840
R^2	0.215	0.209	0.320	0.315	0.237	0.235
Adjust R^2	0.206	0.204	0.313	0.312	0.233	0.234
F	9.079	16.073	19.217	55.507	30.020	72.888
F-test	0.000	0.000	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Results show that shorter trip distance is related to more retail stores, less industrial firms, and heavier traffic at the trip origin, which is consistent with our earlier hypotheses. The significance and magnitude of the relationships between environmental factors and trip distance differ across the three activity/trip types, indicating that different activity types have different sensitivity to environmental factors.

As shown in Table 8-2, the number of retail stores within the 0.25-mile buffer area at the trip origin shows negative and significant associations with non-work related trip distance. One additional retail store is associated with a 0.5% decrease in the distance of shopping trips, a 1% decrease in the distance of leisure trips, and a 0.7% decrease in the distance of other trips. Industrial uses, however, are associated with longer trip distance. One additional industrial firm within the 0.25-mile buffer area is associated with a 3.6% increase in the distance of shopping trips, a 1.7% increase in the distance of leisure trips, and 1.5% increase in the distance of other non-work related trips.

The distance of other non-work related trips is significantly and negatively related to connected node ratio- the indicator of grid street patterns. Ten percent additional intersections that are not cul-de-sacs are associated with a 4.4% decrease in shopping trip distance and a 5.1% decrease in the trip distance of other trips. The density indicator, the number of parcels within the 0.25-mile buffer area at the trip origin, is only significant in predicting the distance of leisure trips. Ten additional parcels are associated with a 0.28% increase in the distance of leisure trips. The small effect of the density indicator after taking traffic conditions into account supports a recent argument that density itself cannot lead to less travel. Some argue that it is the heavy traffic associated with dense developments that has an impact on auto travel demand (Boarnet and Crane 2001). Density itself does not play a role in reducing auto use.

Results show that the distance of non-work related trips is significantly and negatively related to driving activity density at the trip origin. A one-unit increase in driving activity density at the trip origin is associated with a 58% decrease in the distance of shopping trips, is associated with a 60% decrease in leisure trip distance, and is associated with a 56% decrease in the distance of other non-work trips. This indicates that heavy traffic at the trip origin is associated with short trip distance, which is consistent with the earlier hypothesis.

Table 8-3 presents results from the untransformed OLS distance models. Semi-log transformed models are more appropriate than untransformed models because of the positively skewed distributions of the dependent variables (See Figure 8-3). Therefore, the untransformed models were not discussed in the following text.

Table 8-3 Untransformed OLS regression results on trip distance of non-work travel

Variable	**Shopping**		**Leisure**		**Other**	
	Full model	Final model	Full model	Final model	Full model	Final model
Constant	5.979***	5.105***	5.881***	6.020***	7.303***	7.091***
The built environment at the trip origin						
Parcel Count	-0.00096**	-0.00094**	-0.00032		-0.0011***	-0.0011***
Retail Count	0.001		-0.007		-0.005	
Industrial count	0.036		0.035		0.027	
Connected node ratio	-0.961		-1.627*	-1.764**	-2.062***	-1.908***
Traffic conditions at the trip origin						
Driving density	-2.110***	-1.970***	-2.933***	-3.339***	-1.894***	-1.813***
Weather conditions						
Lowest temperature	-0.004		-0.008		0.012	
Precipitation	0.031		-0.319		-0.074	
Trip characteristics						
Home-based	0.005		0.334		-0.092	
Night trip	-0.505		0.883***	0.923***	0.233	
Auto trip	0.150		0.148		-0.497**	-0.534**
Pedestrian trip	-3.339***	-3.421***	-3.405***	-3.519***	-3.943***	-3.958***
Control factors						
HH size	0.050		-0.072		-0.119	
HH income	-0.074		0.002		-0.062	
Residential tenure	-0.242**	-0.235**	-0.153*	-0.140*	-0.103	
Female	-0.386**	-0.352*	0.021		-0.339**	-0.348**
Children	0.776*	0.700*	0.118		-0.896***	-1.158***
Young adult	0.545		-0.690**	-0.719**	0.026	
Old	-0.133		-0.005		-0.414*	-0.398*
White	-0.012		0.130		0.163	
Employed	0.808***	0.784***	-0.112		0.132	
Multiple jobholders	0.146		0.159		-0.236	
Auto ownership	0.053		0.138		0.366***	0.257***
Traffic information	0.407	0.433*	0.093		0.208	
Commute attitude	0.176		0.390*	0.396**	-0.223	
Transit attitude	-0.387		-0.031		-0.458**	-0.459**
Summary statistics						
N	2092	2092	2318	2318	4840	4840
R^2	0.070	0.064	0.134	0.128	0.091	0.086
Adjust R^2	0.059	0.060	0.124	0.125	0.086	0.085
F	21.122	63.268	39.011	139.035	48.711	120.838
F-test	0.000	0.000	0.000	0.000	0.000	0.000

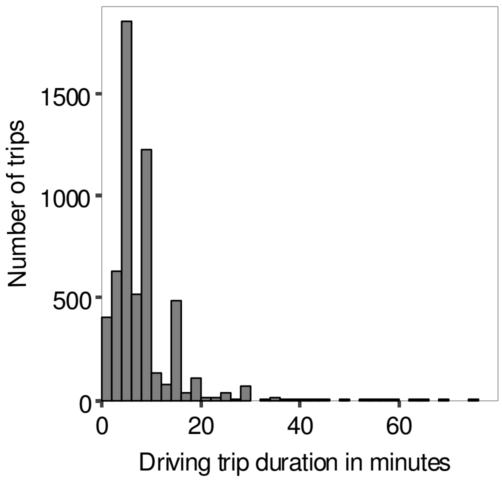
Legend: * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Mode-Specific Duration Models

The findings in the previous chapter show that compact development patterns and heavy traffic at the trip origin is associated with short distance of non-work travel. In this section, mode-specific duration models were developed to test whether heavy traffic and dense developments at the trip origin and the destination are associated with slow driving and whether presence of sidewalks at trip origins and the destinations are associated with fast walking. The research findings are expected to provide insights into whether the presence of dense developments, heavy traffic, and sidewalks can influence the relative attractiveness between walking and driving.

Given the fact that environmental factors throughout the travel route influence trip duration, this analysis excludes trips longer than two miles to ensure that the effect of the environment factors at the trip origin and the destination is testable. The exclusion of long-distance trips further reduces the noise in the models. In addition, walking is not favorable for trips longer than two miles. Excluding long-distance trips provides better bases to compare driving models and walking models.

Two sets of mode-specific models were developed, respectively focusing on driving trips and walking trips. See Figure 8-4 for frequency distributions of driving trip duration and walking trip duration. I did not develop models for transit and bicycle modes because transit speed does have sufficient spatial variation and the bicycle trips were too few to develop models for bicyclists. As the distribution of trip duration is positively skewed, semi-log transformed regression was used in the model estimation. See Chapter IV for detailed model specifications.



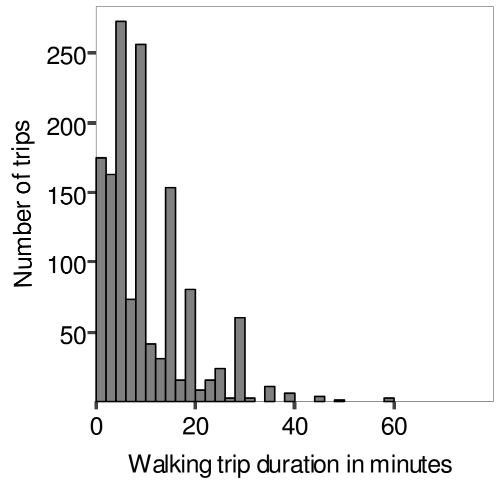


Figure 8-4 Frequency distributions of driving trip duration and walking trip duration

Table 8-4 presents the regression results including the estimated coefficients and their significance. The F-tests in Table 8-4 show that all the duration models are statistically significant at the 0.001 level. The walking trip duration models have R-squares at 0.3, which shows better model performance than driving models.

Table 8-4 Semi-log transformed regression results on mode-specific duration models

Variable	Drive		Walk	
	Full model	Final model	Full model	Final model
Constant	1.325***	1.283***	0.983***	1.118***
The built environment at the trip origin				
Parcel Count	-0.00002		-0.00003	
Connected node ratio	0.239***	0.237***	0.111	
Sidewalk coverage	0.016**	0.021***	-0.002	
The built environment at the trip destination				
Parcel Count	0.00008***	0.000092***	0.00001	
Connected node ratio	0.205***	0.225***	0.123	
Sidewalk coverage	0.009		-0.007	
Traffic conditions at the trip origin				
Driving density	0.115***	0.109***	-0.009	
Traffic conditions at the trip destination				
Driving density	0.045		-0.104	
Weather conditions				
Lowest temperature	-0.000		0.009***	0.009***
Precipitation	0.008		-0.021	
Trip characteristics				
Night trip	0.023		0.056	
Trip distance	0.345***	0.343***	1.222***	1.219***
Control factors				
HH size	-0.018		0.033	
HH income	-0.031***	-0.033***	0.044*	0.039**
Residential tenure	0.004		-0.023	
Female	-0.023		0.033	
Children			-0.086	
Young adult	0.107**	0.105**	0.014	
Old	0.141***	0.164***	0.092	
White	-0.173***	-0.173***	-0.086	
Employed	0.002		-0.029	
Multiple jobholders	-0.021		0.092	
Auto ownership	0.002		-0.064	-0.064*
Traffic information	0.033		0.033	
Commute attitude	-0.027		0.010	
Transit attitude	0.068**	0.061**	0.005	
Summary statistics				
N	5660	5660	1398	1398
R^2	0.201	0.197	0.294	0.286
Adjust R^2	0.197	0.196	0.281	0.284
F	31.162	65.639	13.827	73.207
F-test	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Results show that walking trip duration is not significantly related to the built environment and traffic conditions at the trip origin and destination after controlling for trip distance. On the contrary, driving trip duration was found to be significantly and positively associated with connected node ratio, sidewalk coverage, and driving activity density at the trip origin and the number of parcels at the trip destination. The results support our early hypothesis that walking trip duration and driving trip duration were associated with land use patterns and traffic conditions at the trip origin and destination with different significance, directions, and magnitude. In other words, compact development patterns and heavy traffic are associated with low mobility of auto modes but show no association with the walking mobility.

As shown in Table 8-4, ten percent additional intersections that are not cul-de-sacs (a 0.1-unit increase in connected node ratio) at the trip origin is associated with a 2.4% increase in driving trip duration, with trip distance and other variables held constant. Ten percent additional intersection share at the trip destination is associated with 2.3% increase in driving trip duration. One additional mile of sidewalks at the trip origin is associated with a 2.1% increase in driving trip duration. Ten additional parcels within the 0.25-mile buffer area at the trip destination are associated with 0.09% increase in driving trip duration. A one-unit increase in driving activity density at the trip origin is associated with an 11.5% increase in driving trip duration.

Results show that driving trip duration is not significantly related to weather conditions. However, walking trip duration is positively related to temperature. A 10-Fahrenheit degree increase in temperature is associated with a 9% increase in the duration of walking trips after controlling for trip distance and other variables.

Several socio-demographic factors are significant in predicting driving trip duration, while none of the individual and household factors are significant in the walking trip duration models. This indicates that driving speed varies by personal characteristics, while the speed of walking is less influenced by the socio-demographic factors.

Table 8-5 presents results from the untransformed OLS duration models. Semi-log transformed models are more appropriate than untransformed models because of the positively skewed distributions of the dependent variables (See Figure 8-4). Therefore, the untransformed models were not discussed in the following text.

Table 8-5 Untransformed OLS regression results on mode-specific duration models

Variable	Drive		Walk	
	Full model	Final model	Full model	Final model
Constant	4.717***	5.235***	4.628*	2.742**
The built environment at the trip origin				
Parcel Count	0.000		-0.001	
Connected node ratio	1.571***	1.879***	-0.604	
Sidewalk coverage	0.126		0.157	
The built environment at the trip destination				
Parcel Count	0.000		0.001	
Connected node ratio	1.803***	2.284***	-0.270	
Sidewalk coverage	0.088		-0.338	
Traffic conditions at the trip origin				
Driving density	0.780*	1.119***	0.344	
Traffic conditions at the trip destination				
Driving density	0.616		-0.715	
Weather conditions				
Lowest temperature	0.011		0.081**	0.082***
Precipitation	0.177		-0.209	
Trip characteristics				
Night trip	0.215		0.455	
Trip distance	2.311***	2.294***	12.427***	12.368***
Control factors				
HH size	-0.111		0.033	
HH income	-0.327***	-0.322***	0.139	
Residential tenure	0.073		-0.072	
Female	-0.318		0.095	
Children	0.000	0.000	-0.909	
Young adult	0.912		-0.531	
Old	1.674***	1.779***	0.837	
White	-2.345***	-2.437***	-0.245	
Employed	0.159		-0.362	
Multiple jobholders	-0.160		0.699	
Auto ownership	0.096		-0.583*	
Traffic information	0.321		0.369	
Commute attitude	-0.356		0.094	
Transit attitude	0.671*	0.614*	-0.330	
Summary statistics				
N	5660	5660	1398	1398
R^2	0.088	0.083	0.294	0.282
Adjust R^2	0.084	0.082	0.281	0.281
F	16.454	39.632	8.405	66.174
F-test	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01; standard errors were adjusted for clustering on the household.

Key Findings and Limitations

Table 8-6 summarizes the key findings of this trip distance and duration analysis. Results from the activity-specific distance models show that the distance of non-work related trips is significantly related to the built environment and traffic conditions at the trip origin. More retail stores, fewer industrial firms, and heavy traffic near the trip origin were found to be associated with shorter distance of non-work travel. The magnitude of the associations varies across three activity categories (shopping, leisure, and other non-work related activities).

Table 8-6 Evidence found in the trip distance and duration analysis

Changes in environmental factors	**Changes in non-work trip distance**			**Changes in trip duration**	
	Shopping	Leisure	Other	Drive	Walk
The built environment at the trip origin					
+10 parcels		+0.3%			
+1 retail store	-0.5%	-1.0%	-0.7%	N/A	N/A
+1 industrial firm	+3.6%	+1.7%	+1.5%	N/A	N/A
+0.1 connected node ratio	-4.4%		-5.1%	+2.4%	
+1 mile sidewalks	N/A	N/A	N/A	+2.1%	
The built environment at the trip destination					
+10 parcels	N/A	N/A	N/A	+0.09%	
+1 retail store	N/A	N/A	N/A		
+1 industrial firm	N/A	N/A	N/A		
+0.1 connected node ratio	N/A	N/A	N/A	+2.3%	
+1 mile sidewalks	N/A	N/A	N/A		
Traffic conditions at the trip origin					
+1 driving activity per acre	-58%	-60%	-56%	+11.5%	
Traffic conditions at the trip destination					
+1 driving activity per acre	N/A	N/A	N/A		
Weather conditions					
+10 ˚F in temperature					+9.4%
Precipitation					

Note: N/A: there is no theoretical link between the two variables.

After controlling for trip distance, the duration of driving trips is positively related to street grids, presence of sidewalks, heavy traffic at the trip origin, and land use density at the trip destination. Walking trip duration does not have a relationship with the built environment and traffic conditions at the trip origin and destination but are positively related to warm weather.

The results support our early hypotheses about the negative association between compact development patterns and the distance of non-work trips, and the hypothesis that driving trip duration is positively related to compact development patterns while walking trip duration is not.

A limitation of this trip distance and duration analysis is that the trip distance variable contains measurement error. The trip distance variable used in this analysis is the shortest path distance between the trip origin and the trip destination rather than the real travel distance of a trip. The shortest path distance used in this analysis tends to underestimate the real travel distance since the real trip distance within urban transportation networks is often longer than the shortest path distance between the origin and destination. The amount of underestimation is larger for trips made in congested areas than for trips made in uncongested areas. Therefore, this measurement error may overestimate the effect of traffic conditions on trip distance. Fortunately, the estimated coefficients of traffic conditions are large and significant, which makes this measurement error in trip distance less of a concern.

In mode-specific duration models, the trip distance variable becomes an explanatory variable. Measurement error in this distance variable in duration models causes more complicated problems than in distance models. Long-distance trips contain relatively smaller amount of error than short-distance trips. The negative correlation between the measurement error and the real travel distance may generate biased estimates as well as influence the consistency of OLS regression. However, I only included trips shorter than two miles in the trip duration analysis. The exclusion of long-distance trips reduces the correlation between measurement error and explanatory variables, which makes the extent of measurement error relatively small.

The dataset used in this analysis only contains trips that have both origins and destinations within Orange, Durham, and Wake Counties. Trips coming from or going into surrounding counties are not included in this study. This may exclude more long-distance trips than short-distance trips from the trip sample. For trip duration models, it is not a cause of concern since duration models only focus on trips less than two miles. In trip distance models, as I exclude long-distance trips from the sample, the models might overestimate the effect of each independent variable on trip distance. Thus, we need to be careful when presenting coefficients with small magnitudes in the distance models.

In addition, this analysis uses the built environment and traffic conditions at the trip origin and the destination to predict trip duration. However, theoretically, the built environment and traffic conditions along the travel route can influence trip duration. Thus, omitted variable bias may exist in this analysis.

CHAPTER IX: Summary, Discussion, and Conclusions

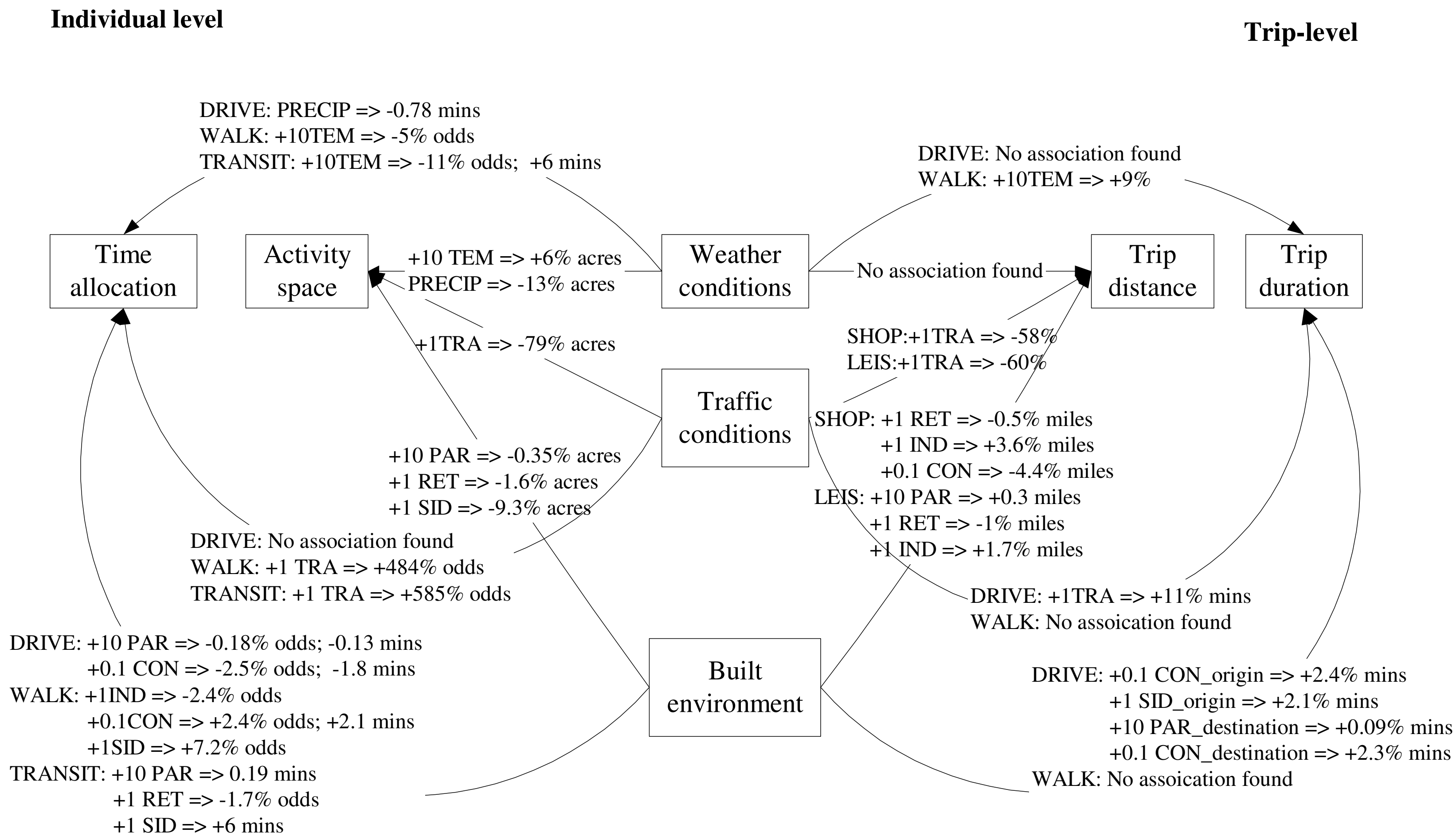
Transportation problems seem immune to efforts to improve them. Increasing evidence suggests that there are no quick "technological fixes" and top-down transportation demand management programs often are controversial and have very limited effectiveness. It is in this vein that researchers have been emphasizing the potential mitigating role of the built environment in urban transportation.

The three analyses presented here, including the block group analysis, the individual analysis, and the trip analysis, provide useful insights into the land use-travel connection. Specific environmental features, such as retail stores, industrial firms, street grids, and sidewalks, were tested in the research. The differences in how the environmental features relate to human activity patterns and individual time use likely will be of great interest to practical planners who have limited resources yet hope to make significant changes in the community. The trip-level distance and duration analysis tested two mechanisms behind the land-use travel connection, based on which transportation solutions can be proposed and more informed policy decisions can be made.

This chapter summarizes the findings of the three analyses in the research, draws conclusion from the findings, discusses the policy implications, and points out future research directions on the subject.

Summary of Findings

This dissertation represents an attempt to understand how factors in the built environment, coupled with traffic and weather conditions, are associated with travel reduction in both the time and space dimensions, and represents an attempt to explore the mechanisms underlying the proposed environment-travel associations. Uniquely, this research has been conducted at three levels, including the block group, the individual, and the trip. Overall, empirical evidence in this research shows that heavy traffic, better connected street networks, more nearby retail stores, dense developments, presence of sidewalks, cold weather, and precipitation are associated with not only smaller individual spatial footprints of daily activities but also less time allocated to travel, especially driving. Figure 9-1 illustrates the key findings in this dissertation. The reminder of this section examines these findings in greater detail.



Legend:

TEMP – temperature (˚F); PRECIP– precipitation; TRA – driving activity density;

PAR– # of parcels; RET – # of retail stores; IND – # of industrial firms;

CON – connected node ratio; SID – sidewalk length in miles; LEIS – leisure trips

Figure 9-1 Summary of findings in the research

My hypothesis set #1 concerns the relationship between land use and activity patterns at the aggregate level. Explore the connection at the aggregate level is important, as activity density, diversity in activity categories, and demographic diversity in activity population in urban spaces relate to the sense of place, the community attractiveness, and the equity and segregation of the social dimension in urban places. Hypothesis set #1 argues that, when demographic environments of an urban space are controlled, compact land use patterns are associated with higher activity density, greater diversity in activity types and population groups, and more alternative transportation mode share in the urban space.

This set of hypotheses is supported conditionally by evidence from the activity pattern analysis at the census block group level (Chapter III). A precise statement of the findings is that some environmental elements of compact land use patterns are associated with higher activity density and diversity, but others are not. In addition, environmental elements relating to activity density are somewhat different from elements relating to the diversity patterns in urban activity systems. Denser residential developments and grid street patterns in an area are not associated with higher diversity in activity types or higher demographic diversity of the individuals who were involved with activities in the area.

In urban spaces, it is easier to achieve activity density through compact land use strategies than to achieve diverse activity types and population groups. All the indicators of compact development patterns positively relate to activity density, but only a few of them (employment density, commercial uses, and presence of sidewalks) are positively associated with diversity in activity categories and demographic diversity in the population engaged in activities.

My hypothesis set #2 lists hypotheses regarding the relationship between land use and activity patterns at the individual level. The relationship was investigated in both the space and the time dimensions, as shown in Chapter VI and Chapter VII.

With respect to the land use and activity space connection, the findings successfully support the hypothesis that compact development patterns are associated with less spatially dispersed daily activity locations. The findings are consistent with the existing evidence found by the cohort of studies on the urban-suburban difference in activity space (Zahavi 1979; Schonfelder and Axhausen 2003; Buliung and Kanaroglou 2006). Rather than focusing on the urban-suburban difference, this research goes beyond earlier studies by quantifying the effect of specific features in urban environments. As shown in Figure 9-1, ten additional parcels within the 0.25-mile buffer area around the home location are associated with a 0.35% decrease in individual daily activity space. One additional retail store in the residential neighborhood is associated with a 1.6% decrease in activity space. And one additional mile of sidewalks within the 0.25-mile buffer area is associated with a 9.3% decrease in activity space. When comparing models for daily miles traveled with activity space models, the two sets of models generate consistent results. The comparison also suggests that compact land use patterns may have a positive impact on activity frequencies (Crane 1999; Ewing and Cervero 2001) and this positive impact offsets the travel reduction effect.

Results from neighborhood cluster models on activity space and daily miles traveled show that the area size of daily activity space and daily miles traveled generally decline from exurban to downtown, being greatest in exurban and smallest in downtown areas. In terms of magnitude, the downtown and urban clusters show a stronger reduction effect on daily activity space than daily miles traveled, which is partly due to the fact that downtown and urban environments can stimulate higher activity demand, leading to more daily miles traveled. When compared with models on direct measures, models on neighborhood clusters show a similar model performance. This indicates that the direct environment measures and neighborhood clusters capture about the same amount of variation in activity-travel behavior, indicating the comprehensiveness of our selected direct measures in describing urban environments.

With respect to the land use and travel time allocation connection, the findings successfully support the hypothesis that presence of sidewalks and grid street patterns are associated with not only more engagement in walking but also more time allocated to walking. Compared to land use mix, street patterns, and pedestrian facilities, land use density plays a minor role in predicting travel behavior. As shown in Figure 9-1, ten additional parcels within the 0.25-mile buffer area is associated with only a 0.18% decrease in the odds of driving and a 0.13-minute decrease in the actual driving time. Walking time allocation is not related to land use density. In addition, after taking traffic conditions into account, the association between land use density and auto travel reduction becomes weak. These findings support a recent argument that density itself cannot lead to less auto use or more walking, and it is the heavy traffic associated with dense developments that has an impact on auto travel demand (Boarnet and Crane 2001). Results also show that walking has a higher sensitivity to built environment factors than driving.

However, the findings fail to support the hypothesis that compact development patterns relate to more time allocated to out-of-home activities and leisure activities. However, this research found that travel time allocation is strongly related to the built environment at the residential location while activity time allocation seems insensitive to the built environment in the Triangle context.

Traffic conditions at the residential location and weather conditions play an important role in both the individual spatial footprint and individual time allocation. Heavy traffic in the residential neighborhood, cold weather, and precipitation are associated with smaller daily activity space and fewer daily miles traveled. Heavy traffic in the residential neighborhood and warm temperature are associated with higher chances of being engaged in out-of-home activities and leisure activities outside the home. These findings suggest that it is important to incorporate a comprehensive list of environmental factors (more than the built environment) into modeling individual activity patterns.

Heavy traffic at the home location does not significantly relate to less driving time allocation, which is inconsistent with our hypothesis that urban traffic at the residential location is associated with less driving in that it suppress auto travel demand. However, traffic conditions significantly relate to walking and transit trip generation. Thus, a precise statement of the finding is that heavy traffic in the residential neighborhood may not be associated with less driving but may be associated with more alternative mode travel. Weather conditions also show no association with driving, while high temperature was found to be associated with less walking. These results indicate that, when studying alternative mode travel, it is very important to take traffic and weather conditions into account.

My hypothesis set #3 is dedicated to understanding the mechanism underlying the land use and travel behavior connection by disaggregating the elements of travel such as distance and duration and specifying the travel mode and the activity context. This set of hypotheses was tested in Chapter VIII.

In the trip-level distance and duration analysis, I found that shorter distances of shopping and leisure trips are related to compact land use patterns and urban traffic. After controlling for trip distance, longer driving trip duration was found to be associated with compact land use patterns.

With respect to the land use and trip distance connection, the findings support the early hypothesis about the negative association between compact land use patterns and distances of non-work related trips. Evidence shows that more retail stores, fewer industrial firms, better street connectivity, and denser developments at the trip origin are associated with decreased distances of shopping and leisure trips. As shown in Figure 9-1, one additional retail store within the 0.25-mile buffer area around the trip origin is associated with a 0.5% decrease in shopping trip distance and a one percent decrease in leisure trip distance. Heavy traffic at the trip origin also is associated with shorter shopping and leisure trip distance. No association was found between trip distance and weather conditions. The effect size of environmental factors on trip distance varies across activity types, indicating the importance of incorporating activity context in modeling the land use and travel connection.

With respect to the land use and trip duration connection, I found that grid street patterns, sidewalks, dense developments, and heavy traffic at the trip origin and/or destination are associated with longer duration of driving trips after controlling for trip distance. I did not find any significant relationships between walking trip duration and land use patterns and traffic conditions. This finding supports our hypothesis that environmental factors are associated with trip duration in different ways depending on travel modes. Compact land use patterns and heavy urban traffic increase the relative attractiveness of walking versus driving. Among the elements in compact land use patterns, grid street patterns, indicated by connected node ratio, have the strongest association with long driving trip duration. Ten percent additional intersections that are not cul-de-sacs at the trip origin is associated with a 2.4% increase in driving trip duration, with trip distance and other factors held constant. This finding supports the hypothesis that more intersections lead to longer driving time in that more intersections often mean lower speed and more stops.

Weather conditions are not significantly associated with the distance or the duration of driving trips, while warm weather is associated with increased walking trip duration. A 10- Fahrenheit degree increase in temperature is associated with a 9% increase in walking trip duration after controlling for trip distance.

Overall, this research suggests that the built environment, coupled with traffic and weather conditions, plays an important role in shaping individuals' footprints in both the space and time dimensions. The research findings conditionally confirm the association between compact development patterns and travel reduction. More importantly, this research extends understanding of what kind of environmental features can bring intensity and diversity of human activities into urban places, what kind of environmental features can facilitate individuals in minimizing their daily travel (especially auto travel) for fulfilling their activity needs, and by which mechanisms certain environmental features are associated with travel reduction. In addition, this research presents an activity-based and time use approach to study the land use-travel connection, which fills the gap between activity modeling and land use-travel modeling.

Discussion

The previous section summarizes the findings in this dissertation. In this section, I undertake the discussion of several key analysis findings.

Activity time budget or travel time budget?

This research found that travel time allocation is strongly related to urban form factors at the residential location while activity time allocation (out-of-home activities and leisure activities) seems insensitive to urban form in the Triangle context. This finding fail to support the hypothesis that compact development patterns relate to more time allocated to out-of-home activities and leisure activities. The findings question the constant travel time budget theory (Prendergast and Williams 1981; Mokhtarian and Chen 2004; Zahavi 1979), and suggest rather a possible activity time budget.

The finding indicates that no matter what kind of urban form at the residential location, people with the same socio-demographics and attitudes tend to have the same activity time budget. However, people with the same individual and household characteristics may allocate different time to travel if they live in neighborhoods with different urban form. This finding makes the land use-travel connection even more important as it suggests that for those who live in an area with fewer retail stores and more curvilinear streets, they have to substitute their at-home minutes for daily travel.

What are the most important urban form factors?

To decide which of the urban form factors are most important for explaining individual footprints in place and time, I further calculated standardized regression coefficients for all the urban form factors used in this research. Figure 9-2 visually presents the revealed associations in this study. Note that the associations between urban form and travel time allocation (including both engagement decision and time use decision) were examined using the Heckman selection model that incorporates both logistic model and OLS model. The numbers presented on the right side of Figure 9-2 are logit standardized regression coefficients calculated using the “fully standardized logistic regression coefficient” equation (Menard 1995; Menard 2004), which describe the effect of urban form on engagement decisions only.

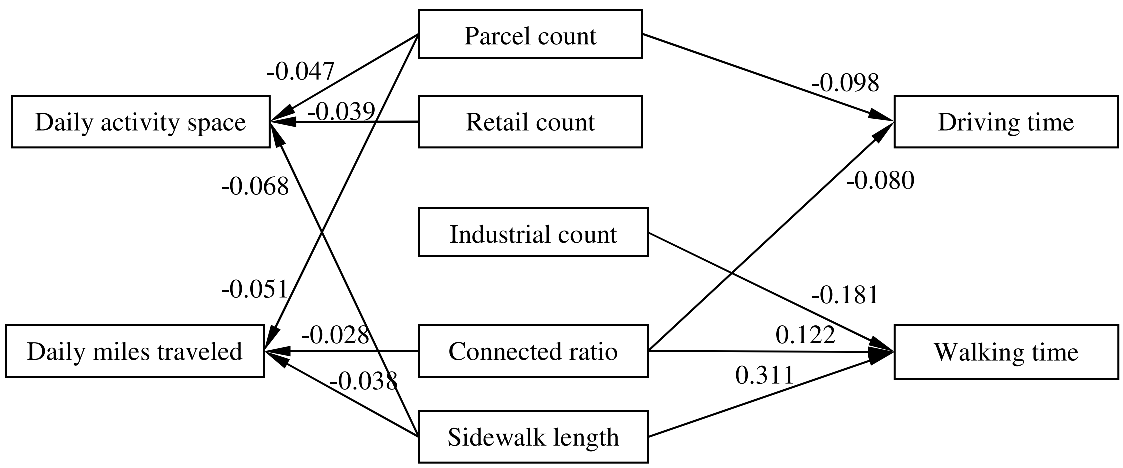


Figure 9-2 Standardized coefficients of the urban form factors

The standardized coefficients show that sidewalk coverage is the most important urban form factor relating to daily activity space, followed by the density dimension and the proximity to retail stores. However, in terms of travel reduction, sidewalk coverage is the second most important environment dimension, less important than land use density but more important than street patterns.

In terms of reducing auto use, land use density is about as important as street patterns (slight difference). For daily walking time, the presence of sidewalks in the residential neighborhood is the most important factor with a positive effect, followed by the presence of industrial firms in the neighborhood that have a negative impact. Grid street patterns are also an important factor in promoting walking behavior.

As the effect sizes of different environmental features on activity-travel behavior have a wide range, practitioners may have multiple solutions to improve transportation problems, e.g. compact developments, mixed land uses, traffic claming, sidewalk construction, and congestion pricing. Among the solutions, some of them may not be justified by their small potential effect and their lower flexibility. Thus, a careful assessment of the effectiveness of each solution should be made in advance of any implementation.

The effect of the confounding factor—urban traffic

Existing research on the urban form and travel connection has found evidence on the travel reduction effect of land use density (Cervero and Radisch 1996; Handy and Clifton 2001; Krizek 2003; Shay, Fan et al. 2006; Shay and Khattak 2007). At the same time, an argument arises from the fact that most research does not incorporate urban traffic into modeling the urban form and travel connection. That is, density itself cannot lead to less auto use or more walking, and it is the heavy traffic associated with dense developments that has an impact on auto travel demand (Boarnet and Crane 2001).

To address this issue, this research considers urban traffic as a confounding factor in the relationship between urban form and individual activity-travel behavior. Figure 9-3 outlines how daily miles traveled vary by land use density and traffic conditions in the residential neighborhood. I estimated daily miles traveled, and the uncertainty surrounding it, for the two extremes of traffic conditions (5% and 95% centiles) and across the range of land use density, while holding other variables at their means. Statistical software packages including Clarify 2.0 (King, Tomz et al. 2000) and Stata 8.0 were used to estimate the expected values and their uncertainty. For the case of a neighborhood with no traffic and the other case of a neighborhood with heavy traffic, expected value algorithm were repeated to approximate 95-percent confidence interval around the value of daily miles traveled.

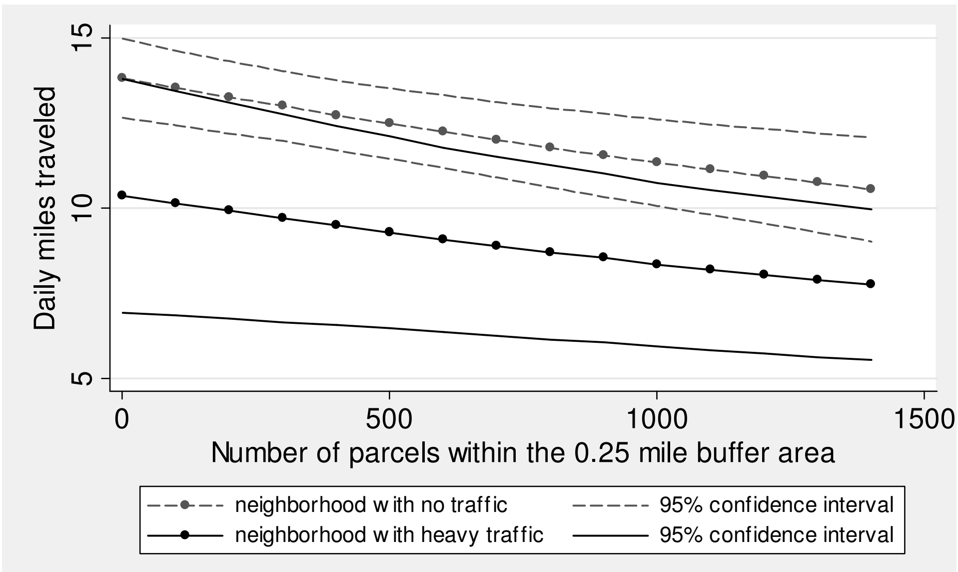


Figure 9-3 Daily miles traveled by land use density

The results appear in Figure 9-3, which illustrates the regression findings quite sharply: daily travel distance decreases as density increases, and decreases with the presence of heavy traffic in the residential neighborhood. The figure also reveals that uncertainty associated with daily travel distance shows different patterns for the two extremes of traffic conditions. For the extreme of no traffic, uncertainty associated with daily travel distance is greatest at the highest density value: the band within the two dashed lines, which represent 95-percent confidence intervals, are widest when the neighborhood is very densely developed. On the contrary, for the extreme of heavy traffic, uncertainty associated with daily travel distance is greatest at the lowest density value. In addition, the case of no traffic has a generally narrower uncertainty band than the case of heavy traffic.

This confirms the early identification that urban traffic is a confounding factor in the context. Traffic conditions in the residential location not only are significantly associated with the individual's daily travel distance, but also can influence the patterns of uncertainty associated with daily travel distance. More specifically, heavy traffic in the neighborhood is associated with higher levels of uncertainty in travel distance. Further, the combination of heavy traffic and dense developments is associated with lower levels of uncertainty in travel distance than the combination of heavy traffic and low density. The combination of no traffic and dense developments has higher levels of uncertainty in travel distance than the combination of no traffic and low density.

The urban form effect depending on mode of travel

Results show that time allocations to different activity/travel categories have dramatic differences in the sensitivity to the urban form factors in this analysis. As shown in Figure 9-2, driving is sensitive to the density indicator and connected node ratio only, while walking is sensitive to industrial uses, sidewalks, as well as connected node ratio.

Figure 9-4 and Figure 9-5 shows the probability of driving/walking and the actual driving/walking time by connected node ratio and their associated uncertainty illustrated by 95-percent confidence intervals. The two figures indicate that connected node ratio has opposite impacts on driving and walking time allocations. More interestingly, the uncertainty patterns of time allocation variables also differ by travel mode. As shown in Figure 7, the uncertainty levels of daily walking time is generally lower than those of daily driving time.

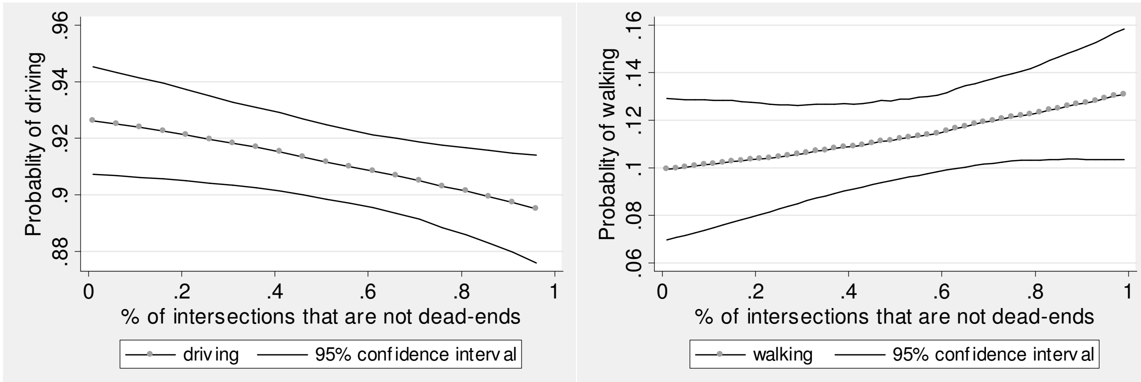


Figure 9-4 Probability of driving/walking by connected node ratio

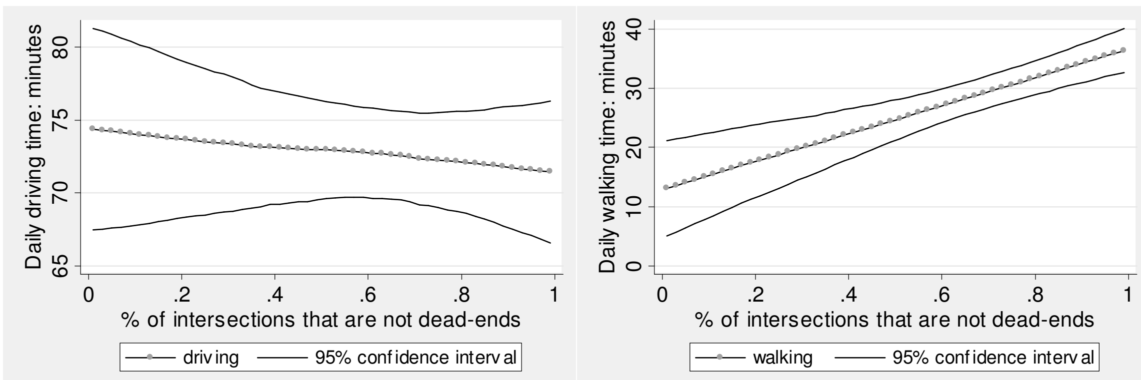


Figure 9-5 Daily driving/walking time by connected node ratio

The findings show that walking and driving are inherently different, indicating the importance of developing mode-specific models for studying time allocation.

Individual effects of environment elements versus synergy effects of neighborhood clusters

To fully investigate the built environment and activity-travel behavior connection, this research uses two different measurements of the built environment. For one of the measurements, indicators were generated for the key dimensions of the built environment including land use density, land use diversity, street connectivity, and pedestrian environments. Indicators of such dimensions were generated at the 0.25-mile buffer area level. The other measurement of the built environment utilizes factor and cluster analyses to identify a neighborhood typology including the downtown, urban, suburban, industrial, “gated”, and exurban neighborhoods.

These two measurement technologies come with different advantages and drawbacks. Analysis of specific environmental measures can reveal which dimensions in the built environment are the most influential ones in terms of changing travel behavior, while analysis of neighborhood clusters can capture the collective and interactive effects involving multiple environment features.

Analysis results show that models of specific environmental measures and models of neighborhood clusters have a similar model performance. The R-squares in both sets of models are about the same, very close to 0.1. This indicates that the neighborhood clusters capture about a same amount of variation in activity-travel behavior as the specific environmental measures plus the traffic measure. In other words, besides the amount of variation captured by the key built environment dimensions, the neighborhood clusters also can captures traffic conditions in residential neighborhoods. Based on the findings, I recommend neighborhood typology as an effective way to describe the built environment, with the caveat that identified neighborhood clusters may represent other urban environments as well as the built environment.

Individual-level models versus trip-level models

Comparing trip-level and individual-level modeling results shows interesting results, indicating the importance of investigating the land use and travel connection at both levels. Results from the final model of daily miles traveled show that a 0.1-unit increase in connected node ratio is associated with a 1.8% decrease in daily miles traveled, and is associated with a 1.8-minute decrease in daily driving time. However, results from the final model of trip distance show that the same amount of increase in connected node ratio is associated with a 4.4% decrease in distance of shopping trips, and is associated with a 2.4% increase in duration of driving trips. As you can see here, street connectivity has a stronger association with the distance of each trip than the total daily distance traveled by each individual. This is partly due to that street connectivity not only can influence the average distance of trips, but also can influence trip frequency.

In terms of the time dimension, street connectivity is associated with the duration of driving trips and the total daily driving time in opposite directions. However, the findings are reasonable. Street connectivity may promote alternative mode travel, which may have a reduction effect on the number of driving trips. At the same time, street connectivity means more stops and lower auto speed limits, which may prolong duration of each driving trip.

The discussion above shows that, in order to gain a clear understanding of the land use and travel connection, it is important to investigate the connection at both the individual level and the trip level.

The Tobit model versus the Heckman selection model

Both the Tobit model and the Heckman selection model are meant to address the missing data bias and dependent variables with many zero values. These two kinds of models were used to model time allocation variables in this research because such variables are only observable when the individual choose to be engaged in activities and travel.

The Heckman selection models generally provide more informative results than the Tobit models. Variables relating to the engagement decision are different from variables relating to the conditional decisions about the actual activity or travel time. For example, industrial firms and sidewalks in the residential neighborhood are significantly associated with the propensity of walking, but for those who chose to walk, both variables are not associated with daily walking time. The findings point out the importance of using the two-stage model structure in analyzing daily activity and travel time allocation variables. Without a two-stage model structure, we can not disentangle the effect of factors on the engagement decision from the effect on the actual time allocation decision.

Although the Heckman model is more appealing the Tobit model in many ways, the Tobit model has its strengths. For example, the number of parcels is positively significant in the Tobit model of walking time allocation. In the Heckman selection model, the number of parcels positively relates to both the probability of walking and the actual walking time, but either of the positive relationships is significant. Thus, the Heckman selection model may underestimate the significance of the variables that may aggregately have a significant effect on time allocation (including both the engagement decision and the conditional decision of the actual activity or travel time). However, due to the fact that the Tobit model cannot adjust the intra-household autocorrelation, I cannot safely draw conclusions about the significance of effects.

Conclusions

On one hand, the findings support the notion that transportation problems can be ameliorated through the use of land use strategies. Less spatially dispersed daily activity locations, less daily time allocated to driving, and more daily time allocated to walking were found to be related to dense developments, grid street patterns, more retail stores, fewer industrial firms, and presence of sidewalks. On the other hand, evidence from this study shows that the strength of the land use-travel connection is conditional on other environmental factors such as traffic and weather conditions, as well as activity context such as activity type and time of day.

To conclude, less spatially dispersed daily activity locations are related to dense developments, more retail stores, and more sidewalks. Among these three factors, sidewalk coverage is the most important. The urban form effect on daily miles traveled aggregates the effect on trip making and the effect on the distance of each trip. Even though the positive effect on trip making may offset the negative effect on trip distance, land use density, street grids, and sidewalks are associated with fewer daily miles traveled. Here, density becomes the most important factor relating to total daily distance traveled.

Surprisingly, the research shows no evidence about the association between urban form and time allocated to out-of-home activities and leisure activities. However, importantly, urban form factors are significant in predicting mode-specific travel time allocation. Both the probability of driving and the actual driving time are negatively related to land use density and connected node ratio. The probability of walking is negatively related to industrial uses in the residential neighborhood. Better connected streets are associated with more walking and longer walking time. The presence of sidewalks is positively associated with the engagement of walking, and is the most important factor in promoting walking behavior.

Different activity/travel categories have dramatic differences in the sensitivity to the environmental factors in this analysis. Not only do trips with different modes respond to the environmental factors in different ways, trips related to different activity categories also show differences in the environmental sensitivity. Industrial uses at the trip origin are associated with shopping trip distance but not with leisure trip distance. Walking trips are more vulnerable to weather conditions than driving.

For research and policy analysts, this study has demonstrated a useful and systematic methodology for analyzing the effect of specific environmental elements (including land use density, retail uses, industrial uses, street connectivity, sidewalks, traffic conditions, temperature, and precipitation) on both the spatial and temporal properties of activity and travel behavior.

One of the contributions of this study is to systematically test the connection between land use and activity-travel behavior from three angles—the census block group, the individual, and the trip. Results show that the individual effects can not be simply summed to determine the implications for the public interest. For example, connected node ratio at the census block group level shows a positive association with driving activity density within the census block group, while at the individual level, connected node ratio within the 0.25-mile buffer area around the home location shows a negative association with driving time allocation. This suggests to future researchers that, as cities become more complex, it is not sufficient to study the land use and travel connection at either aggregate levels or disaggregate levels. In urban planning, examining the clusters of activities/trips in urban spaces is as important as investigating individual activity-travel behavior.

Based on the economic theory of demand and the psychological theory of environment-behavior interactions, the research developed a detailed theoretical framework explicitly providing mechanisms by which land use influences transportation. Analyzing the land use and travel connection within this specific theoretical framework permits us to develop testable hypotheses and derive specific conclusions.

The treatment of urban form and land use in this research is extensive. Both direct measures such as the number of retail stores, the number of industrial firms, connected node ratio, and presence of sidewalks and a typology of neighborhood types (including 6 categories from downtown to exurban) were used to analyze land use and activity-travel behavior. The use of direct measures improves the transferability of the results to other regions and helps to make more practical and more specific planning recommendations. The use of neighborhood clusters provides an intuitive spatial representation of urban environments and captures the collective and interactive effects involving multiple environmental features on activities and travel.

Another methodological contribution of this study is to provide working definitions of activity density and diversity that can be used in future research. Kernel density estimation was used to generalize driving destinations to the entire study area and generate driving destination density—a proxy measure of urban traffic conditions. Entropy measures were used to describe diversity in the types and the times of activities occurring within the census block group, and the race, income, and age mix in the population who accomplished activities within the census block group.

For planning practitioners, this research can help them propose specific and safe land use solutions to societal and transportation problems. In particular, the census block group level activity pattern analysis provides insights into how to create active places with demographic diversity. Given the finding that land use density in a census block group is not positively related to activity diversity or demographic diversity in the population who were involved with activities within the census block group, this analysis delivers a message to practitioners that high development density or compact developments themselves can not lead to social diversity. Only when compact developments are combined with affordable housing, commercial land uses, and employments can social diversity be achieved.

Findings from the individual activity space and time allocation analysis offers guidance on land use and transportation planning to achieve goals of encouraging the use of local opportunities, improving individual quality of life, reducing auto use, and promoting alternative mode travel. In particular, differences in how specific environmental features relate to human activity patterns and individual time use likely will be of great interest to practical planners who have limited resources yet hope to make significant changes in the community. The findings also shed light on what kind of environmental elements are necessary to allow individuals to be engaged in all their required activities with shorter travel distances and possibly by non-motorized modes. Furthermore, the trip-level distance and duration analysis tested two mechanisms behind the land-use travel, based on which safer transportation solutions can be proposed and more informed policy decisions can be made.

In addition to built environment factors at the home location, the trip origin, and the trip destination, the research considered traffic conditions and weather conditions as another important set of variables. The inclusion of traffic and weather conditions not only improves the estimates of built environment factors, but also helps us propose more practical and more context-sensitive policy implications.

Limitations and Future Directions

The transferability of findings for the Triangle area in North Carolina to other urban regions is somewhat limited. The Triangle area in North Carolina, one of the most rapidly growing areas in the U.S., has the highest educated population (by percentage) in the country. Compared to other metro areas in U.S. with similar population density, the Triangle area has a much higher percentage of transit trips and non-motorized trips. Travel in the Triangle has risen substantially during the past decade. However, the Triangle also has increased the capacity of the freeways to carry traffic, which has improved traffic conditions and led to only modest growth in congestion. Given the uniqueness of the Triangle area, the results of this study may not be generalized to highly congested regions, regions with poor transit services, and regions depending on heavy industry sectors such as manufacturing and mining. In addition, the travel survey data were collected during January 31 to May 26, 2006—the winter and spring seasons in central North Carolina, which does not contain travel data in either extremely cold weather or in hot weather. The research was not able to detect the non-linearity between temperature and activity-travel behavior. Therefore, I cannot generalize the research results to the coldest regions up north and the hottest regions down south. Future research could apply a similar methodology to analyze the interrelationship between the built environment, activity space, and time allocation in other geographic regions.

This dissertation examines activity space and time allocation separately. A possible extension of this study is to develop integrated activity space-time measures of activity-travel behavior and to examine how activity space-time measures are related to factors in urban environments. The literature provides several examples where space-time accessibility measures were developed to describe the space-time constraints of activity participation at the individual level (Miller 1991; Kwan 1999). An attempt should be made to link the built environment to activity space-time measures to facilitate the understanding of how urban design strategies may shape individual space-time interactions.

This study uses a secondary dataset that only contains daily activity and travel data on weekdays. It would be somewhat premature to draw a conclusion that compact land use patterns decrease individual activity space. We do not know whether residents in central cities make longer weekend trips than suburban residents. Future research could focus on weekly activity space to gain a more complete understanding about how the built environment may shape the spatial properties of activity patterns.

This is a cross-sectional study that does not allow us to make inference about changes. Although the land use changes and other changes in the built environment are much slower and may not be immediately affected by changes in activity engagement and travel behavior, the environment-behavior relationship is bidirectional. Future research could collect data at multiple sites or collect panel data.

The research findings on trip distance and duration could be further placed into the consumer demand framework to provide insights into how urban design can contribute to travel demand management. As the trip distance and duration closely relate to trip price/cost, findings from this travel time research can be used to shed light on how well direct regulatory policies such as pricing compare with more indirect planning interventions such as urban design. Findings from this sort of comparison can help policy makers make more informed decisions.

Finally, the rapid spread of information and communication technologies (ICTs) has been transforming the basic concepts of space and time: the two fundamental dimensions of human life. The spatiotemporally adjusting technologies not only can directly influence our daily lives, bust also can structurally transform cities and urban systems (Janelle and Gillespie 2004) and then have an interaction impact on individual activity engagement and travel. For example, ICT allows travel time to be used more productively, more pleasantly or more intensely, possibly leading individuals to accept longer travel times since a higher utility is derived from the time spent traveling (Dijst 2004). Also, because ICT may have different impacts on travel depending on the travel mode, ICT may bring about mode choice effects. For instance, working on a laptop and using the Internet or watching a DVD can be done when traveling by public transport but not as easily while driving a car (Dijst, 2004). Future research should collect information about the use of ICTs in activity and travel datasets, integrate ICTs within urban environments, and examine whether the use of ICTs reinforce or counteract the land use-travel connection. Research of this sort can shed light on the use of ICTs in facilitating efficient and sustainable mobility.

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