TRAVEL AND BUILT ENVIRONMENT: EVIDENCE FROM 23 DIVERSE REGIONS OF THE UNITED STATES

by

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A dissertation submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Metropolitan Planning, Policy and Design

Department of City and Metropolitan Planning

The University of Utah

May 2017

The University of Utah Graduate School

STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

I have opted for a three-paper dissertation, studying the relationship between travel and the built environment for three types of trips: walk and bike trips by the entire population, trips from home to school and back for students, and trips of all types by the elderly. As part of my dissertation, I have gathered the most extensive set of regional travel surveys that anyone has ever collected, specifically including 815,160 trips by 81,056 households in 23 regions. I have also linked travel records to so-called D variables for buffers of different widths around households and routes from home to school. The five D variables, widely used in travel research, are development density, land use diversity, street network design or connectivity, destination accessibility, and distance to transit. The main goal of this dissertation is to determine how we can promote walking and biking, especially for students and seniors.

From the first paper, walk mode choice in the 23 regions depends primarily on land use diversity, street connectivity, and transit accessibility, while bike mode choice depends primarily on street connectivity and transit accessibility. The resulting trip chain shows that accessibility of destinations to one another may be almost as important as accessibility of residences to destinations. The second paper analyzes student travel to school in the 14 regions. I find that the most important D variables in the decision to walk or bike to school is development density and street network design or connectivity, and the least important is land use diversity. While not a D variable exactly, the need to cross

major roads or commercial developments has strong negative impacts on active travel to school. In the third paper, the analysis of variance (ANOVA) tests show that seniors living in compact neighborhoods are more active than those living in sprawl neighborhoods. They generally travel more and travel more by walking and public transportation, yet travel less by automobile.

The resulting models and findings in this dissertation are appropriate for post-processing outputs of conventional travel demand models, and for sketch planning applications in traffic impact analysis, climate action planning, and health policy implementations.

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ACKNOWLEDGEMENTS

I would never have been able to finish my dissertation without the guidance and help of my committee members, and support from my wife.

Frist of all, I would like to express my most sincere gratitude and appreciation to my advisor, Dr. Reid Ewing, a great scholar, educator, and mentor, for his guidance, support, caring, patience, and inspiration throughout the development of this dissertation and my whole PhD study and research.

I would also like to thank Prof. Bartholomew and Dr. Nelson for giving me feedback on my dissertation. Special thanks go to Dr. Porter and Dr. Zhang, who were able to attend my final defense with a short notice.

Finally, I would like to thank my wife, Chong Li. When I worked on my dissertation for 3 months, she took the full responsibility of taking care of our baby.

CHAPTER 1

INTRODUCTION

Shifting travel from the automobile to walk and bike (also called active or nonmotorized transportation) is a core strategy for reducing greenhouse gases, regulated air pollutants, road infrastructure expenditures, traffic fatalities, and other social, economic, and environmental costs of automobile use. Also, walk and bike are more affordable transportation modes comparing with automobile. It is one way to promote social equality for lower income people. At the same time, walk and bike are widely recommended for their health benefits as physical activities. To help policy makers, planners, and developers promote walking and biking, it is necessary to understand the relationship between built environment and people’s travel choices, especially for different cohorts like students and seniors. The goal of this dissertation is to identify the relationship between people’s travel choice and built environment and how we can promote walking and biking, especially for students and seniors, in an urban context.

Despite more than 5 decades of research into travel-demand modeling, there are currently few functional models that predict walk and bike trips. In many models, only trips by vehicles are modeled, and trip rates are related only to sociodemographic characteristics of people, rather than characteristics of place. Therefore, in my dissertation, firstly I will build walk and bike choice models based not only on sociodemographic characteristics of people but also built environment characteristics of place, with controlling for weather conditions.

Secondly, I will examine how students travel to and from school and what kinds of built environments along the shortest route between schools and homes affect their travel choices. National Household Travel Surveys (NHTS) show that the number of children walking or biking to school has significantly declined today, compared with 50 years ago (Botchwey et al., 2014; Ewing et al., 2004). Travel to and from school can be a source of physical activity added to a child's daily total energy expenditure (Ahlport et al. 2008). Perhaps more importantly, exposing children to walking and biking at an early age can help establish healthy habits, increasing the likelihood that they will use these modes of transport later in their life (Schlossberg et al., 2006).

Thirdly, I will examine seniors' travel behavior: where older adults go (destinations) and how they get there (travel modes); and what characteristics of the built environment are important to promote healthy aging (more active travel). When getting old, people want to "age in place" or live in their homes or communities as long as possible (Yen & Anderson, 2012). A good place for aging should have good accessibility for the elderly and promote more physical activities. Examining the changes of travel behavior will help us understand more clearly the emerging accessibility needs of older adults and improve transportation infrastructure systems to cater to those needs.

1.1 Commonalities and Differences in the Three Studies

I have opted for a three-paper dissertation, studying the relationship between travel and the built environment for three types of trips: walk and bike trips by the entire population, trips from home to school and back for students, and trips of all types by the elderly. As part of my dissertation, I have gathered the most extensive set of regional travel surveys that anyone has ever collected, specifically including 815,160 trips by 81,056 households in 23 regions. I have also linked travel records to so-called D variables for buffers of different widths around households and routes from home to school. The five D variables, widely used in travel research, are development density, land use diversity, street network design or connectivity, destination accessibility, and distance to transit. All three studies in this dissertation used this dataset with the main goal of determining how we can promote active living (walking and biking) by increasing density, diversity, design, and destination accessibility, and reducing distance to transit.

Each of the three studies is also different from each other in terms of studied population, research questions, unit of analysis, and additional methods (Table 1.1). The significant contribution of study one to the literature is that I analyzed trip chaining to test the importance of accessibility of destinations versus the importance of accessibility of destinations to walk. For study two, I limited my sample to school trips that were within 2 miles, where walking and biking are in the choice set of students' travel to school. It does not make sense at all to include a trip that is 10 miles because no student would walk 10 mile to school. In the third study, principle component analysis (PCA) and analysis of variance (ANOVA) were employed to test whether built environment matters to keep seniors active.

Table 1.1 Summary of the three studies

	Study one	***Study two***	***Study three***
Population	general population	students (K-12)	senior (65 or older)
Research question	walk and bike; accessibility of destinations vs. residences	promote active travel to school	Keep senior active
Unit of analysis	individual trips and households	individual school trips	seniors and senior households
Sample size	81,056 households	21,892 school trips	28,060 seniors
Travel outcomes	trip frequency	mode choice	trip frequency
Methods	Trip chaining, hurdle model	multinomial logistic regression	PCA, ANOVA, hurdle model

1.2 Travel Behavior and Built Environment

In the literature, there are at least 200 studies of the association between travel and built environment (Ewing & Cervero, 2010). Indeed, there are at least 13 literature reviews and two meta-analyses of this vast literature (Badoe & Miller, 2000; Cao et al., 2009; Cervero, 2006; Crane, 2000; Ewing & Cervero, 2001; Ewing & Cervero, 2010; Handy et al., 2005; Heath et al., 2006; Leck, 2006; McMillan, 2005, 2007; Pont et al., 2009; Saelens et la., 2003; Saelens & Handy, 2008; Stead & Marshall, 2001).

Built environment variables generally include the following: land use patterns; the transportation system, the physical infrastructure of roads, sidewalk, etc., as well as the service this system provides; and urban design, the arrangement and appearance of the physical elements in a community (Saelens & Handy, 2008). For example, residents of communities with higher density, greater connectivity, and more land use mix report higher rates of nonmotorized trips. Based on previous studies, Ewing and Cervero (2010) categorized all built environment variables impacting travel choices in terms of the five Ds (Table 1.2): Density, Diversity, Design, Destination accessibility, and Distance to

Table 1.2 The D variables

D Variable	Measurement
Density	Density is always measured as the variable of interest per unit of area. The area can be gross or net, and the variable of interest can be population, dwelling units, employment, or building floor area. Population and employment are sometimes summed to compute an overall activity density per areal unit.
Diversity	Diversity measures pertain to the number of different land uses in a given area and the degree to which they are balanced in land area, floor area, or employment. Entropy measures of diversity, wherein low values indicate single-use environments and higher values more varied land uses, are widely used in travel studies. Jobs-to-housing or jobs-to-population ratios are less frequently used.
Design	Design measures include average block size, proportion of four-way intersections, and number of intersections per square mile. Design is also occasionally measured as sidewalk coverage (share of block faces with sidewalks); average building setbacks; average street widths; or numbers of pedestrian crossings, street trees, or other physical variables that differentiate pedestrian-oriented environments from auto-oriented ones.
Destination accessibility	Destination accessibility measures ease of access to trip attractions. It may be regional or local (Handy, 1993). In some studies, regional accessibility is simply distance to the central business district. In others, it is the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones. The gravity model of trip attraction measures destination accessibility. Local accessibility is a different animal. Handy (1993) defines local accessibility as distance from home to the closest store.
Distance to transit	Distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces to the nearest rail station or bus stop. Alternatively, it may be measured as transit route density, distance between transit stops, or the number of stations per unit area. In this literature, frequency and quality of transit service are overlooked.

transit (Ewing & Cervero, 2010).

Furthermore, a review of 42 published studies by Saelens and Handy (2008) confirmed that there are consistent positive relationships between walking for transportation and density, land use mix, distance to destinations, and street connectivity. Specifically, people who use public transit or live in high-density urban areas have more walking to and from transit (Besser & Dannenberg, 2010). Better network connectivity is associate with increased walking frequency (Sehatzadeh et al., 2011). T-intersections or 3-way intersections lead to poor connectivity and represent nongrid street patterns and dead-ends, considered as a barrier to walking and biking (Cervero & Duncan, 2003; Sehatzadeh et al., 2011; Wells & Yang, 2008). Other intersections (four- or more-way intersections) lead to increased connectivity, thus providing people with a greater variety of potential routes (Leslie et al., 2007; Sehatzadeh et al., 2011). The more varied the land use mix, the more conducive it is to walk to various destinations (Leslie et al., 2007). Street connectivity and land use mix improve accessibility across neighborhoods (Handy & Xing, 2011; Saelens et al., 2003).

1.3 Conceptual Framework

Based on the literature, the conceptual framework underlying this dissertation is shown in Figure 1.1. Individuals' travel behaviors or travel choices are associated with personal sociodemographic status, the surrounding neighborhood development, regional characteristics, as well as weather conditions, and social and cultural norms. Sociodemographic characteristics of an individual include gender, age, income, household size, etc. Individuals in different life stages have different travel activities. For

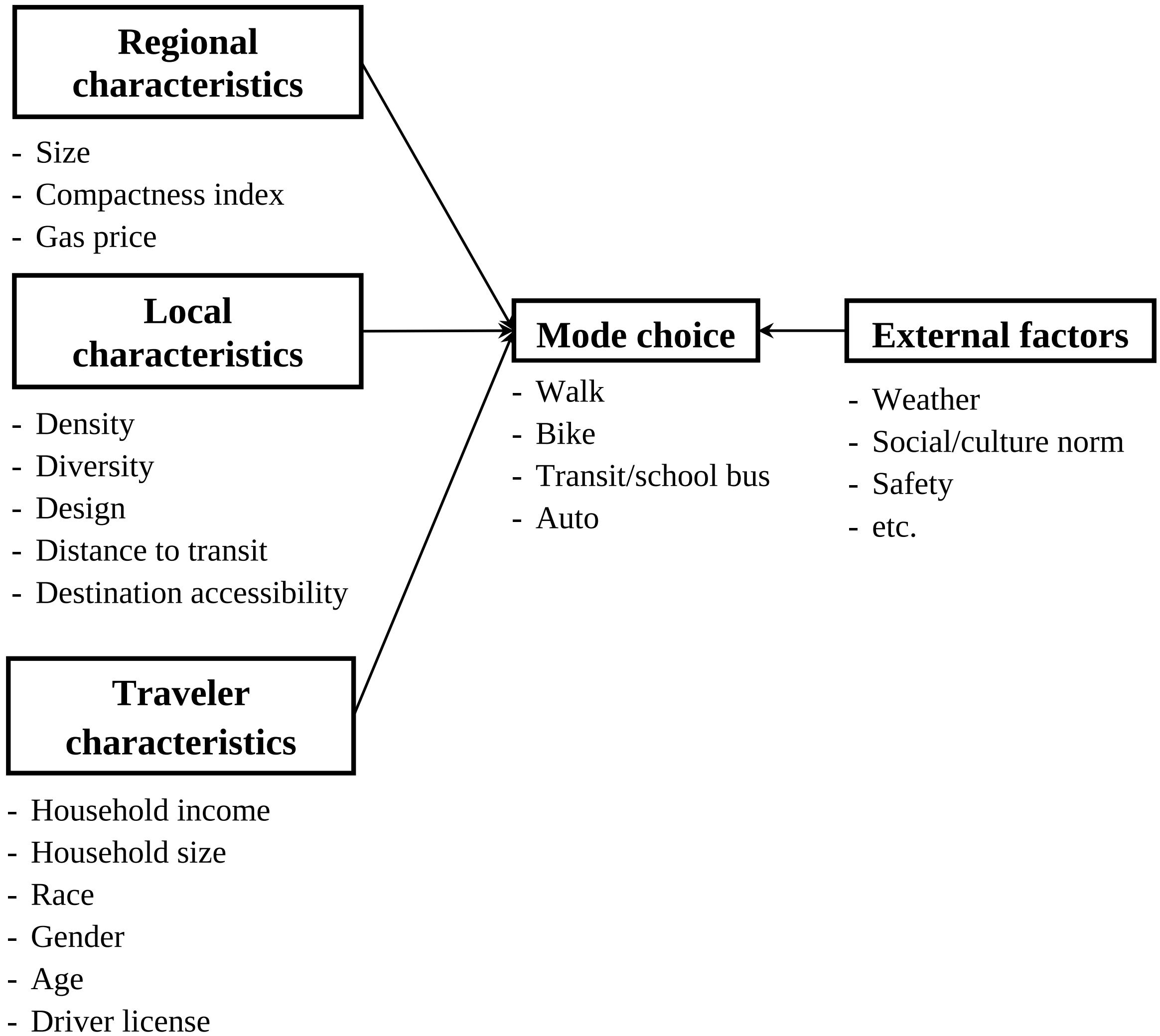

Figure 1.1 Conceptual framework

example, youths travel to school, adults travel to work or shopping, older people travel for exercise or leisure.

The land uses and streets provide the physical setting in which individuals make travel choices. If the travel distance is long, an automobile or public transit constitutes the choice set. For walking or biking to be a choice, the distances between origins and destinations should be walkable or bikeable ("walkable" and "bikeable" are imprecise distances that depend on the individual). Meanwhile, the streets between origins and destinations should be walkable or bikeable, i.e., complete with sidewalks or bike lanes, crossing intersections, etc. Urban land use patterns, including density, diversity, and design, generate walkable and bikeable distances.

1.4 Data Sources

The most widely used data source to study travel behavior is household travel survey. Household travel survey data are the fundamental input for regional travel demand modeling and forecast. Many regional metropolitan planning organizations (MPOs) conduct their own travel survey for their uses. In the last 5 years, I have been contacting regional MPOs and collecting household travel survey data. A main criterion for inclusion of regions in this study was data availability. Regions had to offer regional household travel surveys with XY coordinates, so I could geocode the precise locations of trip ends. It is not easy to assemble databases that meet this criterion, as confidentiality concerns often prevent metropolitan planning organizations from sharing XY travel data. The resulting pooled dataset consists of 815,160 trips generated by 81,056 households (Table 1.3) in 23 regions (Figure 1.2), from which senior trips could be extracted and mode choices analyzed.

The regions included in my household travel survey sample were, in addition, able to supply GIS data layers for streets and transit stops, population and employment for traffic analysis zones, and travel times between zones by different modes for the same or close enough to the years that the household travel surveys were conducted (Table 1.4). In addition to these GIS layers, I collected data of weather conditions from Climate

Table 1.3 Regions (metropolitan areas) included in this dissertation

Regions	***Survey year***	***Surveyed household***	***Surveyed trips***
Atlanta, GA	2011	9,575	93,681
Austin, TX	2005	1,448	14,249
Boston, MA	2011	7,826	86,915
Denver, CO	2010	5,551	55,056
Detroit, MI	2005	939	14,690
Eugene, OR	2009	1,674	16,563
Greensboro, NC	2009	2,023	17,561
Houston, TX	2008	5,276	59,552
Indianapolis, IN	2009	3,777	37,473
Kansas City, KS	2004	3,022	31,779
Miami, FL	2009	1,433	11,580
Minneapolis-St. Paul, MN-WI	2010	8,234	79,236
Phoenix, AZ	2008	4,314	37,811
Portland, OR	2011	4,508	47,551
Provo-Orem, UT	2012	1,464	19,255
Rochester, NY	2011	3,439	23,146
Sacramento, CA	2000	3,520	33,519
Salem, OR	2010	1,668	16,231
Salt Lake City, UT	2012	3,491	44,576
San Antonio, TX	2007	1,563	14,952
Seattle, WA	2006	3,908	40,450
West Palm Beach, FL	2009	944	7,166
Winston-Salem, NC	2009	1,459	12,168
Total		**81,056**	**815,160**

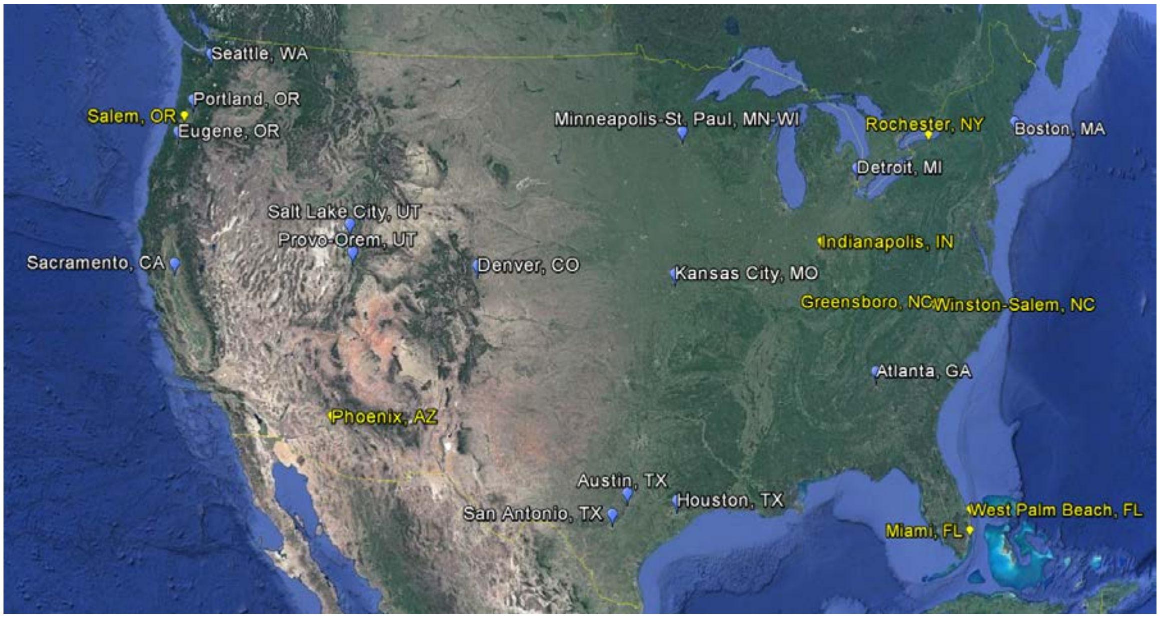

Figure 1.2 Map of regions (metropolitan areas) included in this dissertation

Table 1.4 Data sources and usage

Data	***Type***	***Source***	***Usage or information***
household travel daily	survey	regional MPOs	travel choice, personal and household characteristics, household location
parcel with land use	shapefile	regional MPOs, county accessors	calculate land use mix entropy
street network	shapefile	regional MPOs, state DOTs	use to generate network buffer and intersections
transit stop	shapefile	regional MPOs, transit agencies	calculate transit stop density
socioeconomic data	table	regional MPOs, US census	calculate job-population density
travel analysis zone (TAZ)	shapefile	regional MPOs	calculate employment accessibility
Travel time skim	table	regional MPOs	calculate employment accessibility
road function classification	shapefile, table	regional MPOs, state DOTs	identify major roads
library	table with locations (survey data)	Institute of Museum and Library Services	relevant destinations
museum	table with locations (universe data)	Institute of Museum and Library Services	relevant destinations

Table 1.4 continued

Data	***Type***	***Source***	***Usage or information***
parks	shapefile	state and city public data	relevant destinations
street smart walkscore	table with geographic information	Walkscore	measure walkability at census tract level
weather conditions	table	NOAA	calculate average weather conditions and days with extreme weather

Data Online of National Centers for Environmental Information in the same years with the household travel survey data for each region.

1.5 Methodology

1.5.1 Buffers to Capture Built Environment

It is important to define a spatial unit that can best capture local built environments that affect individual's travel behavior. There is no right answer to which spatial unit is preferred. Predefined spatial units have been used a lot in the literature, such as census block group boundary, census tract boundary, and traffic analysis zone (TAZ). The problem of these predefined geographic areas is that they are too big and cannot accurately capture built environment for walking and biking. For instance, the size of TAZs usually ranges from census block group to census tract or even several square miles in area. Walk and bike trips tend to be much shorter than that. The average distances for walking and biking are 0.7 miles and 2.6 miles, respectively, in National Household Travel Survey (NHTS) 2009. The origin and destination of a walk trip might be contained within one TAZ in many cases.

For walking and biking behavior study, road network buffer has been proven more appropriate than circular buffer or any predefined spatial units such as TAZs, census block groups, etc. (Oliver et al., 2007). To capture the built environment around households, the location information for households is also needed.

The next question is to what extent the built environment is most relevant to individual's travel decision. Theoretically, buffers (distances from household locations) could be wide or narrow. Even a determinant as straightforward as walking distance could be anywhere from one quarter mile to one mile or more. For Chapters 2 and 4 in this dissertation, buffers are established around household geocode locations with three different buffer widths, one quarter mile, one half mile, and one mile. Built environmental variables were computed for each household and all three buffer widths.

For Chapter 3, a one-quarter-mile buffer along the shortest route between home and school is used. The micro built environment along the routes to school is important for active travel. These are factors that influence the experience of walking or biking on the street, which further affect the decision of mode choice. A one-quarter-mile buffer width was used because that is wide enough to capture other possible routes between home and school. Based on the household travel survey data, students' home and school were identified first. Then, the shortest route between each student's home and school was calculated by using network analysis in GIS.

1.5.2 Analysis Techniques

In each study of this dissertation, different techniques of analysis and modeling have been used based on the specific research questions and the nature of the data structure. These techniques include principal component analysis (PCA), analysis of variance (ANOVA), multinomial logistic regression, two-stage hurdle models (first stage – logistic regression; second stage – negative binomial regression), and multilevel modeling.

In the first and third studies, I modeled trip frequency, which is a count variable with significant zero values. I used the two-stage hurdle model to handle that – logistic regression at the first stage to determine whether a household wants to walk or bike;

negative binomial regression at the second stage to determine how many walk or bike trips a household has after they decide to walk or bike. In the second study, I am interested with what mode students use to travel to school, so I employed multinomial logistic regression to estimate a mode choice model.

All of the three studies are based on the data from multiple regions. With the data from multiple regions, the data structure is hierarchical, with households or students nested within regions. The best statistical method to deal with nested data is multilevel modeling (MLM), also called hierarchical modeling (HLM). MLM accounts for dependence among observations, in this case the dependence of households or students within a given region on characteristics of the region. All households or students within a given region share these characteristics. This dependence violates the independence assumption of ordinary least squares (OLS) regression. Standard errors of regression coefficients based on OLS will consequently be underestimated. Moreover, OLS coefficient estimates will be inefficient. MLM overcomes these limitations, accounting for the dependence among observations and producing more accurate coefficient and standard error estimates (Raudenbush & Bryk, 2002).

Regions such as Boston and Houston are likely to generate very different travel patterns regardless of household or student and around built environment characteristics. The essence of MLM is to isolate the variance associated with each data level. MLM partitions variance between the household or student level (Level 1) and the region level (Level 2) and then seeks to explain the variance at each level in terms of D variables. MLM is used for all the modeling processes in this dissertation.

1.5.3 Spatial Autocorrelation

Spatial autocorrelation, which began with the discipline of geography, has been a common issue in planning now. Spatial autocorrelation measures the correlation of a variable with itself through space (Anselin, 1988). Observations made at different locations may not be independent. Measurements made at nearby locations may be closer in value than measurements made at locations farther apart. This phenomenon is called spatial autocorrelation. Any study that uses spatial data should address this issue first. If there is spatial autocorrelation and a study does not control for it, the results will be biased. The effects of whatever has been tested will be misleading, either overestimated or underestimated.

The way to test spatial autocorrelation in a dataset as I have is also a challenge. I have tested spatial autocorrelation for the dataset in this dissertation by using global Moran's *I* and local Moran's *I*. Using the walk trips as an example, the global Moran's *I* is 0.13 with a significant z-core, which provides evidence that there is a spatial autocorrelation issue in the dataset. Then, I tried the local Moran's *I* to identify where the spatial autocorrelations are. The results show that 90% of the local Moran's *I* are not statistically significant, which means the majority of the individual locations (households) do not have the spatial autocorrelation issue.

I have plotted the data and find that there are clear spatial patterns. The values of households within the same regions tend to similar. The values of households within different regions vary a lot. Some regions have high walk and bike trips, some regions have very low walk and bike trips.

Back to the Moran's *I* tests, these actually all make sense. The spatial autocorrelation of global Moran's *I* is the overall spatial patterns of region to region. There is a spatial autocorrelation issue over the whole dataset, but locally, the spatial autocorrelation is weak within each region, which is indicated by the fact that 90% local Moran's *I* are not significant. This is also consistent with the travel pattern analysis that the travel patterns are very different from region to region. For instance, the walk mode share is as high as 22.1% in Bostin and as low as 3.1% in Houston.

Given the nested structure of the dataset in this dissertation, households nested within regions, it is not surprising that there is spatial autocorrelation at the regional level. The employment of multilevel modeling technique is specifically to deal with data that share characteristics among groups (regions in this case).

1.6 Highlights

This dissertation will advance our understanding of the influence of built environment on travel choice, especially for students and seniors, in several ways:

- Providing results with external validity by pooling household travel and build environment data from 23 diverse US regions. This is the largest sample of household travel records ever assembled for such a study outside the National Household Travel Survey (NHTS). And relative to NHTS, this dataset provides much larger samples for individual regions and permits the calculation of a wide array of built environmental variables based on the precise location of households. NHTS provides geocodes (identifies households) only at the census tract level.
- Analysis of walk behavior in trip chaining to test the importance of

accessibility of destinations and residences. The concepts of “destination accessibility” and “residential accessibility” are concepts discussed in the early literature on travel and the built environment, but forgotten more recently.

- Limiting school trips that are less than 2 miles, where walk and bike are possible options in students’ mode choice set, and computing the built environment within the buffer along the shortest route between home and school.
- Use of principal component analysis (PCA) to extract built environment and analysis of variance (ANOVA) tests to see if elderly trips differ by neighborhood type and income level.
- Measuring build environment consistently across the 23 regions and testing relevant variables to walk, bike, students and seniors, including parks, libraries, museums, Walkscore, and weather condition.
- Use of multilevel modeling (MLM) to account for dependence of households in the same region on shared regional characteristics.
- Estimation of ‘hurdle’-style models to account for the excess number of zero values in the distributions of dependent variables.
- Testing of built environmental variables for different buffer widths around household locations to see which scale best explains travel behavior; use of buffer around the shortest route between home and school.
- Modeling of bike trips, heretofore precluded by small samples of bike trips in individual regional household travel surveys.

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CHAPTER 2

WALK AND BIKE: EVIDENCE FROM 23 DIVERSE REGIONS OF THE UNITED STATES

This chapter studies walk and bike trips by pooling household travel, built environment, and weather condition data from 23 diverse U.S. regions with more external validity than any to date. Of the 23 regions, only 9.0% of all trips in my sample are by walking and 1.2% of all trips are by biking, while 83.9 of all trips are by car. Even for trips of less than 1 mile from origin to destination, only 35.7% of trips are by walking and 2.1% of trips are by biking. The built environment is implicated in these surprisingly low mode shares.

I employ multilevel modeling to account for the dependence of households in the same regions on shared regional characteristics and estimate two-stage hurdle models to account for the excess number of zero values in the distributions of dependent variables. Walk mode choice depends primarily on land use diversity, street connectivity, and transit accessibility, while bike mode choice depends primarily on street connectivity and transit accessibility. Other factors may enter into the decision to use a car rather than walk or bike. In addition to long distances of trips and low values of the D variables, both extreme temperature and precipitation discourage walking and biking, but precipitation has stronger influence than temperature does.

On multipurpose linked trips (three or more trips in a series from home to one destination, from that destination to another destination, and eventually back to home), the resulting trip chain shows that, surprisingly, 85% of walk trips were involved in complex trip chains. Even 20% of walk trips are within complex trip chains that start and end with an automobile trip, which means people drive somewhere, then leave their cars and walk from destination to destination before returning home. This tells us that accessibility of destinations to one another may be almost as important as accessibility of residences to destinations.

2.1 Introduction

Despite more than 5 decades of research into travel-demand modeling, it is a challenge to develop models that reliably predict walk and bike trips (Kuzmyak et al., 2014; Liu et al., 2012; Singleton & Clifton, 2013). This study proposes walk and bike trip generation models, which are based on attributes of built environment around households and regional characteristics. Weather condition and sociodemographic influences on walking and biking are controlled as potential confounders.

In the past 2 decades, there have been two fields interested in walking and biking (Saelens & Handy, 2008). The transportation planning field treats walking and biking as modes of transportation. In this field, studies make the connection between the built environment and travel behavior. The public health field represents walking and biking as a form of leisure-time physical activities. Studies in this field focus on the connection between the built environment and walking and biking for recreation or exercise.

Shifting travel from the automobile to walking and biking is also a core strategy for reducing greenhouse gases, regulated air pollutants, road infrastructure expenditures, traffic fatalities, and other social, economic, and environmental costs of automobile use (Alliance for Biking and Walking, 2012; Jacobsen, 2003; Krizek et al., 2009). At the same time, walking and biking are widely recommended for its health benefits (Frank et al., 2007; Pucher & Dijkstra, 2003).

When assessing the benefits, costs, and priorities of proposed pedestrian and cyclist improvements for the government or developers, it is necessary to answer the following question: What kinds of built environments encourage people to choose to travel on foot?

Conventional travel-demand modeling procedures generally predict total trip making (or in older models, trip making by vehicle) and mode choice based on variables such as a household's demographic characteristics, the time and cost of traveling by competing modes, and the spatial characteristics of the built environment through which the trip occurs. In a four-step model, if total trips can be generated (including nonmotorized trips), then it should be possible to distribute trips in the trip distribution step, split trips between motorized and nonmotorized modes in the mode choice step, and then assign motorized and nonmotorized separately to their respective networks. However, even though there are several ways to handle nonmotorized modeling within a four-step model, nonmotorized modeling is often not carried past the trip generation step in such models owing to local data and resolution limitations.

An alternative approach, analogous to direct demand modeling of transit ridership (direct ridership modeling), is pursued in this paper (Cervero, 2006). Using household travel survey data from 23 diverse regions of United States and consistent built environment measurements, this study proposes a walk trip generation model and bike trip generation model.

2.2 Literature Review

Trip generation is "the process by which measures of urban activity are translated into numbers of trips" (U.S. Department of Transportation, 1977, p. 1-25). Trip generation analysis is used to forecast the number of trips for different purposes in terms of land use patterns and socioeconomics. For instance, a neighborhood in a suburban area might generate work commute trips mostly by automobile, whereas a shopping center close to a downtown light rail station might generate more shopping trips by public transit. Trip generation studies aim to quantify the relationship among the built environment, human activity, and travel behavior.

2.2.1 Walking and Biking in Current Travel Demand Models

2.2.1.1 ITE Trip Generation Studies

Planners, engineers, developers, and government decision makers all rely on trip generation to predict traffic impacts of new development projects (Shoup, 2003). The Trip Generation Manual and Trip Generation Handbook of the Institute of Transportation Engineers (ITE) are standard sources for analysis of traffic impacts. ITE's Trip Generation Manual provides estimates of the number of vehicle trips generated by a specific land use based on trip surveys of suburban developments constructed after the 1960s. The trip rates given by ITE are mostly generated in single-use suburban development dominated by automobile travel. As the report describes, "Data were primarily collected at suburban localities with little or no transit service, nearby pedestrian amenities, or travel demand management (TDM) programs" (ITE 2012, vol. 1, p. 1), and "All data presented in this manual represent VEHICLE trip generation rather than person trip generation" (ITE 2012, vol. 1, p. 11). Further, ITE advises: "At specific sites, the user may want to modify the trip generation rates presented in this document to reflect the presence of public transportation service, ridesharing or other TDM measures, enhanced pedestrian trip-making opportunities, or other special characteristics of the site or surrounding area" (ITE 2012, vol. 1, p. 1). Walk and bike trips, the focus of this paper, are not captured by the ITE manuals.

2.2.1.2 Four-Step Models

Travel demand models are primarily used to predict the number of vehicle and transit trips that will use the road and transit networks in the future based on projections of future land use patterns and future network capacities. The conventional four-step model has become the workhorse of long-range transportation planning. Its steps include trip generation, trip distribution, mode choice (or mode split), and route choice (trip assignment) (Beimborn et al., 1996; McNally, 2008; Zhou et al., 2009). However, the conventional four-step model has limitations when walk and bike are considered as a transportation modes. In the conventional four-step model, an urban area is divided into a series of geographic subareas called travel analysis zones (TAZs). Although TAZs tend to be rather homogenous in terms of land uses (e.g., entirely residential or largely commercial) that would seem to suggest that most walk and bike trips will be interzonal, the size of TAZs usually ranges from census block group to census tract or even several square miles in area. Walk and bike trips tend to be much shorter than that. The average distances for walking and biking are 0.7 miles and 2.6 miles, respectively, in National Household Travel Survey (NHTS) 2009. Though the origin and destination of a walk trip might be contained within one TAZ in many cases, a surprisingly high percentage of walk and bike trips are actually intrazonal (For example, 56% walk trips from the Portland household travel dataset are intrazonal), which means that the conventional four-step model often excludes walking in the trip generation step. Furthermore, if walking and biking are included in trip generation, trip rates often ignore local land use and street network characteristics since the four-step model reduces land use patterns to a single point (called the zone centroid) and the street networks to one or more links to the external street network (called centroid connectors). A four-step model that aggregates urban characteristics at TAZ level cannot represent the actual built environment affecting pedestrians and cyclists.

The first regional travel model to explicitly include nonmotorized modes appeared more than 20 years ago (Porter et al., 1999; Singleton & Clifton, 2013), but current regional pedestrian and cyclists modeling practices vary considerably. A recent review reported that between one-half and two-thirds of large metropolitan planning organizations (MPOs) include nonmotorized travel in their trip-based models, with about half the models separating out nonmotorized trips in the mode choice step (Liu et al., 2012). The percentages would be smaller, of course, for small and medium-size MPOs. Clifton et al. (2016) present a framework to improve how travel demand models represent walking and biking trips and demonstrate an application in the Portland, Oregon, region. There are challenges for MPOs to incorporate nonmotorized travel into regional travel demand models, including limited nonmotorized travel behavior data, limited built environment data, the aggregate nature of TAZ data, limited modeling resources, and even lack of decision-maker interest (Liu et al., 2012; Singleton & Clifton, 2013).

2.2.1.3 Direct Demand Model

Direct demand modelling (DDM) is another tool used to forecast travel. DDM departs from the sequential process of the four-step model by attempting to develop a one-step equation for trip estimation based on socioeconomic characteristics, travel times, travel cost, mode availability, etc. (Anderson et al., 2006; Wardman, 1997). A typical strategy for DDM is to use multiple linear regression to estimate the trips between origin and destination by a specific mode. Many direct demand models have been developed for forecasting travel outside the four-step process and ITE trip generation methodology, but these models have been mostly for prediction of transit trips. Only few studies have done this for nonmotorized travel (such as Baran et al., 2008; Cao et al., 2006; Shay et al., 2006).

2.2.2 Accessibility and Trip Chain

Accessibility is defined in terms of ease of access to desired activities. The more activities available within a given travel time, the better the “accessibility” of a location. Good accessibility offers the potential for “maximum contact with minimum effort.” Two types of accessibility may affect household travel behavior. Residential accessibility refers to the ease of access to activities from one’s place of residence, destination accessibility to ease of access to activities from other activities, whether work, school, shopping, or recreational sites. Destination accessibility is potentially significant in that it affects travelers' ability to efficiently link trips for different purposes into chains or tours or, better still, complete more than one activity at a single stop.

Accessibility to regional activities has much more effect on household travel patterns than does density or land use mix in the immediate area. The benefits of accessibility are primarily in the form of shorter auto trips, and also shift to alternative modes when a cluster of destinations are accessible. The relationship between built environment and travel can be fully understood only in terms of multipurpose trip making.

The study of trip chaining in travel behavior started as early as the 1970s. Back to 1978, Adler and Ben-Akiva argued that there is a need for expanding the scope of existing travel forecasting models to explicit considerations of trip chaining behaviors (Adler & Ben-Akiva, 1978). In recent years, with the availability of travel data and the development of activity-based modeling techniques, studies have been done to evaluate the interactions between the model choice and trip chain. The key finding is that people usually make a complex trip chain pattern first, and then their mode choices (Krygsman et al., 2007; Ye et al., 2007; Yang et al., 2016). Also, a study found that complex trip chain pattern is a barrier to public transit use (Hensher & Reyes, 2000).

2.2.3 Challenge of Walk and Bike Trip Generation

The widely used built environment D variables mainly measure neighborhood characteristics such as development density and land use diversity. When design is operationalized, it is usually in terms of neighborhood street network characteristics such as intersection density and percentage of four-way intersections (Ewing & Cervero, 2010). Other design characteristics are omitted for lack of available data from national or local sources. For example, there is no national source of sidewalk data, and even local geographic information systems seldom include a sidewalk layer. Physical features of a specific street impact an individual's sense of safety and comfort, which further impact people's travel choices. Ewing and Handy (2009) identify street environments associated with walking behavior by using ratings from an expert panel. Failure to include micro environment characteristics such as street design in walk and bike trip generation models can compromise the internal and construct validity of the research (Cervero & Duncan, 2003). First, a conceptual framework of how built environment may influence walk and bike trip generation is needed (Oliver et al., 2007). Second, finding sufficiently detailed data on the built environment that can be spatially matched to sufficiently detailed data on travel behavior is a challenge (Handy et al., 2002). Since walking and biking distance is short compared to automobile trips, more refined spatial unit is necessary to identify the spatial location of respondents and objectively and accurately capture their local environments (Liu et al., 2012). The challenge of finding detailed built environment data to be matched with travel behavior, cited by Handy et al. 13 years ago, has decreased with the increasing use of Google Street View and related products. At least three manuscripts have compared Street View to in-street audits, and have concluded that for the vast majority of built environment attributes, Street View performs just fine (Griew et al. 2013; Kelly et al., 2013; Rundle et al., 2011).

Also, weather condition is an important factor that influences walk and bike mode choice (Böcker et al., 2013; Nankervis, 1999a; Saneinejad et al., 2012). It has been found that rates of walking and biking trips appear to exhibit some seasonal and daily fluctuation. Precipitation and temperature markedly affect pedestrian and cyclists volumes (Aultman-Hall et al., 2009; Miranda-Moreno & Nosal, 2011; Nankervis, 1999b).

This study proposes walk and bike trip generation models that incorporates more built environmental variables than any to date, while controlling for weather conditions and sociodemographic influences.

2.3 Methodology

2.3.1 Data Collection

The most widely used data source to study travel behavior is the household travel survey. Household travel survey data are the fundamental input for regional travel demand modeling and forecast. Many regional metropolitan planning organizations (MPOs) conduct their own travel survey for their uses. In the last 5 years, we have been contacting regional MPOs and collecting household travel survey data. A main criterion for inclusion of regions in this study was data availability. Regions had to offer regional household travel surveys with XY coordinates, so we could geocode the precise locations of trip ends. It is not easy to assemble databases that meet this criterion, as confidentiality concerns often prevent metropolitan planning organizations from sharing XY travel data. The resulting pooled dataset consists of 81,056 households in 23 regions, from which walk and bike trips could be extracted and mode choices analyzed.

The regions included in our household travel survey sample were, in addition, able to supply GIS data layers for streets and transit stops, population and employment for traffic analysis zones, and travel times between zones by different modes for the same or close enough to the years that the household travel surveys were conducted.

All the GIS layers that were used to compute built environment are:

- parcel level land use data with detailed land use classifications; from these we can compute detailed measures of land use mix;
- street networks and intersections; from these we can build the buffer widths and compute intersection density;
- transit stops; from these data we can compute transit stop densities;
- population and employment at the block or block group level; from these we can compute activity density;
- TAZs with socioeconomic information (population and employment);
- travel times for auto and transit travel from TAZ to TAZ (so-called travel time skims); from these and TAZ employment data we can compute regional employment accessibility measures for auto and transit.
- walkscore, street smart walkscore measuring the walkability of neighborhood at census travel level

At present, we have consistent datasets for 23 regions (Table 2.1). The regions are as diverse as Boston and Portland at one end of the urban form continuum and Houston and Atlanta at the other. To our knowledge, this is the largest sample of household travel records ever assembled for such a study outside the NHTS. Relative to NHTS, our database provides much larger samples for individual regions and permits the calculation of a wide array of built environmental variables based on the precise location of households. NHTS provides geocodes only at the census tract level.

Table 2.1 Regions (metropolitan areas) in the dataset

Regions	***Year of data***	***Regions***	***Year of data***	***Regions***	***Year of data***
Atlanta, GA	2011	Indianapolis, IN	2009	Sacramento, CA	2000
Austin, TX	2005	Kansas City, KS	2004	Salem, OR	2010
Boston, MA	2011	Miami, FL	2009	Salt Lake City, UT	2012
Denver, CO	2010	Minneapolis-St. Paul, MN-WI	2010	San Antonio, TX	2007
Detroit, MI	2005	Phoenix, AZ	2008	Seattle, WA	2006
Eugene, OR	2009	Portland, OR	2011	West Palm Beach, FL	2009
Greensboro, NC	2009	Provo-Orem, UT	2012	Winston-Salem, NC	2009
Houston, TX	2008	Rochester, NY	2011		

2.3.2 Variables

The final dataset contained 815,160 trips made by 81,056 households in 23 regions. To maintain a full complement of independent variables for subsequent analysis, trips were dropped for lack of travel mode and households were dropped for missing any of the following variables: household size, vehicle ownership, etc. The greatest loss of cases was due to unknown household income. As is often the case in travel surveys, household income went unreported by a large number of respondents. We could exclude household income to maintain a larger sample size, but household income was too important from a theoretical perspective to be omitted from the mode choice analysis.

The unit of analysis is the households, so the dependent variables are numbers of walking and biking trips made by households. Four variables were created based on travel modes (Table 2.2).

Independent variables include socioeconomic characteristics and built environment variables that have been reported as important factors on travel choice by different studies in the literature. These built environment variables cover all of the Ds,

Table 2.2 Dependent and independent variables

Variable	*Description*	*N*	*Mean*	*S.D.*
Dependent variables –household				
anywalk	any household walk trips (1 = yes, 0 = no)	81,056	0.23	0.42
walktrips	number of household walk trips (for households with any walk trips)	18,622	3.88	3.34
anybike	any household bike trips (1 = yes, 0 = no)	81,056	0.04	0.19
biketrips	number of household bike trips (for households with any transit trips)	3,042	3.14	2.53
Independent variables – sociodemographic characteristics				
hhsize	household size	81,056	2.5	1.36
workers	number of workers in the household	81,056	1.24	0.88
hhincome	real household income (in 1000s of 2012 dollars)	81,056	76.87	49.52
Independent variables – built environment within buffers				
actdenqmi	activity density within ¼ mile buffer (population + employment per square mile in 1000s)	81,056	6.65	11.01
jobpopqmi[1]	job-population balance within the ¼ mile buffer	81,056	0.58	0.27
entropyqmi[2]	land use entropy within the ¼ mile buffer	81,056	0.21	0.26
intdenqmi	intersection density within the ¼ mile buffer	81,056	195.32	289.36
int4wayqmi	the percentage of 4-way intersections the ¼ mile buffer	81,056	27.67	28.96
stopdenqmi	transit stop density within the ¼ mile buffer	81,056	24.64	46.17
actdenhmi	activity density within the ½ mile buffer (population + employment per square mile in 1000s)	81,056	6.53	10.51
jobpophmi	job-population balance within the ½ mile buffer	81,056	0.60	0.26

[1] The job-population index measures balance between employment and resident population within a buffer. Index ranges from 0, where only jobs or residents are present within a buffer, not both, to 1 where the ratio of jobs to residents is optimal from the standpoint of trip generation. Values are intermediate when buffers have both jobs and residents, but one predominates. jobpop = 1 – [ABS (employment – 0.2*population)/(employment + 0.2*population)], ABS is the absolute value of the expression in parentheses. The value 0.2, representing a balance of employment and population, was found through trial and error to maximize the explanatory power of the variable.

[2] The entropy index measures balance between three different land uses. Index ranges from 0, where all land is in a single use, to 1 where land is evenly divided among the three uses. Values are intermediate when buffers have more than one use but one use predominates. The entropy calculation is:
entropy = -[residential share*ln (residential share) + commercial share*ln (commercial share) + public share*ln (public share)]/ ln (3), where ln is the natural logarithm of the value in parentheses and the shares are measured in terms of total parcel land areas.

Table 2.2 continued

Variable	***Description***	***N***	***Mean***	***S.D.***
entropyhmi	land use entropy within the ½ mile buffer	81,056	0.34	0.28
intdenhmi	intersection density within the ½ mile buffer	81,056	141.55	100.12
int4wayhmi	the percentage of 4-way intersections the ½ mile buffer	81,056	26.81	22.32
stopdenhmi	transit stop density within the ½ mile buffer	81,056	22.53	32.94
actden1mi	activity density within the ½ mile buffer (population + employment per square mile in 1000s)	81,056	6.75	9.54
jobpop1mi	job-population balance within the ½ mile buffer	81,056	0.62	0.25
entropy1mi	land use entropy within the ½ mile buffer	81,056	0.46	0.27
intden1mi	intersection density within the ½ mile buffer	81,056	113.53	78.73
int4way1mi	the percentage of 4-way intersections the ½ mile buffer	81,056	26.04	18.44
stopden1mi	transit stop density within the ½ mile buffer	81,056	20.18	25.89
railhmi	rail station within ½ mile buffer (1 = yes, 0 = no)	81,056	0.07	0.61
emp10a	percentage of regional employment within 10 min by car	81,056	7.05	10.14
emp30t	percentage of regional employment within 30 min by transit	81,056	19.71	22.63
walkscore	the walkscore of the census tract where the household is	81,056	37.87	25.38
Independent variables – region				
reginpop	population within the region 1000s	23	2317.77	1678.13
gasprice	average gasoline prices for 2010 at the region	23	2.90	0.13
compact	measure of regional compactness index developed by Ewing and Hamidi (2014); higher values of the index correspond to more compact development, lower values to more sprawling development	23	97.64	26.90
temp_low	annual average of low temperature	23	42.25	14.01
temp_high	annual average of high temperature	23	75.04	8.40
dayt32	number of days the low temperature <= 32 °F	23	32.43	39.17
dayt90	number of days the low temperature >= 90 °F	23	53.65	48.30
annprecip	annual precipitation in inch	23	38.19	16.35
dayp50	number of days the precipitation >= 0.50 inch	23	24.83	11.41

from density to demographics.

What extent of the built environment is most relevant to individual's travel decision? Theoretically, buffers (distances from household locations) could be wide or narrow. Even a determinant as straightforward as walking distance could be anywhere from ¼ mile to 1 mile or more. In this study, buffers were established around household geocode locations with three different buffer widths, ¼ mile, ½ mile, and 1 mile. Built environmental variables were computed for each household and all three buffer widths.

Point, line, and polygon data from the different sources were joined with buffers to obtain raw data, such as the number of intersections within buffers. These were then used to compute refined built environmental measures such as intersection density, which is simply the number of intersections divided by land area within the buffer. Additionally, Walkscore was tested to see its explanatory power of walk and bike choices.

This study also includes nine variables at the regional level: population measuring the size of a metropolitan area, compactness index measuring the overall built environment of a region, gas price, and six weather variables measuring weather condition. The weather variables were collected from Climate Data Online of National Centers for Environmental Information in the same years with the household travel survey data for each region. With different measures, a total of 33 independent variables are available to explain senior travel choice in this study. All variables are consistently defined from region to region.

2.3.3 Model Selection

2.3.3.1 Multilevel Modeling

With the household travel survey from 23 regions, our data structure is hierarchical, with households nested within regions. The best statistical method to deal with nested data is hierarchical modeling (HLM), also called multilevel modeling (MLM). HLM accounts for dependence among observations, in this case the dependence of households within a given region on characteristics of the region. All households within a given region share these characteristics. This dependence violates the independence assumption of ordinary least squares (OLS) regression. Standard errors of regression coefficients based on OLS will consequently be underestimated. Moreover, OLS coefficient estimates will be inefficient. HLM overcomes these limitations, accounting for the dependence among observations and producing more accurate coefficient and standard error estimates (Raudenbush & Bryk, 2002).

Regions such as Boston and Houston are likely to generate very different travel patterns regardless of household and around built environment characteristics. The essence of HLM is to isolate the variance associated with each data level. HLM partitions variance between the household level (Level 1) and the region level (Level 2) and then seeks to explain the variance at each level in terms of D variables.

2.3.3.2 Count Data and Hurdle Model

The dependent variables (household walk trips and bike trips) are count variables, with nonnegative integer values, many small values, and few large ones. This kind of distribution is ordinarily modeled with Poisson or negative binomial regression.

However, if there is a much larger number of observed zeros than assumed by a Poisson or negative binomial distribution, the distribution is said to be “zero-inflated” and an alternative analytical approach is required. One solution to the zero-inflated distribution is two-stage hurdle models (Greene, 2012; Hu et al., 2011). “In some settings, the zero outcome of the data-generating process is qualitatively different from the positive ones. The zero or nonzero values of the outcome is the result of a separate decision whether or not to ‘participate’ in the activity. On deciding to participate, the individual decides separately how much to, that is, how intensively [to participate]” (Greene, 2012, p. 824).

In a two-stage hurdle model, stage 1 categorizes households as having at least one walk or bike trip or not, and uses logistic regression to distinguish these two states. The stage 2 model estimates the number of walk or bike trips generated by households with any (positive) walk or bike trips. Either Poisson regression or negative binomial regression can be used at stage 2. The difference between these two methods is their assumptions about the distribution of the dependent variable.

Negative binomial regression is more appropriate than Poisson regression if the dependent variable is over-dispersed, meaning that the variance of the count is greater than the mean. Popular indicators of overdispersion are the Pearson and $\chi 2$ statistics divided by the degrees of freedom, so-called dispersion statistics. If these statistics are greater than 1.0, a model is said to be over-dispersed (Hilbe, 2011). By these measures, in this study, both the number of walk trips and bike trips are over-dispersed, and thus the negative binomial model is more appropriate than the Poisson model.

In sum, this study will use multilevel logistic regressions and multilevel negative binomial regressions to model the data. The equations of the regressions are as follow:

First stage of hurdle models (multilevel logistic regression):

Level 1: $P(y = 1 \mid x_1, \dots x_n) = 1/(1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i}) \quad (2.1)$

Level 2: $\beta_0 = \gamma_{00} + \sum_{j=1}^{m} \gamma_{0j} W_j + u_{0j} \quad (2.2)$

$\beta_i = \gamma_{i0} \quad (2.3)$

Where: *P* refers to the probability of the dependent variable equals 1,

β_0 refers to the intercept of the dependent variable at the level 1,

β_i refers to the coefficient of independent variables at the level 1,

x_i refers to the independent variables at the level 1,

γ_{00} refers to the overall intercept,

γ_{0j} refers to the coefficient of independent variables at the level 2,

W_j refers to the independent variables at the level 2,

u_{0j} refers to the random error component for the deviation of the intercept,

γ_{i0} refers to the overall coefficients.

Second stage of hurdle models (multilevel negative binomial regression):

Level 1: $E(y = 1 \mid x_1, \dots x_n) = e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)} \quad (2.4)$

Level 2: $\beta_0 = \gamma_{00} + \sum_{j=1}^{m} \gamma_{0j} W_j + u_{0j} \quad (2.5)$

$\beta_i = \gamma_{i0} \quad (2.6)$

Where: *E* refers to the estimated value of the dependent variable,

β_0 refers to the intercept of the dependent variable at the level 1,

βi refers to the coefficient of independent variables at the level 1,

x_i refers to the independent variables at the level 1,

γ_{00} refers to the overall intercept,

γ_{0j} refers to the coefficient of independent variables at the level 2,

W_j refers to the independent variables at the level 2,

u_{0j} refers to the random error component for the deviation of the intercept,

γ_{i0} refers to the overall coefficients.

2.4 Travel Pattern Analysis

2.4.1 Descriptive Analysis

The overall travel patterns in the 23 regions dataset are shown in Table 2.3. The mode shares are 9% walk, 1.2% bike, 2.7% transit, and 83.9% auto. This is very consistent with the model shares in 2009 NHTS. Even for trips of less than 1 mile from origin to destination, only 35.7% of trips are by walking and 2.1% of trips are by biking.

The walk mode share ranges from 3.5% in San Antonio up to 22.1% in Boston. The regions with the top three walk mode shares are Boston, Portland, and Eugene. The bike mode share ranges from 0.2% in San Antonio to 4.2% in Eugene. The regions with the top three bike mode shares are Eugene, Austin, and Portland. The transit mode share ranges from 0.2% in Austin to 8.7 in Boston. The regions with the top three walk mode shares are Boston, Portland, and Denver. The three regions with highest non-auto mode shares are Boston – 32.2%, Portland – 26.2%, and Eugene – 19.4. The three regions with the lowest non-auto mode shares are Kansas City – 4.8%, Houston – 4.4%, and San Antonio – 4.4%. Additionally, Boston has the lowest VMT per capita and Eugene has the lowest VMT per household. These findings are not surprising based on the common

Table 2.3 Comparison of mode shares in different regions

Regions	Survey year	Household	Trips	Mode share (%)				VMT per capita	VMT per household
				Walk	Bike	Transit	Auto		
Atlanta, GA	2011	9,575	93,681	5.4	0.3	1.9	87.1	24.02	50.84
Austin, TX	2005	1,448	14,249	4.0	3.1	0.2	90.7	24.33	61.5
Boston, MA	2011	7,826	86,915	22.1	1.4	8.7	64.9	17.55	38.97
Denver, CO	2010	5,551	55,056	12.2	1.4	4.1	80.8	18.08	37.19
Detroit, MI	2005	939	14,690	8.2	0.6	3.9	81.0	30.27	74.4
Eugene, OR	2009	1,674	16,563	12.2	4.2	3.0	79.2	19.31	32.77
Greensboro, NC	2009	2,023	17,561	6.7	0.4	0.3	90.4	39.68	59.78
Houston, TX	2008	5,276	59,552	3.1	0.5	0.8	90.5	26.96	74.35
Indianapolis, IN	2009	3,777	37,473	6.3	1.0	1.7	88.1	22.12	48.11
Kansas City, KS	2004	3,022	31,779	3.6	0.3	0.9	91.3	22.59	42.44
Miami, FL	2009	1,433	11,580	11.2	0.7	2.0	83.7	27.22	44.68
Minneapolis-St. Paul, MN-WI	2010	8,234	79,236	6.0	1.5	2.0	87.5	23.96	43.26
Phoenix, AZ	2008	4,314	37,811	8.7	1.2	0.8	86.6	33.27	56.79
Portland, OR	2011	4,508	47,551	17.7	2.9	5.6	71.0	20.12	43.21
Provo-Orem, UT	2012	1,464	19,255	8.6	1.8	0.6	87.2	34.42	69.17
Rochester, NY	2011	3,439	23,146	4.3	1.0	1.0	93.0	23.97	37.52
Sacramento, CA	2000	3,520	33,519	4.7	1.6	1.2	91.2	29.23	62.66
Salem, OR	2010	1,668	16,231	10.3	1.2	2.1	83.8	22.50	48.72
Salt Lake City, UT	2012	3,491	44,576	7.1	1.6	1.7	88.3	30.82	60.58
San Antonio, TX	2007	1,563	14,952	3.5	0.2	0.7	91.8	20.89	50.67
Seattle, WA	2006	3,908	40,450	8.3	1.0	2.8	83.2	22.79	47.29
West Palm Beach, FL	2009	944	7,166	10.8	0.9	0.6	86.3	29.55	45.28
Winston-Salem, NC	2009	1,459	12,168	6.2	0.3	0.4	91.0	38.06	59.74
Total		**81,056**	**815,160**	**9.0**	**1.2**	**2.7**	**83.9**	**24.60**	**53.74**

sense of these metropolitan areas. Boston is one of the most traditional neighborhoods with a good public transportation system, and Portland is becoming an exemplary planning model in the US in terms of its more recent compact developments and investments in bike and public transportation infrastructures. Houston and San Antonio are more typical sprawling suburban developments with more extreme summer temperatures.

In the 23 regions, the average walk and bike distances are 0.63 mile and 2.43 miles (Table 2.4), respectively, which are both slightly shorter than the national average in 2009 NHTS. The average walk and bike time are 11.50 minutes and 20.52 minutes, respectively. The average walk and bike distance vary across regions. In Sacramento, the average walk distance is as long as 2.75 miles, where in Atlanta and Denver, the average walk distance is as short as 0.28 miles. The longest average bike distance is 5.19 miles in Austin and shortest average bike distance is 1.44 miles in Salem. Although the overall average walk distance is around ½ mile, the average walk distance is different from region to region. When planning pedestrian-related work, planners should be careful to assume the ½ mile walking distance in their own regions.

2.4.2 Trip Chain Analysis

A trip chain, also called a trip tour, refers to a series of linked trips that start at home and end at home. According to the number of trip stops, a trip chain can be classified into a simple chain with one outside stop or a complex chain with multiple outside stops. So, a simple chain is chains with two trips, and a complex chain is chains with three or more trips.

Table 2.4 Comparison of walk and bike in different regions

Regions	***Walk***			***Bike***		
	# of trips	***average distance (mile)***	***average time (minute)***	***# of trips***	***average distance (mile)***	***average time (minute)***
Atlanta, GA	5,014	0.28	10.85	315	1.89	19.88
Austin, TX	573	0.74	9.16	438	5.19	25.83
Boston, MA	19,184	0.46	9.59	1,193	1.97	19.56
Denver, CO	6,693	0.28	9.55	744	1.56	17.47
Detroit, MI	1,204	1.16	16.69	84	1.51	17.75
Eugene, OR	2,027	0.33	10.26	700	1.52	17.17
Greensboro, NC	1,170	0.69	14.45	63	2.38	15.21
Houston, TX	1,852	1.20	9.10	267	2.30	10.55
Indianapolis, IN	2,367	0.50	10.95	373	1.74	20.02
Kansas City, KS	1,130	0.86	11.28	108	1.69	18.06
Miami, FL	1,294	0.67	13.98	83	2.27	20.05
Minneapolis-St. Paul, MN-WI	4,786	1.10	16.29	1,150	2.92	27.03
Phoenix, AZ	3,280	0.72	18.02	437	2.63	18.76
Portland, OR	8,400	0.34	8.91	1,353	1.96	20.93
Provo-Orem, UT	1,648	0.66	13.45	343	2.12	14.43
Rochester, NY	996	1.17	16.22	225	2.85	23.89
Sacramento, CA	1,570	2.75	12.48	547	3.08	15.10
Salem, OR	1,671	0.32	10.13	196	1.44	18.27
Salt Lake City, UT	3,161	0.88	16.26	691	3.20	25.07
San Antonio, TX	528	0.57	9.74	29	2.14	14.14
Seattle, WA	3,372	1.17	12.33	387	3.94	25.64
West Palm Beach, FL	773	0.77	13.22	61	2.47	17.20
Winston-Salem, NC	759	0.67	13.87	31	2.49	23.71
Total	**73,452**	**0.63**	**11.50**	**9,818**	**2.43**	**20.52**

This study deviates from standard practice in its classification of trips. Standard practice, which has its origins in conventional travel modeling, classifies trips as either home-based work (HBW), home-based other (HBO), and non-home-based (NHB). These trips are treated as independent of each other, when in fact they are necessarily linked. So in this trip chain analysis, all trip chains should start from home, either for work purposes (the most important "peg") or other purposes. It comes closer to capturing households' complex travel behavior than does the standard scheme.

In this study, I am particularly interested with walk and bike travel behavior. However, bike mode is less likely involved into a trip chain with other modes, especially with walk and auto. Once an individual leaves home with a bicycle, he or she probably will travel with it for the following trips. So here, I just focus on walk trips in a trip chain. The statistics of walk trips in trip chains are shown in Table 2.5. There are several significant findings.

First, there are more walk trips that happened in complex chains than simple

Table 2.5 Walk trip distribution in trip chains

Walk trips in simple chain			
Mode of first trip	***Purpose of first trip***		***Total***
	HBW	***HBO***	
All	2,243	26,878	29,121
Walk trips in complex chain			
Mode of first trip	***Purpose of first trip***		***Total***
	HBW	***HBO***	
Walk	1,365	25,064	26,429
Bike	344	324	668
Transit	469	438	907
Auto	3,547	11,163	14,710
Total			42,714

chains. This is surprising. Common sense is that walk is limited by distance primarily, so people are more likely to walk from home for a specific trip that is walkable. However, this shows that more walk trips are involved in complex trip chains. People do walk for multiple purposes or have a trip made by walking when they are on a trip for other purposes. These walk trips probably happen in neighborhoods where the physical built environment is supportive to walk.

Second, the majority, 76%, of walk trips happened either in sample chains (29,121, 40% of the total walk trips in the sample) or complex chains started with walk (26,429, 36% of the total walk trips in the sample). All of these walk trips should be around people's homes. This means that accessibility of residences to a mix of land uses is the key to encourage people to walk. If there are multiple destinations close to home, people will walk from home to one destination, and then walk to another one, and so on. This supports transportation and health studies in the literature that the built environment around home locations is important.

Third, another surprising finding is that 20% (14,710) of walk trips happened in a trip chain that is started with auto. People drive to workplaces or some other places, then leave their cars there and walk. This tells us that accessibility to shopping by itself is relatively unimportant, as is accessibility to workplaces. However, if it is a workplace with good accessibility to shopping, services, schools, and other, people can efficiently link trips for different purposes into a chain, and involve walk in the chain. This means the accessibility of destinations is, at least, as important as the accessibility of residences

2.5 Modeling Results

Walk and bike trips were estimated with HLM 7, Hierarchical Linear and Nonlinear Modeling software (Raudenbush et al., 2010). HLM 7 allows the estimation of multilevel models for continuous, dichotomous and count variables, and for the last of these, HLM 7 can account for overdispersion. Different variables may emerge as significant in different models, so trial and error was used to arrive at the best-fit models for the travel outcomes of interest. For the same D variables measured in three different buffer widths, only one of them was included in the model at the same time. Variables were substituted into models to see if they were statistically significant and improved goodness-of-fit. For each dependent variable, we were looking for the model with the most significant *t*-statistics and the greatest log-likelihood.

2.5.1 Walking

The best-fit model for the dichotomous variable, any walk, is presented in Table 2.6. The likelihood of a household making any walk trips increases with household size and number of workers in the household. The likelihood of any walk trips increases with job-population balance and land use entropy within ¼ mile of home. The likelihood of any walk trips increases with activity density, intersection density, and percentage of four-way intersection within 1 mile of home. These measures of density, diversity, and design place destinations within walking distance of home. The likelihood of any walk trips increases with accessibility to employment within 10 minutes by auto and with transit stop density within 1 mile of home. Transit service is complementary to walking, as households within good transit access tend to own fewer vehicles. The likelihood of

Table 2.6 Multilevel logistic regression model of log odds of any walk trips

	Outcome variable is anywalk			
	coefficient	standard error	*t*-ratio	*p*-value
constant	-9.837	1.452	-6.775	< 0.001
hhsize	0.298	0.016	18.101	< 0.001
workers	0.051	0.022	2.319	0.020
emp10a	0.007	0.004	1.808	0.070
jobpopqmi	0.145	0.046	3.156	0.002
entropyqmi	0.468	0.067	6.962	< 0.001
actden1mi	0.015	0.004	3.845	< 0.001
intden1mi	0.002	0.001	2.225	0.026
int4w1mi	0.003	0.002	2.177	0.029
stopden1mi	0.007	0.002	3.840	< 0.001
walkscore	0.005	0.001	4.910	< 0.001
compact	0.004	0.002	1.940	0.071
temp_low	0.054	0.010	5.521	< 0.001
temp_high	0.083	0.018	4.500	< 0.001
dayt32	0.004	0.002	1.835	0.086
dayt90	-0.025	0.005	-5.365	< 0.001
annpreci	-0.089	0.015	-5.968	< 0.001
dayp50	0.094	0.018	5.271	< 0.001
Pseudo-R2: 0.57				

any walk trips also increases with Walkscore of the census tract that the household is located and regional compactness. Higher walkscore means the walkability of a neighborhood is better. The more compact a region is, the more destinations are within a walkable distance.

For the weather conditions, the likelihood of any walk trips increase with regional annual average low temperature, average high temperature, and number of days with temperature lower than 32 °F and decreases with number of days with temperature greater than 90 °F. This means, generally, people are more likely to walk in conditions of warm temperature. Either extreme low or high temperature discourages people to walk. I do not have a good explanation for the positive sign of number of days within temperature lower than 32 °F. The likelihood of any walk trips also decreases with annual precipitation and increases with number of days with precipitation higher than 0.5 inches. This makes sense. After controlling for annual precipitation, more days with precipitation higher than 0.5 inches mean fewer days with any precipitation in a given year. Hence, the two variables together mean precipitation also discourages households making any walk trips.

The number of walk trips for a subset of households that make walk trips increases with household size and declines with household income and number of employed members (Table 2.7). The last of these relationships is counterintuitive but actually makes sense. The overwhelming majority of walk trips are for non-work purposes. Workers are otherwise engaged rather than walking during the workday. The number of walk trips increases within these D variables: land use entropy ½ mile from

Table 2.7 Multilevel negative binomial regression model of household walk trips (for households with any walk trips)

	Outcome variable is walktrips			
	coefficient	standard error	*t*-ratio	*p*-value
constant	0.246	0.158	1.562	0.135
hhsize	0.145	0.009	15.957	< 0.001
workers	-0.057	0.007	-8.446	< 0.001
income	-0.0007	0.0002	-3.170	0.002
emp30t	0.004	0.001	3.120	0.002
entropyhmi	0.233	0.047	4.924	< 0.001
intden1mi	0.0008	0.0002	3.412	0.001
stopden1mi	0.002	0.0004	4.484	< 0.001
walkscore	0.002	0.0004	3.929	< 0.001
compact	0.003	0.001	2.637	0.017
annpreci	-0.015	0.006	-2.331	0.031
dayp50	0.021	0.009	2.467	0.024
Pseudo-R2: 0.18				

home, intersection density and transit stop density within 1 mile of home. It also increases with transit accessibility to employment within 30 minutes and regional compactness.

The number of walk trips also decreases with annual precipitation and increases with number of days with precipitation higher than 0.5 inches. This is the same relationship with any walk trips. After controlling for annual precipitation, more days with precipitation higher than 0.5 inches mean fewer days with any precipitation in a given year. Hence, the two variables together mean precipitation discourages walk trip frequency. One interesting finding is that none of the four temperature variables is statistically significant. After deciding to walk, the number of walk trips is not affected by temperature anymore.

Probably the most interesting finding is that walk trip frequency depends on the built environment at a larger scale than the usual ¼ mile walk distance assumed by planners. In fact, according to the NHTS, the average walk trip length in the USA varies by trip purpose from 0.52 miles for shopping trips to 0.88 miles for work trips. The overall average is 0.70 miles, which implies a relevant environmental scale of ½ to 1 mile.

2.5.2 Biking

The likelihood of a household making any bike trips depends on household size, number of workers, and household income (Table 2.8). All of the three have a positive relationship. For built environment variables, it depends on diversity and design variables, specifically within job-population balance within ½ mile of home, percentage

Table 2.8 Multilevel logistic regression model of log odds of any bike trips

	Outcome variable is anybike			
	coefficient	standard error	*t*-ratio	*p*-value
constant	-5.486	0.438	-12.523	< 0.001
hhsize	0.319	0.023	13.681	< 0.001
workers	0.178	0.043	4.089	< 0.001
income	0.001	0.0007	1.857	0.063
emp30t	0.008	0.005	1.839	0.065
jobpophmi	0.304	0.095	3.215	0.002
int4whmi	0.011	0.002	4.672	< 0.001
stopdenhmi	0.003	0.001	2.792	0.006
intden1mi	0.003	0.001	3.188	0.002
compact	0.010	0.003	3.119	0.006
regpop	-0.0002	0.00006	-2.900	0.010
annpreci	-0.079	0.025	-3.146	0.006
dayp50	0.090	0.033	2.694	0.015
Pseudo-R2: 0.62				

of four-way intersections within ½ mile of home, and intersection density within 1 mile of home. It also depends on transit stop density within ½ mile of home and transit accessibility to employment within 30 minutes. This transit relationship may be explained by the same phenomena as with walking. Bicycle use may be complementary to transit use.

Regional compactness is also significant, suggesting that compact regions encourage bike trips. However, regional population is negatively related to any bike trips, suggesting that small metropolitan regions encourage bike trips. This makes sense that biking to destinations is more feasible in small metropolitan areas and this finding is consistent with the literature (Ewing et al., 2015). Additionally, the likelihood of any bike trips decreases with annual precipitation and increases with number of days with precipitation higher than 0.5 inch. This may be explained by the same phenomena as with walking. After controlling for annual precipitation, more days with precipitation higher than 0.5 inch mean fewer days with any precipitation in a given year. Hence, the two variables together mean precipitation discourages households making any bike trips.

Bike trip frequency for the subset of households that make bike trips increases with household size, increases with intersection density within one-half mile, increases with percentage of four-way intersection with a mile, and increases with transit stop density within ½ mile (Table 2.9). The second and third of these relationships suggests the importance of an interconnected street network as a facilitator of biking, perhaps because it shortens trip distances or provides routing options. It may simply mean that bicyclists are not channeled up and down the suburban hierarchy of streets and therefore can avoid high-speed arterials. The fourth of these relationships is explained by the same phenomena as before that bicycle use may be complementary to transit use.

Bike trip frequency for the subset of households that make bike trips increases with regional annual average low temperature, regional annual average high temperature, number of days with temperature lower than 32 °F, and number of days with precipitation

Table 2.9 Multilevel negative binomial regression model of household bike trips (for households with any bike trips)

	Outcome variable is biketrips			
	coefficient	standard error	*t*-ratio	*p*-value
constant	1.656	0.278	5.946	< 0.001
hhsize	0.091	0.008	11.203	< 0.001
intdenhmi	0.0005	0.0002	2.520	0.012
stopdenhmi	0.002	0.0005	4.703	< 0.001
int4w1mi	0.003	0.0008	3.804	< 0.001
temp_low	-0.006	0.002	-3.518	0.003
temp_high	-0.008	0.003	-2.208	0.040
dayt32	-0.002	0.0008	-2.628	0.017
dayp50	-0.009	0.002	-5.520	< 0.001
Pseudo-R2: 0.14				

more than 0.5 inches. These relationships suggest that both high and low temperature and precipitation make biking a less favorable travel choice. This is the model that may be underspecified. Other variables may prove significant as the sample of households with bike trips expands with the addition of other regions. The current sample is 3,042 households, not as many as the sample for walking.

2.6 Discussion and Conclusion

This study explained walk and bike trips generation by households using household travel survey data, built environment variables at neighborhood level, and regional characteristics in 23 diverse regions of United States. The built environment at different scales must be considered for different travel modes. Motorized trips are more heavily impacted by regional spatial patterns, while nonmotorized trips are more heavily impacted by the built environment of the neighborhood (Greenwald & Boarnet, 2001; Handy et al., 2002)

To capture neighborhood built environments, road network buffers based on household locations were used instead of a circular buffer or predefined unit like TAZs. The network buffer can more accurately represent the physical environment surrounding the household than can a circular buffer or TAZ. Also, the study tested built environment variables for three different buffer widths around household locations to see which scale best explains walk and bike behavior.

The results show that sociodemographic characteristics are strong predictors of walk and bike trip generation, which is consistent with the literature (Ewing & Cervero, 2010). Specifically, household size, the number of workers in a household, and household income influence the probability of a household making any walk and bike trips, and also the walk and bike trip frequencies.

Characteristics of the built environment around homes are also significant. All the D variables are associated with walk and bike trip generation. However, land use diversity, street connectivity, and transit accessibility seem more important than other D variables to walk trip generation. Street connectivity and transit accessibility seem more important than other D variables for bike trip generation. Additionally, with including more and more regions, compactness index is statistically significant in three of the four models. Regional compactness is important to both walk and bike trip generation.

This study also tested built environmental variables for different buffer widths around household locations to see which scale best explains walking and biking behavior. The relevant built environment is anywhere from ¼ to 1 mile. However for certain built environment variables, the smaller scale seems to have more predictive power than the larger scale. For other variables, the scale effects are reversed. Specifically, diversity – represented by job-population balance and land use entropy – has more predictive power at ¼ mile and ½ mile. Design and distance to transit – represented by intersection density, percentage of four-way intersection, and transit stop density – have mostly predictive power at a mile.

This study controlled the regional weather conditions when examining the effects of built environment on walk and bike, which has not been done much in the literature. Average and extreme temperature and precipitation were used to measure weather conditions. The results show that weather conditions do have influences on walk and bike trip generation. Both extreme temperature and precipitation discourage walk and bike trip generation, but precipitation has a stronger influence than temperature does.

The trip chain analysis shows that accessibility of residences and accessibility of destinations are both important. The majority of walk trips happened either in sample chains or complex chains started with walk. All of these walk trips should be around people's homes. This means that accessibility of residences to a mix of land uses is the key to encourage people to walk. At the same time, good accessibility of destinations, like workplaces or shopping places, to other activities is also important to encourage walking. A shop that is close to an individual's place of employment may be quite accessible (as indicated by the frequency of use) even though it may be quite distant from the individual's place of residence, because employees could visit it on foot when they are at the workplaces if accessibility were improved to the point where people can walk.

I conclude by acknowledging the limitations of this study. Though it covered the D variables, the study still omits certain variables that have presumptive effects on household walk and bike choice. Parking supplies and prices, particularly at the destination end of trips, may strongly affect mode choices of individuals. Urban design qualities such as windows overlooking the street, continuous building facades, and active uses at street level have been shown to affect pedestrian volumes (see Chapter 5 of Ewing and Clemente, 2013). For lack of data on streetscapes, these qualities have not been modeled. Finally, for lack of data on modal attitudes and residential preferences, the study fails to control for residential self-selection.

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CHAPTER 3

STUDENT TRAVEL: EVIDENCE FROM 14 DIVERSE REGIONS OF THE UNITED STATES

Active travel to school (walk and bike) can play an important role in increasing physical activity and reducing obesity among children. However, by analyzing student travel to school in the 14 regions, I find that of school trips, only 12.7% are walking trips, 1.7% are biking trips, 33.9% are school bus trips, and 50.9% are car trips. Even among trips of less than 2 miles from home to school, reasonable for walking or biking, 45.7% of these trips are by car. This begs the question of why more school trips are not by active modes of transportation. Is the built environment, basically low values of the D variables, implicated in these results?

In this chapter, I conducted a multilevel multinomial logistic regression to estimate a school travel mode choice model based on student travel dailies from 14 diverse U.S. regions. The built environment is measured around the shortest route from home to school consistently. I find that the important built environment variables in the decision to walk or bike to school are development density and street network design or connectivity, and the least important is land use diversity. Land use diversity even has a negative relationship with walking to school. While not a D variable exactly, the need to cross major roads or commercial developments has strong negative impacts on active travel to school too.

3.1 Introduction

Travel to and from school can be a source of physical activity adding to a child's daily total energy expenditure (Ahlport et al., 2008). Active transportation to school can play an important role in increasing physical activity and reducing obesity among children. Perhaps more importantly, exposing children to walking and biking at an early age can help establish healthy habits, increasing the likelihood that they will use these modes of transport later in their life (Schlossberg et al., 2006).

However, National Household Travel Surveys (NHTS) show that the number of children walking or biking to school is significantly lower today, compared with 50 years ago. According to the most recent 2009 NHTS, only 9.6% of students between the ages of 5 and 15 walked to or from school, and 1.1% biked. In 1969, at the time of the first Nationwide Personal Transportation Survey (predecessor to NHTS), 48% of students walked or biked to school (Ewing et al., 2004). By 2009, even children living close to school were not walking much. In 1969, 87% of children who lived within 1 mile of school walked, and only 7% were obese. Today, however, only 31% of children living within 1 mile from school walk, and perhaps relatedly, 17% of children are obese (Botchwey et al., 2014).

Why the decline in walking and biking to school? Built environment of neighborhoods, characteristics of children and households, and children and parents' attitudes have all been reported to affect student travel choice by both quantitative and qualitative studies. However, evidence in literature from each study using data for single regions, specification of different models, and different metrics to represent the built environmental variables are not consistent. Built environmental factor influences on school mode choice remains an issue.

This study examines the relationship between mode of school trips and a large range of factors that might affect student mode, by pooling household travel and built environment data from 14 diverse U.S. regions and using consistently defined built environmental variables captured around the shortest route to school. Also, this study tests variables that have not been studied much in the literature such as major roads and weather conditions.

3.2 Literature Review

Distance is reported as a primary factor that impacts children walking or biking to school by many studies (Black et al., 2001; Bringolf-Isler et al., 2008; Emond & Handy, 2012; Ewing et al., 2006; Frank et al., 2007; Larsen et al., 2012; McDonald, 2007; Mitra & Builung, 2012; Müller et al., 2008; Schlossberg et al., 2006; Stewart, 2011; Timperio et al., 2006; Yarlagadda & Srinivasan, 2008). For over 50 years, the U.S. has been shifting away from small, neighborhood schools to larger schools in lower density areas (Botchwey et al., 2014). Schools have been increasing in size and drawing students from ever-larger areas. This means relatively few students live within appropriate distances from school to walk or bike, which may account for much of the decline in walk and bike mode shares.

However, as already noted, even short school trips are now made primarily by automobile, indicating that other factors are at work. The walkability of neighborhoods has been linked to travel mode choices in the general population and would be expected to affect walking and biking to school. Residential density, intersection density, street connectivity, land use mix, access to recreation or open space, and the presence of street trees are reported to be positively associated with the choices of walking and biking to school (Botchwey et al., 2014; Frank et al., 2007; Giles-Corti et al., 2011; Larsen et al., 2012; Marique et al., 2013; Mitra & Buliung, 2012; Panter et al., 2008; Stewart et al., 2012).

The travel behavior literature emphasizes the importance of such built environmental variables in travel decision making, which have been categorized in terms of the five Ds: density, diversity, design, destination accessibility, and distance to transit (Ewing & Cervero, 2010). Density is always measured as the variable of interest, like population and employment, per unit of area. Diversity measures pertain to the number of different land uses in a given area and the degree to which they are balanced in land area. Entropy and employment and population ratios are frequently used. Design measures usually include average block size, proportion of four-way intersections, and number of intersections per square mile. Distance to transit is usually measured in terms of transit stop density or distance to the closest stop. Destination accessibility measures ease of access to trip attractions, such as number of jobs reachable within a given travel time or distance to the closest nonresidential trip attraction.

However, these relationships are not always found to apply to students (Ewing et al., 2004; Wong et al., 2011; Yarlagadda & Srinivasan, 2008). Apparently, school trips are different from other trip. They tend to be unlinked to other activities, and thus reduce the need for proximity to other land uses. They are mandatory, thus the walking environment may be less important than it is with discretionary travel. Environmental correlates of active transport in children and adults may differ. Even negative relationships between walking and biking to school and residential densities, mixed land uses, and intersection density (or connectivity) are reported (Larsen et al., 2012; Timperio et al., 2006). Built environmental factor influences on school mode choice remains an issue in the literature.

Route safety is another factor that influences student travel choice. Traffic speed, traffic volume, and lack of sidewalks have been identified as barriers to walk and bike to school (Ahlport et al., 2008; Chaufan et al., 2012; Timperio et al., 2006). In 2005, the United States Congress created the Safe Routes to School (SRTS) program to improve route safety and increase the number of children walking and biking to and from school through educational efforts, encouragement programs, and road improvements at or near schools. Studies have found that SRTS programs do have immediate effects of making more students walk or bike to and from school (McDonald et al., 2013; McDonald et al., 2014; Stewart et al., 2014). However, there are questions about which programs are more effective and how early exposure to regular walking and biking affects individuals over several years (McDonald, 2015).

Empirical results also indicate that the characteristics of child, like age, gender, and ethnicity, and employment and work flexibility characteristics of the parents have strong impacts on the mode choice decisions (Kerr et al., 2007; Wilson et al., 2010; Yarlagadda & Srinivasan, 2008). Boys are more likely to use active travel modes than girls (Larsen et al., 2012; McMillan et al., 2006; Robertson-Wilson et al., 2008). Older children are more likely to use active travel modes than younger children (Sidharthan et al., 2011). Children from higher income neighborhoods are less likely to actively travel than children from lower income neighborhoods (Larsen et al., 2012).

A supportive physical environment (including short distance to school, good walkability, safe route, etc.) is a necessary but insufficient condition to encourage active travel to school. Children and parents' safety concerns are also important factors (Banerjee et al., 2014; Bringolf-Isler et al., 2008; McDonald & Aalborg, 2009; McMillan, 2005; Napier et al., 2011; Romero, 2010; Rosenberg et al., 2006; Stewart, 2011; Wilson et al., 2010; Zhu & Lee, 2009), especially the decision making of parents as the gatekeepers of younger children (Giles-Corti et al., 2009). Nearly half of parents driving their children less than 2 miles did not allow their child to walk to school without adult supervision. Ahlport et al. (Ahlport et al., 2008) reported that fear of child abduction was the number one barrier identified by parents and children, but many other factors, including the flexibility of parent work schedules, parent motivation, and the physical load students must carry to and from school, also influence parents' decisions about whether or not children walk or bicycle to school. Planning interventions can only overcome some of the barriers to increased active transport (Schlossberg et al., 2006).

3.3 Methodology

This study employs a cross-sectional research design to determine the relative influence of individual, household, built environment, regional factors, and weather conditions on student travel choice. The unit of analysis for the study is the individual school trip made by students in kindergarten through 12th grade (K-12), as reported in regional household travel surveys.

3.3.1 Data Collection

The most widely used data source to study travel behavior is the household travel survey. Household travel survey data are the fundamental input for regional travel demand modeling and forecast. Many regional metropolitan planning organizations (MPOs) conduct their own travel survey for their uses. In the last 5 years, we have been contacting regional MPOs and collecting household travel survey data. A main criterion for inclusion of regions in this study was data availability. Regions had to offer regional household travel surveys with XY coordinates, so we could geocode the precise locations of trip ends. It is not easy to assemble databases that meet this criterion, as confidentiality concerns often prevent metropolitan planning organizations from sharing XY travel data. The resulting pooled dataset consists of 815,160 trips made by 81,056 households in 23 regions, from which school trips could be extracted and mode choices analyzed.

The regions included in our household travel survey sample were, in addition, able to supply GIS data layers for streets and transit stops, population and employment for traffic analysis zones, and other related data for the same or close enough to the years that the household travel surveys were conducted.

All the GIS layers that were used to compute built environment are:

- parcel level land use data with detailed land use classifications; from these we can compute detailed measures of land use mix;
- street networks and intersections; from these we can build the buffer widths and compute intersection density;
- transit stops; from these data we can compute transit stop densities;
- population and employment at the block or block group level; from these we

can compute activity density;

- TAZs with socioeconomic information (population and employment);
- road function classifications; from these we can identify major roads;
- relevant destination – parks.

Point, line, and polygon data from the different sources were joined with buffers to obtain raw data, such as the number of intersections within buffers. These were then used to compute refined built environmental measures such as intersection density, which is simply the number of intersections divided by land area within the buffer. In addition to these GIS layers, we collected data of weather conditions from Climate Data Online of National Centers for Environmental Information in the same years with the household travel survey data for each region.

The unit of analysis for the study was the individual school trip, which were made by K-12 students travelling from or to school. School trips were identified by trip purpose reported in the household travel survey. If the trip purpose of either the origin or destination of a trip was attending school, this trip was counted as a school trip. Trips that were for school-related activities were not included. To identify K-12 students, two criteria were used: the age of the traveler should be from 5 to 18 and the level of school that the traveler is attending should be Kindergarten to Grade 12. Not every household travel survey provided both pieces of information, so any traveler that met either of the two criteria was counted as a K-12 student. However, there were nine regions missing key information in the household travel survey so that we could not identify school trips made by K-12 students. We also did not include individual trips in which the travel distance is more than 100 miles.

At present, we have consistent datasets for 14 regions (Table 3.1). The regions are as diverse as Boston and Portland at one end of the urban form continuum and Houston and Atlanta at the other. To our knowledge, this is the largest sample of household travel records ever assembled for such a study outside the NHTS. And relative to NHTS, our database provides much larger samples for individual regions and permits the calculation of a wide array of built environmental variables based on the precise location of households. NHTS provides geocodes only at the census tract level.

3.3.2 Buffer of Shortest Route to School

What extent of the built environment is most relevant to students' travel decisions? Theoretically, buffers could be wide or narrow. Even a determinant as straightforward as walking distance could be anywhere from ¼ mile to 1 mile or more. In the literature, one ¼ and ½ mile are the most widely used widths, but 1 mile or even wider distances have also been used. The other thing is where to build the buffer. Trip ends (destinations and/or origins, in this case homes and/or schools) are used a lot in the literature. However, there are a few studies using the buffer around the shortest route

Table 3.1 Regions (metropolitan areas) in the dataset

Regions	***Year of data***	***Regions***	***Year of data***
Atlanta, GA	2011	Minneapolis-St. Paul, MN-WI	2010
Boston, MA	2011	Phoenix, AZ	2008
Denver, CO	2010	Portland, OR	2011
Detroit, MI	2005	Rochester, NY	2011
Eugene, OR	2009	Sacramento, CA	2000
Houston, TX	2008	San Antonio, TX	2007
Indianapolis, IN	2009	Seattle, WA	2006

between homes and schools to studying student active commuting (Larsen et al., 2012; Panter et al., 2010).

In this study, we chose to establish a ¼ mile buffer along the shortest route between home and school and computed the built environmental variables for each school trip within the buffer. The micro built environment along the routes to school is important for active travel. These are factors that influence the experience of walking or biking on the street, which further affect the decision of mode choice. A ¼ mile buffer width was used because we think that is wide enough to capture other possible routes between home and school. Based on the household travel survey data, students' home and school were identified first. Then, the shortest route between each student's home and school was calculated by using network analysis in GIS. The use of the buffer of the shortest route to school is one of the distinctions of this study compared to most studies in the literature.

3.3.3 Choice Sets

Practically speaking, certain modes were unavailable to certain students, and their choice sets had to be restricted. For school trips in this sample, the trip distance ranged up to 57 miles. No student could be expected to walk or bike this far. Therefore, a cutoff value of 2 miles was established for travel distance. Thousands of school trips in the sample were restricted to two or three modes. The model was estimated with school trips with travel distance was less than 2 miles.

3.3.4 Variables

The final dataset contained K-12 school trips for which origin and destination were known. Cases were dropped for lack of travel mode or if travel mode was “others”. The unit of analysis is the individual school trip. The dependent variable is travel mode of an individual trip with values as walk, bike, transit, school bus, and auto. A categorical variable was created based on travel mode (see the next section for a discussion of model selection).

To maintain a full complement of independent variables for subsequent analysis, cases were dropped for missing any of the following variables: household size, vehicle ownership, household income, etc. The greatest loss of cases was due to unknown household income. As is often the case in travel surveys, household income went unreported by a large number of respondents. We could exclude household income to maintain a larger sample size, but household income was too important from a theoretical perspective to be omitted from the mode choice analysis. We included two extra variables that have been reported as important factors for student’s mode choice in the literature: number of siblings and possession of a driver’s license.

Built environment characteristics cover all D variables – density, diversity, design, and distance to transit – except destination accessibility. The destination accessibility usually measures the accessibility to regional employment, which does not seem relative to school trips. Additionally, we tested a few more built environment variables: whether the shortest route crosses a major road, area of parks and open space within the buffer, the presences of libraries and museums within in the buffer. The major roads were identified as A1, A2, or A3 by Census Feature Class Codes (CFCCs). We also included variables at the regional level: population measuring the size of a metropolitan area, compactness index measuring the overall built environment of a region, gas price, and three weather variables measuring weather condition.

In the end, we identified 21,892 school trips made by 11,185 K-12 students in the 14 regions. The dependent and independent variables tested in this study are shown in Table 3.2. Sample sizes and descriptive statistics are also provided. A total of 26 independent variables is available to explain student travel choice. All variables are consistently defined from region to region.

3.3.5 Model Selection

McFadden developed the logit (MNL) model to explain choices made among alternatives when attributes of the alternatives themselves, and attributes of decision makers, both influence outcomes (McFadden, 1981). In the choice of travel modes, the attributes of alternative modes such as travel time, and attributes of travelers and their households such as income, would be expected to influence choices (see Figure 3.1). Thus, the logit model will be chosen as the preferred specification in this study.

To increase statistical power and external validity, we pooled household travel data from 14 diverse regions. The data and model structure are hierarchical, with trips "nested" within regions. The best statistical approach to nested data is multilevel modeling (MLM), also called hierarchical modeling (HLM). MLM accounts for dependence among observations, in this case the dependence of trips within a given region on characteristics of the region. All trips within a given region share these characteristics. Regions such as Boston and Houston are likely to generate very different

Table 3.2 Variable description and descriptive statistics

Variable	***Description***	***N***	***Mean***	***S.D.***
Dependent variable				
mode	categorical variable indicating the travel mode (1 = walk, 2 = bike, 3 = transit, 4 = school bus, 5 = auto)	21,892	3.72	1.59
Independent variables – trip				
tdist	travel distance (in mile)	21,892	0.99	0.56
Independent variables – sociodemographic characteristics				
female	student's gender (1 = female, 0 = other)	21,892	0.48	0.50
license	driver's license owned by a student (1 = yes, 0 = other)	21,892	0.08	0.27
age	age of the student	21,892	11.06	8.45
sibling	the number of siblings of the student	21,892	2.22	1.00
hhsize	household size	21,892	4.35	1.19
worker	mumber of worked in the household	21,892	1.65	0.77
hhincome	real household income (in 1000s of 2012 dollars)	21,892	93.21	53.41
vehcap	number of motorized vehicles per capita in the household	21,892	0.52	0.26
Independent variables – built environment within the quarter mile buffer of the shortest route from home to school				
actden	activity density within the buffer (population + employment in 1000s / area of the buffer)	21,892	6.63	8.98
jobpop[3]	job-population balance within the buffer	21,892	0.66	0.24
respct	the percentage of residential land within the buffer	21,892	54.82	26.41
compct	the percentage of commercial land within the buffer	21,892	6.34	7.58
pubpct	the percentage of institutional land within the buffer	21,892	9.86	8.88
entropy[4]	land use entropy within the buffer	21,892	0.52	0.23

[3] The job-population index measures balance between employment and resident population within a buffer. Index ranges from 0, where only jobs or residents are present within a buffer, not both, to 1 where the ratio of jobs to residents is optimal from the standpoint of trip generation. Values are intermediate when buffers have both jobs and residents, but one predominates. jobpop = 1 – [ABS (employment – 0.2*population)/(employment + 0.2*population)], ABS is the absolute value of the expression in parentheses. The value 0.2, representing a balance of employment and population, was found through trial and error to maximize the explanatory power of the variable.

[4] The entropy index measures balance between three different land uses. Index ranges from 0, where all land is in a single use, to 1 where land is evenly divided among the three uses. Values are intermediate when buffers have more than one use but one use predominates. The entropy calculation is: entropy = -[residential share*ln (residential share) + commercial share*ln (commercial share) + public share*ln

Table 3.2 continued

Variable	***Description***	***N***	***Mean***	***S.D.***
intden	intersection density within the buffer	21,892	117.31	65.97
int4way	the percentage of 4-way intersections within the buffer	21,892	26.67	18.47
stopden	transit stop density within the buffer	21,892	20.19	34.43
mjroad	a dummy variable indicating the shortest route crosses a major road (1 = yes, 0 = other), major roads were identified as CFCC = A1, A2, or A3	21,892	0.68	0.47
park	a dummy variable indicating whether there are parks within the buffer (1 = yes, 0 = no)	21,892	0.72	0.45
Independent variables – region				
regpop	population within the region 1000s	14	3093.57	1616.05
gasprice	average gasoline prices for 2010 at the region	14	2.89	0.15
compact	Measure of regional compactness index developed by Ewing and Hamidi (2014); higher values of the index correspond to more compact development, lower values to more sprawling development	14	97.20	27.73
temp_low	annual average of low temperature	14	36.07	12.40
temp_high	annual average of high temperature	14	77.26	7.27
annprecip	annual precipitation (in inch)	14	36.86	14.61

(public share)]/ ln (3), where ln is the natural logarithm of the value in parentheses and the shares are measured in terms of total parcel land areas.

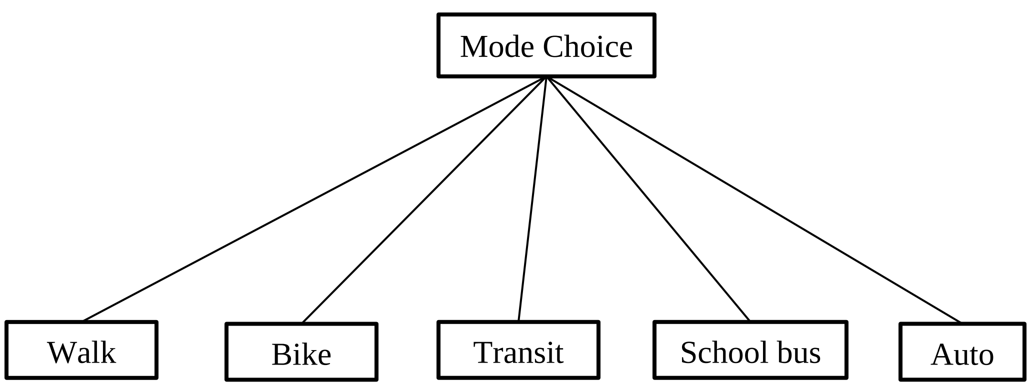


Figure 3.1 MNL structure of mode choice

travel patterns regardless of household and school characteristics. The essence of MLM is to isolate the variance associated with each data level. MLM partitions variance between the trip/individual/household level (Level 1) and the region level (Level 2) and then seeks to explain the variance at each level in terms of D variables (Figure 3.2). We can expect to explain a good portion of the variance at Level 1 given the large number of available variables and the large sample of trips. We cannot expect to explain much of the variance at Level 2 with such a small sample of regions. Variables such as regional population (as a measure of region size) may not prove statistically significant predictors of travel choice due to limited degrees of freedom. Still, there is a statistical advantage to partitioning the variance as MLM does, and estimating a random effects model. Regional variance is captured in the random effects term of the Level 2 equations. In the model estimations, only the intercepts were allowed to randomly vary across Level 2 units. The best model that fits the data structure would be multilevel multinomial logistic regression.

The final equation of the multilevel multinomial logistic regression model is as follows:

$$\text{Level 1:} \quad P(Y_k = 1) = e^{\beta_{01}+\beta_{i1}X_{i1}} / \left(1 + \sum_{k=1}^{k-1} e^{\beta_{ok}+\beta_{ik}X_{ik}}\right) \qquad (3.1)$$

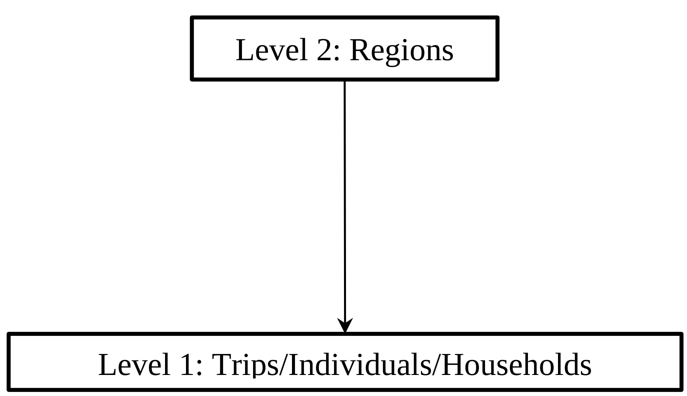


Figure 3.2. Data and model structure

$$P(Y_k = 2) = e^{\beta_{02}+\beta_{i2}X_{i2}} / (1 + \sum_{k=1}^{k-1} e^{\beta_{ok}+\beta_{ik}X_{ik}}) \quad (3.2)$$

… …

$$P(Y_k = K) = 1/(1 + \sum_{k=1}^{k-1} e^{\beta_{0k}+\beta_{ik}X_{ik}}) \quad (3.3)$$

Level 2: $\beta_{0k} = \gamma_{00k} + \gamma_{0jk}W_{0jk} + u_{0jk}$ (3.4)

$$\beta_{ik} = \gamma_{i0k} \quad (3.5)$$

Where: *P* refers to the probability of the dependent variable equals *k*,

K refers to the k categories of the dependent variable,

β_{0k} refers to the intercept at the level 1 when the dependent variable equals *k* (*k* ranges from 1 to *K*),

β_{ik} refers to the coefficient of *i* independent variables at the level 1 when the dependent variable equals *k*,

x_{ik} refers to the independent variables at the level 1 when the dependent variable equals *k*,

γ_{00k} refers to the overall intercept when the dependent variable equals *k*,

γ_{0jk} refers to the coefficient of independent variables at the level 2 when the dependent variable equals *k*,

W_{0jk} refers to the independent variables at the level 2 when the dependent variable equals *k*,

u_{0jk} refers to the random error component for the deviation of the intercept,

γ_{i0k} refers to the overall coefficients of *i* independent variables when the dependent variable equals *k*.

3.4 Travel Pattern Analysis

Of all the 43,000 school trips, 50.9% of them were made by driving, 12.7% of them were made by walking, 1.7% of them were made by biking, and 33.9% of them were made by school bus. Of the 21,892 school trips that travel distance is less than 2 miles, 45.7% of them were made by driving, 22.8% of them were made by walking, and 2.8% of them were made by biking. No surprise, driving to school still was the first choice. This is consistent with 2009 NHTS.

There is great variation in mode shares from region to region. Across regions for all school trips, the walk share varies from a low of 7.4% for Atlanta to a high of 37.7% for Boston and the bike share varies from a low of 0.0% for Detroit to a high of 10.8% for Eugene (Table 3.3). In two regions, Eugene and Portland, active travel (walking and biking) becomes the dominant means of travel to school for less than 2 mile school trips.

There were 4,981 walk trips and 608 bike trips of the total 21,892 school trips. The average trip distance and travel time for walk trips were 0.58 mile and 13.2 minutes. The average trip distance and travel time for bike trips were 0.90 miles and 12.7 minutes. For walk trip, 48% of trip distances were under 0.5 mile and 76% of trip distances were under 1 mile. For bike trip, 53% of trip distances were under 1 mile and 72% of trip distances were under 1.5 miles. See more details in Figure 3.3 (1). Figure 3.3 (2) shows the distribution of walk and bike trips by age. For walk trips, it generally spreads out in age 8 to 16 with around 7 %. Students who are either younger than eight or older than 16 walk much less. For students who are younger than 8, parents probably have safety concerns for them to walk. For students who are older than 16, students probably start to get driver’s licenses and drive to school. For bike trips, it is more concentrated at age 9 to

Table 3.3 Comparison of mode shares of school trips (travel distance ≤ 2 miles) in different regions

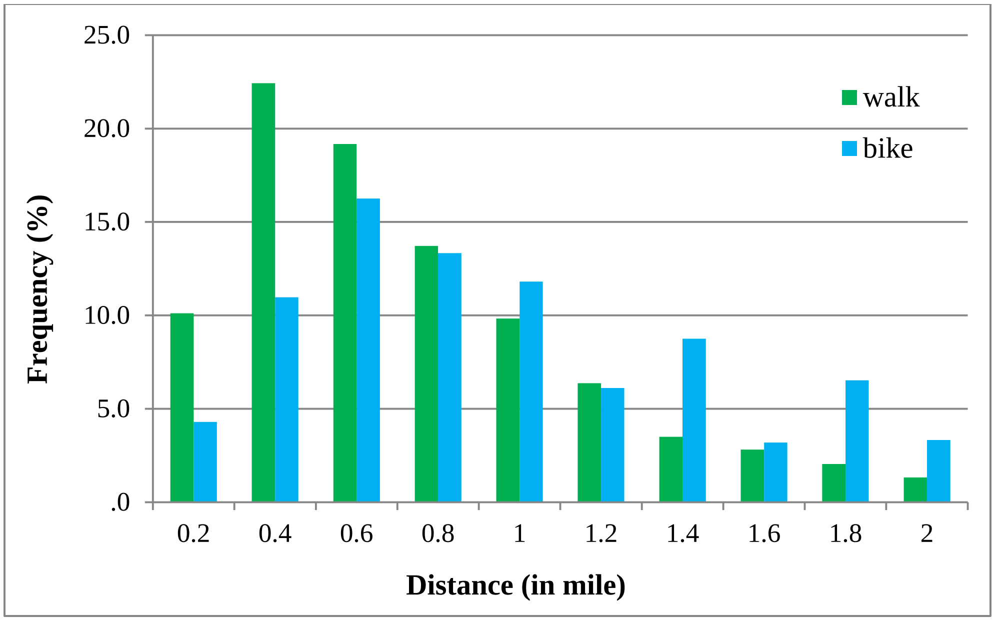
	Survey Date	Surveyed School Trips	Mode share (%)				
			Walk	Bike	Transit	School bus	Auto
Atlanta	2011	4,293	7.4%	0.7%	0.0%	52.6%	39.3%
Boston	2011	2,784	37.7%	2.4%	0.1%	17.7%	42.1%
Denver	2010	1,718	32.7%	3.9%	0.0%	9.1%	54.3%
Detroit	2005	822	39.9%	0.0%	3.0%	13.9%	43.2%
Eugene	2011	649	37.1%	10.8%	0.6%	16.0%	35.4%
Houston	2008	1,982	12.7%	4.1%	0.1%	25.1%	57.9%
Indianapolis	2009	855	15.1%	0.7%	1.6%	50.6%	31.9%
Kansas City	2004	1,364	14.1%	0.9%	0.1%	30.4%	54.6%
Minneapolis-St. Paul	2010	1,448	14.2%	2.1%	0.4%	41.3%	41.9%
Phoenix	2008	745	29.3%	7.1%	1.1%	24.0%	38.5%
Portland	2011	1,879	32.7%	4.6%	0.2%	26.9%	35.6%
Sacramento	2000	906	22.7%	5.2%	1.1%	8.0%	63.0%
San Antonio	2007	732	19.7%	0.8%	0.0%	18.4%	61.1%
Seattle	2006	1,715	30.6%	3.0%	0.1%	15.2%	51.1%
Total	**-**	**21,892**	**22.8**	**2.8**	**0.4**	**28.4**	**45.7**

13, where each age group has higher than 10%. This is quite interesting.

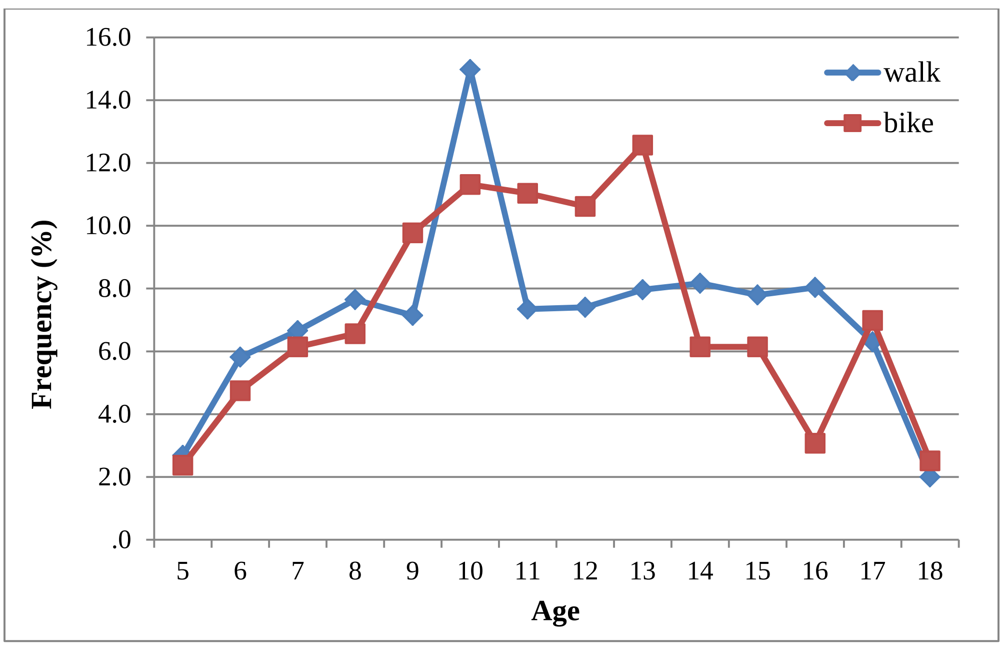
From a planning practice perspective, there are two important findings of student’s travel choice from this travel pattern analysis. First, the average travel time for both walking and biking is about 13 minutes. This is the average travel time for active travel to school, no matter if it is walking or biking. Second, students at age 9 to 13 are more likely to bike than students in other ages.

3.5 Modeling Results

We modeled mode choice for school trips with HLM7, Hierarchical Linear and Nonlinear Modeling software (Raudenbush et al., 2010). HLM7 allows the estimation of multilevel multinomial logistic models. In the model estimations, only the intercept was



(1)



(2)

Figure 3.3 Distributions of tip distance and age for walk and bike allowed to randomly vary across Level 2 units. All of the coefficients at Level 2 were treated as fixed. This is referred to as a random intercept model (Raudenbush & Bryk, 2002).

The auto was treated as the reference case. The utilities of other modes were modeled relative to the auto. The final model of school trip mode choice is shown in Table 3.4 and 3.5. These tables present the same basic information in different forms. In Table 3.4, coefficient values indicate the effects of independent variable on mode choice probabilities. In Table 3.5, the elasticity for each independent variable is presented. It expresses the marginal effects of independent variables on mode choice probabilities, that is, percentage changes in probabilities associated with a 1% change in each independent variable. Elasticities are commonly used in travel research to summarize relationships between travel outcomes and explanatory variables. The values presented are point elasticities at the mean values of the independent variables. The pseudo R2 of the model is 0.80.

3.5.1 Travel Distance Influences

As expected, students with shorter walk and bike distance to and from school are significantly more likely to walk and bike. The elasticities are -0.58 and -0.13, respectively. For walking, distance has the greatest elasticity at level 1 in the mode, which means distance is the primary factor that influences student's choice of walk. The probability of walking is more sensitive to travel distance than biking. Perhaps this is because the speed of walking is slower than biking. A small increase of distance would take a much longer time to walk.

Table 3.4 Multilevel multinomial logistic regression of school trips, using auto as reference case

	Walk	***Bike***	***Transit***	***School bus***
constant	-2.472	-6.541	-34.392	-4.114
Level 1				
tdist	-2.269***	-0.513***	0.383	0.696***
female	-0.354***	-0.776***	-0.206	-0.138***
license	-0.962***	-0.761***	-0.602	-1.558***
age	0.042***	0.016***	0.150***	-0.035***
sibling	-0.020	-0.205***	-0.207	0.006
hhsize	-0.044	0.103*	-0.114	0.046*
worker	-0.090***	0.014	0.204	-0.089***
hhincome	-0.002***	0.004***	-0.010***	-0.004***
vehcap	-0.986***	-1.959***	-2.488***	-0.968***
actden	0.019***	0.021***	-0.016	0.011*
jobpop	-0.189*	0.085	-0.193	0.124
res_pct	0.0004	0.003	-0.011	0.001
com_pct	-0.007*	-0.039***	-0.029	-0.007*
pub_pct	0.024***	0.010	-0.034	-0.001
entropy	-0.318*	-0.013	1.283	-0.070
intden	0.0002	0.003**	0.002	-0.003***
int4way	0.003**	0.002	0.016**	-0.005***
stopden	0.006***	0.002	0.006	-0.011***
mjroad	-0.110**	-0.220**	-0.395	0.322***
park	-0.055	0.247**	-0.785**	-0.062
Level 2				
compact	0.009**	-0.002	0.011	-0.011
regpop	0.00002	-0.0002	-0.0002	-0.00007
gasprice	1.492*	1.388	7.383***	1.031
temp_low	0.007	0.029	-0.091***	-0.043**
temp_high	-0.012	0.008	0.173**	0.046
annprecip	-0.011*	-0.016	-0.028	0.015
Pseudo R2: 0.80				

**** < 0.01 **< 0.05 *<0.1*

Table 3.5 Elasticity estimates from the multilevel multinomial logistic regression

	Walk	***Bike***	***Transit***	***School bus***
tdist	-0.58	-0.13		0.18
female				
license				
age	0.12	0.05	0.42	-0.10
sibling		-0.12		
hhsize		0.11		0.05
worker	-0.04			-0.04
hhincome	-0.05	0.10	-0.24	-0.10
vehcap	-0.13	-0.26	-0.33	-0.13
actden	0.03	0.04		0.02
jobpop	-0.03			
res_pct				
com_pct	-0.01	-0.06		-0.01
pub_pct	0.06			
entropy	-0.04			
intden		0.09		-0.09
pct4way	0.02		0.11	-0.03
stopden	0.03			-0.06
mjroad				
park				
compact	0.22			
regpop				
gasprice	1.10		5.46	
temp_low			-0.84	-0.40
temp_high			3.42	
annprecip	-0.10			

3.5.2 Sociodemographic Influences

Female students are less likely to walk or bike to school than take a car, and even less likely to take a school bus. With age increases, the probabilities of walking, bike, or using public transportation increase. This makes sense because when children get older, they are more independent and parents have less concern for their safety when not driving them to school. Students with more siblings are less likely to bike.

Students from households with higher income and more vehicles per capita are less likely to walk, use transit, or a school bus than to take a car. It is obvious why greater vehicle availability and higher income would make these alternatives less attractive relative to car travel. An interesting finding is that the probability to bike increases with household income. This leaves us a question why that is.

Students holding drivers' licenses are less likely to walk, bike, or take a school bus than those without drivers' licenses. Based on elasticities, the influence of drivers' licenses on school bus is stronger than on walk and bike. This makes perfect sense. Students living too far from school to walk or bike are prime candidates for school bus service until they reach driving age, at which time they become prime candidates for driving themselves and if their families' financial situation permits it.

3.5.3 Built Environment Influences

The most important findings from the built environment influences are major road. The probability of walking and biking to school significantly decreases when the shortest route to school crosses a major road; the elasticities are -0.02 and -0.04, respectively. Most likely, major roads are wide and have more traffic. Walking or biking across a major road increases the travel time (both the time to cross the major road and the time waiting for the traffic single) and the chance of accidents. This factor has not been studied much in the literature.

The surprising finding is that the probability of walking to school is negatively related to job-population balance and land use entropy, which means students are less likely to walk to school in more mixed use areas. The probability of biking to school is not significantly related to job-population balance or land use entropy. Also, the higher percentage of commercial land uses, the lower probability of walking or biking to school. This is opposite to the relation with the general mode choice that land use diversity is the strongest built environment for walking and biking, but makes sense. The destination of school trips is either school or home. The mixed used areas with commercial uses are attractions for general travel and generate internal walking and biking trips, but not for school trips. Additionally and more importantly, areas with more mixed land uses have a higher concentration of cars, which threatens the safety of students walking or biking on the street, even though overall mixed land uses generate lower share of vehicle trips and higher share of walking, biking, and transit trips (Tian et al., 2015).

Of the many built environment variables, the regional compactness index proved to have the most significant influence on walking. Students living in compact regions are more likely to walk. The probability of walking to school has an elasticity of 0.22 with respect to regional compactness. This is the largest elasticity among all built environment variables on walking. Interestingly, regional compactness did not have a significant effect on biking and transit.

Of other built environment variables, activity density has positive relations with walking and biking. Percentage of public land, percentage of four-way intersection, and transit stop density have positive relations with walking. Intersection density has a positive relation with biking. These relationships are consistent with mode choice of general travel. Streets with higher intersection density or more four-way intersection generate more route choices. Transit uses usually involve some walking or biking.

3.5.4 Other Influences

Interesting but not surprising, gas price has strong influence on walking and transit usage with elasticities of 1.10 and 5.46, respectively. With the increase of gas price, the cost of driving to school increases. Other alternatives, walking or using transit, start to be considered as options of travel to school. The interesting part is that the elasticity for transit is so big.

Weather does have influence on student's choice of active travel to school. Students are less likely to walk in regions in which the average annual precipitation is high. This means that the chance of students walking to school decreases on days with precipitation. This agrees with the effects of weather on general travel.

3.6 Discussion and Conclusion

This study estimated student travel-to-school mode choice using regional household travel data and built environmental variables from 14 diverse regions across Unites States. The mode choices were estimated with multilevel multinomial logistical regression. The results show that students with shorter walk and bike distance to school proved significantly more likely to walk and bike. This finding is consistent with the literature showing that distance is a primary factor impacting students walking or biking to school. If distances are too long, students may not use active travel modes, even in supportive environments. On the other hand, if home is close enough to school, students may use active travel modes, even in unsupportive environments (e.g. active travel is the dominant choice for less than 2 mile school trips in two regions).

The results also confirm sociodemographic influences on student mode choices.

Female students with driver licenses from households with higher incomes and more vehicles per capita are less likely to use active travel modes to school. It makes perfect sense that when students holding drivers' licenses and their families' financial situation permits, active travel modes become less attractive. But the reason for boys being more likely to walk and bike than girls is not clear.

This study also provides evidence on which built environmental factors along the shortest route between home and school influence student mode choices. The findings are interesting. Not every built environmental factor has the same relationships with student travel choice as with general travel. Development density, street design, and transit service are still important to increase students' walking and bike, but not land use diversity. These findings agree with safety concerns in the literature and the study that found more school travel–related collisions happen on highways and interstates and arterial roads and where there are traffic generating land uses (Yu, 2015). Additionally, student travel choice differs from region to region. Students in compact regions are more likely to use active modes than students in sprawling regions.

This study points to the importance of factors at different levels – individual and household, built environment around schools, and regional – for student mode choice. From a planning perspective, this study suggests that promoting more compact and pedestrian-bicyclist friendly developments can be expected to have beneficial effects on student active travel. From a policy perspective, this study suggests that policies aimed at increasing the cost of driving (i.e., taxes on vehicle ownership and gas price) may also be effective in shifting students away from driving to school.

Weather has been reported as an important factor on individual's travel behavior and travel choice in general (Böcker et al., 2013). This study tests whether this is the case for school travel too. The results show that weather does have significant impacts on school travel, especially walk. Weather conditions, precipitation and temperature, have strong impact on both walk and transit use. Precipitation discourages students to actively travel to school. The impact of weather on biking has not been found in this study. There are two possible reasons. First, due to data availability, the weather conditions measured in this study are an annual average, instead of the actual weather on the travel day. They could be very different. Second, the samples in this study are limited to trips with travel distance less than 2 miles. Shorter trips might be less impacted by weather. We cannot control or change weather. Still from a planning perspective, by knowing the influence of weather on student's travel choice, it benefits planners to address the influence of weather when designing safe routes to school projects. Also with controlling for weather condition in the model process, it helps to uncover the true relationship between built environment and student's travel choice.

Though this study covered sociodemographic status, built environmental variables, and regional characteristics, there are other factors omitted that can be measured objectively and have presumptive effects on student travel choice. Firstly, SRTS programs have been reported to have immediate effects of making more students walk or bike to and from school. This study has not identified the existing SRTS programs in all the study areas and failed to control for influence of SRTS programs on walking and biking.

Another variable that has been omitted in this study is school enrollment. The utility of walking and biking was expected to decline with enrollment, as schools would be drawing from larger areas. Whether this variable would be significant after controlling for travel distance to and from school is anyone's guess. School enrollment was important in one study (Kouri, 1999) and did not prove significant in another study (Botchwey et al., 2014). It is necessary to test with a larger sample.

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CHAPTER 4

SENIOR TRAVEL BEHAVIOR: EVIDENCE FROM 23 DIVERSE REGIONS OF THE UNITED STATES

As most of developed countries, the senior age group has become the fastest growing group of the population in the United States. When people are getting old, they want to “age in place”. A good place for aging should have good accessibility for the elderly and promote more physical activities. To face the aging society, I ask the following questions: do seniors travel differently with younger adults and does built environment matter to keep seniors active? In this chapter, I aim to answer these questions by using analysis of variance (ANOVA) and multilevel modeling based on a dataset from 23 diverse regions of the United States. Most importantly, this dataset contains the widely used built environment variables, socioeconomic characteristics, and weather conditions.

I find that much a higher percentage, about 60%, of their trips are home based. The top activities for travel are grocery shopping, personal business including medical visits, and other social/recreational/religious events. The model results show that diversity, design, and destination accessibility by transit are the most important neighborhood built environments to encourage seniors to walk. The analysis of variance (ANOVA) tests show that compared with those living in sprawling neighborhoods, seniors living in compact neighborhoods generally travel more in total, and hence can be deemed more active and mobile, which is a good thing as people age. They also travel more by walking and public transportation, which is also a good thing for their health. They travel less by automobile as well, which is a good thing for traffic safety as driving ability declines at advanced ages.

4.1 Introduction

People want to "age in place" or live in their homes or communities as long as possible when they are old (Yen & Anderson, 2012). A good place for aging should have good accessibility for the elderly and promote more physical activities. It is widely accepted that physical activity is important to maintain health and has positive effects in the prevention and treatment of many chronic diseases and age-related disabilities (Chudyk et al., 2014). Designing age-friendly neighborhoods with destinations nearby encourages older adults to get out and be physically active (Winters et al., 2014). Walking and biking are relatively easy ways for older adults to be physically active (Kemperman & Timmermans, 2009).

Globally, the population aged 65 or older is estimated to increase from 524 million in 2010 (8% of total), to 1.5 billion (16% of total) in 2050; the 85-and-over population will increase five times over the same period (World Health Organization, 2011). Particularly in postindustrial Western countries, the aging of the Baby Boom generation (born 1946–1964) promises a greater older population increase for decades to come. In the United States, the population aged 65 or older will double from 40.2 million in 2010 (13% of total) to 88.5 million (20.2% of total) in 2050; the 85-and-over population will increase from 5.8 million in 2010 (1.9% of total) to 19 million in 2050 (4.3% of total) (Vincent & Velkof, 2010).

The Baby Boom generation is aging and continues to out travel each previous generation; there is no evidence to assume that as they reach retirement age that trend will end. Also, seniors today are remaining active and working well into their older age and the age group has continued to increasingly contribute to total travel. These increases will be echoed by the Baby Boom generation and must be considered by traffic forecasters, researchers, and policy makers in the future.

To face the aging society, we ask the following questions: do we know enough about seniors' travel behavior and are we planning to meet seniors' travel needs? The research questions for this study are the following: Where do seniors go? How do they get to their destinations? What factors influence their travel choices? What can planners do to improve active living?

This study aims to answer these questions based on a dataset of seniors' travel dailies from 23 diverse regions of the United States. This dataset is the largest sample of household travel records ever assembled outside of the National Household Travel Survey. The overall sample consists of 81,914 trips made by 12,453 senior households. Number of trips, types of activities, trip duration, and mode choice were evaluated to analyze senior's travel patterns. More importantly, the dataset contains the widely used built environment variables for travel research, density, diversity, design, distance to transit, and destination accessibility, consistently in all the regions. Multilevel modeling (MLM), also called hierarchical modeling (HLM), was used to test the impact of built environment on senior's mode choices.

4.2 Literature Review

4.2.1 Senior's Travel Behavior

Research on older adult travel behavior has studied trends and patterns in terms of trip numbers, trip distances, trip purpose, and mode choice. Older adults have different socioeconomic characteristics and different travel behaviors, compared to young adults. According to the 2009 national household travel survey, older adults have smaller household size (without children, 93% are a couple or single) and fewer vehicles, compared with all households. Most of them are unemployed (Samus, 2013), and their travel behaviors are strongly influenced by possession of driver's licenses, and living with or without a partner (Hensher, 2007).

Evidence shows that total trips and mean distances decline when age advances (Boschmann & Brady, 2013; Mercado and Paez, 2009; Moniruzzaman et al., 2013; Newbold et al., 2005; Scott et al., 2009), including transit and active trips (Moniruzzaman et al., 2013; Samus, 2013). Currie and Delbosc's (2010) study shows that older adults demonstrated 30% lower trip making overall compared to young adults in Australia.

Older adults travel for different reasons than those in the labor force. Destinations most relevant to older adults are grocery stores, malls, restaurants, and medical offices (Chudyk et al., 2014; Newbold et al., 2005; Samus, 2013; Winters et al., 2014).

The car is still found to be the most convenient and major transport option for older people (Cao et al., 2010; Davis et al., 2011; Newbold et al., 2005; Scott et al., 2009; Zeitler, 2013), though some studies have found the mode of travel shifts away from the car as people age (Boschmann & Brady, 2013; Cao et al., 2010; Golob & Hensher, 2007). Many older people shift from car driver to car passenger and then to public transportation because of loss of driver licenses (Golob & Hensher, 2007). Still, transit trips accounted for only a small proportion of the overall travel among older people (Broome et al., 2009; Vine et al., 2012). Driver friendliness, convenient bus stop locations, ease of entry/exit, and information usability are prioritized barriers and facilitators of transit use for older people (Broome et al., 2010). Additionally, destinations that facilitate more social interaction generate more walking among seniors (Nathan et al., 2012; Winters et al., 2014).

4.2.2 Senior Travel and Built Environment

The relationship between built environment and travel behavior is well studied in the literature. Built environments are often characterized in terms of D variables. The Ds all have an effect on travel behavior (Ewing & Cervero 2010). The first three Ds—development density, land use diversity, and urban design—were coined by Cervero and Kockelman (1997). Two additional Ds—destination accessibility and distance to transit—were included in later research (Ewing & Cervero 2001; Ewing & Cervero 2010). These D variables have been widely used to explain trip distances, trip frequencies, mode choices, and overall vehicle miles traveled.

Studies on senior travel behavior have found that the relationships applying to the general population also apply to older adults in general (Chudyk et al., 2014; Frank et al., 2010; Li et al., 2005; Moniruzzaman et al., 2013; Winters et al., 2014). However, there are certain built environment variables that are particularly associated with active travel and physical activity in older adults. Land use mix is one of the mostly reported variables in the literature for older adults. There is a positive relationship between the sum of destinations within walking distance of home and the number of walk trips by seniors (Cao et al., 2010; Frank et al., 2010; Hanson et al., 2012; King et al., 2003; Mercado & Paez, 2009; Michael et al., 2006; Nagel et al., 2008). Older adults who live in diverse use neighborhoods have higher activity levels, instead of staying at home or traveling outside their neighborhoods (Rosso et al., 2013). Street design quality, like the presence and condition of sidewalks, presence of benches, safe street crossings, etc., is another key issue for older adults reported in the literature (Hanson et al., 2012). Additionally, quality of the transit services is a big concern for older people taking public transit (Boschmann & Brady, 2013; Broome et al., 2010; Mercado et al., 2010). Access to open space can increase older people's physical activity levels (Kemperman & Timmermans, 2009; King et al., 2003).

4.2.3 Impact of Weather on Travel Behavior

With climate change becoming a global issue, weather has been getting more and more attention by travel behavior study (Böcker et al., 2016). Studies have reported the influence of weather conditions on individual's mode choices, especially walk and bike (Böcker et al., 2013; Koetse & Rietveld, 2009). Precipitation and temperature are the most widely used measures of weather conditions. In general, studies report there is negative influence of precipitation and warmer/colder temperature on walk and bike (Böcker et al., 2013; Nankervis, 1999; Saneinejad et al., 2012).

The impact of weather conditions on transit ridership has also been studied in the literature. By using an hourly ridership model, a study in New York City found the adverse impact of weather conditions on transit ridership and ridership on weekends was more severe (Singhal et al., 2014). To identify perceived barriers of using buses, a study found participants reported a need for bus shelters to provide adequate seating, shade, and protection from weather conditions (Broome et al., 2010). Another study in Brisbane, Australia found a nil association of precipitation and temperature and transit usage by using (Kashfi et al., 2015). However, after conducting a literature review of 54 studies, Böcker et al. (2013) concluded that "the existing studies present an incomplete and fragmented picture of the impact of weather on travel behavior, which makes effective planning for climate change a harsh job" (p. 71).

In sum, in 2004, a review conducted by Cunningham and Michael (2004) found studies on the impact of the built environment on physical activity for older adults were limited and the findings were inconsistent. Ten years later, Garin et al. (2014) showed evidence from 48 papers that some built environment variables impact on older people health, but there is need for further investigation to clarify this relationship. Additionally, studies of senior travel behavior have acknowledged the potential influence of weather condition on senior's travel choice in the literature. However, to our knowledge, there is no study having controlled for weather conditions when studying the relationship of built environment and senior travel behavior.

4.3 Methodology

This study employs a cross-sectional research design to understand seniors' travel behavior and determine the relative influence of household characteristics, built environment, regional factors, and weather conditions on seniors' travel choice.

4.3.1 Data Collection

The most widely used data source to study travel behavior is the household travel survey. Household travel survey data are the fundamental input for regional travel demand modeling and forecast. Many regional metropolitan planning organizations (MPOs) conduct their own travel survey for their uses. In the last 5 years, we have been contacting regional MPOs and collecting household travel survey data. A main criterion for inclusion of regions in this study was data availability. Regions had to offer regional household travel surveys with XY coordinates, so we could geocode the precise locations of trip ends. It is not easy to assemble databases that meet this criterion, as confidentiality concerns often prevent metropolitan planning organizations from sharing XY travel data. The resulting pooled dataset consists of 81,056 households in 23 regions, from which senior trips could be extracted and mode choices analyzed.

The unit of analysis for the study is the senior households, which are households that only have seniors. Originally, we identified about 20,000 households with seniors, but we chose to focus on the households with only seniors for three reasons. First and most important, accessibility and mobility become a more important or serious issue when seniors live with themselves, especially when they lose their drivers' licenses. For seniors living with other adults, they could get help from others and their travel behaviors might be affected by others. Second, from a planning perspective, this way would be more helpful for polices about senior housing and planning. Third, we still have enough samples when we just focus on senior households, even though the sample size goes down to 12,453 households. We also do not include individual trips for which the travel distance is more than 100 miles.

The regions included in our household travel survey sample were, in addition, able to supply GIS data layers for streets and transit stops, population and employment for traffic analysis zones, and travel times between zones by different modes for the same or close enough to the years that the household travel surveys were conducted.

All the GIS layers that were used to compute built environment around household locations are:

- parcel level land use data with detailed land use classifications; from these we can compute detailed measures of land use mix;
- street networks and intersections; from these we can build the buffer widths and compute intersection density;
- transit stops; from these data we can compute transit stop densities,
- population and employment at the block or block group level; from these we can compute activity density;
- TAZs with socioeconomic information (population and employment);
- travel times for auto and transit travel from TAZ to TAZ (so-called travel time skims); from these and TAZ employment data we can compute regional employment accessibility measures for auto and transit;
- Relevant destinations including library, museum, and park;
- Street Smart Walkscore at census tract level.

Point, line, and polygon data from the different sources were joined with buffers to obtain raw data, such as the number of intersections within buffers. These were then used to compute refined built environmental measures such as intersection density, which is simply the number of intersections divided by land area within the buffer.

What extent of the built environment is most relevant to seniors' travel decisions? Theoretically, buffers (distances from household locations) could be wide or narrow. Even a determinant as straightforward as walking distance could be anywhere from ¼ mile to 1 mile or more. In this study, buffers were established around household geocode locations with three different buffer widths, ¼ mile, ½ mile, and 1 mile. Built environmental variables were computed for each household and all three buffer widths.

At present, we have consistent datasets for 23 regions (Table 4.1). The regions are as diverse as Boston and Portland at one end of the urban form continuum and Houston and Atlanta at the other. To our knowledge, this is the largest sample of household travel records ever assembled for such a study outside the NHTS. And relative to NHTS, our database provides much larger samples for individual regions and permits the calculation of a wide array of built environmental variables based on the precise location of households. NHTS provides geocodes only at the census tract level.

4.3.2 Variables

The final dataset contained 81,914 trips made by 12,453 senior households in 23 regions. To maintain a full complement of independent variables for subsequent analysis, trips were dropped for lack of travel mode and households were dropped for missing any of the following variables: household size, vehicle ownership, etc. The greatest loss of cases was due to unknown household income. As is often the case in travel surveys, household income went unreported by a large number of respondents. We could exclude household income to maintain a larger sample size, but household income was too important from a theoretical perspective to be omitted from the mode choice analysis.

Table 4.1 Regions (metropolitan areas) in the dataset

Regions	***Year of data***	***Regions***	***Year of data***	***Regions***	***Year of data***
Atlanta, GA	2011	Indianapolis, IN	2009	Sacramento, CA	2000
Austin, TX	2005	Kansas City, KS	2004	Salem, OR	2010
Boston, MA	2011	Miami, FL	2009	Salt Lake City, UT	2012
Denver, CO	2010	Minneapolis-St. Paul, MN-WI	2010	San Antonio, TX	2007
Detroit, MI	2005	Phoenix, AZ	2008	Seattle, WA	2006
Eugene, OR	2009	Portland, OR	2011	West Palm Beach, FL	2009
Greensboro, NC	2009	Provo-Orem, UT	2012	Winston-Salem, NC	2009
Houston, TX	2008	Rochester, NY	2011		

The unit of analysis is the senior households, so the dependent variables are numbers of trips made by senior households using different travel modes. Five variables were created based on travel modes (Table 4.2). Bike trips were not included due to the small sample size. There were only 106 households with bike trips even in this large dataset.

Independent variables include socioeconomic characteristics and built environment variables that have been reported as important factors on travel choice by different studies in the literature. These variables cover all of the Ds, from density to demographics.

Three particular variables are included: parks, libraries, and museums. These are destinations that may play important roles in seniors' travel behavior, given the fact that seniors have much higher percentage trips for social/religious/recreational purposes. Dummy variables are created based on the presences of parks, libraries, and museums within certain buffer widths. Additionally, Walkscore is tested to see its explanatory power of seniors' travel behavior.

Table 4.2 Dependent and independent variables

Variable	*Description*	*N*	*Mean*	*S.D.*
Dependent variables –household				
anywalk	any household walk trips (1 = yes, 0 = no)	12,453	0.16	0.37
walktrips	number of household walk trips (for households with any walk trips)	1,981	3.18	2.42
anytransit	any household transit trips (1 = yes, 0 = no)	12,453	0.04	0.21
transittrips	number of household transit trips (for households with any transit trips)	556	2.84	1.60
trips	total number of trips made by household	12,453	6.58	4.16
Independent variables – sociodemographic characteristics				
hhsize	household size	12,453	1.44	0.52
workers	number of workers in the household	12,453	0.37	0.59
hhincome	real household income (in 1000s of 2012 dollars)	12,453	52.05	38.33
vehcap	number of motorized vehicles per capita in the household	12,453	1.00	0.52
Independent variables – built environment within buffers				
actdenqmi	activity density within ¼ mile buffer (population + employment per square mile in 1000s)	12,453	6.70	10.63
jobpopqmi[5]	job-population balance within the ¼ mile buffer	12,453	0.57	0.27
entropyqmi[6]	land use entropy within the ¼ mile buffer	12,453	0.22	0.27
intdenqmi	intersection density within the ¼ mile buffer	12,453	202.28	262.90
int4wayrmi	the percentage of 4-way intersections the ¼ mile buffer	12,453	29.60	30.08
stopdenqmi	transit stop density within the ¼ mile buffer	12,453	27.80	52.01
libraryqmi	library within ¼ mile buffer (1 = yes, 0 = no)	12,453	.03	.18
museumqmi	museum within ¼ mile buffer (1 = yes, 0 = no)	12,453	.07	.26

[5] The job-population index measures balance between employment and resident population within a buffer. Index ranges from 0, where only jobs or residents are present within a buffer, not both, to 1 where the ratio of jobs to residents is optimal from the standpoint of trip generation. Values are intermediate when buffers have both jobs and residents, but one predominates. jobpop = 1 – [ABS (employment – 0.2*population)/(employment + 0.2*population)], ABS is the absolute value of the expression in parentheses. The value 0.2, representing a balance of employment and population, was found through trial and error to maximize the explanatory power of the variable.

[6] The entropy index measures balance between three different land uses. Index ranges from 0, where all land is in a single use, to 1 where land is evenly divided among the three uses. Values are intermediate when buffers have more than one use but one use predominates. The entropy calculation is:
entropy = -[residential share*ln (residential share) + commercial share*ln (commercial share) + public share*ln (public share)]/ ln (3), where ln is the natural logarithm of the value in parentheses and the shares are measured in terms of total parcel land areas.

Table 4.2 continued

Variable	***Description***	***N***	***Mean***	***S.D.***
parkqmi	park within ¼ mile buffer (1 = yes, 0 = no)	12,453	.04	.20
actdenhmi	activity density within the ½ mile buffer (population + employment per square mile in 1000s)	12,453	6.67	10.52
jobpophmi	job-population balance within the ½ mile buffer	12,453	0.60	0.27
entropyhmi	land use entropy within the ½ mile buffer	12,453	0.35	0.28
intdenhmi	intersection density within the ½ mile buffer	12,453	145.76	81.64
int4wayhmi	the percentage of 4-way intersections the ½ mile buffer	12,453	28.61	22.68
stopdenhmi	transit stop density within the ½ mile buffer	12,453	24.63	37.35
libraryhmi	library within ½ mile buffer (1 = yes, 0 = no)	12,453	.12	.33
museumhmi	museum within ½ mile buffer (1 = yes, 0 = no)	12,453	.19	.39
parkhmi	park within ½ mile buffer (1 = yes, 0 = no)	12,453	.08	.27
actden1mi	activity density within the 1 mile buffer (population + employment per square mile in 1000s)	12,453	6.89	9.54
jobpop1mi	job-population balance within the 1 mile buffer	12,453	0.62	0.25
entropy1mi	land use entropy within the 1 mile buffer	12,453	0.47	0.26
intden1mi	intersection density within the 1 mile buffer	12,453	115.79	60.85
int4way1mi	the percentage of 4-way intersections the 1 mile buffer	12,453	27.63	18.84
stopden1mi	transit stop density within the 1 mile buffer	12,453	21.54	26.99
railhmi	rail station within ½ mile buffer (1 = yes, 0 = no)	12,453	0.07	0.81
emp10a	percentage of regional employment within 10 min by car	12,453	7.88	10.74
emp20a	percentage of regional employment within 20 min by car	12,453	30.43	25.61
emp30a	percentage of regional employment within 30 min by car	12,453	51.12	32.15
emp30t	percentage of regional employment within 30 min by transit	12,453	20.64	22.98
library1mi	library within 1 mile buffer (1 = yes, 0 = no)	12,453	.35	.48
museum1mi	museum within 1 mile buffer (1 = yes, 0 = no)	12,453	.44	.50
park1mi	park within 1 mile buffer (1 = yes, 0 = no)	12,453	.15	.36
walkscore	the walkscore of the census tract where the household is within	12,453	39.45	24.54

Table 4.2 continued

Variable	***Description***	***N***	***Mean***	***S.D.***
Independent variables – region				
reginpop	population within the region 1000s	23	2317.77	1678.13
gasprice	average gasoline prices for 2010 at the region	23	2.90	0.13
compact	measure of regional compactness index developed by Ewing and Hamidi (2014); higher values of the index correspond to more compact development, lower values to more sprawling development	23	97.64	26.90
temp_low	annual average of low temperature	23	42.25	14.01
temp_high	annual average of high temperature	23	75.04	8.40
dayt32	number of days the low temperature <= 32 °F	23	32.43	39.17
dayt90	number of days the low temperature >= 90 °F	23	53.65	48.30
annprecip	annual precipitation in inch	23	38.19	16.35
dayp50	number of days the precipitation >= 0.50 inch	23	24.83	11.41

This study also includes nine variables at the regional level: population measuring the size of a metropolitan area, compactness index measuring the overall built environment of a region, gas price, and six weather variables measuring weather condition. The weather variables were collected from Climate Data Online of National Centers for Environmental Information in the same years with the household travel survey data for each region. With different measures, a total of 46 independent variables are available to explain senior travel choice in this study. All variables are consistently defined from region to region.

4.3.3 Model Selection

With the household travel survey from 23 regions, our data structure is hierarchical, with senior households nested within regions. The best statistical method to deal with nested data is hierarchical modeling (HLM), also called multilevel modeling (MLM). HLM accounts for dependence among observations, in this case the dependence of households within a given region on characteristics of the region. All households within a given region share these characteristics. This dependence violates the independence assumption of ordinary least squares (OLS) regression. Standard errors of regression coefficients based on OLS will consequently be underestimated. Moreover, OLS coefficient estimates will be inefficient. HLM overcomes these limitations, accounting for the dependence among observations and producing more accurate coefficient and standard error estimates (Raudenbush & Bryk, 2002).

Regions such as Boston and Houston are likely to generate very different travel patterns regardless of household and around built environment characteristics. The essence of HLM is to isolate the variance associated with each data level. HLM partitions variance between the household level (Level 1) and the region level (Level 2) and then seeks to explain the variance at each level in terms of D variables.

The dependent variables (household walk trips, transit trips, and total trips) are count variables, with nonnegative integer values, many small values, and few large ones. This kind of distribution is ordinarily modeled with Poisson or negative binomial regression. However, if there is a much larger number of observed zeros than assumed by a Poisson or negative binomial distribution, the distribution is said to be "zero-inflated" and an alternative analytical approach is required. One solution to the zero-inflated distribution is two-stage hurdle models (Hu et al., 2011; Greene, 2012). "In some settings, the zero outcome of the data-generating process is qualitatively different from the positive ones. The zero or nonzero values of the outcome is the result of a separate decision whether or not to 'participate' in the activity. On deciding to participate, the individual decides separately how much to, that is, how intensively [to participate]" (Greene, 2012, p. 824).

In a two-stage hurdle model, stage 1 categorizes households as having at least one walk or transit trip or not, and uses logistic regression to distinguish these two states. The stage 2 model estimates the number of walk or transit trips generated by households with any (positive) walk or transit trips. Either Poisson regression or negative binomial regression can be used at stage 2. The difference between these two methods is their assumptions about the distribution of the dependent variable.

Negative binomial regression is more appropriate than Poisson regression if the dependent variable is over-dispersed, meaning that the variance of the count is greater than the mean. Popular indicators of overdispersion are the Pearson and $\chi 2$ statistics divided by the degrees of freedom, so-called dispersion statistics. If these statistics are greater than 1.0, a model is said to be over-dispersed (Hilbe, 2011). By these measures, in this study, the number of walk trips and the number of total trips is over-dispersed, and thus the negative binomial model is more appropriate than the Poisson model. The number of transit trips is not over-dispersed, and thus the Poisson model is more appropriate than the negative binomial model. The equations of the models are as follow:

First stage of hurdle models (multilevel logistic regression):

$$\text{Level 1:} \quad P(y = 1 \mid x_1, \dots x_n) = 1/(1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i}) \tag{4.1}$$

$$\text{Level 2:} \quad \beta_0 = \gamma_{00} + \sum_{j=1}^{m} \gamma_{0j} W_j + u_{0j} \tag{4.2}$$

$$\beta_i = \gamma_{i0} \tag{4.3}$$

Where: P refers to the probability of the dependent variable equals 1,

β_0 refers to the intercept of the dependent variable at the level 1,

β_i refers to the coefficient of independent variables at the level 1,

x_i refers to the independent variables at the level 1,

γ_{00} refers to the overall intercept,

γ_{0j} refers to the coefficient of independent variables at the level 2,

W_j refers to the independent variables at the level 2,

u_{0j} refers to the random error component for the deviation of the intercept,

γ_{i0} refers to the overall coefficients.

Second stage of hurdle models (multilevel Poisson regression):

Level 1: $E(y = 1 \mid x_1, \dots x_n) = e^{\beta_0 + \sum_{i=1}^{n} \beta_i x_i}$ (4.4)

Level 2: $\beta_0 = \gamma_{00} + \sum_{j=1}^{m} \gamma_{0j} W_j + u_{0j}$ (4.5)

$\beta_i = \gamma_{i0}$ (4.6)

Where: *E* refers to the estimated value of the dependent variable,

β_0 refers to the intercept of the dependent variable at the level 1,

βi refers to the coefficient of independent variables at the level 1,

x_i refers to the independent variables at the level 1,

γ_{00} refers to the overall intercept,

γ_{0j} refers to the coefficient of independent variables at the level 2,

W_j refers to the independent variables at the level 2,

u_{0j} refers to the random error component for the deviation of the intercept,

γ_{i0} refers to the overall coefficients.

4.4 Travel Pattern Analysis

To better understand the travel pattern of the elderly, it is necessary to compare elderly with other adult cohorts, such as Generation X (born 1965 to 1976) and Baby Boomers (born 1946 to 1964). Since most of my data are around 2010, I got three cohorts for comparison: Generation X – age 34-45, Baby Boomers – age 46-64, and elderly – age 65 or older.

4.4.1 Descriptive Analysis

The comparison of travel patterns among different cohorts, Generation X, Baby Boomers, and elderly, are shown in Table 4.3. With age increases, the average number of trips and vehicle miles traveled per person decreases within these three cohorts. Among these three cohorts, baby boomers have the longest average travel time and distance per trip. Elderly have the shortest longest average travel time and distance per trip.

In terms of travel mode shares, the auto mode share is dominant for all three cohorts. The auto mode share of the elderly is about 90%. The walk mode shares decrease with the age increases through the three cohorts. Although the decrease is slight, from Generation X (8.49%) to Baby Boomers (8.47%), the decrease is quiet significant from Baby Boomers (8.47%) to elderly (7.06%). The bike mode share is pretty similar to walk mode share. However, for transit mode share, baby boomers have the highest among the three cohorts. In sum, compared to younger cohorts, elderly travel less by

Table 4.3 Comparison of senior travel patterns among different cohorts

			Gen X	**Baby Boomers**	**Elderly**
Person	Sample size		29,241	61,005	28,060
	Average number of trips per person		5.03	4.70	4.45
	VMT per person		29.56	28.41	23.59
Trip	Sample size		146,985	287,028	124,909
	Time per trip (minute)		18.18	19.38	17.98
	Distance per trip (mile)		6.80	7.08	5.84
	Mode shares (%)	Walk	8.49	8.47	7.06
		Bike	1.29	1.04	0.43
		Transit	2.83	3.08	1.74
		Auto	86.58	86.48	89.71
	Trip purposes (%)	HBW	18.61	19.55	6.21
		HBO	44.52	42.77	59.30
		NHB	36.46	37.30	34.28

walking, biking, and using transit.

For the trip purpose, no surprise, elderly have much less home-based work (HBW) trips since many of them are retired and do not work anymore. At the same time, seniors have more home-based other (HBO) trips and less non-home-based (NHB) trips. This means that more travels are related with home for seniors. From the planning perspective, the accessibility of home locations is more important for seniors than for other adults.

In the household travel survey data, the categories of trip destinations are different from region to region. In order to conduct a descriptive analysis, we unified and summarized the destinations into a few major categories. Table 4.4 shows the comparison of destinations for the two senior cohorts and comparison adult cohort.

First, not surprisingly, seniors have a slightly higher percentage of non-work-related activities at home and much lower percentage of work or work-related activities. This confirms the findings from trip purposes pattern in Table 4.3. Second, seniors have a

Table 4.4 Percentage of top destinations for seniors

		Younger adults	**Seniors (65 – 74)**	**Seniors (75+)**
home activities, non-work-related		31%	32%	34%
work or work related		19%	7%	4%
all shopping		12%	17%	18%
*	groceries shopping	6%	9%	12%
*	other shopping (clothing, hardware, etc.)	9%	9%	9%
eat meal out at restaurant		5%	6%	6%
personal business (laundry, dry cleaning, barber, bank, health care, etc.)		8%	12%	14%
*	health care	2%	3%	5%
social/religious/recreational		8%	12%	13%

** based on regions that have these categories separately.*

higher percentage of shopping trips, and these differences are mainly from groceries shopping. Especially for age 75+ senior group, the percentage of their groceries shopping is twice that of the comparison adult group. Third, senior groups have a higher percentage of personal business (laundry, dry cleaning, barber, bank, health care, etc.) and social/religious/recreational activities. The percentages of these activities are even higher for the age 65-74 senior group than age 75+ senior group. In sum, compared with young adults, seniors have less work-related activities and they have more activities related to groceries shopping, personal business, and social/religious/recreational.

4.4.2 Analysis of Variance

To answer the question whether seniors living in compact neighborhoods are more active than those living in sprawl neighborhoods, analysis of variance (ANOVA) was employed. The dependent variables were the travel outcomes of each senior, including number of total trips, number of walk trips, number of transit trips, and number of auto trips. Number of bike trips was not included due to small sample size.

Whether the place was compact or sprawling was defined based on the D variables measured within a ½ mile buffer of the senior's home (in Table 4.2). First, a principal component analysis (PCA) was applied to measure neighborhood compactness. Density was represented by actdenhmi, diversity by entropyhmi, design by intdenhmi and int4wayhmi, destination accessibility by emp30a and emp30t, and distance to transit by stopdenhmi. They were combined into a single principal component, which was a linear function of these D variables. The jobpophmi was dropped due to the wrong sign and low factor loading. The extracted principal component has an eigenvalue of 2.65, meaning that this one component explains the combined variance as 2.65 of the original variables. Factor loadings (correlations between the principal component and component variables) range from 0.519 for diversity to 0.775 for distance to transit, as shown in Table 4.5. Second, using factor score coefficients for the first principal component, the built environment was categorized into two groups – compact if the factor score is above the average and sprawling is the factor score is below the average. This categorical built environment variable became the independent variable for the ANONA test, along with household income.

When studying the effect of built environment on travel, sociodemographic characteristics should always be controlled. Household income was used here as the representative of socioeconomic status. Income was also categorized into two groups – high income group for those above the median and low income group for those below the median. With these two independent factors, a two-way ANOVA test was conducted for each of the travel outcomes. The results are presented in Table 4.6.

The estimated marginal mean value, instead of descriptive mean or actual mean, is reported because the estimated marginal mean is the mean response for each factor,

Table 4.5. Factor loadings on built environment measure

D variables	***Measures***	***First Component***
Density	actdenhmi	0.720
Diversity	entropyhmi	0.519
Design	intdenhmi	0.546
	int4wayhmi	0.552
Destination accessibility	emp30a	0.553
	emp30t	0.596
Distance to transit	stopdenhmi	0.775
Eigenvalue	2.65	
Explained variance	37.88%	

Table 4.6 Results of two-way ANOVA for the effects of income and built environment on seniors' travel behavior

	Income (high vs. low)			**Built environment (compact vs. sprawl)**		
	Estimated marginal means	***F***	***P-value***	**Estimated marginal means**	***F***	***P-value***
number of total trips	0.387	137.270	< 0.001	0.128	15.044	< 0.001
number of walk trips	-0.022	2.438	0.118	0.267	357.981	< 0.001
number of transit trips	-0.043	42.086	< 0.001	0.118	314.134	< 0.001
number of auto trips	0.470	213.519	< 0.001	-0.281	76.143	< 0.001

adjusted for any other variables in the test. The estimated marginal means for income and built environment are adjusted for the covariation between them. This, of course, is the reason for including income in the test – particularly, we want to see if the built environment factor still has an effect, beyond the effect of income.

The results show the significance of the variation between compact and sprawl neighborhoods, even when household income has been controlled for. The F values show the ratio of variation between neighborhoods (or income groups) to the variation within neighborhoods (or income groups) – higher ratios suggest a stronger effect, as indicated by the low p-value. For the number of total trips, both income and built environment have significant effects, though the income effect is greater than built environment effect based on F values. The average number of total trips for seniors living in compact neighborhoods is statistically higher than those for seniors living in sprawling neighborhoods.

For both numbers of walk and transit trips, the built environment effects are greater than income. Built environment has the strongest effect on number of walk trips. Seniors living in compact neighborhoods generate significantly higher numbers of walk and transit trips. Seniors within higher incomes generate significantly lower number of transit trips.

Income has the strongest effect on number of auto trips. Seniors within higher income generate much greater numbers of auto trips. After accounting for the strong effect of income, built environment still has a significant effect on auto trips. Seniors living in compact neighborhoods generate statistically lower numbers of auto trips.

In sum, these findings support the literature that built environment have a significant effect on senior's travel behavior after controlling for sociodemographic characteristics. More important, these findings tell us that seniors living in compact neighborhoods are more active than those living in sprawl neighborhoods. They generally travel more and travel more by walking and public transportation, yet travel less by automobile.

4.5 Modeling Results

Walking, transit trips, and total trips were estimated with HLM 7, Hierarchical Linear and Nonlinear Modeling software (Raudenbush et al., 2010). HLM 7 allows the estimation of multilevel models for continuous, dichotomous, and count variables, and for the last of these, HLM 7 can account for overdispersion. Different Ds may emerge as significant in different models, so trial and error was used to arrive at the best-fit models for the travel outcomes of interest. For the same D variables measured in three different buffer widths, only one of them was included in the model at the same time. Variables were substituted into models to see if they were statistically significant and improved goodness-of-fit. For each dependent variable, we were looking for the model with the most significant *t*-statistics and the greatest log-likelihood.

4.5.1 Walking Trips of Senior Households

The best-fit model for the dichotomous variable, any walk, is presented in Table 4.7. The likelihood of a senior household making any walk trips increases with household size, number of workers, and household income and decreases with vehicle per capita.

The likelihood of any walk trips increases with land use entropy within ¼ mile of

Table 4.7 Multilevel logistic regression model of log odds of any walk trips

	Outcome variable is anywalk			
	coefficient	standard error	*t*-ratio	*p*-value
Constant	-8.715	2.524	-3.453	0.004
hhsize	0.114	0.069	1.658	0.097
workers	0.176	0.058	3.026	0.003
vehcap	-0.935	0.127	-7.370	< 0.001
income	0.003	0.001	2.379	0.017
emp30t	0.007	0.003	2.232	0.026
entropyqmi	0.362	0.143	2.530	0.012
museumqmi	0.342	0.113	3.019	0.003
actden1mi	0.016	0.004	3.804	< 0.001
intden1mi	0.002	0.001	2.239	0.025
int4w1mi	0.005	0.003	1.837	0.066
park1mi	0.215	0.066	3.243	0.002
temp_low	0.071	0.015	4.698	< 0.001
temp_high	0.079	0.033	2.380	0.030
dayt32	0.007	0.003	2.179	0.004
dayt90	-0.027	0.008	-3.406	0.004
annpreci	-0.078	0.027	-2.926	0.010
dayp50	0.075	0.032	2.310	0.035
Pseudo-R2: 0.37				

home and activity density, intersection density, and percentage of four-way intersections within a mile of home. These measures of density, diversity, and design place destinations within walking distance of home. The likelihood of any walk trips also increases with museum within ½ mile of home, park within a mile of home, and regional accessibility to employment within 30 minutes by transit. Museums and parks are more relevant destinations for seniors; this is consistent with the finding in the travel pattern analysis that seniors have a higher percentage of trips for social/religious/recreational purpose. Transit service is complementary to walking, as senior households with good access to transit tend to own fewer automobiles, having transit available for their travel.

At the regional level, the likelihood of any walk trips increases with regional annual average low temperature, average high temperature, and number of days with temperature lower than 32 °F and decreases with number of days with temperature greater than 90 °F. This means, generally, either extreme low or high temperate discourage seniors to walk. I do not have a good explanation for the positive sign of number of days within temperature lower than 32 °F. The likelihood of any walk trips also decreases with annual precipitation and increases with number of days with precipitation higher than 0.5 inch. This makes sense. After controlling for annual precipitation, more days with precipitation higher than 0.5 inches mean fewer days with any precipitation in a given year. Hence, the two variables together mean precipitation also discourages seniors to walk.

The number of walk trips for the subset of senior households that make walk trips increases with household size, number of workers, and household income and decreases with vehicle per capita (Table 4.8). The number of walk trips increases with these D

Table 4.8 Multilevel binomial negative binomial model of household walk trips (for households with any walk trips)

	Outcome variable is walktrips			
	coefficient	standard error	*t*-ratio	*p*-value
Constant	0.541	0.131	4.140	0.001
hhsize	0.151	0.057	2.645	0.009
workers	0.046	0.028	1.619	0.105
vehcap	-0.224	0.064	-3.487	0.001
income	0.001	0.0006	1.743	0.081
emp30t	0.002	0.001	2.726	0.084
entropyqmi	0.196	0.080	2.463	0.014
intden1mi	0.0007	0.0003	2.166	0.030
stopden1mi	0.002	0.0008	2.450	0.015
compact	0.002	0.0006	3.006	0.008
annpreci	-0.009	0.005	-1.911	0.071
dayp50	0.013	0.007	1.847	0.080
Pseudo-R2: 0.15				

variables: land use entropy within ¼ mile, intersection density and transit stop density within a mile of home, and accessibility to employment within 30 minutes by transit. It also increases with regional compactness and number of days with precipitation higher than 0.5 inches and decreases with annual precipitation at regional level. The more compact a region is, the more destinations are within a walkable distance. The relationship of walking to D variables has already been discussed, as has the relationship of walking to weather condition. Probably the most interesting finding is that walk trip frequency depends on the built environment at a larger scale than the usual ¼ mile walk distance assumed by planners. This is consistent with the finding by a previous study in the literature (Ewing et al., 2015).

4.5.2 Transit Trips of Senior Households

The likelihood of a senior household having any transit trips increases with household size and number of employed members and decreases with vehicle per capita (Table 4.9). It also depends on diversity and design of the environment around a senior household, which are measured by land use entropy within ¼ mile and intersection density and percentage of four-way intersection within a mile of home. Two transit service variables affect the likelihood of transit trips: transit stop density within a mile of home and percentage of regional jobs that can be reached within 30 minutes by transit. At a regional level, the likelihood of transit trips is also affected by regional compactness, population size, and gasoline price. Large and compact metropolitan areas have better transit service. The increasing gasoline price increases the cost of driving, which encourages mode shifts and the use of transit.

The number of senior household transit trips for the subset of senior households

Table 4.9 Multilevel logistic regression model of log odds of any transit trips

	Outcome variable is anytransit			
	coefficient	standard error	*t*-ratio	*p*-value
Constant	-9.910	3.323	-2.982	0.008
hhsize	-0.435	0.111	-3.929	<0.001
workers	0.827	0.087	9.480	<0.001
vehcap	-2.896	0.205	-14.126	<0.001
emp30t	0.019	0.005	3.698	<0.001
entropyqmi	0.356	0.173	2.053	0.040
intdenqmi	0.00018	0.00008	2.171	0.030
Int4whmi	0.0046	0.0028	1.642	0.100
stopden1mi	0.005	0.0015	3.372	0.001
compact	0.012	0.007	1.799	0.088
regionpop	0.00023	0.0001	2.394	0.027
gasprice	2.109	1.198	1.761	0.094
Pseudo-R2: 0.58				

that use transit increases with household size and decreases with vehicle per capita (Table 4.10). Transit trip frequency increases with land use entropy within ¼ mile and job-population balance within a mile of home, two measures of land use mix. It has long been speculated that, in general, mixed-use areas would generate more transit trips because of the feasibility of trip chaining on the access trip to transit, that is, stopping along the way to conduct other personal business. It seems the case for seniors too. Transit trip frequency also increases with regional population size and decreases with days with temperature greater than 90 °F.

4.5.3 Trip Frequency of Senior Households

The number of senior household total trips increases with household size, number of employed members, vehicle per capita, and real household income (Table 4.11). Total trip frequency increases with the availability of museum within ½ mile of home, presence of a rail station within ½ mile of home, and regional compactness. Seniors living in metropolitan areas that are compact and have better transit service generate more trips.

Table 4.10 Multilevel Poisson regression model of transit trips (for households with any transit trips)

	Outcome variable is transittrips			
	coefficient	standard error	*t*-ratio	*p*-value
Constant	0.495	0.170	2.908	0.010
hhsize	0.170	0.066	2.576	0.011
vehcap	-0.131	0.030	-4.335	<0.001
entropyqmi	0.334	0.075	4.431	<0.001
jobpop1mi	0.258	0.067	3.833	<0.001
regionpop	0.00005	0.00003	1.736	0.100
dayt90	-0.002	0.0009	-2.214	0.041
Pseudo-R2: 0.51				

Table 4.11 Multilevel negative binomial regression model of senior household total trips

	Outcome variable is total number of trips			
	coefficient	standard error	*t*-ratio	*p*-value
Constant	0.848	0.080	10.593	< 0.001
hhsize	0.616	0.028	22.267	< 0.001
workers	0.039	0.014	2.841	0.005
vehcap	0.038	0.021	1.834	0.066
income	0.001	0.0002	3.750	< 0.001
museumhmi	0.058	0.016	3.597	0.001
railhmi	0.027	0.002	14.099	< 0.001
compact	0.0008	0.0004	2.081	0.051
dayt90	-0.0007	0.0003	-2.313	0.032
dayp50	-0.002	0.001	-2.534	0.021
Pseudo-R2: 0.37				

This means they are more active. The number to total trips also decreases with days within temperature greater than 90 °F and precipitation higher than 0.5 inch. High temperature and precipitation discourage seniors to travel in general.

4.6 Discussion and Conclusion

Summarizing across the travel pattern analyses and preceding models, we find the following results about senior's travel behavior and choice.

Baby Boomers have the highest average trip distance and travel time per trip among Generation X and elderly. Elderly have the lowest values. Travel frequency decreases with age increases. The senior group has the smallest number of trips per person. The mode share analysis confirmed the literature that the auto is the dominant travel mode for seniors. Seniors' mode shares of walk, bike, and transit are lower than Generation X and Baby Boomers. Especially, the use of bike mode for seniors is limited. Even with this large dataset, we still did not have a large enough sample to model bike trips.

No surprise, seniors have much less work-related trips and other trips go up. The destination analysis shows where these trips go and how they are distributed for different destinations. Shopping, personal business (laundry, dry cleaning, barber, bank, health care, etc.), and social/religious/recreational are the top activities for seniors. This tells planners that the accessibility of senior home locations to services, especially grocery stores and social and health care facilities, is more important for seniors than for other adults.

The sociodemographic characteristics show that seniors living in bigger households or households with more workers generate more walking trips, transit trips, and travel more frequently, which basically means that seniors living with others and/or still working are more active.

Consistent with the literature, all the D variables influence senior household travel decisions. However, not every D variable has the same strength. Land use entropy within ¼ mile of home is the strongest built environment variable. It is statistically significant in four of our five models and each has the greatest coefficient in the specific model. Intersection density and percentage of four-way intersection are important to walk, but within a larger scale – 1 mile buffer of home. Transit is also important as shown in the models by transit stop density and destination accessibility by transit. Overall, the model results show that the D variables – diversity, design, and destination accessibility by transit – are the most important neighborhood built environment to keep seniors active. Density, which is only significant in one model, is less important.

There are two specific destinations that have strong explanatory power of senior's travel behavior: museum and park. Seniors living in places with the presence of museum and park are more likely to walk. Seniors living in places with presence of museum generate more trips. This is consistent with the travel pattern analysis that seniors have much higher percentage of trips related to social/religious/recreational purpose. Museums and parks represent the destinations that meet seniors' travel need of these purposes. Also, perhaps places with more museums are more cosmopolitan.

Walkscore is also tested in this study and it is not significant in any of the models. This tells us that Walkscore has no explanatory power of senior travel behavior. This is not surprising. Walkscore measures neighborhood walkability mainly based on destinations and street designs, which are already captured by other variables in the models.

The regional compact index is also significant in three models. Senior households in compact regions generate more walk trips, are more likely to use transit, and have higher travel frequency. Together, the two-way ANOVA tests and MLM results show that seniors living in compact neighborhoods are more active than those living in sprawl neighborhoods. They generally travel more and travel more by walking and public transportation, yet travel less by automobile.

Weather has been reported as an important factor on individual's travel behavior and travel choice in general (Böcker et al., 2013). This study tests whether this is the case for seniors too. The results show that weather does have significant impacts on senior's travel. Weather conditions, precipitation and temperature, have strong impact on both walk and overall trip frequency, and less impact on transit usage. Extreme temperature and precipitation discourage seniors to leave their homes and travel, especially by walking. We cannot control or change weather. Still from a planning perspective, by knowing the influence of weather on senior's travel behavior and choice, it benefits planners to address the influence of weather when designing housing or other facilities for seniors. Also with controlling for weather condition in the model process, it helps to uncover the true relationship between built environment and senior's travel behavior.

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CHAPTER 5

CONCLUSIONS AND IMPLICATIONS

5.1 Key Findings

Generalizing across the three studies in this dissertation, the most significant findings are the following. First of all, built environment matters to people's travel behaviors, and the effect of different D variables on walk and bike for different cohorts is different. Second, the accessibility of destinations is just as important as residential accessibility for encouraging people to walk. Third, land use diversity is important for walking and biking generally, but not for active travel to school. Major road and commercial developments have strong negative impacts on active travel to school. Fourth, seniors living in compact neighborhoods are more active than those living in sprawling neighborhoods. They generally travel more and travel more by walking and public transportation, yet travel less by automobile.

The other findings emerge with great relevance to travel behavior and travel modeling.

5.1.1 Travel Patterns

There is great variation in mode shares from region to region. The following are the key findings of travel patterns across regions:

- Overall, 9.0% of all trips are by walking and 1.2% of all trips are by biking, while 83.9 of all trips are by car. Even for trips of less than 1 mile from origin to destination, only 35.7% of trips are by walking and 2.1% of trips are by biking.
- The walk mode share ranges from 3.5% in San Antonio up to 22.1% in Boston. The regions with top three walk mode share are Boston, Portland, and Eugene.
- The bike mode share ranges from 0.2% in San Antonio to 4.2% in Eugene.
- Across regions for all school trips, the walk share varies from a low of 4% for Atlanta to a high of 26.3% for Boston and the bike share varies from a low of 0.0% for Detroit to a high of 8.4% for Eugene.
- For bike trips in school travel, it is more concentrated at age 9 to 13, where each age group has higher than 10%.
- Comparing to age young adults, seniors travel a little bit less by walking, but much less by biking and using transit. The auto mode share is dominant for seniors. The walk mode share is about 7%.

Travel distance and time for walking and biking:

- In the 23 regions, the average walk and bike distances are 0.63 miles and 2.43 miles, respectively.
- The average walk and bike time are 11.50 minutes and 20.52 minutes, respectively.
- The average distance of active travel to school are 0.58 miles and 0.9 miles, for walk and bike, respectively.

- The average time of active travel to school is about 14 minutes, for both walking and bike.

About seniors:

- When they are getting older, seniors are getting less and less active.
- With age increasing, more and more trips are home related.
- Shopping, personal business (laundry, dry cleaning, barber, bank, health care, etc.), and social/religious/recreational are the top activities for seniors.

5.1.2 The Effect of D Variables on Travel Choices

In all the models in this dissertation, sociodemographic characteristics have strong influences in any travel choices, which is consistent with the literature (Ewing & Cervero, 2010). Overall built environment influences people's travel decisions, though the effects of different D variables vary according to different travel outcomes.

- Land use diversity, street connectivity, and transit accessibility seem more important than other D variables to walk trip generation.
- Street connectivity and transit accessibility seem more important than other D variables for bike trip generation.
- Not every built environmental variable has the same relationships with student travel choice as with general travel.
- Street design and transit service are still important to increase students' walking and bike, but not land use diversity.
- Diversity, design, and destination accessibility by transit are the most important neighborhood built environment to keep seniors active.

- Compactness index is a good measurement to represent regional characteristics.
- Seniors in compact regions generate more walk trips, are more likely to use transit, and have higher travel frequency.

The relevant built environment is anywhere from ¼ to 1 mile. However, for certain built environment variables, the smaller scale seems to have more predictive power than the larger scale. For other variables, the scale effects are reversed. Specifically, diversity – represented by job-population balance and land use entropy – has more predictive power at ¼ mile and ½ mile. Design and distance to transit – represented by intersection density, percentage of four-way intersection, and transit stop density – have mostly predictive power at a mile.

5.1.3 Weather and Other Built Environment

Weather has been reported as an important factor on individual's travel behavior and travel choice in general (Böcker et al., 2013), but has not been widely tested by studies for some particular groups in the literature. For all the studies in this dissertation, weather conditions were controlled for when examining the effects of built environment on walk and bike. The results show that weather conditions do have influences on walk and bike trip generation and students and seniors' travel. Both extreme temperature and precipitation discourage walk and bike trip generation, but precipitation has stronger influence than temperature does. Also with controlling for weather condition in the model process, it helps to uncover the true relationship between built environment and travel behavior.

This dissertation has also tested the explanatory power of Walkscore on travel choices. The results show that Walkscore is a good predictor for general walk modeling, but has no explanatory power of students and seniors' travel behavior. This is not surprising. Walkscore measures neighborhood walkability mainly based on destinations (restaurants, shops, etc.) and street designs, which are captured by other variables in the models at some degree. Perhaps more important is that many destinations included in Walkscore metric are not relevant to students or seniors.

One of the most important findings for student travel to school is that major roads and commercial developments have strong negative impacts on active travel to school. The probability of walking and biking to school significantly decreases when the shortest route to school crosses a major road or commercial development. These factors have not been reported in the literature. Most likely, major roads are wide and have heavy traffic. Walking or biking across a major road increases the travel time (both the time to cross the major road and the time waiting for traffic single) and the chance of accidents. Commercial developments are attractions for traffic. This finding agrees with safety concerns in the literature. A study found that more school travel-related collisions happen on highways and interstates and arterial roads and where there are traffic generating land uses (Yu, 2015).

There are two specific destinations that have strong explanatory power of senior's travel behavior: museum and park. Seniors living in places with the presence of a museum and park are more likely to walk. Seniors living in places with presence of a museum generate more trips. This is consistent with tine travel pattern analysis that seniors have much higher percentage of trips related to social/religious/recreational purpose. Museums and parks may represent the destinations that meet seniors' travel need for these purposes.

5.2 Limitations

I acknowledge that there are several limitations on this dissertation. These include the following:

- Sample of regions;
- Cross-sectional study;
- Street network assumptions;
- Missing variables;
- Self-selection;
- Individual trip purposes;

The sample for the study, while large in terms of trips, covers only 23 regions of the U.S. Thus, for certain outcome variables, I will be unable to predict variations in individual travel behavior across regions. As the sample of regions expands, so will the external validity of the study and the ability to predict variations. Also, based on the cross-sectional research design of this dissertation, it is not appropriate to draw causality conclusions based on the results showing here. Instead, this dissertation shows the association or correlation between travel choices and built environment and other factors that have been tested.

Less importantly, I will use the street network as a proxy for paths of all modes, including walk and bike. This approach assumes that individuals travel only on streets and that all streets have sidewalks, although paths through open lots, parking lots, or parks would be attractive alternatives for walking or biking. A more appropriate approach would use the sidewalk network for walking and bike route network for biking, but it is not possible to construct a complete database. Another limitation related to the street network is that, in the absence of other information, we must assume that travelers follow the most direct path between origin and destination. This is clearly not the case for many trips.

Though this study will cover the D variables and regional characteristics, the study still omits other factors that can be measured objectively and have presumptive effects on people's travel choice. Parking supplies and prices, particularly at the destination end of trips, may strongly affect mode choices of individuals.

Finally, for lack of data on mode attitudes and residential preferences, the study fails to control for residential self-selection. More than anything else, the possibility of self-selection bias has engendered doubt about the magnitude of travel benefits associated with compact urban development patterns. According to a National Research Council report, "If researchers do not properly account for the choice of neighborhood, their empirical results will be biased in the sense that features of the built environment may appear to influence activity more than they in fact do. (Indeed, this single potential source of statistical bias casts doubt on the majority of studies on the topic to date.)" (TRB Special Report 282, 2005, pp. 134-135)

At least 38 studies using nine different research approaches have attempted to control for residential self-selection (Cao, Mokhtarian, & Handy, 2009; Mokhtarian & Cao, 2008). Nearly all of them found "resounding" evidence of statistically significant associations between the built environment and travel behavior, independent of self-selection influences (Cao et al. 2009, p. 389). However, nearly all of them also found that residential self-selection attenuates the effects of the built environment on travel.

Although I have data from 23 regions, the sample sizes still do not seem ample when studying walk, bike, and specific age groups. In the first study in Chapter 2, there are only a few variables that are statistically significant in the bike trips model, where the model may be underspecified. Other variables may prove significant if the sample of households with bike trips expands with the addition of other regions. In the three studies of senior travel behavior in Chapter 4, there are not even enough samples to model bike trips. For a transit trip that has been modeled, there are just about 500 cases. With the limitation of sample size, this dissertation does not model mode choice for different trip purposes, such as home-based work, home-based shopping, non-home-based trips, etc.

5.3 Implications in Policy

First of all, built environment matters to individual’s travel choice. In all three studies in this research, people living in neighborhoods with richer D variables use more active transportation. Neighborhoods with rich D variables are commonly called compact development. The benefits of compact development go beyond increased walking and biking to reduced residential energy consumption, reduced pedestrian and motor vehicle fatalities, increased physical activity and reduced obesity, reduced household transportation costs, decreased crime, increased traffic safety, and increased upward social and economic mobility (Ewing et al., 2016b), increased social interaction and neighborliness, and increased social capital (Ewing & Hamidi, 2015; Ewing et al., 2016). Policies should be made to promote compact development.

This research finds that travel patterns vary from region to region. The first recommendation is that regional MPOs or state departments of transportation should be careful of making long-range land use and transportation policy based on assumptions of national trends or common knowledge. For instance, the common sense of walk distance is about ½ mile, which is also close to the overall average walk distance of this research. However, the average walk distance is different from region to region studied in this research. When planning pedestrian- and cyclist-related facilities, planners should be careful not to assume the ½ mile walk distance in their own regions. If possible, regions should conduct travel data in their own regions to make forecast, planning, and policy. Or studies with more external validity, such as this research, could be a reliable alternative source.

Active travel to school should be considered as early as in the school siting process. Places with supportive physical environment (including short distance to school, good walkability, etc.) are good options. Increasing the number of students walking and biking to school should be a goal of existing schools in their programs. Programs can focus on moving away the barriers preventing students from walking and biking. For instance, they should increase the safety of students across major roads with heavy traffic.

People want to "age in place" or live in their homes or communities as long as possible when they are old. A good place for aging should have good accessibility for elderly and keep them active. Policy should be made to make that happen. Good accessibility for seniors means two aspects. First, good accessibility for seniors should be accessibility by more active and public transportation. Currently, driving is the dominant mode to move around for seniors, which is the least healthy transportation mode. The public transportation mode share is extremely low. More important, when they lose the ability of driving at some point, seniors will rely more on active and public transportation. It suggests that transportation policies should be prepared for that and public transportation should focus more on older people's travel needs to design the system. Second, good accessibility for seniors should be accessibility to what they need. This research shows that seniors' travel needs are different. Their travel destinations are more related to service and social purposes. Also with age increases, more travels are related with the home. The accessibility of home locations to service and social destinations is more important for seniors than for other adults. Housing and land use policies should lean to the direction to make these possible, such as mixed-use development.

The whole world is facing the threat of climate change. Active transportation, as serious transportation modes, is a core strategy for policy to promote healthier and more sustainable transportation. Due to the nature of weather exposure of walking and biking, the understanding of weather on individual travel behavior is critical. This research provides evidence of the influences of weather on walking and bike, especially for students and seniors. We cannot control or change the weather like the built environment. Still from a planning perspective, by knowing the influence of weather on travel choice, it will benefit planners and engineers to address and limit the negative influences of weather on travel when designing walking and biking facilities, safe routes to school projects, and senior housing.

5.4 Implications in Practice

The models developed in this study give us log odds and expected values of variables. Model outputs must be transformed to compute effects. The transformations involve several steps.

For example, for walk trips, the logistic equation in Table 2.6 allows us to compute the odds of any walk trips by exponentiating the log odds, and then to compute the probability of any walk trips with the formula for the probability in terms of the odds.

odds of any walk trips = exp (log odds any walk trips) (5.1)

probability of any walk trips =

odds of any walk trips / (1 + odds of any walk trips) (5.2)

From the negative binomial equation in Table 2.7, we next compute the expected number of walk trips for households with any walk trips, again, by exponentiating:

number of walk trips (for households with walk trips) =

exp (log of expected number of walk trips) (5.3)

The expected number of walk trips for all households is just the product of the two:

Number of walk trip (for all households) =

probability of any walk trips

× *number of walk trips (for households with walk trips)* (5.4)

The models have many potential applications in practice. Most obviously, they can be used to postprocess outputs of conventional four-step travel demand models. Four-step models are patently inadequate when it comes to accounting for density, diversity, and design effects on household travel. They treat all development as if located at the centroids of traffic analysis zones, and local street networks as if completely represented by two or three centroid connectors to the external street network. Thus, they cannot distinguish between dense, mixed, interconnected development, and sprawling single-use development with the same housing and employment totals. They fail to account for the effects of accessibility on trip generation rates. They use crude approximations to predict intrazonal travel. They typically ignore the effects of density, diversity, and design on mode choice.

The literature covers postprocessing applications well (Cervero, 2006; DKS Associates, 2007; Johnston, 2004; Walters et al., 2000). These new models can be used in exactly the same way as earlier elasticity estimates from the literature, which have found their way into regional transportation planning.

Sketch planning applications are limited only by the creativity of planning analysts. A potential sketch planning application could be to assess health impacts. Rates of physical activity, including walking, are inputs to health assessment models. Again, once planners make assumptions about changes in the D variables under future scenarios, increases in walking can easily be computed using these equations. Until now, there has been no empirically grounded methodology for making such projections.

These equations could also be applied to traffic impact analysis. There has been no way to adjust the ITE’s trip generation rates for walking and biking, which has left developers of dense developments at urban sites paying impact fees and other exactions at the same rate as their suburban counterparts. The only adjustment previously allowed was for internal capture of trips within mixed-use developments, which did nothing for the typical infill project. Equations in this study could be used to adjust ITE trip rates for suburban developments to reflect how greater densities and other environmental attributes would affect trip making. There is also specific data collection and research that is going on to address the connection between urban environment, neighborhood characteristics, multimodal accessibility, and nonmotorized trip generation in several major metropolitan areas (e.g., D.C. Department of Transportation; California Department of Transportation). It may be the time to start to adjust the ITE's trip generation rates.

It is my hope that models introduced in this dissertation will find wide application in the planning practice.

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