EFFECTS OF LAND USE AND TRANSPORTATION INFRASTRUCTURE ON DISTANCE TO WORK IN INDIVIDUAL CAR RIDERS

by

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DISSERTATION

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Abstract

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The University of Texas at Arlington, 2021

Supervising Professor: Dr. Rod Hissong

Studying travel behavior has become a means of addressing car dependency, greenhouse gas emission, and environmental protection. Many studies have examined the effects of socioeconomic and built environmental factors on Vehicle Miles Traveled (VMT) but there is a limited literature examining the role of these factors on home-to-work distance.

If one of the concepts of developing new freeways and toll roads is providing faster and more reliable commutes, then it is assumed that new high-speed road infrastructure will lead to a higher commuting distance.

This study used the 2017 National Household Travel Survey, U.S. Census, GIS, and Longitudinal Employer-Household Dynamics (LEHD) data to develop two models to analyze the effects of total mileage of limited access roads (tollway and highway) in urban areas on home-to-work distance. In addition, other socioeconomic, built environment, demographic, and behavioral factors were considered in these models as control variables.

The findings indicated that an individual's longer home-to-work distance is associated with more available mileage of limited access roads in the urban area of their home location. Meanwhile, more density, land use diversity, home value, and job/housing balance in the block

group of the individual’s home location has an inverse effect on the individual’s home-to-work distance. In addition, individuals who have a higher household income, are older, or are male have a longer home-to-work distance.

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Spring, 2021

To Earth,
the only home we've ever known.

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Chapter 1

Introduction

Overview

Since humans learned to use means of transportation other than their feet, traveling distance started to increase. Transportation's evolution—from foot to domesticated animals and, over time, to cars and infrastructure, including highways and tollways—has increased both commuting speed and distance (Glaeser, 2011).

Over the last three decades, researchers have become concerned with issues such as less physical activity, obesity, air pollution, greenhouse gas emission (GHG), deforestation, and new developments on natural habitats. Some studies indicate these issues are linked to car dependency (Cervero & Murakami, 2010), while researchers in urban and transportation planning are examining different factors that affect travel demand. Built environment is one of the main subjects of these efforts, in addition to factors such as individual choice.

Transportation, land use, and travel demand are interdependent. Indeed, an urban area's form is a consequence of transportation (E. Glaeser, 2011; McMillen & McDonald, 2011). Glaeser (2011) argues that residential suburbs are the result of advances in transportation technology such as the steam railroad, streetcar, and the automobile, as well as the discovery of oil. Historically, due to higher transportation costs, inner cities hosted firms and wealthy residents while the poor lived in the city's outskirts, where jobs were limited. With new inventions in transportation technologies and roadway expansions transportation costs decreased, direct access to the ports or railways was no longer as valuable and the outer city became more accessible. As a result, both firms and wealthy families now had the opportunity to move to the less expensive and abundantly available land in the outskirts of cities. (Gobillon, Selod, and Zenou, 2007). Indeed, these improvements transformed suburbs from being the refuge of outcasts to the haven of the wealthy.

The automobile industry's advancing technology—coupled with new roads—paved the way for low-density suburban developments. With freeway networks, people were incentivized to drive everywhere because transportation was cheaper (Moretti 2012). New roads and automobiles made suburbia more accessible. This outward directed and area-expansive urban growth has been simply referred to as Urban decentralization. As a new norm of urban structure, urban decentralization necessitated expanding the suburban road system, including highways and toll ways, and resulting in even longer travel distances to work. As a result, improved transportation networks, in addition to more efficient and convenient cars, allowed people to travel more miles in less time. People could spend the same amount of travel time and live further from work.

The Purpose Statement

Commuting claims 22% of the average annual person miles of travel and is one of the most important components of traveling in general. What makes commuting important is its repetitive, consistent, and predictable nature. Most commutes happen during a certain window of time every day, creating traffic congestion peak hours. As a result, understanding home-to-work distance helps us understand transportation infrastructure and service needs. Home-to-work distance is also a major factor influencing land use development patterns.

Over the years, home-to-work distance has changed dramatically. As described by Anas, Arnott, and Small (1998), prior to 1850 the most common forms of commuting consisted of walking and horse-drawn carriages. For this reason, population and activities were located close to the city centers. Transportation technology advancements extended commuting distances but reduced the time required. As a result, the necessity of employment and households being in close proximity was diminished.

According to the Federal Highway Administration (FHWA), and as shown in figure 3, miles traveled to work per person increased 44% from 1983 to 2017. Figure 1 shows that, on average, people drove 8.5 miles to their work in 1983, increasing to 12.2 miles in 2017. Despite home-to-work distance exhibiting a steady increase of 44% until 2001, it the decreased 2% until 2009 and has continued its positive trend (FHWA, 2016). This decrease in home-to-work distance coincided with the 2007–2009 recession era (Figure 2), when unemployment rates soared and the number of workers driving to work dwindled.

Figure 1: *Average Person Trip Length to Work (Miles) 1983-2017*

(Federal Highway Administration, 2017)

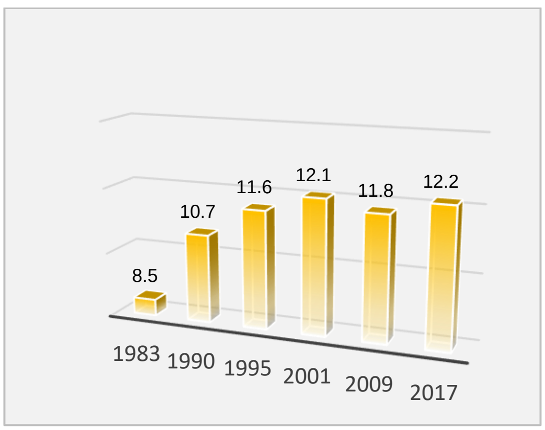


Figure 2: *Unemployment Rate 1983-2017*

(Federal Highway Administration, 2017)

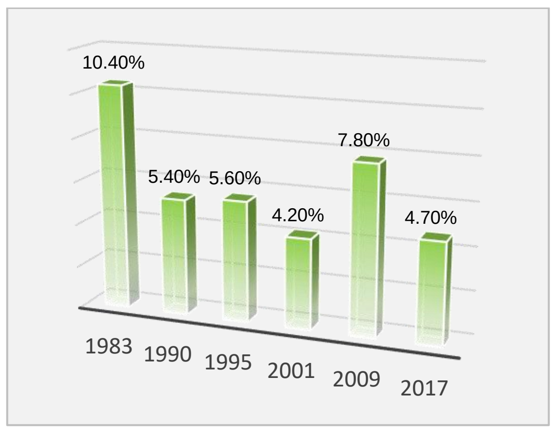


Figure 3: *Average Annual Person Miles of Travel to Work per Household (Miles) 1983-2017*

(Federal Highway Administration, 2017)

The factors contributing to longer commuting distances has been an area of rich debate among researchers. While some primarily blame urban decentralization for longer commutes (García-Palomares 2010), others have argued that the privacy and comfort of driving inevitably led to the “rational consumer” choosing cars over other forms of transportation and, consequently, increasing their home-to-work distance. Steg (2003) went so far as to suggest that besides thel instrumental functionality of personal automobiles, car ridership represented the cultural and psychological values of freedom and independence. Some have argued that a community’s level of car dependency is a product of several factors, including the location of urban facilities (Naess, 2016).

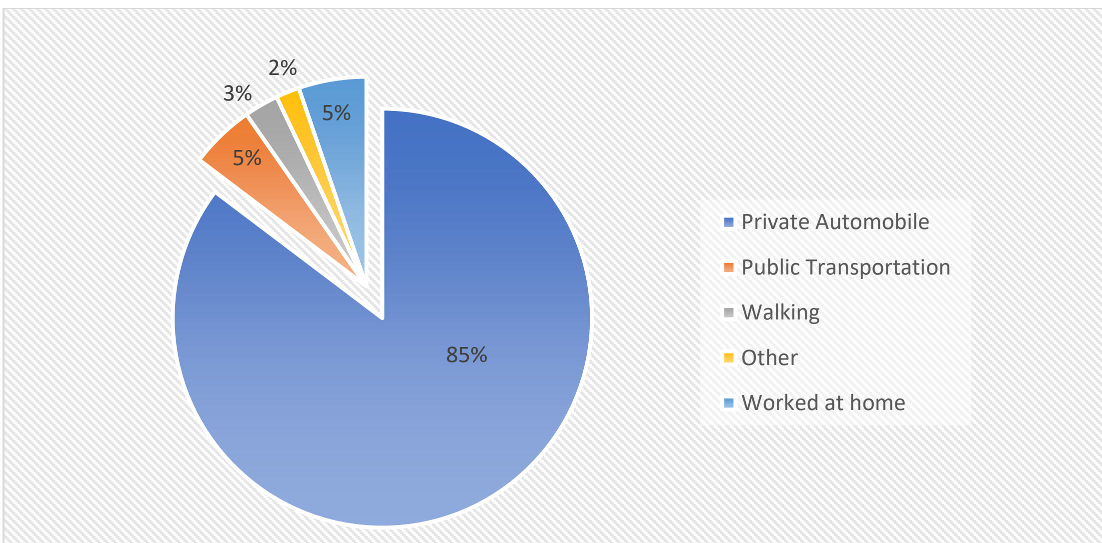
Relevance to Environmental Policies

According to the United Nations Panel on Climate Change (IPCC), humans had a considerable influence on global climate due to greenhouse gas (GHG) emissions over the past 100 years. A primary byproduct of fossil fuel combustion is CO_2 which is a greenhouse gas. To pursue sustainable development, the Brundtland Commission report (UN World Commission on

Environment and Development) recommended reducing fossil fuel consumption (WCED, 1987). As presented in Figure 4, 85% of total commuting to work is performed by automobiles, with 76% driving alone (American Community Survey, 2017). Almost every car relies on fossil fuels either directly or indirectly, including cars with electric engines (Naess, 2016).

Also, fossil fuels are not a renewable source of energy. International conflicts are inevitable if global dependency on fossil fuels does not change (Naess, 2016). Considering its environmental impacts, the cost of driving is higher than it may seem because drivers only directly pay a small portion of this cost. While they only pay 2 cents per mile for gas, they cause 3 to 5 cents in pollution costs and 10 cents in accident costs, as well as 3 cents for road damage caused by trucks (O'Flahrty, 2005).

Figure 4: *Means of Commute to Work 2017 (American Community Survey 2017)*



Relevance to Equity Policies

Studying and addressing the factors contributing to travel demand with the aim of curbing dependency on private cars is considered an effective way to shed light on the social and environmental inequality imposed on us by this phenomenon.

Residents of car dependent cities and metro areas spend more time and money on traveling to their destinations (Naess, 2016). Low income households whose car ratio to number of drivers in the household is lower, people without a driving license, the elderly, and the disabled are marginalized in those areas where transportation infrastructure is mostly planned for private cars. Relatively, the job market shrinks for those who lack access to privately owned cars, specifically in less dense areas with no public transit (Naess, 2016).

Problem Statement

Since the late 20th-century, car dependency and its side effects have concerned researchers. Air pollution, higher GHG emissions, higher commuting distances, and obesity are some of the many aspects of car dependency. Glazier has found that the suburban design of communities promotes car dependency and discourages walking and physical activity, resulting in major metabolic syndrome factors (e.g., obesity, diabetes) rising in those communities (Glazier et al., 2014). In a study done by Zhang et al. (2014), higher neighborhood car dependency was associated with higher risk of obesity in urbanized areas.

In addition, the loss of environmentally fragile lands and regional open spaces, greater air pollution, higher energy consumption, the diminishing diversity of living species, excessive removal of native vegetation, and ecosystem fragmentation (Johnson, 2001) are just a few examples that should make us more mindful about the choices we make, at both the personal and public level.

Kaplan et al. (2008, p. 247) addressed the significant impact of inter-state freeways on suburbanization. Progressive technology in both the transportation and IT industries, growing demand for jobs and housing, land availability, and a lack of efficient environmental preservation policies helped unique urban form emerge—one characterized by dependence on automobiles and Broadacres development (Federal Highway Act, 1956). In addition, more highways and cheaper gasoline led to an increased tendency towards longer commuting distances. Longer commutes have even been promoted by homeownership subsidizing programs, with suburban areas offering more living space for lower costs. According to Glaeser (2011), two key advantages of car-based living are speed and space.

Figure 5: *Private Transport Energy Consumption Levels (MJ per capita), (Kenworthy, 2003)*

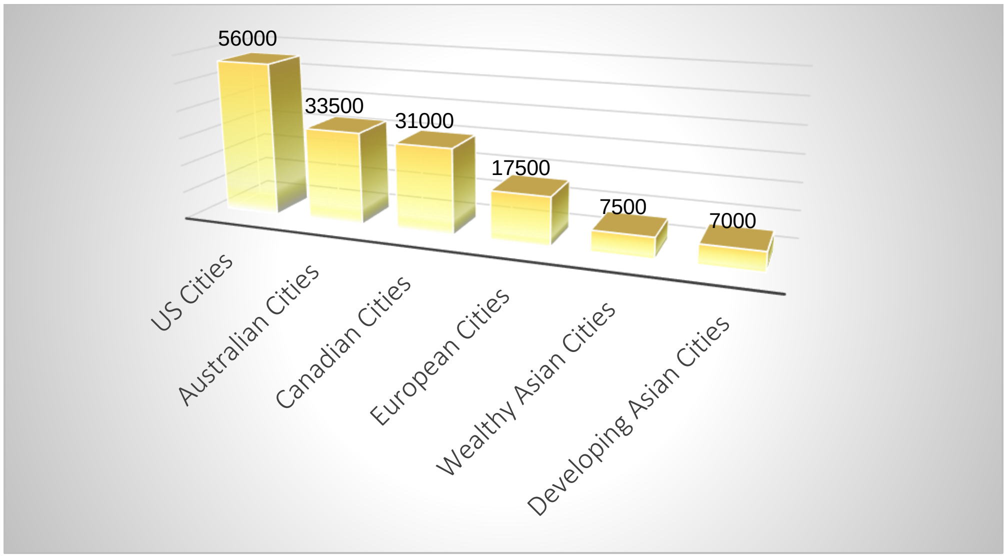


Figure 5 displays the total transportation energy consumption in different parts of the world in 2003. The unit for measuring energy consumption is megajoules (MJ) per person. Private transport energy consumption in the U.S. cities is nearly three times the average of other world cities. One reason behind higher transport energy consumption in U.S. is low density and horizontal developments. When urban areas opt for horizontal growth (i.e., urban decentralization) rather than vertical growth, natural resources such as forests, wetlands, meadow, and animal habitats are destroyed both for infrastructure and buildings.

Horizontal development in places with abundant land seems to be more reasonable. The justification for horizontal growth over vertical growth focuses on cost efficiency. However, if we consider the environmental costs of these developments the justification for horizontal growth over vertical growth will decrease dramatically.

Commuting distance to work is inversely related to density. A car dependent society leads to greater fuel consumption and, with it, greater carbon emissions. Additionally, the combination of heat islands (resulting from more paved lands) and heat-emitting buildings (resulting from, for example, black asphalt shingles on family homes) with greater levels of carbon emissions will exacerbate the greenhouse effects and, subsequently, climate change (Rosenfeld et al., 1995).

According to Price et al. (2001), in 1997, 23% of global greenhouse gas emissions were caused by transportation. By 2013, GHG increased to 27%. Since most of cars still rely on fossil fuels, regional carbon emissions have a strong positive relationship with regional commuting distances (Kwon, 2005).

During the 20th century, the increased availability of highways built with federal subsidies[1] in every direction from each city made intra-city transportation less expensive. For this reason, both firms and households considered relocating their bases further from the central city to obtain more space with the same budget. The migration of households and firms to the outskirt of the cities consequently increased the daily commutes with the car.

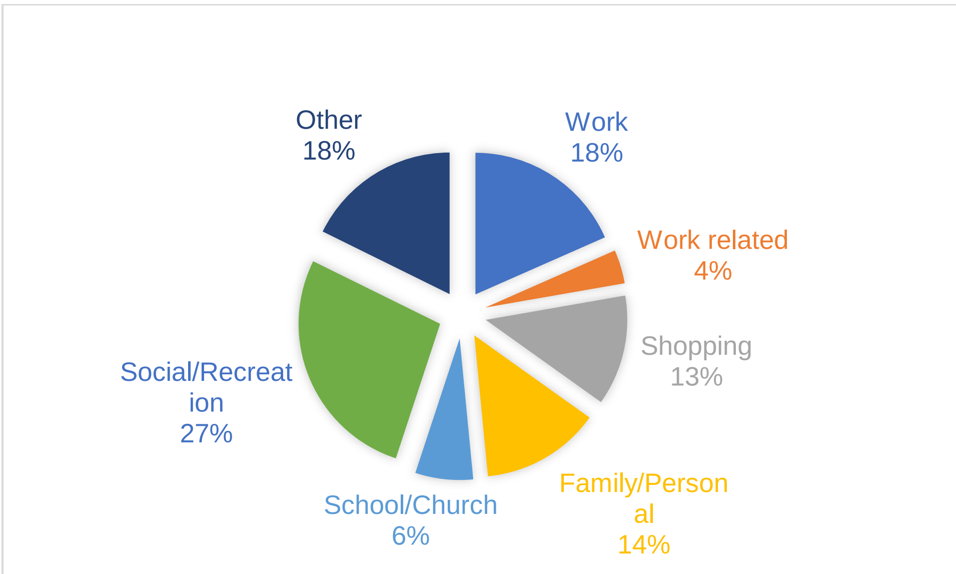
Arguably the most common daily commute is between home and work. Other forms of commuting such as grocery store trips and entertainment are typically not daily routines for most of the population. Several studies have highlighted the important role of the daily work commute in determining a home location and even in restricting one's buffer for job hunting (Ben-Akiva, Weisbrod, and Lerman, 1980).

[1] These highways were funded through the excise tax, which is 3% of the Federal Government's total annual income. The Federal-Aid Highway Act of 1952 first authorized the funding for system construction, but it was only $25 million a year for fiscal years (FY) 1954 and 1955. Legislation in 1954 authorized an additional $175 million annually for FY 1956 and 1957. Revenue from the federal gas tax and other motor-vehicle user taxes was credited to the Highway Trust Fund to pay the federal share of interstate and all other federal-aid highway projects. In this way, the act guaranteed construction of all segments on a "pay-as-you-go" basis, thus satisfying one of President Eisenhower's primary requirements that the program be self-financing and not contribute to the federal deficit. (FHWA, 2015).

As shown in Figure 6, annual person miles traveled (PMT) for work and work related trips claim 22 percent of total trips per households trailing social/recreation trips which is not a recurring trip for most households.

Figure 6: *Average Annual Person Miles of Travel per Household by Trip Purpose*

(Federal Highway Administration 2017)



In areas of lower density, where housing and jobs are spread over a broad territory, people have to drive long distances to commute and perform other daily tasks. Indeed, long commutes often result from an imbalance between job sites and residential sites (Brueckner, 2000). According to Sarzynski et al. (2006), long commutes reduce the likelihood of using alternative modes of transportation as travelers desire more convenience (i.e., personal vehicles).

In contrast, increasing regional density, mixed use developments, and concentration of activities can decrease commuting distance. In short, greater development density tends to reduce commuting distances (Glaeser and Kohlhase, 2004). That is why many researchers have suggested increasing regional density, particularly housing densities, to reduce travel distance and alleviate congestion (Cervero 1989a). Greater density can also increase the feasibility of commuting via public transit while offering more travel choices to those who lack a private vehicle.

Research Objectives and Research Questions

The purpose of this research is to determine the effects of increased accessibility on home-to-work distance. The existing literature lacks a clear description of the effects of tollways and highways (limited access roads) on travel behavior. Therefore, this research examines the role of tollways and highways accessibility and their effect on journey-to-work distance, in addition to other factors. Specifically, this research tests whether length of tollways and highways (limited access roads) in an Urban Area may influence the length of individual's home-to-work distance.

Previous studies have examined the effect of both socioeconomic and built environment factors on commuting distance.(Sang 2008; Sultana & Weber 2007; Bloomfield 1996; Blumen 1994; Hecht 1974; Crane 2000; Sermons & Koppelman 2001; Weinberger 2007; Weber & Sultana 2008) The role of population density, employment density, freeway and tollway accessibility, as built environment factors, and socioeconomic factors such as household income are examined in this research. To analyze these factor, this study utilizes the 2017 National Household Travel Survey (NHTS), 2017 Longitudinal Employer-Household Dynamics (LEHD) data, and the EPA's Smart Location Database at the block level. Traditionally, studies have focused on VMT, whereas the present study focuses on home-to-work distance.

It is important to note the constraints on this research. Although some studies insist on gathering in-depth individual choice data to understand the mechanisms behind travel behavior, this methodology is not feasible for a non-sponsored study such as this dissertation. Also, one of the challenges of predicting commuting distance is its complexity due to the geographical separation between residences and workplaces. The present study addresses this challenge by utilizing different theories, datasets, and models.

Despite these limitations, this research attempts to build its foundation on the previous studies while contributing to our understanding of the role of toll road accessibility on commuting distance. This research also addresses policies aimed at lowering commuting distance as a means of balancing travel demand.

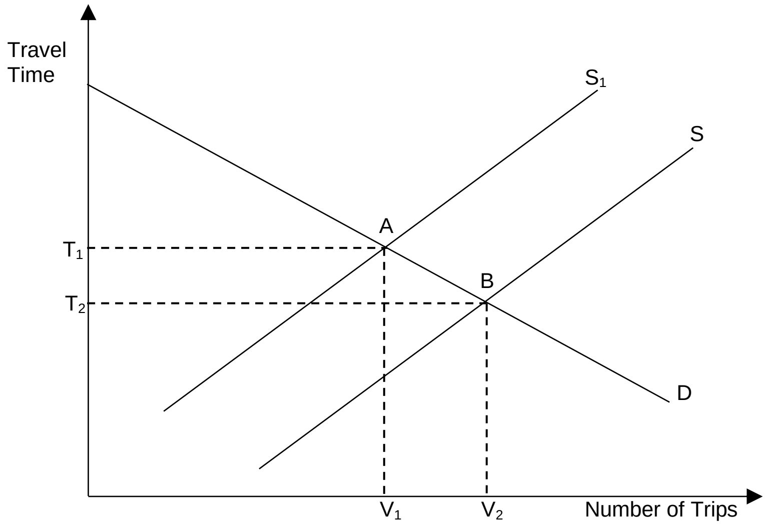
Chapter 2
Theories

This chapter explores the theories that built the foundation of the current study. Travel Demand theory, Bid-Rent theory, and Hotelling theory are the three main theories that will be discussed.

Travel Demand Theory

Thomas A. Domencich and Daniel McFadden, Father of discrete choice Model, presented the relationship between travel time in a corridor with the number of trips in the same corridor (Figure 7). (Domencich and McFadden 1975) Supply and demand curves typically have a monetary measure on the vertical axis. However, they used travel time as a representation of the cost of the trip. In this model, the negative slope of the Demand curve (D) demonstrates the fact that whenever travel time per trip decreases (as a measure of the cost per trip), demand for trips increases. On the other hand, the positive slope of the Supply curve (S1 and S2) shows that, for a given capacity, whenever volume increases, congestion will occur, speed will decrease, and travel time will increase. Their model perfectly describes the negative relation between travel time and number of trips demanded. However, they didn't study the relation between travel time and trip distance.

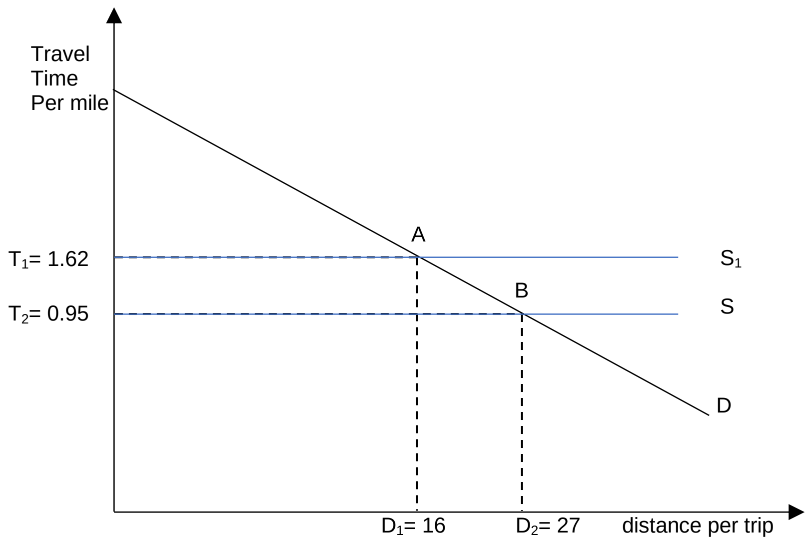
Figure 7: *Equilibration of travel demand and system performance*



I developed a variation of the Domencich and McFadden model to demonstrate the relation between travel time per mile and distance per trip with minor twist to the original model. They used Travel time per trip as the vertical axis in a supply and demand curve and my model has Travel time per mile on the vertical axis. In addition, for the horizontal axis, Figure 8 has length of the trip rather than number of trips. Also, McFadden and Domencich focused on the capacity of the system and its effect on the speed and, subsequently, on travel time, however, the focus of my model is on the design of the system rather than the capacity.

Figure 8 displays demand and supply side in a road network of a region. In figure 8, demand curve (D) represents an inverse relationship between travel time per mile and demand for commute distance. Lower travel time per mile reflects lower cost of commuting per mile. Like most goods and services, when the price of a good or service declines consumers (drivers) consume more of the good. In this case the good is distance of commute. It is expected that drivers tend to drive more miles per trip if travel time per mile is less.

Figure 8: *Demand for Longer Trip Distance*



Both capacity and design of each road can affect average speed and ultimately the average travel time in that road. I assumed constant network capacity and just considered network design. Based on this assumption, S_1 and S_2 represent performance of collectors/arterials and freeways/tollways, respectively. Since capacity and congestion are constant, the average speed in each network design is constant too. Because of different design of these two road types, average speed is lower, and hence travel time is greater, in collectors and arterials (with all the intersections and traffic lights) than is travel time on limited access highways and tollways where average speed is higher. Based on data collected from google map, average travel time per mile for Collectors/Arterials is 1.62 minute (37 mile per hour), while average travel time per mile for Highway/Tollway is 0.95 minute (63 mile per hour). According to US Census, average commute time is 26.1 minutes. Which means in our hypothetical model, a commuter who chooses a collector/arterial road is able to drive 16 miles in 26.1 minutes. However, a commuter who chooses a highway/toll way is able to drive 27 miles (9 more miles) within the same time.

Bid-Rent-Rent theory

Alonso explains that firms tend to locate in inner circle closest to CBDs to benefit from economy of agglomeration (Alonso 1964). Based on this theory, demand for land closest to CBDs with accessibility is high. As a result, these areas have higher rents and consequently higher density. The reason behind higher demand for these areas despite their high rent, is that firms and companies are willing to pay higher rents to access the benefits of agglomeration economies due to higher density of these areas. Subsequently, higher rent makes land closest to the CBD available to those with the highest competitive bids.

Since land is most valuable in the inner circle and efficiency is a key factor, the available residential units are smaller, relative to units in areas of less dense land use, and vertical growth is encouraged. As a result, density is increased. High density employment typically dominates but residential population is present in the CBD. The compact design ensures that residents who work in the CBD have a relatively short journey-to-work trip.

Hotelling's theory

In March of 1929, Harold Hotelling published an article in "The Economic Journal". In this article, *Stability in Competition*, he shared his theory of how competing firms tend to imitate each other's decisions such as quality of goods and location of the firms. Based on this theory, more firms tend to be located closer to CBDs which is comprised of high-density areas. Consequently, job diversity will increase in CBDs. Workers who have enough income to live close to CBDs, have a denser and more diverse job market within a shorter commute distance. However, households who live in areas with less land use and employment diversity, need to commute more to reach to their jobs. One game changing factor, such as a higher speed tollway or highway, can encourage a household to live farther from the job location to benefit from cheaper and bigger dwelling unit.

Chapter 3

Literature Review

Urban Form and Travel Behavior

Low density urban decentralization pattern of the American suburban life emerging after world II, bred discussions amongst scholars for or against this phenomenon. New theories, concepts and trends was surfaced and new horizon for scholars was formed. For example, one of the major concepts arising from these constructive discussions was smart growth principles aiming at some of the less desirable effects of urban decentralization. Smart growth as a relatively young trend that promised sustainable development with a unique sense of community and place offered two major principles: preserving open spaces and farmlands and providing different ranges of transportation choices for a more accessible space. According to Bento et al. (2005), smart growth initiatives have attempted to address three major concerns: (1) preserving open spaces, (2) reducing public service costs, and (3) reducing automobile dependency (Bento et al. 2005).

Jan Brueckner argues that despite the fact that urban decentralization is mostly the result of increase in population growth and household income and decrease in commuting costs, however, certain market failures (externalities) has distorted these forces, resulting in excessive growth. Underestimating the cost of losing open spaces, social cost of long commute and traffic congestion, and cost of building new infrastructures for low density urban pattern have created market failures. According to Brueckner (2001), excessive urban decentralization is a consequence of ignoring these three market failures.

Bento et al. studied the effect of urban form and transit supply on vehicle ownership and vehicle miles traveled (VMT). They combined measures of urban form such as city shape, spatial distribution of population, and job-housing balance in addition to public transit supply and studied the effects of these measures on Vehicle miles traveled (VMT) and vehicle ownership in 114 U.S.

cities. They also used demographic factors such as age, race, and household size and to socioeconomic factors such as income and education as their control variables.

They based their study on a simple monocentric model with minor modification to allow for public transit and spatial distribution of the firms. According to their constructed model, a household determines the number of trips to make by automobile and public transit. Ultimately the frequency of transit service and the number of transit stops as well as route miles supplied will affect the mode choice and VMT. In other words, road network, residential land use pattern, and employment distribution are major factors in mode choice and VMT.

They used three different methods to predict their models. They used binary logit model for mode choice, multinomial logit models for vehicle choice (ownership), and Ordinary Least Square model for Vehicle Miles Traveled (VMT) of vehicles. Based on their models, they concluded that individual measures of urban form and public transit supply have small but statically significant effect on travel demand. They found that 10% increase in population centrality decreases commute by 1%. Transit supply has the same effect on commuting but only half as large. They also concluded that both urban form and transit supply influence number of vehicles owned and the amount of VMT drived. Also, they observed that more dense and compact cities, encouraged fewer number of cars owned by households and increase in population centrality reduced VMT. One of the most important part of their observation was that the effect of all these factors were small. Table 2-1 provides a summary of the variables that was used in Bento et al study.

Table 1 *Descriptive statistics : Dependent, policy, and control variable (Bento et al. 2005)*

Dependent variables
Annual Miles Traveled
Commute Mode Choice
Vehicle Ownership

Policy variables (Accessibility)
Urban Form
City Shape
Land Area
Road Density
Public Transit Supply

Control Variables
Employment status
Lifecycle
Income
Education
Race
Weather
Population Centrality
Population Density
Job-Housing Balance

In another study, Cervero and Duncan (2006) studied the effect of job-housing balance and retail-housing mix on automobile dependence. The study intended to find which of the two elements of job-housing balance or retail-housing mix, would affect vehicle travel. Previous research has shown that placing retail stores and services near residential areas reduced the number of shopping trips in those neighborhoods by 25% (Cervero, 1996). Others have found that job-housing balance can reduce vehicle miles traveled (VMT) in a region by 15% (Ewing, Deanna, and Li 1996).

Cervero and Duncan (2006) used two different log-linear regression models to study each of these factors. They first studied job-housing balance and its effect on miles traveled per vehicle. Their primary data source was 2000 Bay Area Travel Survey (BATS). These data include a detailed 2-day travel diary for each person aged 16 or more in 16,000 households. They used block group level Census Transportation Planning Package (CTPP) Part II, and individual TAZ (Traffic Analysis Zones) level of Metropolitan Transportation Commission (MTC, the nine-county Bay Areas designated Metropolitan Planning Organization) to obtain employment data categorized by place of work. They also used the MTC to obtain zone-to-zone travel distances and time spent on highway networks during peak hours.

For studying the relationship of travel behavior and land use, they used principles of accessibility (opportunities for reaching desired destinations). They counted number of jobs, retails, and services within 4 miles of the respondents' home location. Instead of assigning a certain distance as the computation buffer based on previous studies, they did an empirical study and found out that the 4-mile ring best predicted the actual travel behavior model.

For job-accessibility, they both counted the total number of jobs in 4 miles from home locations, and they also counted number of available same occupational category of the respondent. All jobs in the region was categorized in three different groups; 1- executive/professional, 2- support/service, and 3- blue collar. If the respondent's current job was blue collar, then all blue collar jobs in the 4 miles buffer from his home location was counted. However, they used number of retail and service industry jobs within a certain distance of the home location to measure retail and service accessibility.

For travel measures, they used both Vehicle Miles Traveled (VMT), and Vehicle Hours Traveled (VHT). VMT is often related to energy consumption and Greenhouse Gas (GHG) emission and VHT describes impacts on individuals. They excluded trips made by mass transit, walking, and cycling. They also categorized trips in two differ rent groups; 1- work trips and 2- shopping and personal services tour trips. Based on their study, they found out that occupationally matched measure of job accessibility had a strong effect on VMT, for 10% increase in same occupationally category within 4 miles of the respondents' home location, his VMT is expected to experience a 3.29% decrease. Also, the results suggested that male drivers, and respondents who owns a professional/managerial job tend to have higher VMT. Surprisingly coefficients for age, Latino, and income was insignificant.

Although 42.8% of total VMT in San Francisco Bay area in year 2000, was for shopping and personal services and only 36.7% for commuting, however, access to job reduced VMT 72.5% more than access to shopping and services. They also, observed that Bay Area workers in professional-managerial category had higher accessibility to jobs. Higher land prices and less affordable housing will result in displacement of lower income families from inner cities with higher job concentration. While, employees with higher paid jobs are able to live closer to jobs and have better access to jobs. Table 2-2 encapsulates the variables that Cervero and Duncan used in their 2006 study.

Table 2 *Descriptive statistics: Dependent, policy, and control variable (Cervero and Duncan 2006)*

Dependent variables
Daily work tour VMT **Daily work tour VHT** **Daily shopping-services tour VMT** **Daily shopping-services tour VHT**

Control Variables
Motor vehicle per licensed driver **Driver’s license (no=0, yes=1)** **Personal income>$40,000 per year (no=0, yes=1)**

Policy variables (Accessibility)	Executive/professional employment (no=0, yes=1)
Occupationally matched jobs within 4 miles	**Private sector job (no=0, yes=1)**
Total jobs within 4 miles	**Fulltime student (no=0, yes=1)**
Retail and service Jobs within 4 miles	**Employee flex-time privileges (no=0, yes=1)**
	Age (years)
	Latino (no=0, yes=1)
	Male (no=0, yes=1)

Travel Behavior and Travel Demand

Urban Transportation primarily focuses on the movement of people and the supply and demand for transportation facilities. People make decisions based on their needs and the environment they live in. They make decisions on the purpose, frequency, timing, destination (trip length), and the mode of their daily trips which in long term affects the decision on home and work locations and on automobile ownership. Travel Demand Theory should also consider consumption behavior since travel is related to activities such as work, shopping, and recreation (Domencich and McFadden, 1975). As Kanafani (1983) stated, “Travel demand analysis is the process of relating the demand for transportation to the socioeconomic activities that generate it.”

Most travel demand studies mainly focus on mode choice assuming that frequency, timing, and distance of trips are the result of the demographic factors. However, all of these factors are interrelated and should be studied. For example, if travel time by bus is reduced for one destination, this can affect both mode choice and travel frequency (Domencich and McFadden, 1975).

Travel demand models assume that people respond to transportation policy changes, in a continuous way. However, recent studies have shown that people with different socioeconomic characteristics may respond differently to the same transportation stimulus. For example, a new tollway may affect a high-income family's travel behavior more than a low-income family, since paying tolls is less feasible for a family with lower financial means (Heggie and Jones, 1978).

Travel behavior is the study of what people do over space, and how people use transport. Number of trips, mode of transportation (driving, walking, biking, ...), type of destination (work, social, leisure,), distance to destination, route choice, and number of vehicles per household are elements of studying travel behavior.

According to Næss (2006), trip generation results from the need to engage in an activity at another location and travel demand is determined by patterns of land use. A key goal of social theories and behavioral studies of travel behavior is analyzing the relationshiop between urban structure and agents.

Home-to-Work Distance

Regarding home-to-work distance, the U.S. Census Bureau (2016) technically defines "work travel" as commuting from a residence to and from a workplace. Statistically, work trip purpose is the largest trip purpose category, originating from residential locations. Since most workers do not work remotely and most work trips occur at similar times (morning and afternoon peak hours), work trips have a considerable impact on the roadway capacity of cities while consuming significant time and energy (Lapin, 1964). Between 1950 and 2011, the U.S. population doubled; meanwhile, people drove 6 times as many miles in 2011 than they did in 1950 (Kramer, 2013). According to American Association of State Highway and Transportation Officials (AASHTO) in 2013, home-to-work distance claims 19% of all person miles of total travel.

"Occupation, income, transportation mode, residential characteristics, and personal preferences determine home-to-work distance" (Selman 2000). One of the main subjects to address travel demand reduction in recent urban planning studies has been the built environment.

In this study we are going to study both individual commuters' attributes and also the location attributes for the home location. As a result, several factors in each group will be taken into consideration which will elaborated upon in following paragraphs.

Location Attributes.

Density.

Development patterns represent one key factor influencing commuting distances (Squires, 2002). For example, as urban areas develop more compact growth, automobile travel is reduced in those areas (Burchell et al. 2005). Other research indicates that home-to-work distances are increasing as workers preferentially live in low density areas and work in central cities (Sultana and Weber, 2007).

Population density, dwelling units per area, employment density, and building floor area are typically considered when measuring density. The activity density per areal unit, an index that combines population and employment density, is also used widely. Researchers have found inconsistent results when studying population density. In less dense areas, longer trips—which are often traveled by private cars—result in more miles traveled, whereas people living in denser areas are more likely to travel shorter distances and use public transit (Burchell et al., 2005; Newman and Kenworthy, 1999; Holtzclaw et al., 2002). A study of 370 urbanized areas indicated that higher population density has a strong positive correlation with lower commuting distances by vehicle (Cervero and Murakami, 2010). Golob and Brownstone (2005) investigated the effect of population density on built environment, and a study by the Oak Ridge National Laboratory (ORNL) showed that higher population density reduces vehicle commuting distances (Transportation Research Board, 2009). Furthermore, research by Ewing and Cervero (2010) indicated that job and population densities are only weakly related to travel behavior when controlling for other variables.

Diversity.

Although this variable concerns about land use diversity, sometime job-to-housing, job-to-population, or floor area ratio are calculated to address this variable. But more often an entropy is measured in which a low value means less land use per land area, or floor area, or employment and a high value means more diversity of land uses in the same units. Through analyzing over 40 major suburban employment centers, Cervero (1989b) introduced the concept of longer commutes relating to a region's job-housing balance, and it has been a key topic of study regarding urban structure and travel behavior ever since. Many subsequent analyses noted that job-housing balance can serve as an efficient tool for reducing commute distances. For example, Bento et al. (2005) and Cervero and Duncan (2006) both found an inverse relationship between commuting distance and job-housing balance.

Destination Accessibility.

Job accessibility is a key factor influencing commuting behavior in urban environments. For example, an analysis of 30,000 home-to-work automobile trips in the Montreal Metropolitan Region highlighted the significance of urban form and job accessibility (Manaugh, Miranda-Moreno, and El-Geneidy, 2010). According to Duranton and Turner (2001), by decreasing travel time and providing access to places far from workers' home locations, highway developments encourage both longer trips and more trips.

For this study, the distance to tollways and highways are of interest. Based on the travel demand theory represented in figure 8, tollways and highways have higher average speed and lower travel time compared to arterials and collectors. A household residing in a neighborhood closer to a tollway or highway, will have a vaster geographical job market based on the advantage of a high speed road network. They can commute farther with maintaining their average travel time by using a limited access highway or tollway.

Individual Commuter's Attributes.

Gender and Age.

Several studies have suggested that gender plays a role in commuting distance, with male drivers commuting longer distances on average (Cervero and Duncan, 2006; Schwanen, Dieleman, and Dijst, 2004; Rodriguez Gamez, 2012). According to Scwanen et al., older women and married women with young children tend to have a shorter commute(Schwanen, Dieleman, and Dijst 2004). According to a study by Levinson and Kumar (1997), the age group that commutes most is employees between the ages of 30 and 50.

Household Income.

As we mentioned before, according to bid-rent theory, denser areas and land close to CBDs are more expensive. As a result, only bidders who are able to pay higher price can reside in those areas. Also, Travel Demand curves described in figure 8 can help explain the role of income in commuting to work distance. Per this figure, travel time is a measure of the home-to-work distance cost. Workers who have higher income, have higher value of time. In other words, higher travel time for a high income worker costs more than the same travel time for a lower income worker. A worker who earns $100 dollar in an hour, will face a higher cost of spending his time in commuting. While, a worker who earns only $20 and hour may commute because his value of time is less and also, he wants to benefit from a farther and cheaper dwelling unit.

Household Size and Home price.

As previously discussed, based on Alonso's bid rent theory, denser, more accessible lands have higher rent and are more expensive. Because of the higher price per square foot, average floor area of residential units in denser areas are less, compared to low density areas. This will encourage middle income households to live farther and commute more since they cannot afford living in higher density neighborhoods with high rent. This condition is intensified, when we are dealing with a larger household size. In other words, married couples with children, tend to commute more in order to benefit from larger dwelling units. In contrast, households without children may have lesser need for space and may choose to live in higher density neighborhoods. A combination of lower home price and available higher speed road network such as tollways and freeways encourage workers to live farther from their work and benefit from larger dwelling unit without much sacrifice.

Limited Access Highways and Tollways

A limited access highway and tollway a road that has limited or no access to adjacent property and it is separated from opposing traffic flow. As a result of these characteristics, average speed in limited access highways and tollways is higher than arterials and collectors with conventional crossroads. In this study the hypothesis is being tested to examine whether limited access facilities encourages higher home-to-work distance. For testing this hypothesis, total mileage of both highways and tollways in the urban areas were taken into account.

Limited access highways and tollways can affect different aspects of travel behavior. Some of these effects, as Harvey stated in 1994, are as follows:

- Route Choice: Drivers will choose different routes based on the pricings of it compared to their value of time.
- Time of Travel: Toll roads with variable fees will encourage drivers with more flexible schedule to not use the tollway in peak hours.
- Mode Choice: Commuters always consider the differences between the cost of various commuting modes when it comes to utility maximization.
- Trip Chaining: Individuals with low time values may combine various trips when using toll roads, while people with higher time values may benefit from congestion-free toll roads to have less linked trips.
- Trip Frequency and Activity Selection: An increase in toll road fees will reduce nonwork trips and also behavioral changes in work trips such as four day work, and work-at-home option.

- Automobile Ownership: Since toll roads is considered a transportation price increase for those who uses them. Therefore vehicle ownership is discouraged especially in low-income families.
- Residential and Employment Location: Lower income individuals may choose less expensive residential and work places. Yet higher-income individuals may live farther from their workplace due to less congested toll roads.
- Residential and commercial Construction: Regional demographic and economic of a certain area may be influenced by the residential and commercial demands based on the toll road accessibility. (Harvey 1994)

Policies Related to Land Use and Transportation

Land use and transportation policies have been shown to influence travel behavior. For example, Garreau (1991) showed that decentralization and the proliferation of ‘edge’ cities have not only changed the urban structure but also commuting patterns in metropolitan areas. Jackson (1987) found that the Home Owners Loan Corporation (HOLC) and the Federal Housing Administration (FHA) significantly impacted suburbs by providing money and loan guarantees, as well as providing a formula to lenders and builders that resulted in inner city neighborhoods not qualifying for financing. These areas were left to deteriorate while money poured into mass-produced suburbs (Jackson, 1987).

With support from the Eisenhower administration, Congress passed the Federal-Aid Highway Act of 1956, which was a joint effort between the FHWA and state officials to improve the ease, speed, and cost of long-distance travel (Levy, 2010). This act was driven in part by the need to create jobs for American soldiers after World War II. Highway construction provided more jobs for those in need of work; it also encouraged longer commuting distances and made it easier to live further from the city. According to Levy (2010), highway systems positively impacted the economy of cities by improving access to central business districts—both from other cities and from the hinterlands.

After decades of policy-makers promoting automobile-centered commuting, the passage of the Intermodal Surface Transportation Efficiency Act (ISTEA) in 1991 signaled a post-Interstate Highway System era. Most notably, the ISTEA represented the first instance in American history of federal acknowledgment of the direct relationship between land use and transportation (Diamond and Noonan, 1996).

Methodologies of Previous Studies

Previous studies, examining relationships between travel behavior and built environment factors, has utilized different methodologies such as linear regression (Pickrell and Schimek 1999; Zhou and Kockelman 2008; Shen 1998; Shay and Khattak 2007; Raja 2012; Ferris 1982; Kitamura, Mokhtarian, and Laidet 1997), logistic regression (M. Zhang 2004; Sarkar et al. 2015; Nelson et al. 2008; Chaudhury et al. 2016; Neog 2009), hierarchical linear modeling (Long 2007; Hong, Shen, and Zhang 2014; Rodriguez Gamez 2012), negative binomial regression (Shay and Khattak 2007, Wallace, Mannering, and Rutherford 1999; X. Zhang et al. 2014; Boone-Heinonen et al. 2010), analysis of covariance (Barr 2002), poisson regression(Wallace, Mannering, and Rutherford 1999) , ordered probit regression (Angelides 1998), probit regression (McCormack et al. 2012), tobit regression (Chatman 2003), seemingly unrelated regression (X. Cao, Mokhtarian, and Handy 2009b; D. Zhang 2013), propensity score matching (X. (Jason) Cao, Xu, and Fan 2010; Pathak, Wyczalkowski, and Huang 2017; X. Cao, Mokhtarian, and Handy 2009a), multiple discrete continuous extreme value model(Pinjari 2008), copula-based switching model(Sun, Ermagun, and Dan 2017), multiple linear regression (Lucas et al. 2016, Raja 2012), structural equation modeling (Sardari 2018; Aditjandra, Cao, and Mulley 2012; Dillon 2017; de Abreu E Silva, Goulias, and Dalal 2012; Van Acker and Witlox 2007), and multivariate regression (Lee 2014).

Chapter 4

Data & Methodology

Introduction

In previous chapters, the research question was defined, theoretical frameworks backing the research question were presented, and previous studies pertaining the home-to-work distance were reviewed. As it was defined in the first chapter, this study has intended to test the hypothesis that individuals with better accessibility to freeways and tollways have longer commute distance. Per this hypothesis, it was expected that people who have the option of using limited access roads such as tollways and freeways will be able to drive longer distances within a given time due to higher speed. As a result, individuals who live in an urban area with abundance of limited access roads can consider farther job opportunities and therefore commute longer distances.

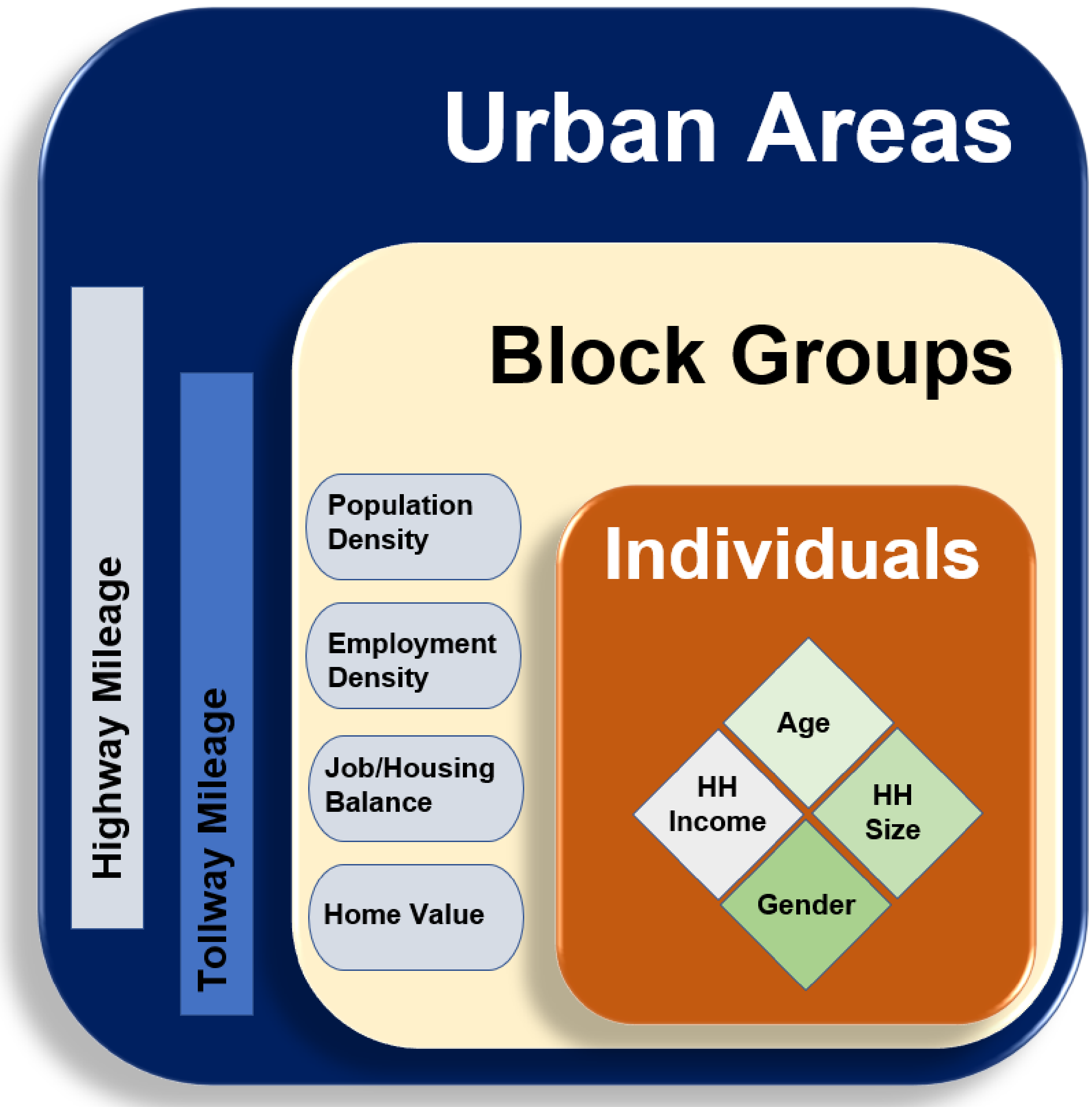
In order to answer the research question of this study, and based on the presented theories and previous literature, a total of eleven variables have been taken into consideration. This chapter will first identify the variables intended for this study and will elaborate on the data sources for all these variables. In the last section of this chapter, the preferred methodology for this study will also be explained and elaborated upon.

Variables

Since 1970, many researchers have shown interest in evaluating travel demand associated with different factors. As discussed partially in Chapter 3, some researchers have investigated demographic and socioeconomic characteristics (e.g., age, sex, race, income, job density, population density, population growth) while others have considered built environment features—e.g., land use patterns, the existence of public transit, etc. (Ferris, 1982; Bloomfield, 1996; Weinberger, 2007; Weber and Sultana, 2008; Blumen, 1994; Hecht, 1974). Few studies have examined the effect of toll roads and highway expansion on home-to-work distance.

As mentioned earlier, in this study and based on the supported theories provided in Chapter Two, eleven variables were taken into consideration. One dependent variable which was Home-to-work distance (HWD) for each individual, two dependent variables which were Tollway Mileage and Highway Mileage in the Urban Area where the respondent resides, and eight control variables, four representing individual's demographic characteristics such as age, gender, household income, and household size and four representing the characteristics of the Census Block Group of each respondent's home location such as population density, employment density, job/housing ratio, and home value. Figure 9, visually presents all the variables that have been considered in the current study, except for the Independent variable which is home-to-work distance. As you can see, we had three levels of variables. With urban area being the highest level, census block group being the mid-level, and household and individual level being the lowest level. Both highway mileage and tollway mileage were considered at the urban area level. population density, employment density, home value, and job/housing ratio were considered at the census block group level. Meanwhile, individual characteristics such as age and gender and household characteristics of each individual such as household income and household size were considered the individual level. The following section will identify the data sources for all the aforementioned variables.

Figure 9: *Dependent and Control Variables Used in This Study*



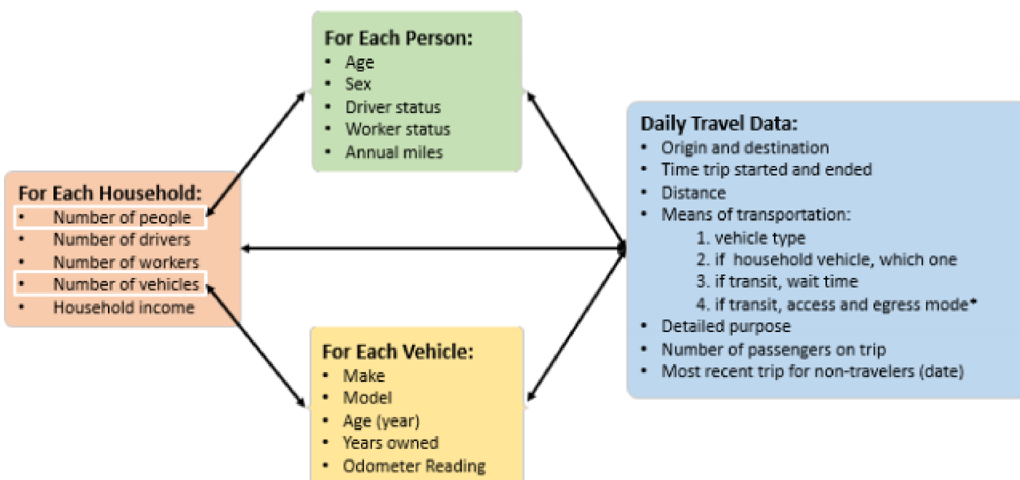
Data

In the previous section, we defined all the variables that were considered in this study. Due to the scope of this study, firsthand data collection was out of the question. As a result, I searched for the best reliable dataset. Consequently, after careful considerations and through consulting with committee members and my peers, I came across four different datasets. These four datasets that were used to form the dataset for this study are as follows; National Household Travel Survey (NHTS), Longitudinal Employer-household Dynamics (LEHD), US Census, and Highway Performance Monitoring System (HPMS). The following paragraphs elaborate on all these different data sources and the variables that have been derived from them.

National Household Travel Survey (NHTS)

The National Household Travel Survey (NHTS) is a survey conducted periodically by the FHWA. The 2017 NHTS dataset included data for 129,696 completed households in the United States. These data are organized into four categories: person, household, daily travel, and vehicle data. Figure 10 illustrates the relationships between all four categories of NHTS data and includes examples of the core variables collected.

Figure 10: *Schematic of the NHTS Data (2017 NHTS Data User Guide, 2018)*



NHTS provides travel behavior data on both personal and household level. It includes daily non-commercial travel by all modes, including characteristics of the people traveling, their household, and their vehicles. FHWA has done eight National Travel surveys since 1969, with the latest being in 2017.

In addition to NHTS public data, restricted data from the NHTS was requested and obtained from FHWA. The NHTS restricted dataset includes households' home locations in Census Block Groups. Fortunately, NHTS 2017 provided data for home-to-work distance, age, gender, household income, and household size, as well as the block group identifier for individual respondent’s home location. Table 3 shows all the fields that were derived from the NHTS 2017 dataset.

NHTS 2017 Person database, had a field called DISTTOWK17. This attribute provided road network distance, in miles, between respondent's home location and school location, sourced using Google Distance Matrix API (NHTS 2017). In addition, age, gender, household income, and house size of each individual were provided by following fields in NHTS 2017 dataset: R_AGE, R_SEX, HHFAMINC, and HHSIZE.

Table 3: *Data Derived from National Travel Survey Dataset 2017*

Variables	Type	Source	Data Level	Year
Home-to-work distance	Dependent	NHTS	Individual	2017
Age	Control	NHTS	Individual	2017
Gender	Control	NHTS	Individual	2017
HH Income	Control	NHTS	Household	2017
HH Size	Control	NHTS	Household	2017
Block Group Identifier for HH Location	NA	NHTS	Household	2017

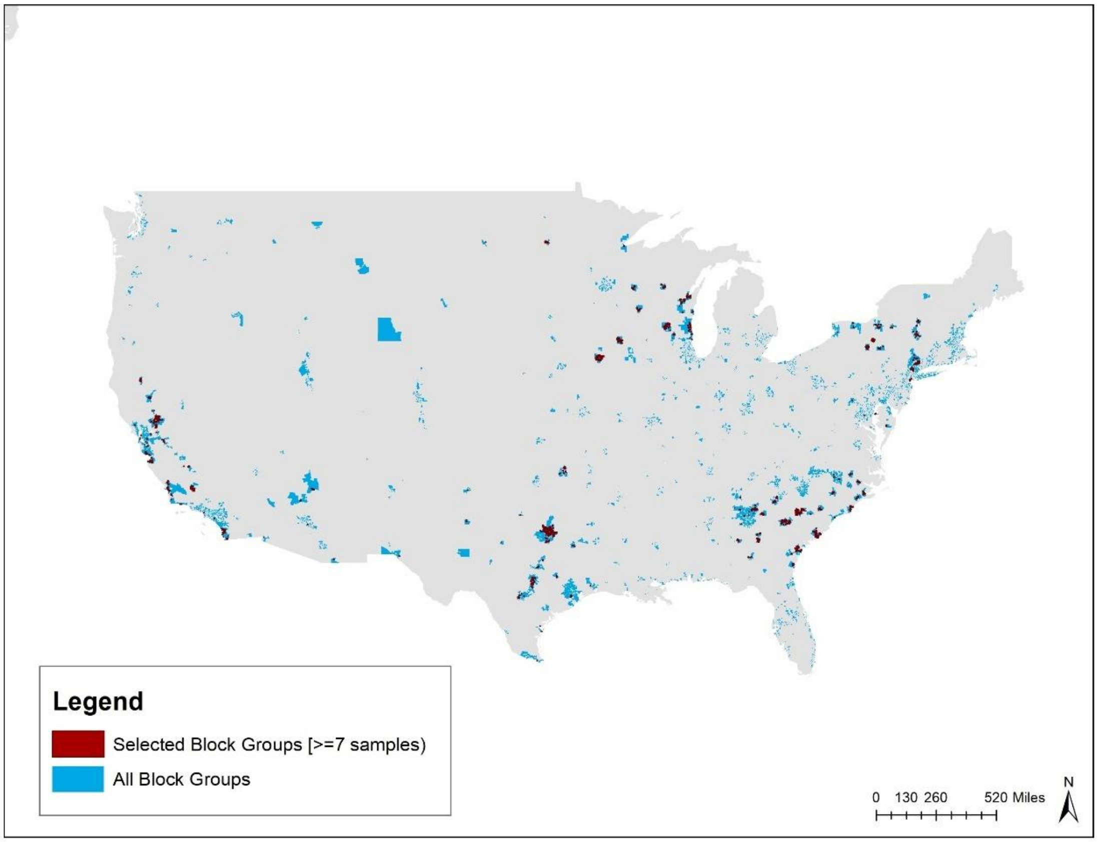
The original NHTS person dataset had 264,235 records with substantial missing data. Therefore, I applied a series of filters to clean the dataset and to remove potential outliers. At first, I selected records that had positive home-to-work distance. Since this variable was my dependent variable, I could not afford any missing data in this field. This filter reduced the number of records to 105,936. The next step was to identify the dataset range and eliminate the outliers. Raw data in DISTTOWK17 attribute ranged from 0.01 miles to 4271.75 miles while average commuting distance in the U.S. was 13.14 miles with a standard deviation of 13.70 in 2017(Federal Highway Administration 2017). QUARTILE.INC function in excel helped identify the data range and eliminate outliers. By applying this function, I was able to identify the higher bound of my dataset which was 56.72 miles. I also rounded up the higher bound from 56.72 miles to 60 miles and considered anything more than 60 miles as outlier which left us with 102,707 records. I have to mention that 97% of all observations were greater than 0 and less than 60 miles, with only 3,229 records out of 105,936 records (only 3%) exceeding 60 miles.

Next, I excluded the records pertaining to individuals who did not have a full-time job in the week prior to this survey and the ones who had the option of working from home. The reasoning behind these filters, was to make sure to only consider daily commuters without the option of working from home or flextime. These two filters reduced the number of records to 82,942.

Since this study focuses on Urban Areas, I removed records with positive rural attribute, which left 66,418 records. Also, since there were only 174 records with over 80 years of age, I considered over age of 80 as outlier and those were eliminated from the data. At this point, the household and individual portion of the data was ready, and I had a dataset consisted of 64,995 records.

A filter crucial for the credibility of the study and due to the methodological considerations was applied to the data. Also, due to the nature of the dataset, the preferred methodology for this study was Hierarchical Linier Modeling (HLM). In a nutshell, we had three levels of data (Individual, Block Group, Urban Area) and we needed to make sure that the two upper levels (block group, and urban area) had enough samples to be considered as a level to avoid bias in our model. In this case we wanted to make sure that the two upper levels (block group, and urban area) had a minimum of 7 samples in each unit. For example, we didn't want to include a block group with only one individual respondent, or an urban area with only one block group. As a result, we had to apply another filter to make sure to only include records that came from block groups that had 7 or more respondents. These two final filters reduced the samples from 64,995 to 12,086. Figure 12 depicts the geographical representation of the selected block groups versus block groups that was taken out of the study due to small number of samples.

Figure 11: *Home Location of 12,086 Drivers' Block Group Location*



U.S. Census Data

The US Census Bureau is the largest federal statistical agency in the United States. Every ten years, Census Bureau administers a nationwide survey to gather information from households. Also, this agency provides yearly population estimates based on the future trends. US Census estimates in 2017 provided data for average home value in each block group. They also provided population and housing unit counts for each block group, which helped in calculating the population density for each block group by using GIS and also produce job/housing ratio by dividing number of jobs derived from LEHD data (which will be elaborated upon in the following section) to number of housing units in each block group obtained from US Census 2017. Table 4 depicts the variables that were directly or indirectly derived from US Census 2017.

Table 4: *Data Derived from US Census Dataset 2017*

Variables	Type	Source	Data Level	Year
Population number in Block Group	NA	Census	Block Group	2017
Population Density in HH Location	Control	Census/GIS	Block Group	2017
Average home price in HH Location	Control	Census	Block Group	2017
Number of Housing Units	NA	Census	Block Group	2017
Job/Housing Ratio	Control	LEHD/Census	Block Group	2017

Longitudinal Employer-Household Dynamics (LEHD) Data

Longitudinal Employer–Household Dynamics (LEHD) data are the result of a partnership between the Census Bureau and U.S. states to provide high quality local labor market information and to improve the Census Bureau's economic and demographic data programs. LEHD data are based on different administrative sources, primarily Unemployment Insurance (UI) earnings data and the Quarterly Census of Employment and Wages (QCEW), and censuses and surveys. Firm and worker information are combined to create job level quarterly earnings history data, data on where workers live and work, and data on firm characteristics, such as industry. This dataset has provided us with data to produce both employment density and job/housing ratio. By utilizing GIS, the total number of jobs in each block group was divided to the area of that block group and job density was produced. Meanwhile, the number of jobs in each block group, obtained from LEHD data, was divided to number of housing units, derived from Census 2017 dataset, to create job/housing ratio for each block group. Table 5 summarizes the information provided in this paragraph.

Table 5: *Data Derived from LEHD Dataset 2017*

Variables	Type	Source	Data Level	Year
Number of Jobs in Block Group	NA	LEHD	Block Group	2017
Employment Density in HH Location	Control	LEHD/GIS	Block Group	2017

Job/Housing Ratio in HH Location	Control	LEHD/Census	Block Group	2017

Equations 1 through 3 present the formulas for calculating three of the built environment factors at block group level.

$$\text{Population Density} = \frac{\text{Total Population in the Block Group}}{\text{Area of the Block Group (acre)}} \quad (1)$$

$$\text{Job Density} = \frac{\text{Total number of Jobs in theBlock Group}}{\text{Area of the Block Group (acre)}} \quad (2)$$

$$\text{Job/housing Ratio} = \frac{\text{Total number of Jobs in theBlock Group}}{\text{Total number of Housing Units in the Block Group}} \quad (3)$$

As it is shown in equation (1), population density is calculated by dividing total number of populations in each block group to the land area of the same block group. Job density was also calculated in a similar manner, except that total number of jobs in each block group was divided by the total land area of that block group. The job/housing ratio values was obtained by dividing total number of jobs in a block group to the total number of housing units in the same block group. This ratio provides a representation for land use diversity in each block group.

Highway Performance Monitoring System (HPMS)

The Highway Performance Monitoring System (HPMS) is a national level highway information system provided by US Federal Highway Administration (FHWA) that includes data on the extent, condition, performance, use and operating characteristics of the nation's highways. HPMS was developed in 1978 as a continuing database, replacing the special biennial condition studies that had been conducted since 1965. The HPMS has been modified several times since its inception. Changes have been made to reflect changes in the highway systems, legislation, national priorities, to reflect new technology, and to consolidate or streamline reporting requirements. As is demonstrated in Table 6, HPMS 2017 provided tollway and highway mileage in each urban area.

Table 6: *Data Derived from HPMS Dataset 2017*

Variables	Type	Source	Data Level	Year
Total Mileage of Tollway in the Urban	Independent	HPMS	Urban Area	2017
Total Mileage of Highway in the Urban	Independent	HPMS	Urban Area	2017

As described in the previous paragraphs and shown in Table 7, eleven variables with three different levels of data were used to build a model to test the hypothesis of this study. Due to the nature of this dataset, there were certain considerations that we had to take into account while choosing the appropriate statistical method to analyze the data. In the following section, I will elaborate on the applied statistical methodology and why we chose this approach.

Table 7: *Variables used in the models*

Variables	Type	Source	Data Level	Year
Y1= Home-to-work distance	Dependent	NHTS	Individual	2017
X_1 = Total Mileage of Tollway in the UA	Independent	HPMS	Urban Area	2018
X_2 = Total Mileage of Highway in the UA	Independent	HPMS	Urban Area	2018
X_3 = Age	Control	NHTS	Individual	2017
X_4 = Gender	Control	NHTS	Individual	2017
X_5 = HH Income	Control	NHTS	Individual	2017
X_6 = HH Size	Control	NHTS	Individual	2017
X_7 = Population Density in HH Location	Control	Census	Blk Group	2017
X_8 = Job Density in HH Location	Control	LEHD	Blk Group	2017
X_9 = Job/housing ratio in HH Location	Control	LEHD	Blk Group	2017
X_{10} = Average home price in HH Location	Control	Census	Blk Group	2017

Statistical Approach

In previous sections we discussed all the variables that were applied in this study. Also, in chapter 2, we studied the theories explaining the relationships between the dependent variable and independent variables. Per all those theories, all interval independent variables in this research, were assumed to have a linear relationship with the dependent variable. Also, a preliminary test results for both Pearson correlation and VIF for all independent variables, didn't show any sign of a significant multi-collinearity. As a result, a form of linear regression seems to be a good fit to this research, which made Linear Regression Model a potential statistical method for this study. As a result, I decided to use Multiple Linear Regression (MLR).

However, upon further research, I realized that due to the nature of this study and the dataset, at least one of the main assumptions of MLR was being violated which was the independence of the error term. In other words, I was studying individuals who had unique demographic attributes while being nested in a certain block group and in a certain urban area. Which meant all individuals in a block group had the same value for their population density and the same amount of toll way mileage in their urban area, despite the requirement of them being independent from one another. This meant that they couldn't be treated as independent observations, which was a violation of a MLR assumption.

The individuals who were the subject of this study, resided in different urban areas. If we aggregated the characteristics of all respondents in each urban area, then other variables such as population density, employment density, land use diversity, and home value for all those individuals residing in the same urban would have been the same. Because these respondents shared the same characteristics, the observation based on these individuals were not independent. This impose a problem on the model because most linear analytic technics such as OLS and MLR call for the independence of the observations as one of their primary assumptions. As a result, with the existence of hierarchical data, standard errors produced by Ordinary Least Square regression (OLS) will be too small. To address this problem, we should either make sure to use data including only independent observations or use a statistical analysis method that suits hierarchical data sets.

One way to deal with this problem is to aggregate lower level data. For example, we needed to aggregate the data for all of the individuals in each urban area and block group. In this case we would have been dealing with average home-to-work distance, average income, average household size and etc. However, by applying this approach, we will lose all valuable individual information that could define the actual relationship between socioeconomic characteristics of each household with home-to-work distance.

One solution while dealing with multi-level dataset, is to utilize Hierarchical Linear Model (HLM). However, when applying linear regression model, such as HLM, we should make sure that we had robust theories supporting the relationships between variables.

As a result, and per advice from my dissertation committee, I decided to use Hierarchical Linear Modeling instead. As previously stated, the reason behind this decision was multi-level design of this study. I wanted to study an individual level variable and its relationship with two urban area level independent variables and eight individual level and block group level variables. As John Nezlek reiterates: “If you have a multilevel data, you have to do multilevel analysis”. In the following section I will elaborate on Hierarchical Linear Modeling.

Hierarchical Linear Modeling

Background

Hierarchical Linear modeling (HLM)—also known as multilevel linear models in Sociology (Goldstein, 1995; Mason et al., 1983), random coefficient regression models in Econometrics (Rosenberg, 1973; Longford, 1993), mixed effects models and random effects models in Biometrics (Elston & Grizzle, 1962; Laird & Ware, 1982; Singer, 1998), and covariance component models in Statistics (Dempster, Rubin, & Tsutakawa, 1981; Longford, 1987; Bryk and Raudenbush, 2002)—is a more complex version of ordinary least squares (OLS) regression. HLM analyzes the variance in outcome variables when using predictor variables with varying hierarchical levels (Woltman et al., 2012).

The term HLM was first applied in the 1970s (Lindley and Smith, 1972, as cited in Bryk and Raudenbush, 2002). However, since no general estimation approach was feasible for the estimation of covariance components at that time, HLM was never utilized except for some very simple problems. Until in 1977, Dempster, Laird, and Rubin developed Expectation-Maximization

(EM) algorithm. EM Algorithm provided a more applicable approach to the covariance component estimation (Bryk and Raudenbush 2002).

What is HLM and Why we use it in Social Science Studies

As explained by Gelman and Hill (2006), “Hierarchical Linear Model or multilevel models are advanced regression models where data are structured in groups and coefficients can vary by group”. HLM is specifically useful in social science studies were dealing with nested data; students nested in their class and in their schools, residents nested in the block group they reside and in their urban areas, employees nested in their divisions and departments and so forth. Individuals residing in a certain neighborhood have unique socioeconomic characteristics while sharing certain properties such as road accessibility, land use diversity, population density, job availability and variables pertaining their neighborhood, their City, and their urban area. In other words, individuals are nested in block group level, block groups are nested in urban area level, urban areas are nested in states.

HLM analysis is applied when the data has a multiple level structure. For this instance, some of our data has been collected in individual level, some of data has been gathered at block group level, and some of the data has been collected in urban area level. It is recommended to refer to these levels by number. Usually, the level that is higher in the hierarchy is refer to as level 1. For example, in this study, measure describing individuals (e.g., Home-to-work distance, age, sex, household income, and household size) were considered level 1 data, while measures describing block group attributes (e.g., population density, job density, job/housing ratio, and average home value) were considered level 2 data, and measures describing urban area (e.g., tollway mileage and highway mileage) were considered level 3 data.

When working with multilevel data, we need to keep in mind that different data levels are nested within each other. For example, individuals are nested in block groups and block groups are nested within urban areas, therefore neither individuals nor block groups are independent observations. In this case, all individuals living in a block group, have the same attributes for both the block group and urban area levels. Table 8 is a truncated table derived from the dataset that was used in this study and is showing data for 9 individuals in a certain block group (Census Id#452001) in City of Flagstaff, Arizona. As it is shown in this table, all 9 individuals have unique values for individual level attributes. However, they all have the same values for block group level and urban area level. The same is true for all block groups in an urban area as well.

Table 8: *Actual data of 9 individuals from the same block group*

Person	Individual Level					Block Group Level		Urban Area Level	
	DisWrk	Age	IsMale	HHSize	HHInc	PopD	JobD	TollMi	HwyMi
1	0.4	44	1	4	87500	1.14	0.32	0	35.59
2	5.58	60	1	3	62500	1.14	0.32	0	35.59
3	3.16	62	1	2	225000	1.14	0.32	0	35.59
4	1.99	62	0	2	137500	1.14	0.32	0	35.59
5	2.02	40	0	2	112500	1.14	0.32	0	35.59
6	1.93	55	1	3	225000	1.14	0.32	0	35.59
7	2.21	24	0	3	15000	1.14	0.32	0	35.59
8	2.87	58	0	1	225000	1.14	0.32	0	35.59
9	4.2	31	1	2	87500	1.14	0.32	0	35.59

As we saw in previous example, level one and level two observations were not independent, therefore, the traditional Ordinary Least-Squares (OLS) techniques such as multiple regression were not applicable for such dataset due to the lack of independence, as the independence of observations is one of fundamental assumptions of OLS techniques and cannot be violated (Nezlek 2008).

Chapter 5
Empirical Analysis

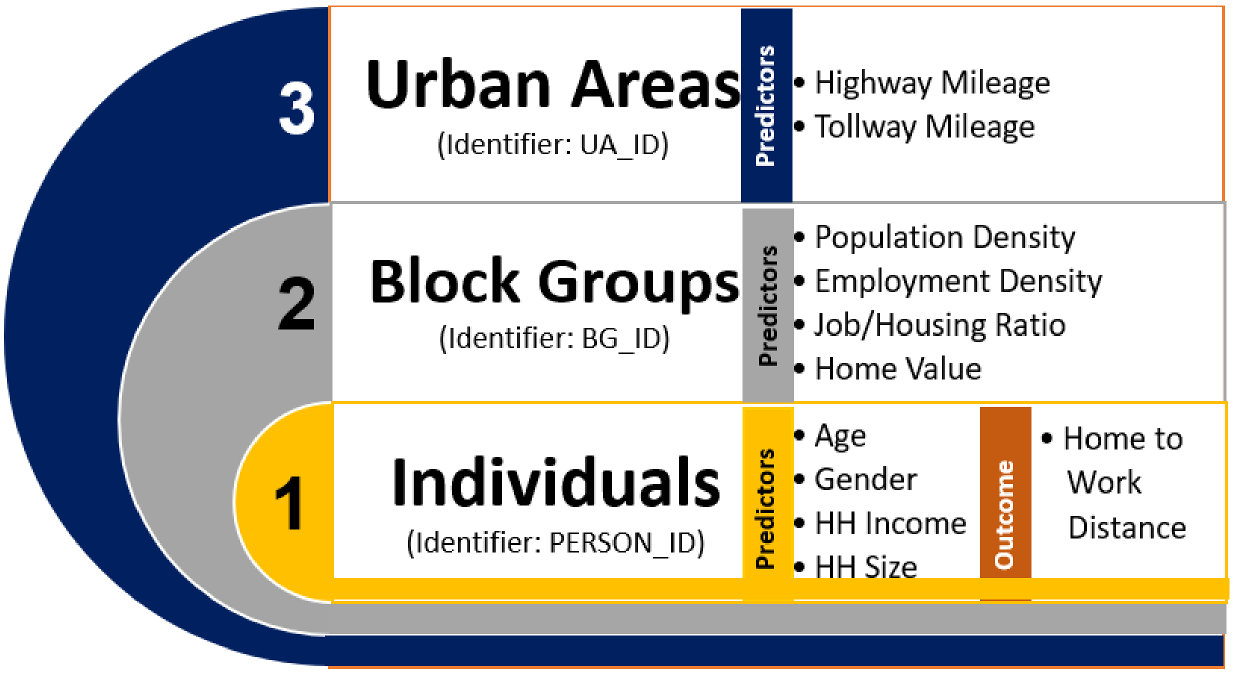
Introduction

As was discussed in the previous chapter, Hierarchical Linear Modeling (HLM) technique was the primary statistic methodology used in this research. This technique helped us analyze the potential effects of built environment and socioeconomic factors on commuting distance. The dependent variable in this study was home-to-work distance and the independent variables were total mileage of tollway and highway in urban areas which are going to be processed in two separate models. This study also examined the effect of some control variables such as person's age, sex, household income, and household size, as well as population density, job density, and job/housing ratio of the block group in which the respondent lived. Figure 12 shows all three levels of data used in this study. Level 1 is individual level and the data for this level was obtained from NHTS 2017 disaggregated data. Also, Level 1 identifier is PERSONID field combined with HOUSEID (Household Identifier) field in NHTS 2017. The outcome (dependent) variable for both models is home-to-work distance and is a Level 1 variable. Other Level 1 predictors (control variables) used in both models are individual's age, sex, household income, and household size.

Level 2 was block group level and block group identifier was BG_ID and was obtained from NHTS 2017 add-on data. We had four Level 2 predictors which are as follows: population density, job density, job/housing ratio, and home value. US Census provided data for population, average home price, and number of housing units in each block group, while, LEHD data provided total number of jobs in each block group. By using GIS, Census data, and LEHD data, we were able to compute both population density and job density for each block group. Also, by dividing number of jobs to number of housing units, we were able to calculate job/housing ratio.

Level 3 was urban area level and urban area identifier was UA_ID and was obtained from US Census. The two predictors (independent variables) in this level were consisted of total mileage of tollway and total mileage of highway in each urban area. The data for both of these variables were obtained from HPMS data and by GIS application, we were able to identify the total mileage in each urban area.

Figure 12: *Variables Used in This Study With Their Associated Data Level*



SPSS software was used to estimate two research models to address the research question of this study. One to examine the effect of the total mileage of tollways in urban areas on individual's home-to-work distance. And the other one to examine the effect of total mileage of highways in urban areas on individual's home-to-work distance, which is respectively referred to as Model 1 and Model 2. All variables with their data sources are listed in Table 9. As you can see, we have one outcome variable and ten predictors with two of them being independent variables and eight of them being control variables.

Table 9: *List of Variables of the Three-Level HLM*

	Identifier	Predictors		Outcome
Level 1	PERSON_ID (Individuals) (NHTS 2017)	P_AGE_LN+1 (Respondent's Age) P_ISMALE (Respondent's Gender) P_HHSIZE_LN+1 (Respondent's Household Size) P_HHINCOME_LN+1 (Respondent's Household Income)	NHTS 2017 NHTS 2017 NHTS 2017 NHTS 2017	P_DISTTOWK17_LN+1 (home-to-work Distance) (NHTS 2017)
Level 2	BG_ID (Block Group) (NHTS 2017)	BG_POPDEN_LN+1 (Population Density) BG_EMPDEN_LN+1 (Employment Density) BG_JOBHOU_LN+1 (Job-Housing Ratio) BG_HOMEVAL_LN+1 (Home Value)	Census/GIS LEHD/GIS LEHD/Census Census	NA
Level 3	UA_ID (Urban Area) (Census 2017)	UA_HWY_LN+1 (Highway Mileage) UA_TOLL_LN+1 (Tollway Mileage)	HPMS HPMS	NA

In this chapter, first, the research design of the study was explained, summary statistics of all explanatory variables were provided, and later on the process of HLM application in SPSS software was delivered. Ultimately, the results of estimated coefficients were interpreted in detail.

Research Design

For this study three levels of analysis was adopted to perform HLM: Level-1 included driver's socioeconomic characteristics at individual level; with level 2 being built environment factors in block group level, and Level-3 included urban area level data for the total mileage of highways and tollways.

HLM is the fundamental technique for analyzing hierarchical datasets. In transportation studies, data are often organized at multiple hierarchical levels: the individual level, household level, block groups, Traffic Analysis Zones (TAZs), and city levels. This necessitates statistical methods that can account for such hierarchy, such as HLM (Woltman et al., 2012). HLM is an advanced form of ordinary least squares (OLS) regression that is implemented to explore variance in the outcome variables when the independent variables have hierarchical levels (Woltman et al. 2012); For example, household’s members in a household share variance according to their common race, income and other common factors. According to Woltman et al. (2012), prior to HLM, hierarchical data were analyzed via simple linear regression techniques, which were insufficient for such analyses due to neglecting the shared variance across hierarchical levels.

In the previous chapter, we discussed that our dataset was consisted of 12,086 records obtained from four different data sources. Each of these records mirrored the socioeconomic attributes of individuals who participated in NHTS 2017 as well as built environment characteristics. This dataset was hierarchical in nature and had presented three data levels; in other words, 12,086 individuals were nested in 1,259 block groups and these block groups were nested in 123 Urban areas across US. As you can see in Table 10, our samples for this study, are distributed in urban areas with various sizes. Nearly one-third of records came from urban areas with less than 200,000 population. Same portion represented urban areas with more than one million population while urban areas with population between 200,000 and 500,000 and urban areas with population between 500,000 and 1,000,000, collectively, claimed the other third portion of the data. Also, this table shows the average representation of block groups in urban areas. as discussed in the previous chapter, each level had to provide enough samples in order to avoid bias and skewed data. For example, we could not consider block groups with only one individual. As a result, we decided to only include block groups with a minimum of 7 individuals to guarantee an unbiased model.

Table 10: *Data Distribution Based on Urban Area Size*

Block Groups with 7 Individual NHTS 2017 respondents or more						
	Level 1	NA	Level 2	Level 3		
Urban Size	# of Person	# of HH	# of BG	#of UA	Ave # of Person in BG	Ave # of BG in UA
01=50,000 - 199,999	4140	2711	400	73	10.4	5.5
02=200,000 - 499,999	2725	1746	277	25	9.8	11.1
03=500,000 - 999,999	996	621	109	10	9.1	10.9
04=1 million or more	4225	2650	473	15	8.9	31.5
Total	**12086**	**7728**	**1259**	**123**	**9.6**	**10.2**

Also, we had to apply natural logarithm to all variables except gender, which was a dummy variable, to change the parametric statistics to non-parametric statistics and to achieve normal distributions for each continuous variable, which is a requirement for linear regression models. In general, parametric statistics is preferred over non-parametric statistics. The reason is that parametric statistics are real values, while non-parametric statistics are based on ranked or ordinal values, which makes it harder to interpret the results and observe actual differences between variables. However, the normalization process for all variables of the model, helped with outlier impact reduction, and provided unified parameter estimates as elasticities. in Figure 13 and 14, the distribution of home-to-work distance, before and after application of natural logarithm, was displayed. As you can see, the normal distribution was achieved by using this technique.

Figure 13: *Histogram of Home-to-Work Distance of the Actual Data*

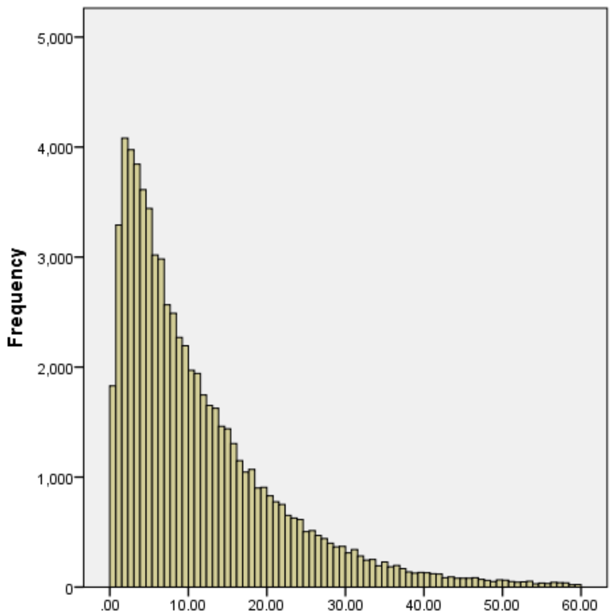
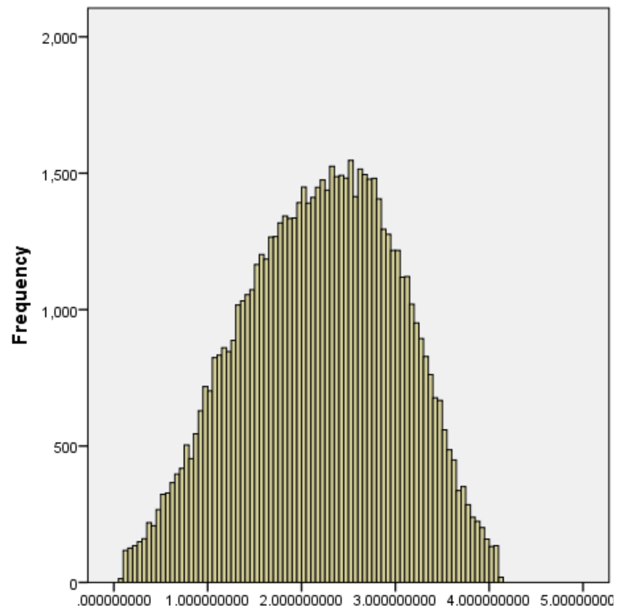


Figure 14: *Histogram of Normalized Home-to-Work Distance*



After converting actual data to natural logarithm, it was time to process the data. In this study, I used the step by step process that was provided in Multilevel and Longitudinal Modeling with IBM SPSS book authored by Ronald Heck, Scott Thomas, and Lynn Tabata (Heck, Thomas, and Tabata 2013). In chapter 4 of this book, they explained and showed step by step process of analyzing a tri-level dataset using SPSS sofware. In the following section summary statistics of data resulted from HLM analysis was presented.

HLM Model

HLM procedures are computationally intensive. If random effects have many levels and the input data set is large, the execution times can be long. In doing the estimation, the procedure needs to invert a matrix (known as the Hessian) the size of which is proportional to the square of the number of total parameters in the model, including those for fixed effects. Computations can begin to constrain available resources once one or more random effects have multiple levels ("SAS User Guide" 2020). The first step in running the models in SPSS, was to make sure defining three levels of data was justifiable. For this purpose, only the dependent variable which is in individual level, and random effect identifiers of the two other data level are added to the model. As is demonstrated in Table 11, all levels are considered significant.

Table 11: *Estimates of Covariance for Different Data Levels*

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		.529517	.007202	73.522	.000	.515587	.543822
Intercept [subject = UA_ID]	Variance	.077508	.014109	5.494	.000	.054250	.110738
Intercept [subject = BG_ID * UA_ID]	Variance	.072117	.005532	13.035	.000	.062049	.083818

Some scholars have suggested to use other methods to justify the use of mixed models (HLM) such as Intraclass Correlation Coefficient (ICC). ICC is evaluated to examine the proportion of variance between groups variance to total variance (Heck et al., 2014). However, other scholars believe that ICC is misleading, primarily because of the ICC's inability to consider variability within class (Gelman and Hill, 2006). According to these scholars, data with multiple levels must be processed with a multilevel analysis, regardless of the ICC ratio (Nezlek, 2008).

Summary Statistics at the Individual Level

As previously stated, NHTS 2017 provided home-to-work distance by calculating road network distance between respondent's home location and work location in miles by using Google Distance Matrix API. This attribute is a continuous variable and is represented as DISTTOWK17 in NHTS dataset. Using continuous variables gave us the advantage of comparing the variable with discrete factors and made it easier to interpret the results. All individual level variables, except for gender, were normalized and transformed by taking natural logarithms. Table 12 displayed summary statistics of Individual level data. Home-to-work distance ranges from 0.1 to 59.76 miles, age ranges from 16 to 80 years, and household size ranges from 1 to 10 people. Household income is a bit different. NHTS 2017, did not provide the actual income for each person and instead it provided the range. Since we wanted to avoid dummy variables where possible, we considered the mean of each category as the declared income. However, since the highest income category was $200,000 or more, we put $225,000 as the highest number, while in reality some respondents may have more household income than $225,000.

Table 12: *Summary Statistics of Individual Level Demographics*

Built Environment Attributes	N	Minimum	Maximum	Mean	Std. Deviation	Source
Home-to-Work Distance	12,086	0.1	59.76	11.53	10.44	NHTS
Age	12,086	16	80	43.7	14.21	NHTS
HH Size	12,086	1	10	2.86	1.31	NHTS
HH Income	12,086	$15,000	$225,000	$105,044	59,797	NHTS

Summary Statistics of Built Environment Data

Built environment attributes associated with home location of each driver, fell into two separate data levels. Population density, employment density, job/housing ratio, and median home value were all in block group level and were derived from US Census and LEHD data. These variables were geocoded and visualized at individual's block group location, with using ArcGIS software.

Table 13 provides a summary of built environment data within block groups. Population density in block groups ranges from 0.5 to 63.46 person per acre, job density ranged from 0 to 177.74 jobs per acre, job/housing ratio ranged from 0 to 36.06 jobs per housing units, and home values ranged from $34,891 to $2,000,000. One thing to remember, since this job/housing ratio is a representation of land use diversity in the block group, higher values represent higher land use diversity in the block group.

Table 13: *Summary Statistics of Built Environment Data Near Home Location*

Built Environment Attributes	N	Minimum	Maximum	Mean	Std. Deviation	Source
Population Density (acre)	1,259	.05	63.46	5.37	5.84	Census/GIS
Job Density (acre)	1,259	.00	177.74	2.20	8.26	LEHD/GIS
Job/Housinng Ratio	1,259	.00	36.03	1.03	2.33	LEHD/Census
Home Value	1,259	$34,891	$2,000,000	$280,810	$176,237	Census

Two other built environment factors, available in urban area level were total mileage of highways and total mileage of tollways. This data was obtained from Highway Monitoring System (HPMS) dataset provided by Federal Highway Association (FHWA). These data provided information about the total mileage limited access roads with is translated into interstates, major highways, as well as tollways in the United States. For these two variables, all urban areas that were associated with the household locations of NHTS 2017 records were identified and then the total number of available freeway and tollway mileage were taken into consideration. Table 14 gives more insights for total mileage of tollways and highways within the urban areas. As it is shown, in our sample there were urban areas with zero mileage of any type of limited access roads. On the other hand, we had urban areas with maximum of 409 miles of tollways and maximum 2451 miles of highways.

Table 14: *Summary Statistics of Built Environment Data for Home Location in Urban Area Level*

Built Environment Attributes	Total Number of Urban Areas	Minimum	Maximum	Mean	Std. Deviation	Source
Total mileage of Tollways	123	.00	409.16	14.86	33.7	HPMS
Total mileage of Freeways	123	.00	2451.643	55.3	138.88	HMPS

Model 1. Mixed Model Analysis – Tollway

To run the first model, I had to choose the variables for this model. Home-to-work distance was our outcome variable with total mileage of tollways in urban areas being the independent variable. In this model eight control variables were included as model predictors as well. With age, sex, household income, and house size in individual level and population density, job density, job/housing ratio, and home value in block group level. In this model, urban area identifier and block group identifier were defined as random effects in SPSS, while other variables were identified as fixed effects.

Table 15 exhibits Model 1 estimates of fixed effects. The results suggest that, except for household size, all other variables are significant. This model suggested that men drive 11% farther than women to work. Block groups with more population density discouraged longer home-to-work distance. One percent change in population density of the block group of where the respondent lived, contributed to almost 16 percent less home-to-work distance. Respondent's age also contributed to longer home-to-work distance. One percent increase in the age of the respondents resulted in 12 percent increase in home-to-work distance. Increase in household income also, was associated with higher home-to-work distance. One percent increase in household income increased home-to-work distance by 12 percent. Abundance of jobs in the block group, on the other hand, made individuals to drive less. One percent increase in job density decreased commuting distance by 10 percent. Job/housing ratio, which was a representation of land use diversity, had a negative effect on home-to-work distance. One percent increase in job/housing ratio decreased home-to-work distance by 8 percent. Total mileage of tollways, which was our independent variable, demonstrated a significant positive effect on home-to-work distance. When total mileage of tollways in an urban area increased by one percent, individuals living in that urban area drove 8 percent more. Home value played a negative role on home-to-work distance as well when one percent increase in home value in a certain block group showed 6 percent less home-to-work distance for the individuals living in the block group. Table 16 also demonstrated significant Wladz test for all data levels and confirmed the necessity of using a multilevel analysis for this study.

Table 15: *Estimates of Fixed Effects[a] for Tollway Model, Calculated by SPSS*

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	1.329352	.286112	1540.964	4.646	.000	.768142	1.890563
P_AGE_LN1	.122429	.020568	12000.369	5.952	.000	.082112	.162746
P_ISMALE	.108249	.013365	11410.311	8.099	.000	.082051	.134447
P_HHSIZE_LN1	-.028780	.022524	11830.435	-1.278	.201	-.072931	.015371
P_HHINCOME_LN1	.120967	.012082	11800.010	10.012	.000	.097284	.144649
BG_POPDEN_LN1	-.157538	.022948	1220.805	-6.865	.000	-.202560	-.112515
BG_EMPDEN_LN1	-.102395	.031810	1169.772	-3.219	.001	-.164806	-.039984
BG_JOBHOU_LN1	-.079706	.040983	1149.733	-1.945	.052	-.160115	.000703
BG_HOMEVAL_LN1	-.061588	.021225	1318.134	-2.902	.004	-.103226	-.019950
UA_TOLL_LN1	.078736	.017088	79.227	4.608	.000	.044725	.112748

a. Dependent Variable: P_DISTTOWK17_LN+1.

Table 16: *Estimates of Covariance Parameters[a] for Tollway Model*

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		.519693	.007067	73.537	.000	.506025	.519693
Intercept [subject = UA_ID]	Variance	.063522	.012390	5.127	.000	.043341	.063522
Intercept [subject = BG_ID * UA_ID]	Variance	.042074	.004237	9.931	.000	.034538	.042074

a. Dependent Variable: P_DISTTOWK17_LN+1.

Model 2. Mixed Model Analysis - Highway

In order to run the second model, I had to choose the variables for this model. Home-to-work distance was our outcome variable with total mileage of highways in urban areas being the independent variable. In this model eight control variables were included as model predictors as well. With age, sex, household income, and house size in individual level and population density, job density, job/housing ratio, and home value in block group level. In this model, urban area identifier and block group identifier were defined as random effects in SPSS, while other variables were identified as fixed effects.

Table 17 shows model 2 estimates of fixed effects. As you can see, this table suggests that except for household size all other variables are significant. This model suggested that home-to-work distance for male drivers was 11 times more than female drivers. Block groups with more population density discouraged longer home-to-work distance. One percent change in population density of the block group of where the respondent lived, contributed to almost 16 percent less home-to-work distance. Respondent’s age also contributed to longer home-to-work distance. One percent increase in the age of the respondents resulted in 12 percent increase in home-to-work distance. Increase in household income also, was associated with higher home-to-work distance. One percent increase in household income increased home-to-work distance by 12 percent. Abundance of jobs in the block group, on the other hand, made individuals to drive less. One percent increase in job density decreased commuting distance by 10 percent. Job/housing ratio, which was a representation of land use diversity, had a negative effect on home-to-work distance. One percent increase in job/housing ratio decreased home-to-work distance by 9 percent. Total mileage of tollways, which was our independent variable, demonstrated a significant positive effect on home-to-work distance. When total mileage of tollways in an urban area increased by one percent, individuals living in that urban area drove 9 percent more. Home value played a negative role on home-to-work distance as well when one percent increase in home value in a certain block group showed 7 percent less home-to-work distance for the individuals living in the block group. Table 18 also demonstrated significant Wladz test for all data levels and confirmed the necessity of using a multilevel analysis for this study.

Table 17: *Estimates of Fixed Effects[a] for Highway Model, Calculated via SPSS*

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	1.119360	.288855	1419.974	3.875	.000	.552732	1.685987
P_AGE_LN1	.122913	.020568	12000.349	5.976	.000	.082596	.163229
P_ISMALE	.108408	.013365	11410.857	8.111	.000	.082210	.134605
P_HHSIZE_LN1	-.027765	.022523	11830.182	-1.233	.218	-.071913	.016384
P_HHINCOME_LN1	.120902	.012081	11801.255	10.008	.000	.097222	.144582
BG_POPDEN_LN1	-.162499	.022967	1218.394	-7.075	.000	-.207557	-.117440
BG_EMPDEN_LN1	-.097576	.031777	1170.559	-3.071	.002	-.159923	-.035229
BG_JOBHOU_LN1	-.087994	.040961	1149.697	-2.148	.032	-.168360	-.007628
BG_HOMEVAL_LN1	-.066370	.021262	1319.418	-3.122	.002	-.108081	-.024659
UA_HWY_LN1	.087459	.017932	101.488	4.877	.000	.051888	.123029

a. Dependent Variable: P_DISTTOWK17_LN+1.

Table 18: *Estimates of Covariance Parameters[a] for Highway Model*

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		.519705	.007067	73.535	.000	.506036	.533743
Intercept [subject = UA_ID]	Variance	.062733	.012181	5.150	.000	.042876	.091786
Intercept [subject = BG_ID * UA_ID]	Variance	.041940	.004227	9.921	.000	.034421	.051100

RESULTS AND DISCUSSION

The results of model 1 and 2 (Table 15 & Table 17) indicate that all socioeconomic factors, except for household size, were significant and had positive impact on the home-to-work distance. As expected, age has a positive impact on HWD. The coefficient for the male dummy variable was found to be positive and statistically significant. Considering the coefficient estimates, HWD of male drivers is 11 times more than females. model results also reveal that household income positively increases HWD (12%). The coefficient of income indicates that a rise of one percent in income will produce a corresponding 12 percent increase in HWD.

The results of the model indicated that all built-environment factors at block group levels, had negative impacts on HWD. The findings suggest that increase in population density, employment density, job/housing ratio, and home value were associated with the reduction of the home-to-work distance.

Also, both tollway mileage (8%) and highway mileage (9%) in the urban area were significant and had positive effects on home-to-work distance. The results indicate that workers located within urban areas with higher highway or tollway mileage have moderately higher HWD. This result is aligned with the research hypothesis. The tollway coefficient indicates a one percent change in tollway mileage results in 8% percent change in home-to-work distance. Similarly, drivers with access to highways have a higher HWD. In other words, a one percent change in highway miles results in a 9% percent change in HWD.

Ultimately, these results suggest that home-to-work distance is suppressed by density and diversity factors for driver's home locations while it is positively increased with accessibility to highways and tollways within the urban areas.

Chapter 6
Conclusion

As was discussed in chapter 3, studies have presented that land use and transportation policies can influence travel behavior. According to Garreau (1991), both decentralization and the proliferation of ‘edge’ cities have changed the urban structure as well as commuting patterns within metropolitan areas. In this study, the effects of several variables were tested on home-to-work distance for each individual. Hierarchical Linear Modeling (HLM) was used to analyze the tri-level dataset that was used in this study. By developing two models that can demonstrate the relationship between independent variables and the dependent variable, this study was able to discuss the role of total toll mileage and total highway mileage in urban areas on individual’s home-to-work distance. In this, first, findings of this study in accordance with current study’s hypothesis will be elaborated upon. Consequently, limitation of this study and policy implications were discussed.

Findings

As was studied in Chapter 4, eleven variables from three different data levels were studied as part of two separate models by using Hierarchical Linear Modeling. The research question of this study, was whether the total mileage of limited access roads affect home-to-work distance. Per this research question that was defined in Chapter 1, the outcome variable (dependent variable) of this study was home-to-work distance with the total mileage of tollway and total mileage of highway in urban areas being two independent variables for two separate models. In Model 1, total mileage of tollway in urban areas was the independent variable with individual level control variables age, gender, household income, and household size in addition to the built environment characteristics of the block group of individuals home location such as population density, job density, job/housing ratio, and home value were considered as control variables.

Model 2, had the same dependent and control variables but the independent variable was total mileage of highway in urban area.

The research question of this study was to find out if availability and total length of tollways and highways (limited access roads) in an Urban Area, affect the length of individual's home-to-work distance. All variables in both models were significant except for the Household size. Table 15 and Table 17 in Chapter 5 presented the coefficients of the Model 1 and Model 2. In Table 15, we saw that the coefficient for tollway mileage in urban area was 0.8. which meant one percent increase in total toll mileage in urban area could increase the home-to-work distance of the individual by 8%. According to Table 17, the coefficient for total highway mileage in urban area for Model 2 was 0.9. This meant that one percent increase in total mileage of highway in urban area could increase home-to-work distance by 9%. Both of these results from Model 1 and Model 2 showed that not only mileage of tollway and highway affected the home-to-work distance, but also this effect was positive. In Chapter 2, we argued that based on travel demand model, we expected total mileage of limited access roads (tollway and highway) to increase home-to-work distance. Since average speed in limited access roads are higher than arterials and collectors, individuals can drive more in less time. As a result, where limited access roads are present, the radius of job search will be increased and individuals are willing to search for jobs farther than home location as long as they can maintain their average commute time.

In both models, male drivers drove 11% further than female drivers. This result was consistent to previous studies as female workers tend to choose jobs closer to home to fulfill their family obligations. Individual's age and income had a positive effect on home-to-work distance. in both models, one percent change in either age of the respondent or her income, showed 12% increase in her home-to-work distance. Since experience and rank comes with age, older adults need to drive more to find the matching career opportunity for their qualifications, while entry level positions are more abundant and one can find an entry level position closer to home. The same argument is true in regards to income. Higher income positions are not as abundant as entry-level low-income opportunities. As a result, higher income individuals are usually driving more in order to be able to have job that matches their expectations.

Per Hoteling theory that was presented in Chapter 2, firms tend to imitate each other in their site selection in order to benefit from economy of agglomeration. That is the reason why more firms tend to locate in CBDs. Also, per Alonso's Bid Rent Theory as a result of high demand for land closest to CBDs, the rent for those lands are higher causing higher home values and also encourages smaller units and vertical development. Consequently, high-rise apartments and vertical developments increases population density and agglomeration of firms increases job density. Per these two theories, we were expecting to see a negative relationship between home-to-work distance and all four-block group level built environment factors.

When firms tend to move to the same location, job density in that location will increase. Also, as a result of a high demand for that land, rent increases too. When rent increases, more units per acre is built to even out the high land value. As a result of vertical development due to response to higher land value, both number of people and number of housing units in those areas will increase. In both models, block groups with one percent increase in their job density showed 10% decrease in home-to-work distance. In general, individuals living in block groups with higher population density and job density had lower home-to-work distance. In other words, one percent increase in population density in a block group, demonstrated 16% decrease in home-to-work distance.

As we discussed before, higher density is associated with higher land price and higher number of housing units. Both models also showed significant and negative relationship between home-to-work distance and home value and job/housing ratio. In Model 1, one percent increase in job/housing ratio was associated with 8% decrease in home-to-work distance and one percent increase in home value was associated with 6% decrease in home-to-work distance. On the other hand, in Model 2, individuals living in block groups with higher home value and job/housing ratio had a lower home-to-work distance. One percent increase in land value was associated with 7%

decrease in home-to-work distance while one percent increase in job/housing ratio was associate with 9% decrease in home-to-work distance.

Research Advantages and Limitations

As it was mentioned in Chapter 1, there was a lacuna in quantifying the effect of availability of limited access roads in an urban area on home-to-work distance. This study was able to answer the research question by reliable and extensive data sources. Also, use of multilevel analysis such as HLM helped process the tri-level dataset set accurately and without computational bias. Records associated with 12,086 individuals from 123 US urban areas was used in this study and the associated built environment factors was studies as well.

However, the dataset that was used was a second-hand data and was not collected as part of this study. If the scope of the study and the financial means would have allowed, we could have been able to have a hybrid research design to include qualitative aspect of the choices that individual's make while choosing their home or work locations. Usually, due to the expenses associated with surveys, open ended tailored surveys for a specific study is not conducted and as a result, researchers are forced to use the existing data.

Since travel behavior is intertwined with built environment factors, more in depth research with focus on commuter's choice is recommended to have a better understanding of the relationship between these two.

Policy Implications

As mentioned previously, the Home Owners Loan Corporation (HOLC) and the Federal Housing Administration (FHA) significantly impacted suburbs by providing money and loan guarantees, as well as providing a formula to lenders and builders that resulted in inner city neighborhoods not qualifying for financing. These areas were left to deteriorate while money poured into mass-produced suburbs (Jackson, 1987).

Furthermore, with support from the Eisenhower administration, Congress passed the Federal-Aid Highway Act of 1956, which was a joint effort between the FHWA and state officials to improve the ease, speed, and cost of long-distance travel (Levy, 2010). This act was driven in part by the need to create jobs for American soldiers after World War II. Highway construction provided more jobs for those in need of work; it also encouraged longer commuting distances and made it easier to live further from the city. According to Levy (2010), highway systems positively impacted the economy of cities by improving access to central business districts—both from other cities and from the hinterlands.

Gradually, after decades of policy-makers promoting automobile-centered commuting, the passage of the ISTEA in 1991 signaled a post-Interstate Highway System era. Most notably, the ISTEA represented the first instance in American history of federal acknowledgment of the direct relationship between land use and transportation (Diamond and Noonan, 1996).

Edward Glaeser (2012) argues that urban concentration will lead to less pollution, less damage to the environment, and greater creativity in urban residents. Since human capital increases with city density, more appealing cities are possible if federal policies revert from their anti-urban agenda (Glaeser, 2012).

In this study we were able to demonstrate that built environment factors such as abundance of limited-access-roads in an urban area had a significant a positive effect on the length of the home-to-work distance. As it was stated in chapter 1, home-to-work distance has been constantly increasing. The reason behind this increase was both technological advances in transportation and also policies that prompted decentralized urban patterns. The result of elevated home-to-work distance is being manifested in different shapes and forms. Living in a car dependent society has, in part, led to a greater proportion of overweight adults than ever before (Frank et al., 2004). Other health issues related to having excess weight, such as diabetes and hypertension are on the rise. For US households, especially for the ones that live in a more car dependent environment, transportation costs swallow a considerable portion of their income. In addition, a car dependent environment denies accessibility to more venerable population such elderly and people with disabilities. In many cities, one cannot become employed if she doesn't have access to a private automobile. Also, natural habitats are being paved to build more roads. Loss of natural habitats have disturbed the natural environment and have caused heat islands. More driving has contributed to more greenhouse gas emission which has led to global warming. As we discussed in Chapter 2 and per Induced Travel theory, in long run, transportation demand will increase when more roads are being built. As planners, we need to be guardians of our environment and help achieve sustainable growth of our urban areas to make peoples life more enjoyable.

Rather than having reactive policies that cure one problem and create other problems, we need to look at the big picture and consider all aspects of the growth to be able to have better policies that addresses the root of the problems. By building new roads and outward expansion, we just add to the problem and we kick the can down the road. If we continue with our current growth pattern, all we get is car dependent urban areas with long home-to-work distance, loss of natural habitats, desserts made out of crisscross highways, and low-density cities that are doomed to bankruptcy in coming decades due to expensive infrastructure maintenance.

Taking new approaches such as Smart Growth initiatives, infill development, and higher density can help us achieve a more functional and efficient urban environment

Last Word

This study was able to address its research question. However, in our ever-evolving world, this study or any other related study should not and could not be considered as the ultimate result and response. Travel behavior is multifaceted that needs careful consideration carefully. It is almost impossible to ignore the role of automobiles in today's life. In the US, private automobiles claim 85% of commutes (American Community Survey 2017) and according to United States Environmental Protection Agency (EPA) 28% of U.S. greenhouse gas emission in 2018 was caused by transportation. We are facing a life changing challenge that might affect our future generations. Global warming is a fact and sea levels are rising, glaciers are melting, natural habitats such as rainforests, north and south pole, prairies, grass lands, jungles, creeks, rivers, oceans,… are all affected by humans both directly and indirectly. This Pale Blue Dot, as Carl Sagan called the earth, is the only home that we have ever known and can guarantee our being. If we do not act dutifully, we are doomed to lose our only home. Hope we can make our future generations proud by keeping their future home safe and habitable.

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