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Unpacking the Complex Relationship between Land Use, Vehicle Travel, and Transportation Greenhouse Gas (GHG) Emissions

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Unpacking the Complex Relationship between Land Use, Vehicle Travel, and Transportation Greenhouse Gas (GHG) Emissions

by

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Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August 2016

Dedication

To my wife, *Eunji Ko*, for her unwavering support and encouragement over the years.

Acknowledgements

Over the five years I have received support and encouragement from a great number of individuals. Dr. Ming Zhang has been my advisor since I entered the program. His guidance has made this a thoughtful and rewarding journey. I would like to show him my great appreciation. I would also like to thank my dissertation committee of Dr. Robert Paterson, Dr. Tiffany Whittaker, Dr. Chandra Bhat, and Dr. Junfeng Jiao for their support over the years as I moved from an idea to a completed study.

In addition, I would not be able to complete this study without support from other individuals in the department. I as a doctoral student had a happy life in Austin thanks to the members of the Department of Community and Regional Planning and of the School of Architecture. I was emotionally supported by these communities including professors, staff, and colleagues. I would like to take this opportunity to thank all of individuals who contribute to my accomplishment.

During data collection, I was also helped by a number of individuals from several state Departments of Transportation (DOT). Thanks to Jasmy Methipara from the Office of Highway Information, I was able to connect with seven DOTs (California, Florida, South Carolina, Tennessee, Vermont, Virginia, and Wisconsin) and provided with needed datasets for this study. I would like to thank all DOT individuals who shared their data with me.

Finally, I would like to express my appreciation to my parents and family as well as friends for their endless love, support, and encouragement.

Unpacking the Complex Relationship between Land Use, Vehicle Travel, and Transportation Greenhouse Gas (GHG) Emissions

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The University of Texas at Austin, 2016

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This dissertation research aims to disentangle the relationship between land use, vehicle travel, and transportation greenhouse gas (GHG) emissions. A great number of studies have paid attention to the impact of land use on transportation GHG emissions using vehicle miles traveled (VMT) as a substitute. Most studies equated VMT reduction with reduction of transportation GHG emissions. Few have examined in depth the varying components that affect transportation GHG emissions in vehicle travel operational dimensions. Moreover, few have applied the use of larger geographic-level land use. These studies, however, have limitations in examining a comprehensive relationship between land use and transportation GHG emissions. This dissertation research therefore focuses on the links between land-use measures at various geographic levels and household vehicle travel characteristics impacts on transportation GHG emissions.

In doing so, this dissertation research consists of the three closely related research questions. Using the 2009 National Household Travel Survey (NHTS), this research first examines whether neighborhood-level land use attributes proportionally affect household daily VMT and transportation GHG emissions (CO_2e). A series of multiple regression models developed in Chapter Four address the impact of land use on household vehicle travel characteristics and transportation GHG emissions. Results suggest that land use

strategies at the neighborhood level such as densification, a mixture of land use, and improvement of road connectivity can play a significant role in reducing vehicle travel. However, these land use changes may cause traffic delays in the area.

Chapter Five focuses on the impact of multiple geographic-level land use (i.e., neighborhood, county, and MSA) on both household VMT and transportation GHG emissions by applying hierarchical linear modeling. Results suggest that the effectiveness of similar strategies can vary by geographic scales at which those strategies are implemented. Chapter Six examines the intervening effects of vehicle travel characteristics on transportation GHG emissions by employing structural equation modeling. Results suggest that land use at various geographic levels influence not only household VMT but also vehicle travel speed and vehicle trip frequency, which together in turn affect household transportation GHG emissions.

Finally, this research presents a case study of the Austin, TX region using the 2006 Austin Travel Survey (ATS) in Chapter Seven. Applying a path model similar to the one developed in the preceding chapter, this study scrutinizes the role of land use in reducing transportation GHG emissions in both regional and local contexts. Results suggest that densification and a mixture of land use are still effective land use strategies to reduce region-wide emissions. However, design improvement can be a double-edged sword because of its unintended effect of reduced vehicle travel speed.

Overall, the findings contend that both travel demand management and mobility management at various geographic levels should be fully discussed in the early stages of planning. In addition, the role of metropolitan planning organizations (MPOs) in controlling regional development should be extended. The expansion of authorities and responsibilities of MPOs may enable the region at all levels to be developed more sustainably.

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Chapter One: Introduction

Background

According to the U.S. Energy Information Administration (EIA), the transportation sector accounts for 28 percent of greenhouse gas (GHG) emissions in the United States and 34 percent of the nation's energy-related carbon dioxide emissions (U.S. EIA, 2011, p. 2). Most GHG emissions (the primary culprit in the climate change) from the transportation sector are produced from light duty vehicles (LDVs), which are associated with passenger travel. To alleviate adverse environmental impacts from the transportation sector, there have been a number of attempts to reduce transport-based energy consumption and associated GHG emissions.

Strategies for reducing GHG emissions from the transportation sector are typically classified into three categories, sometimes referred to as "the three legs of the transportation stool," which include: 1) improving vehicle fuel efficiency, 2) reducing carbon content in fuel, and 3) reducing automobile use (Ewing, Bartholomew, Winkelman, Walters, & Chen, 2008). Policies and strategies, such as efficient vehicle technology development, fuel efficiency standards (e.g., CAFE[1]), alternative fuel requirements (e.g., blends of petroleum-based gasoline with ethanol such as E10) and incentives, feebates (i.e., financial rewards for purchasing efficient and alternative fuel vehicles), and fuel taxes, fall into the first two categories. Those pertaining to land use[2] management, improvement in transportation options, and incentives to choose public transit or non-motorized modes of transportation aim to primarily reduce automobile use, and to ultimately lessen the

[1] Corporate Average Fuel Economy (CAFE) standards are regulations in the U.S., first enacted by the U.S. Congress in 1975, to improve the average fuel economy of cars and light trucks.

[2] Land use is used as a general concept, which represents neighborhood built environment, locational attractions and exclusion (for trips, for example), and broader urban from or spatial structure. This study considers the terms of land use, urban form, and built environment in the same concept, and are used interchangeably throughout the study.

environmental impact of vehicle travel (Litman, 2015). Table 1-1 lists strategies that aim for vehicle travel reduction and their characteristics.

Category	**Strategy**	**Approach**	**Level of Implementation**
Travel Pricing	Road pricing	Economic Incentive	State, Local
	VMT Fees		Unknown
	Fuel Pricing		Federal, State, Local
Provision of Alternative Modes	Transit Investment	Infrastructure Investment	Federal, State, Local
	Bicycle Support Facilities		Local
	Park & Ride Facilities		State, Local
	HOV Lanes		State, Local
Parking Management	Parking Pricing	Economic Incentive	Local
	Mandatory Parking Cash-out		Federal, State, Local
	Parking Supply Limits	Regulation or Incentives	Local
Land Use Planning	Compact, Mixed-use, and Transit-oriented Development	Regulation or Incentives	Local
	Enhance Pedestrian Environment	Regulation, Infrastructure Investment	Local
Other VMT reduction Measures	Telecommuting	Education and Information	Employer-Based
	Compressed Work hours		Employer-Based
	No-Drive Days		Local

Table 1-1: Strategies for Reducing Automobile Use and Their Characteristics.[3]

While economic incentives are considered as a strategy whose results can be seen in the short-term, land use planning and infrastructure may need relatively long time periods for their effects to be realized. Nonetheless, a number of empirical studies support

[3] Retrieved from http://www.fhwa.dot.gov/environment/glob_c5.pdf

the idea that effective management of land use and changes in land use patterns in a given area have meaningful environmental benefits through the reduction in vehicle travel over the years (Cervero & Murakami, 2010; Hong & Shen, 2013; Zahabi, Miranda-Moreno, Patterson, & Barla, 2015). Thus, from the long-term point of view, many municipalities and governmental agencies across the country have paid attention to implementing various land use strategies along with other economic incentives in order to induce fewer vehicle trips. Land use policies can reduce vehicle travel and mitigate transportation related GHG emissions by encouraging the use of sustainable modes of transportation (e.g., walking, bike, and public transit).

Moreover, to achieve the environmental goals of a region through land use management, a variety of policies can be implemented at not only the neighborhood/local (micro) level, but also the regional (macro) level. Policies such as urban growth boundaries, are considered as a regional strategy in their scope, whereas site- or place-based policies such as developer incentives and zoning are more localized efforts. Table 1-2 lists land use-based strategies targeting vehicle travel reduction.

Scope	Measures	Examples of Policies
Micro	Exercising site-based tools, such as developer incentives, zoning requirements, development standards (density standards, requirements for mixed uses, grid street requirements, area or sector plans)	Planned Unit Development (PUD)
	Supporting pedestrian and bicycling activity through facilities for non-motorized modes such as sidewalks and bike lanes, urban design improvements, and traffic calming	Complete streets
	Increasing density and mix of uses to provide opportunities for pedestrian trips, trip-chaining, and transit access	Compact, mixed-use developments
	Orienting higher-density development around commercial centers, transit lines, and community facilities to encourage non-motorized trips	Activity centers / corridors; Transit-oriented developments
	Providing a sub-regional balance of jobs and housing, so that individuals do not need to commute long distances	Regional sub-centers
	Focusing regional development around transit networks	Smart growth
	Increasing the compactness of metropolitan areas	Densification
Macro	Regional planning tools: urban growth boundaries, concurrency requirements, and location efficiency mortgages (LEMs)	Statewide policies

Table 1-2: Land Use Policies in Different Scales.[4]

[4] Retrieved from http://www.fhwa.dot.gov/environment/glob_c5.pdf

Problem Statement

Along with land use policies implemented in practice, there exists a substantial body of literature on the relationship between land use and travel behavior, notably vehicle miles traveled (VMT). However, most of these studies treat VMT reduction and reduction of transportation emissions as the same (Badoe & Miller, 2000; Ewing & Cervero, 2010; Handy, 2005; Systematics, 2009; TRB Report, 2009). Some studies even assume that land use directly influences transportation GHG emissions (Frank, Stone, & Bachman, 2000; Hong & Shen, 2013).

These empirical studies support that compact, mixed-use, transit-oriented development can lead to VMT reduction, which in turn reduces transportation GHG emissions. Others, however, argue that compact development can lead to an emissions "penalty" by lowering average vehicle travel speed (Cox, 2003; Ewing et al., 2008).

VMT can be a good proxy, but not an exact measure of transportation GHG emissions. This is because the amount of vehicle emissions is influenced by several factors beyond distance: for example vehicle travel speed (Wang, Liu, Kostyniuk, Shen, & Bao, 2014) and vehicle characteristics (Reyna, Chester, Ahn, & Fraser, 2015). These vehicle operating characteristics vary by specific land use contexts such as roadway environments as well as neighborhood land use patterns. Few studies have examined the complex effects of land use on vehicle operating performance that produces varying GHG emission output not captured by VMT measures.

Furthermore, most existing studies regarding land use and travel (or transportation GHG emissions) have focused on the scale of individuals' or households' neighborhood (Ewing & Cervero, 2001;2010; Salon, Boarnet, Handy, Spears, & Tal, 2012). These neighborhood-level studies have a lot of strengths because of the fact that over 70 percent of all urban trips are home-based[5]. However, not all trips are made within the neighborhood boundary. In other words, some trips occur far beyond the boundaries of their neighborhoods. Few studies have examined the impact of land use in a variety of geographic levels on travel (Nasri & Zhang, 2015).

These existing studies therefore could lead to a mis-estimation of the environmental benefit of land use policies as they have paid less attention to vehicle travel characteristics, other than VMT, and the impacts of land use at multiple geographic levels[6] on travel. Thus, the purpose of this dissertation is to investigate and disentangle the complex relationship between land use, vehicle travel, and transportation GHG emissions in multiple geographic levels. The study findings are expected to better inform land use planning practice and policymaking aimed at reducing transportation GHG emissions.

RESEARCH SCOPE

The conceptual model for this study posits that land use and transportation GHG emissions are related both directly and indirectly. In the first instance, land use directly influences transportation GHG emissions through the individual's or household's choice on the type of vehicles they own and use. In addition, land use indirectly influences transportation GHG emissions through not only vehicle travel demand (i.e., trip length and frequency), but also vehicle operating performance (e.g., vehicle travel speed, cold starts, stop-and-go movements, etc.). Figure 1-1 illustrates the relationship between land use, vehicle travel, and transportation GHG emissions, which will be examined in this study.

[5] The definition of a home-based trip is that either the origin or destination is the individual's home.
[6] Geographic levels refer to hierarchical geography boundaries. For instance, metropolitan areas and counties are considered a relatively larger geographic level, whereas census tract and block group boundaries are considered a smaller geography.

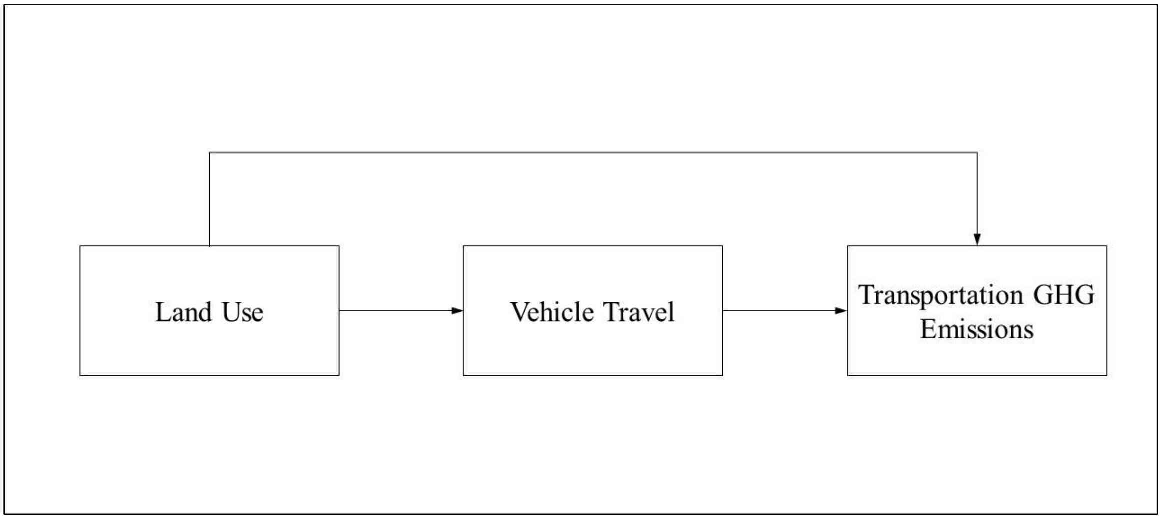

Figure 1-1: Relationship between Land Use, Vehicle Travel, and Transportation GHG Emissions.

RESEARCH QUESTIONS AND OBJECTIVES

Despite the effectiveness of land use management on VMT reduction, the role of land use in reducing transportation GHG emissions needs a further investigation because of its complexity of the relationship. Thus, the primary purpose of this study is to contribute to the ongoing debate on the direction of causality, the magnitude of effects, and the variations of the effects according to geographic levels regarding the land use-transportation GHG emissions connection. Based on the gaps found from the existing research, this study will investigate the following three research questions:

Research question #1: How does land use relate to household transportation GHG emissions?

Research question #1-1: How do land use attributes relate to vehicle travel characteristics (i.e., VMT, vehicle travel speed, and vehicle trip frequency)?

Research objective #1-1: Understanding the impact of land use on vehicle travel speed and vehicle trip frequency

Research question #1-2: To what extent do the land use effects on vehicle operations translate to transportation GHG emissions?

> **Research objective #1-2**: Unpacking the intermediate effects of vehicle travel on transportation GHG emissions and quantifying the total impact of land use on transportation GHG emissions

Research question #2: How do the effects of land use on transportation GHG emissions vary across geographic scales?

> **Research objective #2**: Examining variations in the effects of land use at multiple geographic scales on transportation GHG emissions

The overall objectives of this study are fivefold. First, the impact of land use on vehicle travel characteristics will be examined. Second, the causal relationships between land use and transportation GHG emissions at three geographic levels (i.e., metro-, county-, and neighborhood-level) will be investigated by employing hierarchical linear modeling (HLM) techniques. Third, the impact of land use on household's transportation GHG emissions will be quantified while considering the intermediate (mediator) effects of land use on vehicle travel by applying structural equation modeling (SEM). Fourth, the relationships between land use and transportation GHG emissions within a specific metropolitan area, the Austin, TX region, will be investigated in order to examine the potentials and challenges of compact, mixed-use development in localized context. Lastly, policy implications for maximizing the environmental benefits of land use strategies will be suggested based on the overall research findings.

DISSERTATION OUTLINE

This dissertation is organized into eight chapters. Chapter One addresses the research background, objectives, scope, and questions. Chapter Two reviews the existing literature on the connection between land use and travel as well as transportation GHG emissions. Chapter Three presents the methodology for this study, including the framework and research design as well as the data used for the study. Chapters Four, Five, and Six present the results of the analyses. The results from the case study of Austin are presented in Chapter Seven. The last chapter summarizes the results and draws conclusions based on major findings of the investigation. Then, policy implications are explored to deal with the climate change as well as to achieve the objectives of sustainable development. Limitations and possible improvements on this research are also discussed in this chapter.

Chapter Two: Literature Review

There exists a general agreement over the influence of land use on travel. Studies that examine the link between land use and travel behavior have revealed that changes in land use setting are associated with different aspects of travel, including trip length, trip frequency, and mode choice[7]. Modification of land use settings (e.g., density, land use patterns, road network design, etc.) may lead to changes in one or more aspects of travel and travel behavior. For instance, people living in compact, mixed-use, and well-connected areas with higher public transit service tend to have a lower average level of automobile use, and are likely to shift to sustainable modes of transportation such as public transit, bike, and walking, than those in sprawling (suburban) areas[8].

The link between land use and transportation GHG emissions, however, seems to be more complicated. On one hand, a compact, mixed-use, transit-oriented development contributes to a significant decrease in automobile use among its residents and consequently leads to reduction in transportation GHG emissions. On the other hand, this type of development can cause traffic congestion due to the higher vehicle travel demand in the area. Moreover, the well-connected street network may increase travel time on the road, which results from frequent stop-and-go movements. As a consequence, the slower movement of vehicles generates more emissions. In addition, this type of development may induce more frequent short-distance automobile trips. Unlike the land use and travel connection, many different aspects of travel, which are all influenced by land use to some extent, can play a role in determining transportation GHG emissions. However, the total impact of land use on mitigating transportation GHG emissions has not been adequately

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7 Researchers may include automobile ownership under a broad definition of travel.

8 Sprawling areas are typically characterized as low density, single use of land, poor connectivity (less pedestrian friendly design) and limited or no public transit service.

examined, and a fine-tuned analysis is necessary to begin disentangling the complex relationships between the components.

This chapter will review the state of the knowledge about the three-way relationship between land use, travel behavior—particularly vehicle travel—, and transportation GHG emissions. Further, the gaps from the existing studies will be addressed.

LAND USE AND TRAVEL

Overview

Over the past several decades, the link between land use and travel behavior has been studied intensively. Despite the controversies over the magnitude of the impact and the causal relationship, many studies have provided empirical evidence of the association between land use and travel behavior, mostly represented by VMT (Badoe & Miller, 2000; Boarnet & Crane, 2001; Cervero & Kockelman, 1997; Crane, 2000; Ewing & Cervero, 2001; 2010; Frank, Bradley, Kavage, Chapman, & Lawton, 2007; Handy, 2005). These empirical studies support the idea that modifying one or more elements of land use (i.e., density, diversity, design, etc.) or implementing land use strategies (e.g., neo-urbanist design, smart growth, etc.) influences one or more aspects of travel (i.e., trip length, trip frequency, mode choice, and automobile ownership), which together compose VMT (Ewing & Cervero, 2001). A simple relationship between land use and travel, particularly automobile use, is that as distances between origins and destination decrease, travelers either drive fewer miles or make more trips by other modes of transportation (e.g., walking, bike, or public transit). Decreasing the travel speed of automobiles also makes other travel options more attractive. Consequently, people living in a compact, mixed-use, and transit-oriented neighborhood with non-motorized modes friendly environment tend to drive less on average.

Land Use and VMT

Many noted scholars have conducted comprehensive reviews of the literature on the link between land use and VMT (Badoe & Miller, 2000; Crane, 2000; Ewing & Cervero, 2001; 2010; Handy, 2005). In general, residents in compact, mixed-use, and well-connected neighborhoods with other modes (e.g., transit, walking, bike) friendly facilities tend to drive less and use other transportation modes more (Cervero & Kockelman, 1997; Ewing & Cervero, 2010; TRB, 2009).

D-Variable	Description
Density	Population and employment by geographic unit (e.g., per square mile, per developed acre)
Diversity	Mix of land uses, typically residential and commercial development, and the degree to which they are balanced in an area (e.g., jobs-housing balance)
Design	Neighborhood layout and street characteristics, particularly connectivity, presence of sidewalks, and other design features (e.g., shade, scenery, presence of attractive homes and stores) that enhance the pedestrian- and bicycle-friendliness of an area
Destination accessibility	Ease or convenience of trip destinations from point of origin, often measured at the zonal level in terms of distance from the central business district or other major centers
Distance to transit	Ease of access to transit from home or work (e.g., bus or rail stop within ¼ to ½ mile of trip origin)

Table 2-1: Description of D variables.

Ewing and Cervero (2010; 2001) conducted a meta-study to examine the effects of the built environment on automobile travel demand (i.e., vehicle trips and VMT) and to quantify the magnitude of the effects of different elements of the built environment, commonly cited as D-variables (see Table 2-1).

In the 2001 study, Ewing and Cervero conducted a comprehensive review of 14 studies on the impact of four key elements of the built environment—density, diversity, design, and destination accessibility—on travel demand (Ewing & Cervero, 2001). They also considered an additional element of the built environment—distance to transit—on travel demand in a more recent study (Ewing & Cervero, 2010). These D variables characterize the built environment of a given area. In their earlier study, they found that the combined effects of several urban form variables on travel demand could be significant and larger although the effects of individual variables are modest. Their findings show that destination accessibility has a more substantial impact on VMT than density or diversity, and the regional accessibility is also a very important characteristic influencing household auto travel demand (Ewing & Cervero, 2001). The results from their recent study support their previous findings. In addition, they found that transit use is also related to location proximity to transit stops and street network design. Ewing and Cervero generalized the quantitative effects (i.e., elasticities[9]) of land use and urban design from more than 200 studies that had been published at the time of their investigation. Table 2-2 summarizes the weighted elasticities of VMT with respect to the five D variables.

[9] An elasticity is an expected percent change in the dependent variable when an independent variable increases by one percent.

D-Variable	Description of Measure	Elasticities (e)	Range of Elasticities
Density	Household / Population density	-0.04	0.00 to -0.12
	Job density	0.00	0.02 to -0.06
Diversity	Land-use mix (entropy index)	-0.09	-0.02 to -0.27
	Jobs-housing balance	-0.02	0.03 to -0.06
Design	Intersection / street density	-0.12	-0.08 to -0.31
	% of 4-way intersections	-0.12	0.00 to -0.15
Destination accessibility	Job accessibility by auto	-0.20	-0.03 to -0.31
	Job accessibility by transit	-0.05	-0.03 to -0.13
	Distance to downtown	-0.22	-0.20 to -0.27
Distance to transit	Distance to nearest transit stop	-0.05	-0.01 to -0.19

Table 2-2: Weighted Average Elasticities of VMT with respect to D Variables.

Some studies have addressed the importance of transit supply and easy access to transit service in addition to land use (Bento, Cropper, Mushfiq, & Vinha, 2005; Chen, Gong, & Paaswell, 2008). Transit-oriented developments (TODs) are an example of bringing a new urban form to reduce the share of motorized travel by making driving less attractive. Many studies found a significant effect of TODs on reducing vehicle travel (Holtzclaw, 1994; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002; Zhang, 2010). The concentrated developments along with transit stations are likely to shorten average trip length and consequently generate less driving than low-density developments (Zhang, 2010). In a similar way, mixed-use development brings trip destinations closer together, and along with improved pedestrian/biking environments, leads to fewer and/or shorter driving and more walking and biking (Cervero & Kockelman, 1997; Ewing et al., 2011).

Despite the extensive literature on the relationship between land use and travel, the causality and the magnitude of this link have remained elusive due to the complicated relationship between land use and travel. Hence, some recent studies have attempted to establish the direction of causality and to quantify the effects of the built environment variables on automobile use through methodological improvements (Ewing, Hamidi, Gallivan, Nelson, & Grace, 2014; Wang, 2013). Wang (2013) employed a structural equation modeling (SEM) approach to examine the causal relationship, and the results suggested that land use and transportation-related strategies (e.g., densification, mixture of land-use, and transit improvement) have significant potential for reducing vehicle travel (Wang, 2013). Ewing et al. (2014) estimated two models (cross-sectional and longitudinal models) to capture the relationships between transportation and land use in urbanized areas in the U.S. They found that in addition to population and income, development density, which is highly correlated with other public infrastructure (e.g., freeways and transit service), is the primary driver of VMT.

Self-Selection and Other Impacts on VMT

Besides the neighborhood land use characteristics, vehicle travel is influenced by several other factors that can be broken down into three choice categories—long, medium, and short term (Bhat, Paleti, Pendyala, Lorenzini, & Konduri, 2013; Pinjari, Pendyala, Bhat, & Waddell, 2011; Schwanen & Mokhtarian, 2007). Thus, it is very imperative to disentangle these relationships. Among the set of long term choices, researchers who study the effects of land use on travel at the micro-scale level have struggled with the issue of residential self-selection that obscures the directionality and the causality between land use and travel for several decades (Bhat & Guo, 2007; Mokhtarian & Cao, 2008; Van Wee, 2009). Self-selection in this context refers to the fact that households may choose their residential location based on their travel preference (Brownstone, 2008; Cao, Mokhtarian,

& Handy, 2009; Handy, Cao, & Mokhtarian, 2006; Mokhtarian & Cao, 2008) which generally results from households' attitudes, socio-economic traits, or lifestyles. For instance, people who are concerned about the environment or prefer to take public transit may choose an area with a good transportation system that would determine their travel patterns, or those in a lower socio-economic status (low-income or zero-vehicle households) may choose to live in the same area. In a similar fashion, those who prefer the suburban/rural life style and driving may want to live in the suburbs. If this is the case, instead of the built environment characteristics of a given area, the lifestyle propensity of households that may be determined by attitudes and economic constraints has a significant influence on their activity and travel patterns. Under this circumstance, the effects of land use on travel can be biased and over-estimated, or the causal link between land use and travel may be weaker (Boarnet & Crane, 2001).

Controlling for self-selection effects, thus, is a very critical part of the study on the land use-travel connection. Since the underlying residential self-selection problem results from a nature of cross-sectional data, the best way to deal with this problem is a pure experimental design that randomly assigns the subjects for study to either treatment or control groups (Brownstone, 2008). However, this option is not feasible in practice. Instead, scholars have made several attempts to solve self-selection problems in relation to data, methodology, and research design. In terms of data, many studies with disaggregate data found that the effects of self-selection can be controlled by including a rich set of socio-demographic characteristics of travelers, such as race/ethnicity, household income, household size, the number of workers, and the number of children (Bento et al., 2005).

There have also been many studies dealing with this problem through methodological improvement. With detailed and rich socio-demographic information, land use (residential location, density, etc.) and travel (VMT, vehicle ownership, etc.) are sometimes jointly modeled (Bhat, Astroza, & Bhat, n.d.; Bhat, Astroza, Sidharthan, Alam, & Khushefati, 2014; Brownstone & Golob, 2009; de Abreu e Silva, Goulias, & Dalal, 2012). However, the results from empirical research have bifurcated and thus are inconclusive. Some studies have used instrumental variables to control self-selection biases and found no significant relationship between land use and travel, particularly between density and VMT (Boarnet & Sarmiento, 1998). In contrast, other studies have found a significant link between land use and travel after controlling the self-selection effects, even if the magnitude of the impact of land use on travel is very small (Bhat & Guo, 2007; Vance & Hedel, 2007). Brownstone and Golob (2009) used a system of structural equations to control self-selection biases and found a significant, but small, relationship between density, VMT, and transportation fuel use (Brownstone & Golob, 2009). Bhat et al. (n.d.) jointly modeled residential location and automobile ownership, as well as activity time-use through latent variables, which are indicators of unobserved individual lifestyle, personality, and attitudinal factors (Bhat et al., n.d.).

There are also a number of studies that deal with the self-selection issues through attitude surveys that measure respondents' preference toward the built environment and travel. These studies find that individual attitudes explain most of the variation in travel patterns (Bagley & Mokhtarian, 2002; Kitamura, Mokhtarian, & Laidet, 1997; Schwanen & Mokhtarian, 2007; Van Acker, Mokhtarian, & Witlox, 2014).

The set of long-term choices, particularly residential location choice, also affects the set of medium-term choices such as vehicle and bicycle ownership that also can become critical factors to determine households' or individuals' VMT. Like location choices, the possession of a vehicle or bicycle is also influenced by not only the neighborhood land use characteristics, but the demographic and socio-economic characteristics of households or individuals (Bhat et al., n.d.; Bhat et al., 2013; Pinjari et al., 2011; Zegras, 2010). For instance, Bhat el al. (n.d.) focused on lifestyle propensity, and they found that households with a green lifestyle propensity disposition that is characterized by a preference to live in high density neighborhoods tend to own fewer vehicles. These "green" households are likely to value walkable neighborhoods, live closer to work place, and have an easy access to public transit. Consequently, they tend to own fewer vehicles and drive less (Bhat et al., n.d.). Zegras (2010) found that household incomes are the strongest factor to determine vehicle ownership, but land use factors (neighborhood design characteristics and relative location) are also associated with determining vehicle ownership.

Travel mode choice for commuting is an example of a short-term choice. This choice is also influenced by several factors—the attributes of land use and the characteristics of travelers. Age, gender, and education levels of travelers are examples of factors that affect the travel mode choice for commuting. Besides those factors, the type of employment, such as full-time or part-time, also determines which mode of transportation people take for a commuting trip (Bhat, Sen, & Eluru, 2009). These empirical studies show that land use is not the only factor that affects VMT. Rather, they show the importance of the characteristics of travelers and the intermediate factors for the comprehensive understanding of driving behavior.

LAND USE AND TRANSPORTATION GREENHOUSE GAS EMISSIONS

Overview

Newman and Kenworthy laid out the cornerstone of studying the connection between land use and transportation GHG emissions in the late 1980s. These authors showed that sprawling land-use patterns and low population densities correlate with higher VMT per capita, greater gasoline consumption, less use of public transit, and higher per-capita transportation GHG emissions (Newman & Kenworthy, 1989; 1999). Since then, many studies regarding this topic have been conducted.

Other Measures as Transportation GHG emissions

The relationship between VMT and transportation GHG emissions seems to be quite predictable: as VMT increases, so do emissions. The existing studies on this topic have focused on VMT (Bailey, Mokhtarian, & Little, 2008; Boarnet, 2011; Glaeser & Kahn, 2008) as a proxy to estimate transportation GHG emissions generated by private automobiles. These studies simply translated VMT reduction as emissions reduction. Like the land use and travel study, density as a representative of land-use is of primary interest. These following studies have found that urban density has a negative impact on VMT, although the magnitude of the density effectiveness on the reductions of VMT and transportation emissions varies significantly (Brownstone & Golob, 2009; Ewing, Bartholomew, Winkelman, Walters, & Chen, 2008; Heres-Del-Valle & Niemeier, 2011; Stone, Mednick, Holloway, & Spak, 2007). These studies demonstrate that individuals or households living in a compact neighborhood drive fewer miles than those in less dense area. Consequently, the former group is likely to generate less transportation GHG emissions. On top of density, land use diversity, intersection density, and proximity to transit also have the potential to reduce auto travel, and therefore emissions, by encouraging people to take public transit (if transit is within walking distance), as well as to walk or bike (if destinations are within walking or biking distance) (Ewing & Cervero, 2010; Frank, Greenwald, Winkelman, Chapman, & Kavage, 2010).

Some studies used fuel consumptions, like Newman and Kenworthy in 1989, to examine the effects of urban land-use characteristics on household travel and transportation energy use or fuel consumption (Karathodorou, Graham, & Noland, 2010; Liu & Shen, 2011). Both studies found that urban density is inversely related to fuel consumption. Nevertheless, Liu and Shen (2011) found that density does not have a direct effect on VMT and fuel consumption, but does have an indirect and negative impact on VMT through different channels (Liu & Shen, 2011). There have also been some studies done to introduce emission factors from other resources, such as by the U.S. EIA or National Resources Canada (Barla, Miranda-Moreno, Savard-Duquet, Thériault, & Lee-Gosselin, 2010; Glaeser & Kahn, 2008).

Accurate Measurement of Transportation GHG Emissions

There have also been attempts to improve GHG emissions estimates (Frank et al., 2006; Frank et al., 2000; Hong & Goodchild, 2014; Hong & Shen, 2013). Frank et al. (2000) investigated the influence of land use on air quality in the Seattle, Washington region. They directly estimated vehicle emissions from the 1996 Puget Sound Travel Survey using MOBILE5a and better approximated the effects of the measures of land use on vehicle emissions. They found a significant inverse relationship between land use and vehicle emissions (Frank et al., 2000). Hong and Shen (2013) also analyzed the influence of residential density on road-based transportation emissions using a more recent travel survey and estimating emissions tool. Using MOVES2010, in conjunction with the 2006 Puget Sound Household Travel Survey, they found that increasing residential density still leads to a significant reduction in transportation emissions even though the effects of residential density on transportation is influenced by spatial correlation and self-selection (Hong & Shen, 2013). Hong and Goodchild (2014) estimated the elasticities of CO_2 equivalent emissions with respect to three Ds—density, diversity, and design. They also found that each of these land use measures is negatively associated with transportation emissions. For instance, households living in a neighborhood with higher density, greater diversity, and better connectivity are likely to generate lower emissions (Hong & Goodchild, 2014).

Unintended Outcomes from Land Use Changes

Compact and mixed-use developments sometimes result in less desirable outcomes. In particular, street environments affect driving behavior (or patterns), and in turn influence exhaust emissions and fuel consumption (Brundell-Freij & Ericsson, 2005; Wang, Liu, Kostyniuk, Shen, & Bao, 2014). For instance, on-road street environments, such as higher densities of intersections (either controlled by traffic lights or not), street function (local; main; arterials), speed limit, traffic volume, and number of lanes lead to lower average travel speeds, more speed changes, higher frequency of acceleration/deceleration, and higher demand for power, which all together reduce fuel efficiency (Brundell-Freij & Ericsson, 2005). Moreover, roadside street environments, such as employment density and type of neighborhood, are associated with lower driving speed, more speed change, and lower fuel efficiency (Wang et al., 2014).

Vehicle Type and Transportation GHG emissions

Land use also influences household transportation GHG emissions through the type of vehicle that an individual or a household owns and uses (Bhat, Sen, & Eluru, 2009; Brownstone & Golob, 2009; Fang, 2008; Lee & Lee, 2014). These studies provide the empirical evidence, showing that households located in more densely populated areas are more likely to have fuel efficient vehicles, such as compact passenger cars rather than less fuel efficient cars, such as large vehicles, including pickup trucks, SUVs, and vans.

Complexity of the Land Use and Transportation Emissions Connection

Transportation Emissions as a Function of Vehicle Travel

As shown in existing studies, land use influences travel behavior and other travel characteristics. Not only is VMT influenced by land use, but vehicle operating conditions (e.g., vehicle speed, acceleration/deceleration, and cold starts) are also affected by land use. The choice of vehicle type also relates to land use patterns. As such, all vehicle travel characteristics are closely intertwined, accounting for transportation emissions.

Land Use	Vehicle Miles Traveled	GHG Emissions
Density ○ Household ○ Population ○ Employment Diversity ○ Land use mix ○ Jobs-housing balance ○ Distance to stores Design ○ Street network Destination accessibility ○ Jobs within a specific radius ○ Retails or services within a specific radius Distance to transit ○ Distance to nearest transit stop	Travel Mode Trip Length Trip Frequency Vehicle Ownership **Vehicle Operating Condition** Vehicle Speed Acceleration/Deceleration ○ Number ○ Magnitude Percent Cold Start Ambient Temperature Road Grade/Slope **Vehicle Type** Passenger Heavy-Duty Diesel High Emitter Vehicles	Carbon Dioxide (CO_2) Methane (CH_4) Nitrous Oxide (N_2O) hydrofluorocarbon (HFC)
Stage One →	**Stage Two** →	

Table 2-3: Elements Associated with the Three-Way Relationship in Real World.[10]

[10] Ewing & Cervero, 2010:274 and The Louis Berger Group, Inc., 2004:13

Table 2-3 shows the complexity of the relationship between land use and transportation emissions. As demonstrated in Table 2-3, this relationship consists of two stages. Stage one begins when changes in an element (or elements) of land use occur. Land use changes can be characterized either at a regional scale or at a local scale. Regional scale land use change can be described in terms of large area development patterns of jobs, housing, or shopping, whereas local scale land use change is associated more with design features of buildings, street layout, and the provision of public transportation (The Louis Berger Group Inc., 2004). Altering land use patterns affects travel in several ways. Many previous studies have revealed that "narrower street widths, grid patterns, building faces closer to the street, mixtures of land uses, density of land uses, availability and quality of transit services" (The Louis Berger Group Inc., 2004, p. 16) are associated with lower levels of automobile use and lead to a shift to alternative transportation, such as public transit and non-motorized modes of transportation.

In the second stage, vehicle operating characteristics (vehicle speed, acceleration events, and percentage of cold start) and vehicle characteristics, in addition to VMT, determine the level of transportation emissions. The majority of GHG emissions from vehicle travel are CO_2 emissions resulting from the combustion of petroleum-based fuels such as gasoline or diesel, and relatively small amounts of CH_4, N_2O, and HFC emissions are emitted during fuel combustion as well. Table 2-3 also shows several operating characteristics that are not affected directly by changes in land use but are nevertheless important to consider. Ambient temperature and road grade/slope are also critical for estimating transportation emissions.

As presented in Table 2-3, despite its effectiveness on VMT reduction, land use-based strategies and transportation investment for VMT reduction may face challenges in reducing transportation GHG emissions because of its influence on vehicle operational performance. For instance, denser development and transportation investments may cause congestion on the roads (Barth & Boriboonsomsin, 2008; Handy, 2005; Taylor, 2002). Congested conditions lead to auto travelers driving slower with more frequent stop-and-go movements (acceleration and deceleration), than they would under free-flow conditions. Both of these conditions influence emission and fuel consumption rates (Eisele et al., 2014; Zhang, Batterman, & Dion, 2011). Eisele et al. (2014) found that as driving speed decreases, more emissions are generated. Further, Zhang et al. (2011) found that the transition stage, from free-flow to congestion or vice versa, requires more accelerations and decelerations by drivers than in free-flow conditions, resulting in more emissions generation.

Land Use Impact at Multiple Geographic Scales

Most disaggregate studies regarding the relationship between land use and travel have focused on the relationship between land use at the scale of the individual's or household's neighborhood and travel (Ewing & Cervero, 2001;2010; Salon, Boarnet, Handy, Spears, & Tal, 2012). Although a residential neighborhood is the most relevant single geography unit for the disaggregate travel research because a substantial portion of individuals' or households' trips are home-based, indicating that at least one of their trips ends at their residential location, not all trips are made within the residential neighborhood. The average length of one driving trip (6.8 miles) is well beyond their neighborhood boundary, and even the average length of a walking trip (0.7 miles) is beyond the boundary as well (Ewing et al., 2008). These results show that the built environment at the neighborhood scale alone cannot fully capture the built environment in the extended size of the typical adult or adolescent's activity space.

In addition, the magnitude of changes in travel behavior resulting from changes in the built environment depends on scale. A few recent studies measured the built environment factors at different geographic scales in order to explain the variations in the effects according to the changes in scales (Hong, Shen, & Zhang, 2014; Kwan & Weber, 2008; Zegras, 2010; Nasri & Zhang, 2015). Zegras (2010) found that not only neighborhood design characteristics (e.g., zonal density, the number of intersections per kilometer), but also the built environment characteristics at an intra-metropolitan scale (e.g. distance to CBD) are associated with vehicle use. Nasri and Zhang (2015) attempted to shed some light on the overlooked impact of the larger geographic level built environment on travel behavior. They found that the employment density at the smaller scales is directly related, while the same variable at the higher level is inversely related to both VMT and car ownership. These findings demonstrate that land use policies may affect vehicle travel in different directions when these policies are practiced in different spatial scales. These findings also imply that changing land use policies at the local level alone is not followed by a significant reduction in driving, and suggest that effective land use policies are those which consider the overall form of urban areas and the composition of jobs and services in the entire region (Nasri & Zhang, 2015).

Other studies found that land use variables at a regional level are likely to have a larger association with travel than those at a local or neighborhood level (Cervero & Duncan, 2006; Ewing & Cervero, 2010). For example, improving the jobs-housing balance in a given region had a greater effect in reducing VMT, than in improving access to retail and consumer services by locating them closer to residence (Cervero & Duncan, 2006). Therefore, testing different scales of the built environment against travel in the same study, VMT in particular, would be ideal.

Lastly, measures of the built environment that influence VMT within a neighborhood are likely to differ from those that reduce VMT in a region. Local trips, mostly made by using non-motorized modes, are likely to be influenced by neighborhood scale built environment, such as pedestrian friendly street design and destinations in close proximity. In contrast, regional trips are determined by the location of jobs and shopping destinations in a region relative to a household's residence (TRB, 2009).

Chapter Three: Research Methods

The primary sources of data for this dissertation research are the 2009 National Household Travel Survey (or NHTS; providing data at the national level) add-on samples and the 2006 Austin Travel Survey (ATS; for regional and local levels). These household travel surveys include detailed information about the surveyed individuals' trips and activities, as well as demographic and socio-economic characteristics of the surveyed individuals and households, as well as the characteristics of vehicles each household owns and uses. Moreover, the 2009 NHTS add-on data and the 2006 ATS provide exact geographic coordinates of all trip origins and destinations as well as the surveyed households' residential location, which this study analyzed in conjunction with other location related datasets.

To measure the land use characteristics of the neighborhood for each surveyed household, this study utilized the smart location database (SLD), developed by the EPA, which summarizes more than 90 different indicators associated with the built environment for the national level analysis. These indicators, including density of development, diversity of land use, street network design, accessibility to destinations, and distance to transit, as well as various demographic and employment statistics, are available for all U.S. block groups. The details of the smart location database will be discussed later. For the case study of Austin, TX, the land use variables were derived by utilizing land use and transit datasets from local and regional agencies.

To estimate GHG emissions from household vehicle activities more accurately, this study utilized the Motor Vehicle Emission Simulator (MOVES), which is an emissions modeling tool that is also developed by EPA. This study estimated the carbon dioxide equivalent (CO_2e) by considering vehicle characteristics (e.g., vehicle type, fuel type, and vehicle age) and vehicle operating conditions (e.g., vehicle speed and cold-starts) in addition to VMT.

As illustrated in the previous section, land use influences transportation GHG emissions in many different ways, which are difficult to examine with a simple regression model. Besides multiple regression techniques for the analyses in Chapter Four, hierarchical linear modeling (HLM) techniques were employed for the analyses in Chapter Five, and structural equation modeling (SEM) techniques, which are capable of simultaneously handling a large number of endogenous and exogenous variables for testing joint impacts by controlling for other factors, were employed for the analyses in Chapter Six and Seven.

RESEARCH FRAMEWORK

The conceptual model for this dissertation research was developed from the theoretical and empirical findings of existing literature on the land use and travel connection as well as intuition. The conceptual model presented in this section, however, does not explicitly incorporate all other possible dimensions, particularly those that mediate the relationship between land use and transportation GHG emissions such as trip chaining, etc. Figure 3-1 depicts the conceptual model for the empirical analyses in this dissertation research and the basic causal relationships inferred from the land use and travel (and transportation emissions) literature. Figure 3-1 also depicts which components each chapter tested. This dissertation research addresses the three closely related issues by three separate but closely connected empirical studies in the following three chapters. Along with these three pieces of analyses, the case study of the Austin, TX region was conducted and is discussed in Chapter Seven.

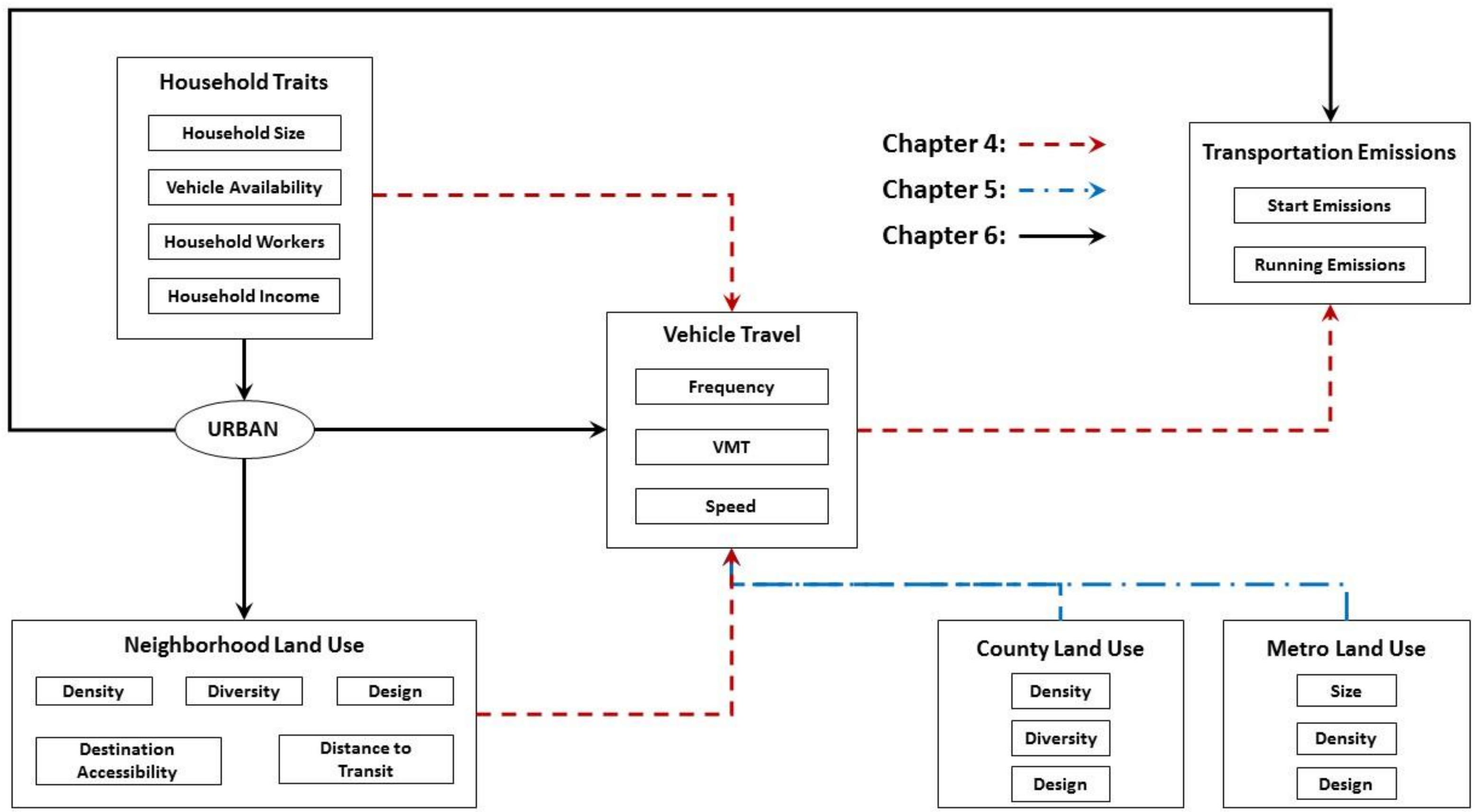

Figure 3-1: Conceptual Model of the Land Use and Transportation Emissions Connection.

The conceptual model is comprised of seven main elements: (1) household traits represent the demographic and socio-economic characteristics of each surveyed household, (2) neighborhood land use represents the characteristics of the built environment of a given neighborhood of each household, (3) county land use and (4) metro land use represent the built environment at these two higher levels of geography, (5) urban, a latent variable, controls self-selection effects, (6) vehicle use describes the household's vehicle travel characteristics, and (7) transportation emissions are the outcomes of the auto-related activities. Table 3-1 lists the variables of interest under each category in Figure 3-1.

Component	**Variable**	**Description**
Household Traits	Household Size	Count of household members
	Vehicle Availability	Number of vehicles per household driver
	Household Worker	Count of household workers
	Household Income	Total household income
Neighborhood Land Use	Density	Population density; Employment density
	Diversity	Land use mix (entropy); Jobs-housing balance
	Design	Intersection density
	Destination Accessibility	Number of jobs within a certain travel time; Population centrality
	Distance to Transit	Distance to the nearest transit stops; Transit frequency
County Land Use	Density	Activity density
	Diversity	Jobs-housing balance
	Design	Road network density
Metro Land Use	Size	Developed land area
	Density	Activity density
	Design	Road network density
Urban	Urban	Indicated by the neighborhood land use characteristics

Table 3-1 is continued on next page

Vehicle Travel	Trip Frequency	Number of vehicle trips made by all household members on the travel day
	Trip Length	Total vehicle miles of traveled by all household members on the travel day
	Trip Speed	Average travel speed of vehicle trips made be all household members on the travel day
Transportation Emissions	Start Emissions	Amount of emissions produced when a vehicle is started
	Running Emissions	Amount of emissions produced when a vehicle is driven

Table 3-1: Study Variables.

Research Hypotheses

In this section, formal hypotheses drawn from the land use and travel behavior (transportation GHG emissions) literature that inform the conceptual model and that were tested in the empirical analyses will be presented.

Urban Residence

Throughout this study, the term, *urban*, refers to a compact, mixed-use, and well-connected area (or a neighborhood) with a higher regional accessibility and public transit service.

Household Characteristics and Urban Residence

Household demographic and socio-economic characteristics may play a role in choosing residential locations for several reasons. For instance, a large household is likely to live in the suburbs because they need more space for their household members. Houses in the suburbs may meet their needs. A household without private automobiles may live in urban neighborhoods because they need other modes of transportation to travel. Urban neighborhoods with higher densities are more likely to provide public transit service. Households with more full-time workers are likely to reside in the urban neighborhoods, where there are numerous employment opportunities. Low income households tend to live in urban areas where relatively less expensive transportation modes are available. However, it is also very likely that those lower income households are being displaced from the urban areas due to the unaffordable housing costs. The relationship between household income and urban residence needs to be further investigated.

Household Characteristics and Vehicle Travel

Household demographic and socio-economic characteristics influence vehicle travel behavior. It was assumed that households with more members (workers), more vehicles available, and more income are likely to use automobiles more than their counterparts. In addition, these household traits also influence the average vehicle travel speed to some extent.

Urban Residence and Vehicle Travel

Thanks to the environment in favor of non-motorized travelers and alternative transportation options, urban residents are less likely to utilize automobile. They tend to drive shorter distances per trip or use other modes of transportation, such as transit, walking, or bike.

Neighborhood Land Use and Vehicle Travel

The development of a neighborhood with higher population and employment densities results in closer trip origins and destinations, on average, and thus shorter trip lengths, on average. Shorter trips also may reduce VMT by making non-motorized modes (e.g., walking and bicycling) more competitive alternatives to the automobile, while higher densities make it easier to support public transit.

Mixing land uses can bring housing closer to jobs and shopping, and thus reduce trip lengths. Because mixed-use neighborhoods offer a variety of employment, shopping, and recreational opportunities within short distances of residences, they facilitate the use of non-automobile travel modes and can shorten car trips.

A street network that provides good connectivity between locations and accommodates non-vehicular travel can make other modes of transportation more attractive than automobiles. Well-connected street networks can also provide more options for routes to destinations, and thus reduce trip lengths.

Higher regional accessibility can result in less travel since distances to potential destinations are shorter. Improving transit access creates the potential to encourage the use of transit, which can reduce vehicle trips, and VMT. Reduced distances to transit can reduce vehicle trips and VMT by encouraging a shift from driving to public transit, but this can also be achieved by encouraging transit users to walk or bicycle to the station rather than drive.

However, there is a strong positive relationship between higher population density and higher traffic volumes. In other words, an increase in population in an area will lead to an increase in VMT in the area. As more vehicle miles occur in a confined geographical location, traffic slows down and is subject to more "stop-and-go" operation. This increases the time spent in traffic (Cox, 2003).

County and Metro Land Use and Vehicle Travel

As neighborhood land use influences vehicle travel, so does land use at higher geographic levels. Plenty of roads in a given region may induce more vehicle travel because of the auto-friendly environment, whereas a good balance between jobs and housing in the region or a restricted regional developed area may obviate the needs to drive a long distance within the region.

Urban Residence and Transportation GHG Emissions

The attractiveness of sport utility vehicles (SUVs) or passenger trucks as compared to compact cars diminishes when density increases. Compact cars are gaining an edge over all but midsize SUVs in dense areas. Fang (2008) found that a 50 percent increase in residential density is associated with a statistically significant, yet small reduction in household truck holdings (i.e., a 1.2 percent reduction), and a larger change in truck VMT (nearly an 8 percent reduction) than in car VMT (1.32 percent) (Fang, 2008). It is also likely that households in denser neighborhoods choose more fuel-efficient vehicles (Brownstone & Golob, 2009). However, there may exist regional variations in vehicle ownership types.

Vehicle Travel and Transportation GHG Emissions

The amount of emissions from the tailpipe of each vehicle is a function of the characteristics of vehicle travel, such as cold start, speed, times a vehicle is started, accelerations, and decelerations, in addition to the number of miles driven. On the macro scale, three characteristics, including trip length, speed, and frequency, determine the amount of emissions for each trip.

RESEARCH DATA

2009 National Household Travel Survey (NHTS)

For the empirical analyses in Chapters Four, Five, and Six, this study utilized the 2009 NHTS, which is a nation-wide and household-based travel survey. This survey was conducted over a 14 month-period from March 17, 2008 through May 7, 2009 as a telephone survey (through the landline), which collected travel data from the civilian, non-institutionalized population of the U.S. The sample was a list-assisted random digit dialing (RDD) telephone number sample, which yields an equal probability sample of households with landline telephones (FHWA, 2011). The total number of households interviewed is 150,147, and the survey includes over one million trips made by people in these households during the survey period.

This survey collected information about households (household structure, number of vehicles, income, etc.), individuals (age, gender, employment status, etc.), and vehicles owned by each household (make, model, year, fuel type, etc.), as well as detailed information on daily trips made by all surveyed individuals in a designated 24-hour period. In particular, for each trip made by each member of every household interviewed, the following information was collected: purpose of each trip (work, shopping, etc.); means of transportation used (car, bus, subway, walk, etc.); duration of trip (i.e., travel time); time of day when the trip took place; day of week when the trip took place; and whether it was a private vehicle trip (FHWA, 2011).

The 2009 NHTS survey also contains twenty add-on samples for selected geographic regions. The add-on data have almost the same data structure, but include origin-destination geocodes for all trip purposes and modes. In addition, the NHTS add-on samples provide the geographic coordinates of each household's residence, which enables it to be spatially joined with the land use dataset from other agencies. In this study, nine add-on regions (states) were considered: California, Florida, Georgia, South Carolina, Tennessee, Texas, Vermont, Virginia, and Wisconsin. While the Georgia sample includes 112 households from the state of Alabama, most Texas households reside in the Austin metropolitan areas. The NHTS add-on dataset for each state, except for the Texas NHTS add-on dataset, was collected from the Department of Transportation (DOT) of each state once the official request was made. As part of request process, the research description and the signed confidentiality agreement form were submitted to the DOT person in charge of this dataset. The Texas dataset is available through Google search. Table 3-2 illustrates the variables of the 2009 NHTS Add-on dataset.

File	Variable	Description
HOUSEHOLD	HOUSEID	Household (HH) eight-digit ID number
	DRVRCNT	Number of drivers in HH
	HH_CBSA	CBSA FIPS code for HH address
	HH_HISP	Hispanic status of HH respondent
	HH_RACE	Race of HH respondent
	HHFAMINC	Derived total HH income
	HHSIZE	Count of HH members
	HHVEHCNT	Count of HH vehicles
	HOMELAT	HH latitude
	HOMELONG	HH longitude
	WRKCOUNT	Number of workers in HH
PERSON	PERSONID	Person ID number
	HOUSEID	Household (HH) eight-digit ID number
	DRIVER	Driver status of subject
	EDUE	Highest grade completed
	R_AGE	Respondent age
	R_SEX	Respondent gender
	WRKR	Has a job
VEHICLE	HOUSEID	Household (HH) eight-digit ID number
	VEHID	HH vehicle number used for trip
	FUELTYPE	Type of Fuel
	VEHTYPE	Vehicle type
Table 3-2 is continued on next page		

VEHICLE	VEHYEAR	Vehicle Model year
	VEHAGE	Vehicle Age
	GSYRGAL	Annual fuel consumption in gasoline equivalent gallons
TRIPS	HOUSEID	Household (HH) eight-digit ID number
	PERSONID	Person ID number
	TDCASEID	Trip number
	TRPMILES	Calculated Trip distance converted into miles
	DRVR_FLG	Subject was driver on this trip
	ENDHOUR	Travel day trip end time – hour
	ENDMINUTE	Travel day trip end time – minute
	ENDTIME	Trip END time in military
	NUMONTRP	Count of total people on trip
	PSGR_FLG	Subject was passenger on trip that only used POV
	STRTHR	Travel day trip start time – hour
	STRTMIN	Travel day trip start time – minute
	STRTIME	Trip START time in military
	TRPHHVEH	HH vehicle used for trip
	TRPTRANS	Transportation mode used on trip
	TRVL_MIN	Derived trip time – minutes
	TRVLCMIN	Calculated travel time
	VEHID	HH vehicle number used for trip
	DWELTIME	Calculated Time (minutes) at Destination
	VMT_MILE	Calculated Trip distance (miles) for Driver Trips
LOCATION	TDCASEID	Trip number
	HOUSEID	Household (HH) eight-digit ID number
	PERSONID	Person ID number
	TRPENDLA	Trip end latitude
	TRPENDLO	Trip end longitude

Table 3-2: Selected Variables in the 2009 NHTS Add-on.

The shaded states in Figure 3-2 illustrate the selected states for the analyses in Chapters Four, Five, and Six, and Table 3-3 lists those regions with the number of households for each region. During the cleaning process, households residing within any Core Based Statistical Areas (CBSAs)[11] whose daily VMTs are lower than the 99th

[11] According to the definition from the U.S. Census Bureau, "Core Based Statistical Areas (CBSAs) consist of the county or counties or equivalent entities associated with at least one core (urbanized area or urban cluster) of at least 10,000 population, plus adjacent counties having a high degree of social and economic

percentile (335 miles) of the entire sample were excluded. As a result of the cleaning process, 55,664 households living in 25,843 census block groups (CBGs) within 435 counties and within 207 CBSAs across nine states were chosen.

Figure 3-2: Selected States for the Study.

However, the sample for this study have some limitations. As seen in Table 3-3, three add-on regions (California, Florida, and Virginia) provided relatively large numbers of households. The over-sampled households for these three states may make the sample of this study difficult to represent the entire population. In addition, the fact that two third

integration with the core as measured through commuting ties with the counties associated with the core. The general concept of a CBSA is that of a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core." Retrieved from https://www.census.gov/geo/reference/gtc/gtc_cbsa.html of the sample reflects these three states may make the study results difficult to be generalized to the other regions that are not covered in this study.

Add-on region	**Number of households**
California	16,798
Florida	12,158
Georgia	5,199
South Carolina	4,219
Tennessee	1,840
Texas	1,361
Vermont	1,078
Virginia	11,813
Wisconsin	1,198
Total	55,664

Table 3-3: Study Regions and Numbers of Sample Households for Analyses.

Moreover, the sample for this study involves a bias that is inherent in a typical form of survey. It is known that White households and educated individuals are more willing to participate in a survey and show a higher response rate. 85 percent of households in the sample is a White household, and over 80 percent of the individuals have a high school diploma or equivalent. The lower educated individuals and non-White households therefore tend to be under represented in this sample. The descriptive statistics of the sample for this study and the population are provided in Appendices for comparison (see **A1-1** and **A1-2** in *Appendices*).

Smart Location Database

The Environmental Protection Agency (EPA) developed a Smart Location Database (SLD) that enables users to compare the location efficiency of various places in a consistent manner. The database summarizes several land use measures for every census block group (CBG) in the U.S. Since the database covers the entire U.S., the attributes were consistently measured. Table 3-4 illustrates data used to develop the SLD.

Data Source	What EPA obtained from the Data Source
2010 Census TIGER/Line shapefiles	2010 geographic boundaries of all CBGs in the U.S.; 2010 block group "centers of population"
2010 Census	Basic population, demographic, and housing data for CBG from the 2010 Census Summary File 1 (SF1): housing units, occupancy and tenure, population, race, ethnicity, age, and sex
American Community Survey (ACS)	Additional socioeconomic and demographic variables from the 2006-2010 ACS Five-Year Estimates: household automobile ownership
Longitudinal Employer-Household Dynamics (LEHD)	Employment variables at the census block level for all 50 states, the District of Columbia, Puerto Rico and the US Virgin Island, except for the territories and the Commonwealth of Massachusetts
InfoUSA	Employment variables for Massachusetts to compensate for the lack of data availability in the LEHD
NAVTEQ	Spatially derived variables such as intersection density and automobile accessibility metrics from the NAVSTREETS layer
US Geological Survey (USGS)	Information about land area protected from development (Protected Areas Database) from PAD-US version 1.3
Center for Transit Oriented Development (CTOD)	Locations of all existing fixed-guideway transit (e.g., heavy rail, light rail, commuter rail, streetcars, bus rapid transit with dedicated right of way and cable cars) stations from TOD Database
General Transit Feed Specification (GTFS)	GTFS data for use in metrics summarizing transit service availability, frequency, and accessibility to destinations via transit

Table 3-4: Data Source for Smart Location Database.

This database was joined with the 2009 NHTS add-on datasets, which lag one year behind the SLD. This study, however, assumed that the one-year differences in terms of land use might be very marginal and constant in many regions over the years, which should not have a significant impact on the study results.

This database includes indicators that are the commonly cited as the “D” variables: residential and employment *density*; land-use *diversity*; *design* of the built environment; access to *destinations*; and *distance* to transit (transit service). Table 3-5 below illustrates the D variables in the database and how they were measured.

D variable	**Description**	**Way to Measure**
Density	A variable of interest per unit of area	Population; household; employment; development; activity (# of trip-ends) per unit of developed area
Diversity	The number of different land uses in a given area and the degree to which they are represented	Entropy; jobs-housing or jobs-population ratios
Design	How friendly the local environment is to non-motorized travel	Street network density and street intersection density by facility orientation (automobile, multimodal, or pedestrian)
Transit service	Access to transit	Transit availability, proximity, frequency, and density
Destination accessibility	Ease of access to trip attractions; the characteristics of a place relative to the broader sub-region or region	# of jobs or shopping opportunities within a given travel time; distance from the central business district

Table 3-5: D variables in Smart Location Database.

These D variables in the SLD have, however, several limitations, mostly due to the data availability. When measuring land use *diversity* variables, housing unit counts and job counts broken down by employment sector were utilized. Thus, the diversity-related measures in this database do not tell how different uses or activities are spatially distributed within each of census block group. In addition, urban *design* variables do not provide information regarding the presence or quality of sidewalks although higher intersection density often indicates more walkable environments. Lastly, the population-weighted CBG centroid and the nearest transit stop were used to derive transit proximity measure. Moreover, simply measuring transit frequency within each CBG may not reflect the quality of current transit service in a given area (Ramsey & Bell, 2014).

Motor Vehicle Emission Simulator (MOVES)

The trip information from both household travel surveys were utilized to estimate emission rates by MOVES2014, which is an emission modeling system developed by the EPA to estimate various types of air pollution emissions from mobile sources. Carbon dioxide equivalent (CO_2e), which is a metric measure of the emissions from various greenhouse gases (GHG) based upon their global warming potential (GWP), was estimated using MOVES by taking into consideration several vehicle characteristics, including: vehicle type (i.e., passenger car or passenger truck), fuel type (i.e., gasoline or diesel), age (e.g. vehicle age 0 through 30), speed (i.e., 16 speed bins), engine start mode (8 operation modes), and time of day (24 hours) in addition to VMT.

In this study, the average vehicle travel speed was assumed to be influenced by land use of a given neighborhood. In turn, the amount of emissions generated significantly varies by the average vehicle travel speed. According to the emission rates estimated by

MOVES, on average, a vehicle emits more per mile when it is driven at a lower speed. Furthermore, the changes in the rates look more dramatic in lower speed ranges (up to approximately average speed of 30 mph), while the changes in the rates look consistent regardless of changes in speed above this point (see Figure 3-3).

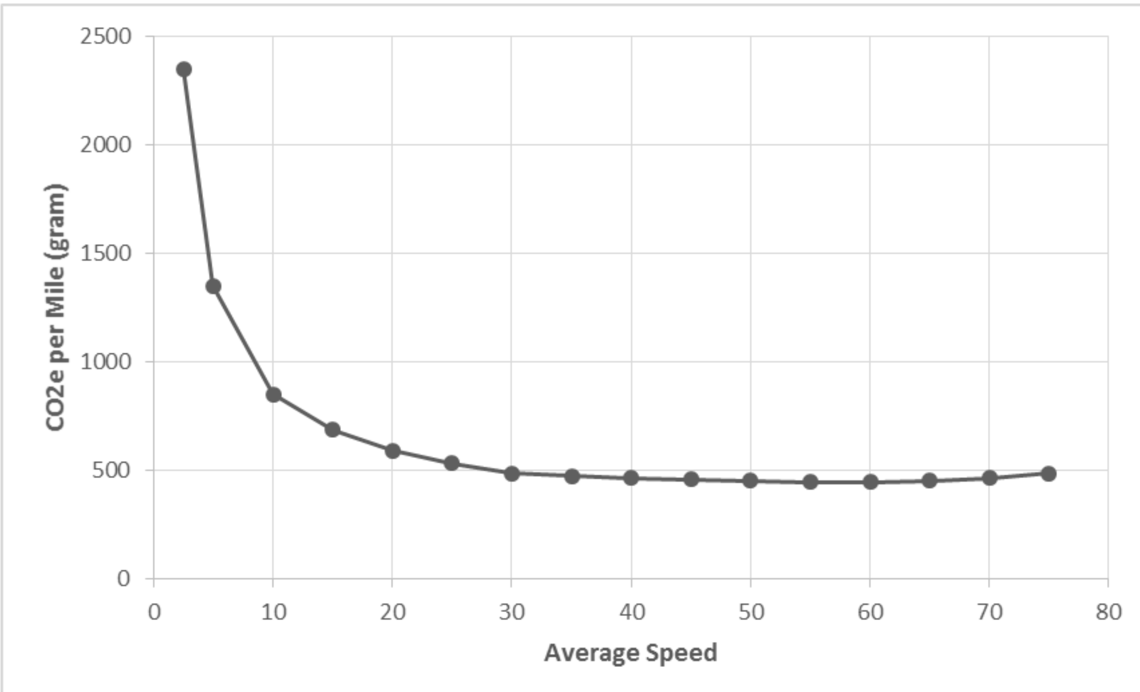

Figure 3-3: Relationship between Average Speed and Emission Rate per Mile.

Emissions from a vehicle are a function not only of VMT and VOS, but also of VT (Ewing et al., 2008). The number of vehicle trips is directly related to the number of vehicle starts, and the amount of emissions per start is associated with engine operation modes. Given that average vehicle operating speed influences emission rates per distance driven, engine operation modes (defined by soak time, which is the duration of time a vehicle's engine is at rest prior to being started) also have effects on emission factors per vehicle start. Simply stated, the longer a vehicle's engine rests, the vehicle emits more when it starts (see Figure 3-4).

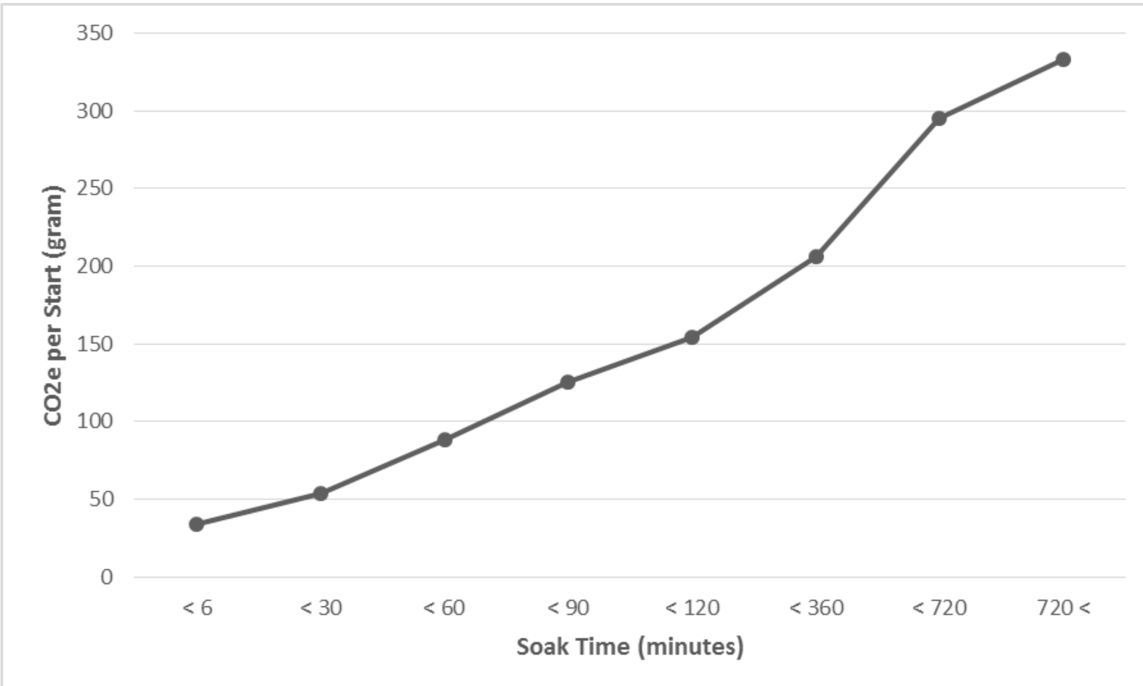

Figure 3-4: Relationship between Engine Operation Mode and Emission Rate per Start.

The link-based CO_2e was calculated considering all factors, including vehicle characteristics, vehicle operating speed, and time of day. The rates for running emissions were first estimated. Then, the rates for start emissions were estimated while considering vehicle characteristics, engine operation mode, and time of day. The time of day in the estimation process reflected the variations in temperature and humidity. The amount of CO_2e for each trip was estimated based on the following equation.

$$CO_2e_i = \text{Start-Emission Rate}_i + (\text{Miles Driven per person in vehicle} \times \text{Running-Emission Rate}_i)$$

CO_2e from trip *i* equals the sum of start emissions of trip *i* (only applied to the trips by drivers because of the difficulty of estimating soak times) and running emissions of trip *i* (i.e., multiplying the number of miles driven per person by the running emission rate for trip *i*). In order to examine the effect(s) of high occupancy, VMT per person was re-estimated based on the information about the population in the vehicle from the travel survey. Emissions for each trip were aggregated into person level, and then aggregated into household level for the analysis. The detailed process for emissions estimation is illustrated in the appendix (see **A2** in *Appendices*).

STUDY VARIABLES

Five categories of variables were derived from various data sources described in the preceding sections. Household demographic and socio-economic characteristics were drawn from the 2009 NHTS add-on household file, while household travel characteristics were derived based on the daily trip file in the same dataset. To derive the neighborhood land use characteristics for each household, the SLD was joined with the NHTS household file based on the information on home locations (i.e., coordinates or census block group identification numbers). Land use characteristics of higher geographic levels were simply derived by aggregating neighborhood-level land use characteristics into a certain level of geography. Lastly, transportation GHG emissions were estimated based on the household travel characteristics by using the MOVES 2014. The study variables are detailed in the following sections.

Household Variables

Four household characteristics that may have the most influence on households' travel behavior were considered. These variables include the number of household members, the number of household vehicles, the number of household workers, and household income in 2009 dollars. All household demographic and socio-economic characteristics considered in the analyses were expected to be directly related with (or to) household daily VMT and transportation GHG emissions.

Neighborhood Land Use Variables

The SLD summarizes land use measures at the CBG level for the entire study area in a consistent manner. Using this nation-wide database, one variable from each D category was considered in the analyses. The neighborhood-level land use variables are detailed as follows.

Density

Density is measured as the variable of interest per unit of area. The SLD variables measure housing units, population, jobs, and activity units (i.e., jobs plus housing) within a block group per unprotected block group acreage. These variables indicate how densely people or employment opportunities are located within a block group. Higher densities should lead to shorter trip lengths by making destinations closer together and make other modes of transportation, such as walking, bike or public transit, more competitive as compared to automobile travel, which can easily serve low-density, dispersed destinations. However, higher densities may cause higher traffic volumes in a given area, which increases the time spent in traffic. This study considered activity density.

Diversity

Land use *diversity* refers to the relative mix of land uses within a given area. In the SLD, these metrics were derived by using housing unit count and job count, broken down by employment sector instead of using the data on land area allocated to different uses within each CBG. As a result, two notable limitations are inherent. First, the diversity-related variables in the SLD do not indicate how well different uses or activities are spatially distributed within a CBG. Another problem is that these variables do not consider activities outside of block group boundaries. This limitation stands out in some higher density urban areas. The size of block groups in these areas tends to be small. Therefore, it is possible that one block with a single use (e.g., residential) might be located next to a block group with multiple uses (e.g., commercial, office) (Ramsey & Bell, 2014).

Nonetheless, mixing different land uses can bring housing closer to jobs and other destinations, such as shopping and recreation, and thus reduce average trip lengths. In addition, other modes of transportation may be more attractive in an area with heterogeneous land use. Employment and housing entropy was considered for the analyses.

Design

Design refers to street network characteristics within a given area. The design variables in the SLD measure urban design feature in terms of street network density and street intersection density by facility orientation (i.e., automobile, multimodal, or pedestrian). Intersection density is often used as an indicator of more pedestrian-friendly urban design, but a high intersection density does not always indicate the presence of the quality of sidewalk. A street network that provides good connectivity between locations and accommodates non-vehicular travel can make other modes of transportation competitive over the automobile. Well-connected street networks can also provide more options for routes to destinations, and thus reduce trip lengths. However, the well-connected street network may require frequent stop-and-go operations, which makes traffic slower. This study considered the street intersection density by all facility orientation (automobile, multimodal, or pedestrian).

Destination Accessibility

Destination accessibility refers to ease of access to trip attractions. In the SLD, the destination accessibility variables measure the number of jobs within a given network travel time (e.g., 45 minutes) by different modes (e.g., auto and transit). The SLD variables also measure accessibility relative to other CBG within the same metropolitan region (i.e., *regional centrality index*). Higher regional accessibility can result in less travel since distances to potential destinations are shorter. However, an area with higher accessibility tends to be a central location within the region to which the area belongs. This area is therefore likely to suffer from higher traffic volumes and concentrated congestions. Since the analyses include a number of different CBSAs, the regional centrality index by automobile (a relative value to each metro area) was used as a proxy for *destination accessibility* (an absolute value).

Distance to Transit

Distance to transit refers to the distance to the nearest rail station or bus stop. The SLD measure both the population-weighted distance to transit of each CBG and transit availability (e.g., transit service coverage), frequency (e.g., transit service frequency per hour), and density (e.g., transit frequency per square mile). Improving transit accessibility can potentially encourage the use of transit, which can reduce vehicular trips. Reduced distances to transit can reduce vehicle trips and VMT by encouraging a shift from driving to public transit, but also by encouraging transit users to walk or bicycle to the station rather than drive. However, higher level of transit service in a given area may make the area congested, which slows the overall traffic in the area. The distance to transit was considered for the analyses. Table 3-6 summarizes the land use variables that were derived from the SLD.

Variable	**Description**	**Method of Calculation**
Activity density	Gross activity density on unprotected land	$\frac{Total\ employment\ and\ housing\ units}{Unprotected\ acreage}$
Diversity	Employment and household entropy	$\frac{-[\sum_{i=1}^{n} P_i \times ln\ P_i]}{ln(n)}$ where P_i is the proportion of employment category *i* in each block group (retail, office, industry, service, entertainment + household)
Design	Street intersection density	$\frac{Total\ intersections}{Total\ land\ area}$
Distance to transit	Distance from population weighted centroid to nearest bus stop (meters)	Minimum walk distance between the population weighted CBG centroid and the nearest transit stop
Destination accessibility	Regional Centrality Index by Auto	$\frac{CBG\ proportional\ accessibility\ to\ regional\ destination}{Max\ CBSA\ proportional\ accessibility\ to\ regional\ desination}$ where proportional accessibility to regional destinations refers to employment accessibility expressed as a ratio of total MSA accessibility

Table 3-6: Land Use Measures.

County and Metro Land Use Variables

The land use variables at the county and CBSA levels were added for the analyses in Chapter Five and Six. All CBG-level variables except for *distance to transit*, were considered for the analyses in these chapters. Exclusion of the distance to transit variable secured the maximum number of cases for the analyses because of the nature of the listwise deletion algorithm, on which HLM 7 software deletes missing data: three quarters of the surveyed households were not served by public transit. The variables for higher geographic levels were derived by aggregating the variables at the CBG level in the SLD into appropriate levels of geography (i.e., county or CBSA). This aggregation process was expected to prevent the measurement biases (Nasri & Zhang, 2015).

County-Level Variables

Three land use variables at the county level were considered. First of all, the gross activity density at the county level was considered. Jobs and housing balance for *diversity* and total road network density for *design* were considered because these measures could be more reasonable at this level of geography. None of the transit and destination accessibility-related variables at this level were considered.

CBSA-Level Variables

Three land use variables at the CBSA level were considered. The size of total unprotected land area of each CBSA was considered. It was expected that households in a larger CBSA are likely to travel and drive more because of a relatively larger daily activity space. Similar to the county level, gross activity density and total road network density at this level of geography were considered.

Travel Variables

Three vehicle travel characteristics that may be the most influential factors to determine the amount of transportation GHG emissions associated with vehicle activities were considered in this study.

Vehicle Miles Traveled (VMT)

The 2009 NHTS add-on datasets recorded the mode of transportation and driver status (i.e., indicating whether a person was a driver or a passenger for a given trip) as well as trip length for each trip. To estimate household daily VMT, only trips whose mode of transportation was one of a privately operated vehicle (POV) (i.e., car, van, SUV, pickup truck, and other truck) were selected first, and then, trips indicating a driver trip were selected. The individual driver's trip lengths, made by any of POVs above, were then aggregated into the household level to compute the total household daily VMT.

Vehicle Operating Speed (VOS)

The individual driver's trips also have the information on the duration of one's travel (i.e., travel time). This travel time information was utilized to estimate average vehicle operating speed (VOS), in conjunction with the length of individual driver's trip. The driver's POV trip length was divided by travel time to compute household average vehicle travel speed.

Vehicle Trip Frequency (VTF)

Similar to the VMT estimation, the individual driver's trips made by any POVs were considered vehicle trips. The number of vehicle trips was then aggregated into the household level to estimate the total household daily vehicle trips frequency.

Transportation GHG Emissions (CO_2e)

As illustrated in the *Motor Vehicle Emission Simulator (MOVES)* section, link-based carbon dioxide equivalent (CO_2e) was estimated while considering vehicle characteristics, the time of day, vehicle travel speed, engine operating mode, and vehicle miles traveled.

Table 3-7 reports the descriptive statistics for the sample for the analyses in the three following chapters. All variables, except for household socio-economic variables, were logarithmically transformed to improve multivariate normality and to make it easier to interpret and compare the outcomes from the models. First of all, logarithmic transformations are convenient ways to reduce variables being skewed. For instance, most variables in this study are right-skewed. By transforming, the distributions of these variables look more normal. In addition, the outcomes in a log-log model represent elasticities, which are an expected change when an independent variable increases by one percent.

Variable	Name	Min.	Max.	Mean	SD
Household demographic and socio-economic characteristics					
Household size	HHSIZE	0	13	2.45	1.24
Household vehicles	HHVEH	0	15	2.23	1.11
Household workers	HHWRKS	0	6	1.03	.90
Household income	HHINC	0	150	69413	49885
Household travel characteristics (n=55,664)					
Vehicle miles traveled (miles)	VMT	0.11	335.00	42.12	37.07
Average household vehicle operating speed (mile/hour)	VOS	0.22	84.00	24.54	10.56
Vehicle trip frequency	VT	1	38	5.86	3.63
Household CO2e (grams)	CO2e	157.40	221022.42	21129.85	17656.49
Household daily gasoline consumption (gallons)	GASDAY	0.003	184.90	3.21	2.75
CBG-level land use characteristics (n=25,843)					
Activity density (per acre)	DEN	0.00	611.37	3.99	8.07
Jobs and housing entropy	DIV	0.00	1.00	.46	.22
Intersection density (per square mile)	DES	0.00	804.58	69.97	63.62
Distance to transit (meters)	DT	0.22	1205.77	541.70	297.55
Regional centrality	DA	0.00	1.00	.46	.23
County-level land use characteristics (n=435)					
Activity density (per acre)	DEN_C	.01	38.65	1.79	2.92
Jobs and housing balance	DIV_C	.17	3.03	1.05	.32
Road network density (miles/acre)	DES_C	.47	27.60	5.06	3.62
CBSA-level land use characteristics (n=207)					
Unprotected land area (mi2)	SIZE_M	59.86	9198.17	2448.75	1837.41
Activity density (per acre)	DEN_M	.02	4.82	1.19	1.30
Road network density (miles/acre)	DES_M	.60	8.17	3.82	1.69

Table 3-7: Study Variables.

ANALYTICAL TOOLS

The ordinary least squares (OLS) regression is widely used to learn more about the relationship between several independent variables and a dependent variable. The multiple regression approaches were applied to examine the relationship between land use and vehicle travel as well as transportation GHG emissions in Chapter Four. Besides this relatively simple statistical approach, this study applied two more advanced statistical techniques as follows.

Hierarchical Linear Model

To understand the scale-sensitive effects of land use on household daily VMT and transportation GHG emissions, hierarchical linear modeling (HLM) approaches were employed. "HLM is a complex form of OLS regression that is used to analyze variance in the outcome variables when the predictor variables are at varying hierarchical levels (Woltman, Feldstain, Mackay, & Rocchi, 2002, page 52)." In other words, HLM is a statistical framework that is designed to analyze *nested relationships* (Anderson, 2012).

The primary interest of this dissertation research is the land use factors that affect household travel. Thus, this study theorized factors associated with the built environment at different geographic levels as well as the households themselves. Each of these factors associated with household travel could be conceptualized as different levels of nesting—households (Level-1) are nested within neighborhoods (Level-2), which are nested within counties (Level-3), which are then nested within metropolitan areas (Level-4)—in which each level potentially impacts household travel.

Thus, this approach is appropriate in this situation because "HLM allows researchers to investigate these nested relationships and either parses them out (i.e., control for higher-level factors to examine the unique effect of a specific variable), or examines the impact of variables at the higher levels (Anderson, 2012, page 1).”

HLM Notation

In this section, the notation for four-level HLM will be presented. The notion for all HLM models can be displayed in two ways: by the level of analysis, or in a single equation called a “mixed model.” Since the four-level model can be complicated, the notation here is displayed by the level of analysis. The following equation represents the Level 1 regression:

$$Y_{ijkl} = \pi_{0jkl} + \pi_{1jkl}\ \alpha_{ijkl} + e_{ijkl}$$

where

Y_{ijkl} refers to the score on the dependent variable for an individual observation at Level 1,

π_{0jkl} refers to the intercept of the dependent variables in group *j,k,l*,

π_{1jkl} refers to the slope for the relationship in group *j,k,l* between the Level 1 predictor and the dependent variable,

α_{ijkl} refers to the Level 1 predictor, and

e_{ijkl} refers to the random errors of prediction for the Level 1 equation

Then, the Level 2 regressions are expressed in the forms below.

$$\pi_{0jkl} = \beta_{00kl} + \beta_{01kl}\ X_{jkl} + r_{0jkl}$$

$$\pi_{1jkl} = \beta_{10kl} + r_{1jkl}$$

where

β_{00kl} refers to the overall intercept,

β_{01kl} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 2 predictor,

X_{jkl} refers to the Level 2 predictor,

r_{0jkl} refers to the random error component for the deviation of the intercept of a group from the overall intercept,

β_{10kl} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 1 predictor, and

r_{1jkl} refers to the error component for the slope (meaning the deviation of the group slopes from the overall slope)

Then, the level-3 and level-4 models are expressed as the following equations.

$$\beta_{00kl} = \gamma_{000l} + \gamma_{001l} W_{kl} + u_{00kl}$$

$$\beta_{01kl} = \gamma_{010l} + u_{01kl}$$

$$\beta_{10kl} = \gamma_{100l} + u_{10kl}$$

where

γ_{000l} refers to the overall intercept,

γ_{001l} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 3 predictor,

W_{kl} refers to the Level 3 predictor,

u_{00kl} refers to the random error component for the deviation of the intercept of a group from the overall intercept,

γ_{010l} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 2 predictor,

u_{01kl} refers to the error component for the slope,

γ_{100l} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 1 predictor, and

u_{10kl} refers to the error component for the slope (meaning the deviation of the group slopes from the overall slope)

$$\gamma_{000l} = \delta_{0000} + \delta_{0001} Z_l + v_{000l}$$

$$\gamma_{001l} = \delta_{0010} + v_{001l}$$

$$\gamma_{010l} = \delta_{0100} + v_{010l}$$

$$\gamma_{100l} = \delta_{1000} + v_{100l}$$

where

δ_{0000} refers to the overall intercept,

δ_{0001} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 4 predictor,

Z_l refers to the Level 4 predictor,

v_{000l} refers to the random error component for the deviation of the intercept of a group from the overall intercept,

δ_{0010} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 3 predictor,

v_{001l} refers to the error component for the slope,

δ_{0100} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 2 predictor,

v_{010l} refers to the error component for the slope (meaning the deviation of the group slopes from the overall slope)

δ_{1000} refers to the overall regression coefficient, or the slope, between the dependent variable and the Level 2 predictor, and

v_{100l} refers to the error component for the slope (meaning the deviation of the group slopes from the overall slope)

Structural Equation Model

Throughout the study, cross-sectional models were estimated to quantify the impact of land use on transportation GHG emissions by considering the intermediate factors (vehicle travel). Structural equation modeling (SEM) approaches were employed to develop path models that account for possible relationships among variables, thus statistically controlling for possible endogeneity problems.

As a modeling tool, SEM has gained acceptance in a range of fields, including education, psychology, public health, and transportation (Golob, 2003). This powerful modeling technique can handle a large number of endogenous and exogenous variables, and allow for the simultaneous prediction of multiple variables in one model. With multiple equations in one model, a variable can be a dependent variable in one equation and an independent variable in another equation. This technique is, therefore, very useful for examining complex relationships by allowing modelers to estimate the relative direct and indirect effects of variables on each other. Moreover, the use of SEM enables researchers to capture many synergistic effects among independent variables (Ewing et al., 2014).

In addition, potential endogeneity problems can be statistically controlled through the use of maximum likelihood estimation (MLE) that allows both one-way and two-way relationships between variables to be modeled (Cervero & Murakami, 2010). Hence, this approach is appropriate to quantify the net effects of the built environment on transportation GHG emissions through various channels.

Mathematical Expression

The mathematical equations of the endogenous and exogenous variables and the disturbance terms are specified in the form below:

$$\mathbf{y} = \mathbf{B}\mathbf{y} + \boldsymbol{\Gamma}\mathbf{x} + \boldsymbol{\zeta} \ ,$$

where $\mathbf{y}$ = $N_y \times 1$ vector of endogenous variables (N_y is the number of endogenous variables including transportation GHG emissions and vehicle travel characteristics),

$\mathbf{B}$ = $N_y \times N_y$ coefficient matrix relating endogenous variables (represents the direct effects from endogenous variables on other endogenous variables),

$\boldsymbol{\Gamma}$ = $N_y \times N_x$ coefficient matrix relating exogenous and endogenous variables (represents the direct effects from exogenous variables on endogenous variables),

$\mathbf{x}$ = $N_x \times 1$ vector of exogenous variables (N_x is the number of exogenous variables including the built environment measures, socio-economic characteristics, and urban latent variable), and

$\boldsymbol{\zeta}$ = $N_y \times 1$ vector of error terms.

Chapter Four: Neighborhood-Level Land Use, Vehicle Travel, and Transportation GHG Emissions

As demonstrated in the *Literature Review* chapter, land use in a given area influences not only the number of miles its residents drive, but also speed and frequency along with other aspects of vehicle travel; these factors together determine the level of transportation GHG emissions. This chapter therefore sets two objectives. First, this chapter examines how the neighborhood-level land use influences household daily VMT and transportation GHG emissions by employing the ordinary least square (OLS) approach. The findings from the analyses suggest that the magnitude of the effects of land use on household daily VMT and transportation GHG emissions (CO_2e) is not identical. Hence, this chapter tests whether the neighborhood-level land use also influences vehicle travel speed and vehicle trip frequency, and how these vehicle travel characteristics affect transportation GHG emissions.

LAND USE, VMT, AND TRANSPORTATION GHG EMISSIONS

This chapter first tests whether land use changes will lead to VMT reduction. A multiple regression model in which household daily VMT was a dependent variable and five D variables were independent variables is specified. Next, this chapter tests whether VMT reduction will proportionally reduce transportation GHG emissions by running the same multiple regression model, but considering household daily transportation GHG emissions (CO_2e) as a dependent variable in the model. Lastly, this chapter examines the relationship between land use changes and vehicle travel speed as well as vehicle trip frequency to identify possible factors to account for the differences in the magnitude of the effects.

Neighborhood-Level Land Use and Household Daily VMT

Table 4-1 presents the results of the multiple regression model with household daily VMT as a dependent variable. As initially expected, all D-variables show a negative sign, and they are statistically significant with the exception of *Distance to transit*. These results suggest that one or more land use changes are likely to influence household daily VMT. Increasing density, mixing land use, improving street network connectivity, or clustering employment opportunities can lead to VMT reduction. The coefficients in Table 4-1 represent the associated percentage change in household daily VMT corresponding to one percent change in each of the land use attributes. For instance, a 1% increase in activity density in a given area may lead to a 0.06% reduction in household daily VMT.

Variable	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Activity density	-0.060**	0.014	-0.096	-4.335	0.000
Diversity	-0.048**	0.014	-0.028	-3.512	0.000
Intersection density	-0.044**	0.016	-0.058	-2.776	0.006
Distance to transit	-0.007	0.012	-0.005	-0.621	0.535
Regional centrality	-0.029**	0.011	-0.022	-2.597	0.009
Household size	0.073**	0.007	0.084	9.705	0.000
Household vehicles	0.095**	0.008	0.098	11.181	0.000
Household workers	0.293**	0.011	0.246	27.220	0.000
Household income	0.002**	0.000	0.108	13.131	0.000
(Constant)	2.601	0.072		35.961	0.000
* significant at 0.05; ** significant at 0.01 R square: 0.196					

Table 4-1: OLS Regression Model of Log-Transformed VMT.

Three explanations for the insignificant coefficient of *Distance to transit* can be suggested. First, only a quarter of the sample (14,640 out of 55,664) live in a neighborhood where public transit is available. This small percentage of the sample might result in the insignificant coefficient for the variable. Second, the impact of transit on household daily VMT can be absorbed by the impact of other land use changes. It is very likely that a regional center with higher density, heterogeneous land use, and better connectivity is served by public transit. Lastly, a majority of households may still use their automobiles as a primary mode of transportation even though they live near rail stations or bus stops.

Besides land use changes, all household demographic and socio-economic characteristics are strongly and positively associated with household daily VMT. The number of household workers seems to be the strongest factor in determining household daily VMT, followed by household income, vehicles, and size. This finding is consistent with previous studies, and seems very reasonable because home-based work trips account for a significant portion of household travel in most cases.

Neighborhood-Level Land Use and Household Daily CO_2e

CO_2e was regressed on the same set of independent variables to test whether VMT reduction and reduction in transportation GHG emissions by land use changes are identical. Table 4-2 presents the results of the multiple regression model with CO_2e as a dependent variable.

Similar to the VMT model (see Table 4-1), all household characteristics have a significant impact on household daily transportation GHG emissions. However, the coefficients do not seem to be identical. One explanation can be suggested for this finding. Household demographic and socio-economic characteristics, as well as residential location, may influence the vehicle types owned and used by households. For instance, households with more children may prefer having a large vehicle, such as SUVs or vans, which generates more GHG emissions compared to smaller/compact passenger cars (Liu & Shen, 2011). Moreover, it is very likely that households living in a dense neighborhood will have more fuel-efficient cars (Brownstone & Golob, 2009).

Variable	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Activity density	-0.047**	0.012	-0.088	-3.993	0.000
Diversity	-0.037**	0.012	-0.025	-3.199	0.001
Intersection density	-0.024	0.013	-0.037	-1.782	0.075
Distance to transit	-0.008	0.010	-0.007	-0.825	0.409
Regional centrality	-0.021*	0.009	-0.019	-2.227	0.026
Household size	0.088**	0.006	0.120	13.792	0.000
Household vehicles	0.087**	0.007	0.105	12.063	0.000
Household workers	0.251**	0.009	0.247	27.379	0.000
Household income	0.002**	0.000	0.091	11.112	0.000
(Constant)	8.919	0.062		144.906	0.000
* significant at 0.05; ** significant at 0.01 R square: 0.203					

Table 4-2: OLS Regression Model of Log-Transformed CO_2e.

In terms of the effects of neighborhood-level land use on household daily transportation GHG emissions, it is certainly worth noting that the coefficients for the land use variables are relatively smaller than those in the VMT model (compared to Table 4-1). For example, the effect of *intersection density* reduced by 45 percent (-0.044 to -0.024), and this coefficient even became statistically insignificant at the 0.05 significant level in the CO_2e model. Other effects with respect to land use changes also reduced, ranging from 14 to 27 percent. The results from two tables (Table 4-1 and 4-2) suggest that VMT reduction through land use changes may not lead to proportional reduction in transportation GHG emissions for several reasons. In the following section, possible factors for these differences will be discussed.

Neighborhood-Level Land Use and Vehicle Travel Speed and Frequency

It is very likely that land use changes influence other aspects of household vehicle travel. For instance, densification efforts may lead to higher traffic volume in the area due to higher travel demand, or a neighborhood with a well-connected street network may require drivers to make more frequent stop and go operations, which results in slower movement in the area. Moreover, bringing origins and destinations closer may result in more frequent short-distance vehicle trips unless people shift to other modes of transportation, such as walking, bike, or public transit. Thus, the effects of land use changes on household average vehicle operating speed (VOS) and daily vehicle trip frequency (VTF) were examined.

Table 4-3 presents the result of an OLS regression model of log-transformed VOS. Interestingly, a well-off household with more vehicles or workers is likely to drive faster. One possible explanation for these results is that these households tend to reside either in the urban periphery or the suburbs, where relatively larger houses are available. These areas are likely to provide their residents with more automobile-friendly environments (e.g., nearby highways), and therefore, they could drive faster than those living in the urban areas.

All land use variables, with the exception of *Diversity*, are negatively associated with household average VOS and are statistically significant. These coefficients indicate that land use changes may lead to slower vehicle movements to some extent in the areas. For instance, the coefficient of -0.065 for *Activity density* suggests that doubling activity density in a given area can reduce the average vehicle travel speed in the area by 6.5 percent. Similarly, other land use changes, such as improving street network connectivity, increasing accessibility to transit, or clustering employment opportunities, may lead to congestion in the area. These findings appear very plausible and demonstrate that land use changes influence the household average vehicle travel speed as well as household daily VMT.

Variable	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Activity density	-0.065^{**}	0.007	-0.222	-9.673	0.000
Diversity	-0.008	0.007	-0.010	-1.205	0.228
Intersection density	-0.015^{*}	0.008	-0.043	-2.002	0.045
Distance to transit	-0.013^{*}	0.006	-0.021	-2.338	0.019
Regional centrality	-0.013^{*}	0.005	-0.022	-2.460	0.014
Household size	0.005	0.004	0.013	1.468	0.142
Household vehicles	0.025^{**}	0.004	0.054	5.964	0.000
Household workers	0.085^{**}	0.005	0.152	16.176	0.000
Household income	0.001^{**}	0.000	0.108	12.778	0.000
(Constant)	3.001	0.035		85.084	0.000
* significant at 0.05; ** significant at 0.01 R square: 0.138					

Table 4-3: OLS Regression Model of Log-Transformed VOS.

Lastly, household daily vehicle trip frequency was regressed on the same set of independent variables in the two previous models. Table 4-4 shows the relationship between household daily vehicle trip frequency and land use changes, as well as household characteristics.

As demonstrated in other studies, the results here show that household demographic and socio-economic characteristics seem to be stronger determinants of household daily vehicle travel frequency than land use measures (Ewing & Cervero, 2010). The coefficients for household variables indicate that a household with more members, vehicles, workers, or earnings are likely to make more vehicle trips. Among them, household workers are the strongest factor, which is then followed by household size, vehicles, and income.

Variable	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
Activity density	0.006	0.008	0.017	0.730	0.465
Diversity	0.003	0.008	0.003	0.383	0.702
Intersection density	0.002	0.010	0.005	0.238	0.812
Distance to transit	0.038**	0.007	0.049	5.510	0.000
Regional centrality	0.033**	0.007	0.043	4.973	0.000
Household size	0.074**	0.005	0.146	16.316	0.000
Household vehicles	0.052**	0.005	0.091	10.113	0.000
Household workers	0.134**	0.006	0.193	20.677	0.000
Household income	0.001**	0.000	0.079	9.384	0.000
(Constant)	0.871	0.044		19.968	0.000
* significant at 0.05; ** significant at 0.01 R square: 0.147					

Table 4-4: OLS Regression Model of Log-Transformed VTF.

In terms of the effects of neighborhood-level land use, the results are very interesting. Households from a neighborhood with easy access to transit or better regional accessibility are likely to make more vehicle trips. Two possible explanations can be suggested for these findings. First, this may reflect the high reliance on private automobiles of the sample. Regardless of the existence of other transportation options, people are still willing to drive their own vehicles to travel. However, the household daily VMT can be smaller in this neighborhood because of relatively closer destinations while they make more frequent automobile trips. Second, the measurement of distance to transit could be inaccurate. The SLD used a weighted population centroid to compute distance to transit of each CBG. However, this result suggests that households still make more short-distance vehicle trips rather than shifting to other modes of transportation.

Vehicle Travel and CO_2e

Lastly, this chapter examines how the three vehicle travel characteristics are associated with household daily transportation GHG emissions. Table 4-5 presents the results of the model in which CO_2e were regressed on three vehicle travel characteristics.

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
VMT	0.917**	0.001	1.073	635.417	0.000
VOS	-0.376**	0.002	-0.207	-152.457	0.000
VTF	0.052**	0.002	0.036	27.513	0.000
(Constant)	7.658	0.006		1229.465	0.000
* significant at 0.05; ** significant at 0.01 R square: 0.956					

Table 4-5: OLS Regression Model of Log-Transformed CO_2e.

As expected, all three vehicle travel variables appear to be statistically significant. The findings show that CO_2e is positively associated with VMT and VTF, but negatively associated with VOS. The elasticity of CO_2e with respect to VMT was expected to be approximately one (i.e., a one-percent decrease in VMT should correspond to one-percent decrease in CO_2e). However, a one percent change in VMT appears to be associated with a 0.92% change in CO_2e because of the secondary effects of VOS and VTF on CO_2e. Table 4-5 shows that not only vehicle travel distance (0.924), but also vehicle travel speed (-0.376) and vehicle trip frequency (0.052) influence transportation GHG emissions. These three variables together can explain 95.6 percent of variations in CO_2e. The remaining variations can be explained by other household vehicle characteristics, such as vehicle type, fuel type, age, etc. The findings from a series of OLS regressions in this chapter demonstrate that VMT reduction through land use changes will not proportionally reduce transportation GHG emissions, mainly due to the secondary effect caused by lowering vehicle travel speed and other factors, such as vehicle trip frequency as well as vehicle characteristics owned and used by households.

SUMMARY

The overall study results suggest that simply converting VMT reduction into transportation GHG emissions reduction (i.e., translating a 1% reduction in VMT into a 1% decrease in CO_2e) can over-estimate the environmental benefits of land-use based strategies at the neighborhood level. This is mainly due to overlooking the secondary effect of reduced vehicle travel speed, as well as disregarding the impact of vehicle trip frequency on transportation emissions. Table 4-6 summarizes elasticities of land use variables tested in this chapter with respect to four outcome variables.

Land Use Variable	CO_2e	Vehicle Travel Characteristics		
		VMT	VOS	VTF
Activity density	-0.047	-0.060	-0.065	0.006
Diversity	-0.037	-0.048	-0.008	0.003
Intersection density	-0.024	-0.044	-0.015	0.002
Distance to transit	-0.008	-0.007	-0.013	0.038
Regional centrality	-0.021	-0.029	-0.013	0.033
Total effect	-0.137	-0.188	-0.114	0.082
* significant at 0.05; ** significant at 0.01				

Table 4-6: Elasticities of Land Use.

Total effects represent the sum of elasticities of all land use variables. According to Table 4-6, a 100% increase in all land use factors can generate 13.7% and 18.8% reductions in transportation GHG emissions and VMT, respectively. These results suggest that the ratio of GHG emissions reduction to VMT reduction is 7 to 10, particularly reflecting lower vehicle travel speed in this study. The difference is more substantial than other studies (Ewing et al., 2008). Thus, the findings suggest that other factors regarding vehicle travel, such as vehicle travel speed and vehicle trip frequency, in addition to vehicle miles traveled, should be taken into account when quantifying the environment impact of land use changes on transportation emissions.

Notwithstanding the secondary effect of reduced vehicle travel speed, the findings from the analyses in this chapter demonstrate that the environmental benefits of land-use based strategies through VMT reduction are far enough to offset the emission penalties by slower vehicle movements. Efforts to increase density (e.g., multi-family housing or office buildings) or improve pedestrian environment (e.g., smaller blocks or intersections) to a given area can lead to a reduction in automobile use. At the same time, however, these efforts may result in slower vehicle movements in the area unless the vehicle travel demand of the area reaches a certain level at which all modes of transportation are unimpeded by any other modes. In terms of vehicle trip generation, it would be necessary to design policies to encourage people to shift to sustainable modes of transportation.

Therefore, it would also be very important to consider the effects of land use based policies on vehicle travel speed and vehicle trip frequency in order to maximize their environmental benefits when the policies are designed, implemented, and evaluated.

Chapter Five: The Impact of Land Use at Multiple Geographic Level on Transportation GHG Emissions

In the preceding chapter, the relationships between land use at the neighborhood level (i.e., CBG) and household daily VMT, as well as transportation GHG emissions were investigated. In reality, however, individuals' or households' travel can also be influenced by land use settings at larger geographic levels (e.g., counties, cities, or metropolitan areas) because they live in a neighborhood within a county or a city that is situated in a metropolitan area. Thus, this chapter examines how land use changes at multiple geographic levels influence household daily VMT and transportation GHG emissions.

Utilizing the same dataset in the previous analyses, this chapter attempts to examine the relationship between land use and household daily VMT as well as transportation GHG emissions at various geographic levels. This study also utilizes the SLD to derive the land use variables at two higher geographic levels (i.e., county and CBSA). Hierarchical linear modeling (HLM) techniques were employed to examine the effects of land use at different geographic levels on household vehicle travel. The findings demonstrate that household daily VMT and transportation GHG emissions are not only influenced by neighborhood-level land use, but also affected by the larger geographical context in a very sophisticated way.

HLM Model Specification

HLM techniques are appropriate for the analyses in this chapter because land use (predictor variables) is at varying hierarchical levels (Woltman et al., 2002). Two outcome variables, including VMT and CO_2e, were considered in the HLM model specifications. Because this study assumed that the land use measures at three geographic levels (i.e., CBG, county, and CBSA), as well as the household traits, influence the outcome variables, four level HLM models were specified. The HLM models here are expected to account for the nested nature of households within CBGs, counties, and CBSAs.

Single-Level Regression Model

Prior to specifying multi-level models, a single-level multiple regression, in which all independent variables were considered as the same level of predictors, was specified. The results of this single-level regression will be compared to the final multi-level regression results later. This single regression equation can be displayed as follows:

$$Y_i = \beta_0 + \beta_i X_i + e_i$$

where:

Y_i = dependent variable measured for i^{th} unit,

X_i = value on the predictor,

β_0 = intercept

β_i = regression coefficient associated with X_i

e_i = error associated with the i^{th} unit

In the context of this study, the regression equation can be redefined as follows, and Table 5-1 displays the results from the single-level multiple regression analysis:

$$Y_i = \beta_0 + \beta_1 \times HHINC + \beta_2 \times HHSIZE + \beta_3 \times HHWRKS + \beta_4 \times HHVEH + \beta_5 \times DEN + \beta_6 \times DIV + \beta_7 \times DES + \beta_8 \times DA + \beta_9 \times DEN\_C + \beta_{10} \times DIV\_C + \beta_{11} \times DES\_C + \beta_{12} \times SIZE\_M + \beta_{13} \times DEN\_M + \beta_{14} \times DES\_M + e_i$$

Variables	Single-Level Regression (VMT)				Single-Level Regression (CO_2e)			
	Coef.	S.E	t-ratio	p-value	Coef.	S.E	t-ratio	p-value
Intercept, β_0	2.172	0.058	37.287	0.000	8.568	0.050	172.896	0.000
HHINC, β_1	0.002**	0.000	24.464	0.000	0.002**	0.000	20.324	0.000
HHSIZE, β_2	0.071**	0.004	18.370	0.000	0.086**	0.003	26.328	0.000
HHWRKS, β_3	0.295**	0.006	53.345	0.000	0.253**	0.005	53.711	0.000
HHVEH, β_4	0.095**	0.004	21.989	0.000	0.088**	0.004	23.754	0.000
DEN, β_5	-0.077**	0.007	-11.044	0.000	-0.064**	0.006	-10.692	0.000
DIV, β_6	-0.038**	0.007	-5.391	0.000	-0.028**	0.006	-4.562	0.000
DES, β_7	-0.048**	0.007	-6.351	0.000	-0.028**	0.006	-4.386	0.000
DA, β_8	0.015*	0.007	2.058	0.040	0.015*	0.006	2.424	0.015
DEN_C, β_9	0.054**	0.017	3.245	0.001	0.062**	0.014	4.318	0.000
DIV_C, β_{10}	-0.106**	0.019	-5.424	0.000	-0.095**	0.017	-5.719	0.000
DES_C, β_{11}	-0.100**	0.028	-3.591	0.000	-0.104**	0.024	-4.374	0.000
SIZE_M, β_{12}	0.050**	0.007	7.568	0.000	0.040**	0.006	7.055	0.000
DEN_M, β_{13}	-0.037*	0.018	-2.101	0.036	-0.040**	0.015	-2.680	0.007
DES_M, β_{14}	0.181**	0.033	5.444	0.000	0.175**	0.028	6.191	0.000
R^2	0.200				0.206			
* significant at 0.05; ** significant at 0.01								

Table 5-1: Single-Level OLS Regression Model of Log-Transformed VMT and CO_2e

The results of the single-level regression models here suggest that the set of independent variables account for approximately 20 and 21 percent of the variance in household daily VMT and CO_2e, respectively. All variables considered appear to be statistically significant.

The corresponding coefficients for the two models are supposed to be identical. However, they seems to be slightly different. The difference in the coefficients for household variables may arise from the type of vehicles that households own based on their economic conditions. For instance, a large household tends to own a bigger car such as a SUV or van, which probably generates more emissions per use. It is also possible that a household may have a compact car as a primary vehicle and a larger car as their secondary vehicle. The results here suggest that the type of vehicles households own can affect to some extent how much more or less they generate transportation GHG emissions.

As demonstrated in the preceding chapter, the differences in the coefficients of land use variables may result from the effects of these variables on other aspects of vehicle travel, such as vehicle travel speed and vehicle trip frequency. Reducing vehicle travel speed can counter the effect of vehicular travel reduction, and the mixed effects on vehicular trip generation rates may cause the difference in the coefficients. These relationships will be investigated in depth in the next chapter.

Unconditional (null) Model

As the first step of HLM, a *one-way analysis of variance* (ANOVA) was performed to confirm that the variability in the outcome variable by groups of different levels is significantly different from zero. This unconditional, or null, model was tested to see whether there were any differences at the group levels on the outcome variables. In other words, the null model serves a purpose to justify the necessity of multilevel modeling (Garson, 2013). The mixed model can be displayed in the following single regression equation:

$$Y_{ijkl} = \delta_{0000} + r_{0jkl} + u_{00kl} + v_{000l} + e_{ijkl}$$

Fixed Effects	Model 1: Unconditional (VMT)				Model 1: Unconditional (CO2e)			
	Coef.	**S.E.**	**t-ratio**	**p-value**	**Coef.**	**S.E.**	**t-ratio**	**p-value**
Intercept, δ_{0000}	3.379	0.015	219.119	<0.001	9.656	0.013	751.089	<0.001
Random Effects	**Standard Deviation**	**Variance Component**	$\chi 2$	**p-value**	**Standard Deviation**	**Variance Component**	$\chi 2$	**p-value**
Within-household,e	1.009	1.018			0.878	0.770		
Intercept (L-2), r_0	0.258	0.066	10128.064	<0.001	0.197	0.039	9751.697	<0.001
Intercept (L-3), u_{00}	0.149	0.022	474.109	<0.001	0.114	0.013	423.855	<0.001
Intercept (L-4), v_{000}	0.084	0.007	227.195	0.127	0.075	0.006	240.716	0.040
Deviance	61161.255				55054.515			

Table 5-2: HLM Results: Unconditional (null) Model.

The combined model looks as it is shown above (Table 5-2). For these models, the most important result to examine is the chi-square test (χ^2) for the variance components. According to the results in Table 5-2, all chi-square values are statistically significant, except for the intercept for the Level-4 (CBSA) in the VMT model. Overall, the results indicate that there are variances in the outcome variables by the Level-2, -3, and -4 groupings, and that there is statistical justification for running HLM analyses (Garson, 2013).

As an additional step, the intra-class correlation (ICC) that represents the percentage of variance in the outcomes (VMT and CO_2e) between groups (CBG, County, and CBSA) can be calculated to determine which percentage of the variance in the outcomes is attributable to group memberships, and which percentage is at the household level. In other words, the ICC falls between 0 and 1 and indicates the proportion of the total variance that lies between groups (Anderson, 2012).

The ICC can be calculated by using the e (Level-1), r_o (Level-2), u_{oo} (Level-3), and v_{000} (Level-4) terms. For instance, the ICC for Level-2 can be calculated by using the following equation, and Table 5-3 reports the ICC values for each level of grouping for each outcome:

$$\text{ICC} = \frac{r_o}{e+r_o+u_{oo}+v_{000}}$$

where:

e = variance at Level-1,

r_o = variance at Level-2,

u_{oo} = variance at Level-3,

v_{000} = variance at Level-4

Group membership / Outcomes	**VMT**	**CO2e**
CBG	0.059	0.047
County	0.020	0.016
CBSA	0.006	0.007

Table 5-3: Intra-Class Correlation Results.

Table 5-3 suggests that approximately 5.9%, 2.0%, and 0.6% of the variance in household daily VMT depended respectively upon the CBG, County, and CBSA where households reside. Similarly, 4.7%, 1.6%, and 0.7% of the variance in household daily transportation GHG emissions are at these three geographic levels, respectively.

In summary, the null model has demonstrated that there are significant effects of higher geographic levels on household automobile use and its associated emissions generation; that multi-level modeling is therefore needed; and that the neighborhood level effect is the most influential factor.

Random Intercept Model

Next, the relationship between household characteristics (Level-1 predictor variables) and the outcome variables (VMT and CO_2e) was tested. In the following models, household characteristics were treated as simple level 1 fixed effects. In other words, the effects of household demographic and socio-economic characteristics do not depend on their residential locations. The mixed model can be displayed as follows:

$$Y_{ijkl} = \delta_{0000} + \delta_{1000} \times HHINC + \delta_{2000} \times HHSIZE + \delta_{3000} \times HHWRKS + \delta_{4000} \times HHVEH + r_{0jkl} + u_{00kl} + v_{000l} + e_{ijkl}$$

Fixed Effects	Model 2: Random Intercept Model (VMT)				Model 2: Random Intercept Model (CO2e)			
	Coef.	S.E.	t-ratio	p-value	Coef.	S.E.	t-ratio	p-value
Intercept, δ_{0000}	3.401	0.014	251.425	<0.001	9.673	0.011	888.439	<0.001
Household Characteristics								
HHINC, δ_{1000}	0.002	0.000	13.407	<0.001	0.001	0.000	11.321	<0.001
HHSIZE, δ_{2000}	0.069	0.006	11.257	<0.001	0.083	0.005	15.803	<0.001
HHWRKS, δ_{3000}	0.276	0.009	30.852	<0.001	0.241	0.008	31.437	<0.001
HHVEH, δ_{4000}	0.116	0.007	17.045	<0.001	0.105	0.006	18.011	<0.001
Random Effects	**Standard Deviation**	**Variance Component**	**χ^2**	**p-value**	**Standard Deviation**	**Variance Component**	**χ^2**	**p-value**
Within-household,e	0.937	0.878			0.808	0.652		
Intercept (L-2), r_0	0.183	0.033	9556.584	<0.001	0.128	0.016	9221.190	<0.001
Intercept (L-3), u_{00}	0.125	0.016	451.439	<0.001	0.086	0.007	389.288	<0.001
Intercept (L-4), v_{000}	0.074	0.006	236.757	0.058	0.065	0.004	252.502	0.012
Deviance	57572.281				51077.661			

Table 5-4: HLM Results: Random Intercept Model.

Regression coefficients were estimated, and their significance confirms the relationship between household characteristics and household daily VMT as well as CO_2e (i.e., all p-values are <0.001). Table 5-4 supports the proposition that all household characteristics considered in the models are significant predictors of household daily VMT and transportation GHG emissions. To be more specific, households with more income, members, workers, or vehicles are likely to drive more, and therefore produce more transportation GHG emissions.

To calculate a measure of effect size, the variance (r^2) explained by the Level-1 predictor variables in the outcome variable was computed by using the following equation:

$$r^2 = \frac{(\sigma^2{}_{null} - \sigma^2{}_{random})}{\sigma^2{}_{null}}$$

$\sigma^2{}_{null}$ is the sigma value obtained in the previous step (null-model testing), and the $\sigma^2{}_{random}$ is sigma value found in the present step (random-model testing). Table 5-5 indicates that household characteristics explain 13.8% and 15.3% of the variance in household daily VMT and CO_2e, respectively.

	VMT	**CO2e**
$\sigma^2{}_{null}$	1.01792	0.77016
$\sigma^2{}_{random}$	0.87787	0.65212
r^2	0.13758	0.15327

Table 5-5: Variance (r^2) Explained by Household Characteristics.

The slightly larger r^2 value for the CO_2e model may result from the explanatory power of household characteristics to account for household vehicle types, which also result in variations in transportation GHG emissions per use.

Means as Outcome Model

As the next step, the significance and directions of the relationship between the higher level predictor variables and the outcome variables were tested. The mixed model is displayed as follows. Similar to the previous model, the higher level predictor variables were treated as fixed effects.

$$\begin{gathered} Y_{ijkl} \;=\; \delta_{0000}+\delta_{0001}+\delta_{0002}+\delta_{0003}+ \\ \delta_{0010}\times DEN\_C+\delta_{0020}\times DIV\_C+\delta_{0030}\times DES\_C+ \\ \delta_{0100}\times DEN+\delta_{0200}\times DIV+\delta_{0300}\times DES+\delta_{0400}\times DA+ \\ r_{0jkl}+u_{00kl}+v_{000l}+e_{ijkl} \end{gathered}$$

Fixed Effects	**Model 3: Means as Outcomes Model (VMT)**				**Model 3: Means as Outcomes Model (CO2e)**			
	Coef.	**S.E.**	**t-ratio**	**p-value**	**Coef.**	**S.E.**	**t-ratio**	**p-value**
Intercept, δ_{0000}	4.046	0.305	13.261	<0.001	10.140	0.260	38.992	<0.001
CBG Level Characteristics								
DEN, δ_{0100}	-0.107	0.014	-7.807	<0.001	-0.091	0.012	-7.746	<0.001
DIV, δ_{0200}	-0.097	0.021	-4.594	<0.001	-0.070	0.018	-3.879	<0.001
DES, δ_{0300}	-0.054	0.015	-3.647	<0.001	-0.034	0.013	-2.654	0.008
DA, δ_{0400}	0.073	0.014	5.158	<0.001	0.059	0.012	4.845	<0.001
County Level Characteristics								
DEN_C, δ_{0010}	0.004	0.035	0.122	0.903	0.023	0.030	0.774	0.439
DIV_C, δ_{0020}	-0.009	0.042	-0.218	0.828	-0.016	0.036	-0.443	0.657
DA_C, δ_{0030}	-0.058	0.064	-0.898	0.369	-0.074	0.054	-1.358	0.175
CBSA Level Characteristics								
SIZE_M, δ_{0001}	0.111	0.015	7.145	<0.001	0.097	0.014	7.129	<0.001
DEN_M, δ_{0002}	0.075	0.038	1.970	0.048	0.050	0.032	1.524	0.127
DES_M, δ_{0003}	0.094	0.079	1.188	0.235	0.102	0.067	1.522	0.128
Random Effects	**Standard Deviation**	**Variance Component**	**$\chi2$**	**p-value**	**Standard Deviation**	**Variance Component**	**$\chi2$**	**p-value**
Within-household, e	1.007	1.014			0.876	0.767		
Intercept (L-2), r_0	0.194	0.037	9558.148	<0.001	0.148	0.022	9296.302	<0.001
Intercept (L-3), u_{00}	0.074	0.006	271.282	0.003	0.054	0.003	260.956	0.011
Intercept (L-4), v_{000}	0.037	0.001	217.163	0.207	0.044	0.002	234.520	0.052
Deviance	60429.481				54443.215			

Table 5-6: HLM Results: Means as Outcomes Model.

Table 5-6 presents the magnitude, direction, and significance of the coefficients from the means as outcome models for household daily VMT and CO_2e. The results indicate that all land use variables at the neighborhood level (CBG) are statistically significant. Density, diversity, and design measures are inversely related with the outcome variables, whereas the destination accessibility measure is directly associated, which is different from the initial expectation. While one variable at the CBSA level (SIZE_M) appears to be significant, none of the county-level variables is significant.

The effect of destination accessibility in the opposite direction may result from inter-zonal travel. In other words, people living in an area with higher destination accessibility may travel beyond the neighborhood boundary, which is very likely. The positive coefficients of SIZE_M suggest that households are likely to drive more and generate more CO_2e as the size of the metropolitan area where they reside increases. It is worth noting that the effect size at the higher geographic level seems to be relatively larger than those at the lower level.

The explained variance in the outcome variables, by the higher level predictor variables, can be computed by using the following equation:

$$r^2 = \frac{(\tau^2{}_{null} - \tau^2{}_{means})}{\tau^2{}_{null}}$$

	VMT	CO2e
$\tau^2{}_{null}$	0.06638	0.03891
$\tau^2{}_{means}$	0.03745	0.02203
r^2	0.43582	0.43382

Table 5-7: Variance (r^2) Explained by Land Use at Three Geographic Levels.

These results confirm that land use variables at three different geographic levels explains about 43% of the between measures variance in both household daily VMT and CO_2e (Table 5-7).

Final Model Specifications

The final models were designed to test the two previous models (random intercept models + means as outcomes models) simultaneously. The combined multi-level regression can be displayed by the following form of equation:

$$\begin{gathered} Y_{ijkl} \ = \ \delta_{0000}+\delta_{0001}+\delta_{0002}+\delta_{0003}+ \\ \delta_{0010}\times DEN\_C+\delta_{0020}\times DIV\_C+\delta_{0030}\times DES\_C+ \\ \delta_{0100}\times DEN+\delta_{0200}\times DIV+\delta_{0300}\times DES+\delta_{0400}\times DA+ \\ \delta_{1000}\times HHINC+\delta_{2000}\times HHSIZE+\delta_{3000}\times HHWRKS+\delta_{4000}\times HHVEH+ \\ r_{0jkl}+u_{00kl}+v_{000l}+e_{ijkl} \end{gathered}$$

Fixed Effects	Model 4: Multi-Level Regression (VMT)				Model 4: Multi-Level Regression (CO_2e)			
	Coef.	S.E	t-ratio	p-value	Coef.	S.E	t-ratio	p-value
Intercept, δ_{0000}	3.269	0.259	12.613	<0.001	9.491	0.217	43.819	<0.001
Household Characteristics								
INC, δ_{1000}	0.002	0.000	14.192	<0.001	0.002	0.000	11.871	<0.001
HHSIZE, δ_{2000}	0.070	0.006	11.582	<0.001	0.084	0.005	16.129	<0.001
WORKER, δ_{3000}	0.280	0.009	31.772	<0.001	0.244	0.008	32.271	<0.001
HHVEH, δ_{4000}	0.091	0.007	13.399	<0.001	0.086	0.006	14.638	<0.001
CBG Built Environment								
DEN, δ_{0100}	-0.064	0.012	-5.165	<0.001	-0.051	0.011	-4.910	<0.001
DIV, δ_{0200}	-0.079	0.019	-4.219	<0.001	-0.055	0.016	-3.445	<0.001
DES, δ_{0300}	-0.064	0.013	-4.856	<0.001	-0.044	0.011	-3.890	<0.001
DA, δ_{0400}	0.046	0.013	3.663	<0.001	0.035	0.011	3.299	0.001
County Built Environment								
DEN_C, δ_{0010}	0.022	0.030	0.758	0.448	0.034	0.024	1.374	0.170

Table 5-8 is continued on next page

DIV_C, δ_{0020}	-0.111	0.036	-3.121	0.002	-0.102	0.030	-3.430	<0.001
DES_C, δ_{0030}	-0.049	0.053	-0.924	0.356	-0.054	0.044	-1.219	0.223
CBSA Built Environment								
SIZE_M, δ_{0001}	0.062	0.014	4.503	<0.001	0.054	0.012	4.503	<0.001
DEN_M, δ_{0002}	-0.007	0.032	-0.206	0.837	-0.018	0.027	-0.665	0.506
DES_M, δ_{0003}	0.190	0.066	2.861	0.005	0.177	0.055	3.193	0.002
Random Effects	**Standard Deviation**	**Variance Component**	**$\chi 2$**	**p-value**	**Standard Deviation**	**Variance Component**	**$\chi 2$**	**p-value**
Within-household,e	0.935	0.875			0.084	0.007	8946.729	<0.001
Intercept (L-2), r_0	0.125	0.016	9176.580	<0.001	0.806	0.650		
Intercept (L-3), u_{00}	0.037	0.001	247.541	0.043	0.014	0.000	238.144	0.097
Intercept (L-4), v_{000}	0.045	0.002	240.296	0.030	0.046	0.002	261.578	0.003
Deviance	56952.475				50589.988			

Table 5-8: HLM Results: Random Intercept Model + Means as Outcomes Model.

Table 5-8 displays the results of final four-level model specifications for both household daily VMT and CO_2e. Regression coefficients are estimated and their significance confirms the relationships between the predictor variables at four levels and the outcome variables.

In these final model results, *jobs and housing* at the county level and *unprotected land area* and *road network density* at the CBSA level reveal statistically significant besides neighborhood-level land use measures. These results suggest that more balanced jobs and housing in a county can lead to reductions in households' vehicle travel and associated emissions generations. At the CBSA level, more roads may induce more vehicular travel demand in a given region whereas a household living in a smaller region tends to reduce vehicle travel less and therefore generate fewer emissions.

Based on the results, it is clear that densification is not an effective strategy for all geographic levels. Although increasing the density of a neighborhood can reduce household VMT and transportation GHG emissions, the same efforts at higher geographic levels either turn out to be insignificant or work in an opposite direction. The results also show that the effects of land use measures at higher geographic levels are larger than those at lower geographic levels. In other words, people can be more influenced by higher-level land use. For instance, a 1% decrease in the road network density of a given metro can lead to a 0.19% and a 0.17% decrease in household daily VMT and CO_2e, respectively, whereas a 1% increase in the intersection density of a given neighborhood can lead to a 0.064% and 0.044 % decrease in the same outcomes.

If the final HLM results are compared to the single-level results (Table 5-1), a couple of important differences present themselves. While the magnitude of the effects of density, diversity, and design at the neighborhood level and CBSA size are all markedly reduced, the effects of jobs and housing at the county level, however, actually increase in magnitude. These differences arises purely by accounting for the nesting of households within various geographical boundaries.

SUMMARY

In this chapter, the effects of land use variables at multiple geographic levels on household daily VMT and CO_2e were examined. The overall results from the empirical analyses suggest that land use based policies might affect household vehicle activity and the associated transportation GHG emissions in different ways or directions when these policies are practiced in different spatial scales. For instance, increasing the density in the neighborhood scale may lead to VMT reduction, while the same intervention in the county scale does not have any impact.

From the policy standpoint, the results in this chapter demonstrate the importance in the planning role not only of local agencies, but also of regional agencies. From the results, it can be inferred that the effects of land use strategies can vary with the geographic level at which those strategies are implemented. For instance, land use management efforts at the neighborhood level may influence household trips for daily needs (e.g., grocery shopping, social service, or recreational purposes), whereas regional level strategies tend to have an influence on relatively longer trips such as work trips. Thus, it would be very important for different levels of agencies to collaborate in order to maximize the region-wide effectiveness of land use management.

The findings from this chapter along with the preceding chapter suggest that VMT reduction may not lead to proportional GHG reduction. Thus, the subsequent chapter will introduce vehicle travel characteristics as intervening variables in order to unpack the relationships among land use, vehicle travel, and transportation GHG emissions.

Chapter Six: The Mediator Effects of Vehicle Travel Characteristics on Transportation GHG Emissions

The previous two chapters have demonstrated that VMT is only a proxy, not an exact measure of household transportation GHG emissions. In other words, a reduction in household daily VMT will not proportionally reduce household daily transportation GHG emissions. Thus, this chapter attempts to improve an understanding of the relationship between land use and transportation GHG emissions by simultaneously accounting for vehicle operating speed (VOS) and vehicle trip frequency (VTF), as well as vehicle miles traveled (VMT). Using the same dataset utilized in the two previous chapters, structural equation modeling (SEM) techniques were applied to describe how land use measures at different geographic levels influence household transportation GHG emissions through changes in vehicle travel characteristics.

STRUCTURAL EQUATION MODEL

Household Daily Gasoline Consumption

The primary aim of this chapter is to disentangle the link between land use and household GHG emissions while accounting for the intervening effects of vehicle travel on transportation GHG emissions. Unlike the previous analyses, this chapter introduces *household daily gasoline consumption* (DAYGAS) as a more objective measure of household transportation GHG emissions, in order to cope with potential confounding problems.[12] The 2009 NHTS vehicle file includes the information about annual fuel consumption in gasoline equivalent gallon for each of household vehicles. Household daily

[12] Since MOVES computed CO_2e based on the number of miles driven, average vehicle operating speed, and vehicle trip frequency, it is very likely that those three vehicle travel characteristics are strongly related to household GHG emissions.

gasoline consumption was derived based on the assumption that household daily gasoline consumption leads to the annual level of gasoline consumption.

$$\textit{Household daily gasoline consumption} = \frac{\sum_i^n Annual\ gasoline\ equivalent\ gallons_i}{365}$$

where:

i = household vehicle id in the NHTS vehicle file

n = total number of household vehicles

Model Specification

Referring to the conceptual model (Figure 3-1) in Chapter Three, the following set of regression equations were formulated:

$$DENSITY_{CBG} = \alpha_1 URBAN + e_1$$
$$DIVERSITY_{CBG} = \alpha_2 URBAN + e_2$$
$$DESIGN_{CBG} = \alpha_3 URBAN + e_3$$
$$DISTANCE\ TO\ TRANSIT_{CBG} = \alpha_4 URBAN + e_4$$
$$DESTINATION\ ACCESSIBILITY_{CBG} = \alpha_5 URBAN + e_5$$
$$URBAN = \beta_0 + \beta_1 SES + e_6$$

First, the latent variable (URBAN) that is measured using five neighborhood level (CBG) land use variables as its indicators was introduced. Next, this study defined this latent variable as a function of the socio-economic status (Nasri & Zhang, 2015). Including only socio-economic characteristics of each household (SES) is not sufficient to control self-selection effects because of the nature of cross-sectional data used in this study and a lack of attitudinal survey data. This URBAN latent variable can capture potential self-selection effects.

Land use measures (LU) at different geographic levels (i.e., neighborhood, county, and CBSA) influence vehicle travel characteristics (i.e., VMT, VOS and VTF), which, in turn, affect *household daily gasoline consumption* (DAYGAS). The latent variable (URBAN) not only captures the urban residence propensity that describes the individuals' or households' desire for certain kinds of land uses of their neighborhood, but also captures their pre-disposed vehicle travel behavior at neighborhood level. Furthermore, urban residency may influence household daily gasoline consumption through their vehicle type choices (e.g., vehicle type, fuel type, model year, etc.).

$$VMT = \beta_0 + \beta_1 \ URBAN + \beta_2 \ LU_{County} + \beta_3 \ LU_{CBSA} + e_7$$

$$VOS = \beta_0 + \beta_1 \ URBAN + \beta_2 \ LU_{County} + \beta_3 \ LU_{CBSA} + e_8$$

$$VTF = \beta_0 + \beta_1 \ URBAN + \beta_2 \ LU_{County} + \beta_3 \ LU_{CBSA} + e_9$$

$$DAYGAS = \beta_0 + \beta_1 URBAN + \beta_2 VMT + \beta_3 VOS + \beta_4 VT + e_{10}$$

Besides the direct effects explicitly specified in the above set of equations, correlations among the land use variables, as well as the vehicle travel characteristics were also assumed in the final model specification.

Path Model

As addressed in the previous section, this chapter assumes the indirect effects of land use measures on household daily gasoline consumption through changes in vehicle travel characteristics, as well as the direct effects of urban residence on household daily gasoline consumption, which is the choice of vehicle type owned and used by a household. To control the self-selection effects and capture the effect of neighborhood level land use, the urban latent variable, along with household demographic and socio-economic characteristics were included in the final path model.

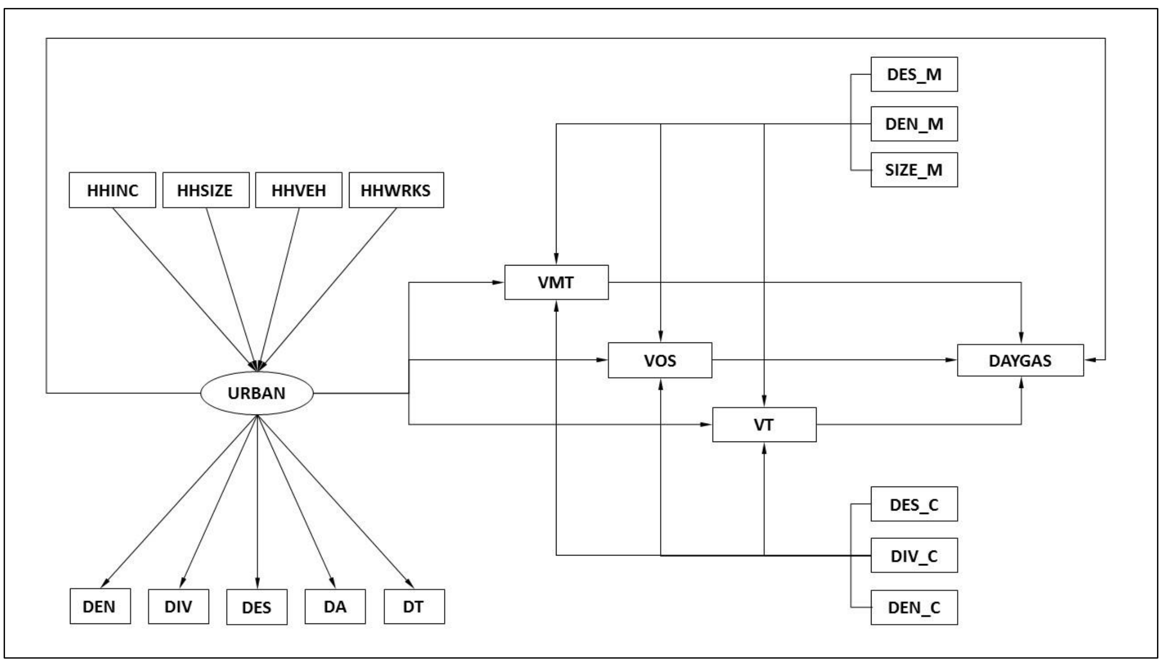

Figure 6-1: Causal Path Diagram.

Figure 6-1 describes the causal path diagram for the final model specification. The rectangle shapes indicate observed variables, and the oval shape represents a latent variable. The urban latent variable that is indicated by five D-variables at the CBG level directly affect three vehicle travel characteristics, which, in turn, influence the amount of gasoline each household consumes on a daily basis. In addition, this study also assumes that land use measures at the two larger geographic levels also influence household vehicle travel patterns as demonstrated in the preceding chapter. At the county level, it was assumed that gross activity density, jobs and housing balance, and road network density influence vehicle travel. Similarly, gross activity density, road network density, and the size of CBSA were also assumed to influence vehicle travel patterns at the CBSA level. Moreover, this study assumes that there is a direct effect of urban residence on household daily gasoline consumption which accounts for the variations in vehicle types households own and use.

ESTIMATION RESULTS

Residence Location and Urban Living Propensity

In this sample, households with fewer family members, workers, and vehicles tend to reside in urban areas which are characterized as a compact and mixed use development (i.e., higher density, greater mixed use, better connectivity, or higher centrality). On the contrary, affluent households with more household members, workers, and vehicles available are likely to live in the remaining areas (e.g., the suburbs or rural areas). (see **A3** in *Appendices* for the detailed statistical results)

Influence of Land Use on Household Gasoline Consumption

This chapter assumes that land use characteristics of a given neighborhood and region where the individual or household lives directly affects household vehicle travel characteristics, which in turn influence the amount of household daily gasoline consumption, a substitute for transportation GHG emissions.[13] In this section, the direct effects of land use variables on three household vehicle travel characteristics will be presented first. Next, the direct effects of the three vehicle travel characteristics on household gasoline consumption will be discussed. At the end of the section, the total effects of each of land use measures on household daily gasoline consumption through changes in vehicle travel will be presented.

Direct Effects on VMT

Table 6-1 summarizes the direct effects of land use on household daily VMT.

Path	**Estimate**	**S.E.**	**Est./S.E.**	**p-value**
URBAN → VMT	-1.230**	0.005	-260.354	0.000
County-level built environment				
Gross activity density → VMT	0.038**	0.006	6.427	0.000
Jobs per household → VMT	0.022**	0.007	3.043	0.002
Road network density → VMT	-0.040**	0.010	-3.913	0.000
CBSA-level built environment				
CBSA size (unprotected land area) → VMT	0.006**	0.002	2.774	0.006
CBSA gross activity density → VMT	-0.014*	0.006	-2.313	0.021
CBSA road network density → VMT	0.020	0.012	1.659	0.097

** $p < 0.05$; ** $p < 0.01$*

Table 6-1: Direct Effects of Land Use at Multiple Geographic Levels on VMT.

Table 6-1 suggests that households living in urban areas tend to drive less compared to those in rural areas. Since the urban latent variable was measured by five neighborhood (CBG) level land use measures, the coefficient of URBAN represent the combined effect of all five land use measures at the CBG level. The neighborhood-level land use variables,

[13] 1 gallon of gasoline consumed is equivalent to 8.7 kilograms (19.18 pounds) of carbon dioxide equivalent.

except for *distance to transit*, are significantly and positively correlated with each other.[14] In addition to the impact of neighborhood land use pattern, the results here demonstrate that household daily automobile use can be influenced by land use measures of higher geographic levels. The results appear very complicated.

The effects of land use variables at the county level are counter-intuitive. The results suggest that households living in a county with more jobs per household and a higher activity density are likely to drive more. These positive coefficients of the density and diversity features are partly due to more short-distance vehicle trips (Nasri & Zhang, 2015) because it is also possible that people still rely on their automobiles as a primary mode of transportation regardless of their residential locations.

The design measure at the county level is also different from the initial expectation. However, the negative coefficient of the road network density feature is partly due to the unfavorable design for drivers. What this means is that a high road network density (except for limited access roads, such as highways, expressways, etc.) is associated with smaller blocks and a number of intersections, which provides a more favorable environment for travelers using sustainable transportation modes (i.e., pedestrians, bicyclers, or transit users) than for motorists. If this is the case, people may be unwilling to drive and may shift to other modes.

At the CBSA level, the size of CBSA is statistically significant and more positively associated with household daily VMT as expected. The positive coefficient (0.006) may be indicative of the fact that households living in larger CBSA are likely to drive more, partly due to more scattered destinations as well as larger daily activity space. The signs of CBSA density and design features are as expected. At the CBSA level, higher activity

[14] For instance, if a given neighborhood has a high activity density, the area is more likely to have a heterogeneous land use pattern and a better road network connectivity. It is also very likely that this area shows a higher centrality score.

density indicates that destinations (i.e., jobs and housing) are relatively more clustered, which reduces the possibility of long-distance travel. However, it is also possible that metropolitan areas with more roads available can induce a higher level of vehicle travel within the region.

Direct Effects on VOS

Table 6-2 presents the direct effects of land use on household average vehicle travel speed.

Path	Estimate	S.E.	Est./S.E.	p-value
URBAN → VOS	-0.305**	0.002	-167.779	0.000
County-level built environment				
Gross activity density → VOS	-0.085**	0.007	-12.333	0.000
Jobs per household → VOS	0.019*	0.008	2.256	0.024
Road network density → VOS	0.071**	0.012	5.926	0.000
CBSA-level built environment				
CBSA size (unprotected land area) → VOS	0.000	0.003	0.076	0.940
CBSA gross activity density → VOS	0.020**	0.007	2.760	0.006
CBSA road network density → VOS	-0.039**	0.014	-2.738	0.006

** $p < 0.05$; ** $p < 0.01$*

Table 6-2: Direct Effects of Land Use at Multiple Geographic Levels on VOS.

As expected, households living in an urban neighborhood are likely to drive slower on average compared to those living in the rest of the areas. This is partly due to the higher travel demand and its associated traffic congestion in the area, which causes frequent stop-and-go movements, resulting in lowering the overall vehicle travel speed.

At the county level, the influences of land use on vehicle travel speeds look similar. Density at this geographic level appears to inversely affect vehicle travel speed, whereas jobs and housing balance and road network density seem to directly influence vehicle travel speed. The same land use variables at the CBSA level, however, appear to have the opposite effects. These results suggest that households in a denser metropolitan areas are likely to drive faster. The higher road network density, however, tends to reduce vehicle travel speed.

Direct Effects on VTF

Table 6-3 reports the effects of land use on vehicle trip frequency.

Path	Estimate	S.E.	Est./S.E.	p-value
URBAN → VTF	-0.372**	0.002	-161.830	0.000
County-level built environment				
Gross activity density → VTF	0.061**	0.009	6.977	0.000
Jobs per household → VTF	0.064**	0.011	5.909	0.000
Road network density → VTF	-0.054**	0.015	-3.491	0.000
CBSA-level built environment				
CBSA size (unprotected land area) → VTF	-0.009**	0.003	-2.683	0.007
CBSA gross activity density → VTF	-0.032**	0.009	-3.390	0.001
CBSA road network density → VTF	0.021	0.018	1.124	0.261

** $p < 0.05$; ** $p < 0.01$*

Table 6-3: Direct Effects of Land Use at Multiple Geographic Levels on VTF.

First of all, households living in an urban neighborhood are likely to make fewer vehicle trips compared to their counterparts. The relationships between land use at higher geographic levels and VTF are, however, rather intertwined, and thus needs further investigation. While activity density at the county level is positively associated with vehicle trip frequency, the same variable at the CBSA level is negatively associated with vehicle trip frequency. It is also worth noting that the effect of CBSA size on VMT shows a positive sign whereas the same effect on VTF has a negative sign. This suggests that households living in a large metropolitan area may drive more miles while making fewer vehicle trips.

The relationship between road network density and vehicle trip frequency at the county and the CBSA levels are opposite.

Along with the findings from the previous chapters, Table 6-1, 6-2 and 6-3 together demonstrate that implementing land use based strategies may have some trade-offs between the benefits of reducing vehicle travel distance and the penalties of causing traffic congestion. Furthermore, the effectiveness of land use policies can vary by the level of practice.

Vehicle Travel and Daily Gasoline Consumption

As demonstrated in the previous chapters, a one percent change in household daily VMT does not correspond to a one percent change in the household daily GHG emissions (CO2e). This study, therefore, assumes that vehicle travel speed and frequency, as well as vehicle miles traveled, can also play a role in determining how much each household consumes gasoline for their daily vehicle activities.

Table 6-4 shows how each of the vehicle travel characteristics influence household daily gasoline consumption. The results suggest that VMT is the strongest determinant of emissions generated, followed by VOS and VTF.

Path	Estimate	S.E.	Est. / S.E.	p-value
VMT → DAYGAS	3.678^{**}	0.065	56.848	0.000
VOS → DAYGAS	-1.512^{**}	0.021	-73.132	0.000
VTF → DAYGAS	-1.084^{**}	0.015	-71.032	0.000

** p < 0.05; ** p < 0.01*

Table 6-4: Direct Effects of Vehicle Travel Characteristics on Household Daily Gasoline Consumption.

Although *household daily gasoline consumption* is a somewhat crude proxy for transportation GHG emissions, these results from Table 6-4 imply that the effects of land use measures on transportation GHG emissions can be over-estimated (Hong & Goodchild, 2014) and that the environmental benefits of land use policies can be offset by lowering vehicle travel speed (Ewing et al., 2008). The effect of vehicle trip frequency is revealed to be different from the initial expectation, which may need further investigation.

Intermediate Effects of Vehicle Travel on Daily Gasoline Consumption

Table 6-5 provides the total effects (i.e., sum of indirect effects) of land use measures of all geographic levels on household daily gasoline consumption.

It is worth noting that the magnitudes of indirect effects of land use measures on household daily gasoline consumption are relatively smaller than the direct effects of the same land use measures on VMT while the signs of coefficients are identical (refer to Table 6-1). This reflects the importance of considering vehicle travel speed. Urban residency appears to reduce the household's daily vehicle travel. But at the same time, it seems to lower vehicle travel speed. Table 6-5, therefore, provides additional empirical evidence of the land use and transportation GHG emissions connection and suggests that the environmental benefits of D variables can be over-estimated unless vehicle travel speed is considered (Hong & Goodchild, 2014).

At larger geographic levels, it was also found that there are some trade-offs between vehicle travel demand and vehicle travel speed. The overall results here suggest that if modifying one element of land use measures lead to VMT reduction, it is also very likely to lower vehicle travel speed in the area, and vice versa.

Level	Path	Est.	S.E.	Est./S.E.	p-value
CBG	URBAN → GASDAY	-3.659^{**}	0.063	-57.999	0.000
	URBAN, VMT, GASDAY	-4.523^{**}	0.070	-64.860	0.000
	URBAN, VOS, GASDAY	0.461^{**}	0.008	59.574	0.000
	URBAN, VTF, GASDAY	0.404^{**}	0.007	57.695	0.000
County	DEN_C → GASDAY	0.203^{**}	0.012	17.163	0.000
	DEN_C, VMT, GASDAY	0.141^{**}	0.022	6.497	0.000
	DEN_C, VOS, GASDAY	0.128^{**}	0.011	12.156	0.000
	DEN_C, VTF, GASDAY	-0.067^{**}	0.010	-6.938	0.000
	DIV_C → GASDAY	-0.018	0.014	-1.277	0.202
	DIV_C, VMT, GASDAY	0.081^{**}	0.027	3.045	0.002
	DIV_C, VOS, GASDAY	-0.029^{*}	0.013	-2.255	0.024
	DIV_C, VTF, GASDAY	-0.070^{**}	0.012	-5.888	0.000
	DES_C → GASDAY	-0.197^{**}	0.020	-9.822	0.000
	DES_C, VMT, GASDAY	-0.148^{**}	0.038	-3.931	0.000
	DES_C, VOS, GASDAY	-0.108^{**}	0.018	-5.904	0.000
	DES_C, VTF, GASDAY	0.058^{**}	0.017	3.487	0.000
CBSA	SIZE_M → GASDAY	0.034^{**}	0.005	7.195	0.000
	SIZE_M, VMT, GASDAY	0.024^{**}	0.009	2.790	0.005
	SIZE_M, VOS, GASDAY	0.000	0.004	-0.076	0.940
	SIZE_M, VTF, GASDAY	0.010^{**}	0.004	2.679	0.007
	DEN_M → GASDAY	-0.049^{**}	0.012	-3.957	0.000
	DEN_M, VMT, GASDAY	-0.053^{*}	0.023	-2.313	0.021
	DEN_M, VOS, GASDAY	-0.030^{**}	0.011	-2.759	0.006
	DEN_M, VTF, GASDAY	0.034^{**}	0.010	3.385	0.001
	DES_M → GASDAY	0.112^{**}	0.024	4.666	0.000
	DES_M, VMT, GASDAY	0.075	0.045	1.661	0.097
	DES_M, VOS, GASDAY	0.059^{**}	0.022	2.736	0.006
	DES_M, VTF, GASDAY	-0.022	0.020	-1.124	0.261

$* p < 0.05$; $** p < 0.01$

Table 6-5: Total Effects of Land Use at Multiple Geographic Levels on Household Daily Gasoline Consumption.

SUMMARY

As demonstrated in this chapter, three vehicle travel (operating) characteristics influencing household daily gasoline consumption, a proxy for transportation GHG emissions, are associated with land use measures at multiple geographic levels in a very sophisticated way. Some land use features are negatively associated, while others are positively associated with vehicle travel demand and speed. Also, the model presented in this chapter shows that the effects of similar land-use strategies can be different according to the geographic levels. At the same time, the findings here suggest that there exist trade-offs between the benefits and risks of implementing land-use based strategies in terms of emissions reduction. By adding VOS and VTF, in addition to VMT, the model specification in this chapter provides a generic picture of the land use and transportation GHG emissions connection, and enables the total effects to be quantified.

Some policy implications can be drawn from the findings. The results provide empirical evidence that VMT reduction is still a very important key to reducing household transportation GHG emissions from driving, but also suggest that strategies to increase vehicle travel speed and reduce vehicle travel frequency should be considered at the same time. This means that simply implementing one strategy does not guarantee maximizing the role of land-use based strategies in reducing transportation emissions from driving. For example, increasing the diversity of an area will reduce households VMT in the area, but decreasing vehicle travel speeds and increasing vehicle trip frequencies in the area will result in minimizing the environmental benefit through VMT reduction. The findings suggest strategies for different geographic levels, as follows.

At the metropolitan level, an urban growth boundary, as Portland has, may reduce household VMT with a geographically restrained daily life zone. Within the boundary, increasing density and clustering destinations closer to each other will reduce vehicle travel demand on the one hand. At the same time, it is important to implement increased road density in order to guarantee the free-flow of vehicle movements without congestion. At the county level, the goal should be to accommodate as many vehicle trips as possible within the same county. In other words, the county's priority should be enabling its residents to meet daily travel requirements within the area.

At the neighborhood (CBG) level, densification, job and housing balance with greater land-use mix, innovative intersections (keeping smaller blocks but enabling a seamless flow of vehicles), and improving transit service should be implemented simultaneously to not only reduce VMT, but also to maintain traffic free-flow. Reducing reliance on automobiles by improving public transit services should be given the highest priority. However, it would be important to keep the seamless flow of vehicles in the area. Thus, the transit system should be given the right of way, but the number of current lanes for vehicles should be kept by reducing the width of each lane. Also, activity centers with features of higher density and greater land-use mix can reduce local VMT. By reducing short-distance vehicle trips and encouraging non-motorized trips (sidewalks, designated bike paths, and bike share programs), it is expected to reduce not only vehicle travel distance, but also vehicle travel frequency. Innovative intersections can provide pedestrians with a good environment with smaller blocks and smoother vehicle movements with traffic signal systems.

Overall, the findings suggest that regional and local agencies should closely work together in order to achieve the environmental goal for the region. In addition, several departments (such as travel demand and mobility) should collaborate. The results of the analysis show that land use at multiple geographic levels influence various travel characteristics and associated transportation GHG emissions.

Chapter Seven: A Case Study of the Austin, TX region[15]

In the preceding chapter, it was discovered that land use based interventions that are practiced at multiple geographic levels can influence household daily transportation GHG emissions through various channels. Thus, the primary purpose of this chapter is to examine the relationship between land use and transportation GHG emissions in a specific metropolitan area by applying the model specification developed in the preceding chapter. The Austin, TX region was chosen primarily for convenience, but also because it encompasses a growth pattern that many of the U.S. metro areas have experienced.

The Austin-Round Rock Metropolitan Statistical Area located in Central Texas consists of five counties, including Travis, Williamson, Hays, Bastrop, and Caldwell.[16] In less than three decades, the population of this area nearly tripled, growing from 585,000 in 1980 to 1.71 million in 2009. Most of this growth took the form of single family residential development along with low-density office, retail and industrial developments, which were located across the suburban fringe of Travis, Williamson, and Hays counties. This population growth accompanied the conversion of a significant amount of the region's land into urban developments (Zhang & Kone, 2009).

To cope with this unexpected pace of outward growth in the region, the Capital Area Metropolitan Planning Organization (CAMPO) incorporated a regional growth concept of 'Activity Centers' for its 2035 Long-Range Transportation Plan (LRTP), adopted in May 2010. The 37 centers are where transportation investments and planning resources could be targeted to encourage development of a connected regional network of

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[15] The study of this chapter has been submitted to *Transportation Research Part D: Transport and Environment* for publication.

[16] The boundary of the Austin-Round Rock metropolitan area is defined by the Office of Management and Budget. In 2013, the Texas Transportation Commission approved an expansion of the boundaries of the Capital Area Metropolitan Planning Organization to include Burnet County.

higher density, and mixed use developments oriented around transportation investments. By 2035, more than 30% of the regional population and about 38% of regional employment are expected to be within the designated centers (CAMPO, 2010).

Meanwhile, the region has experienced increasing traffic congestion because of the higher regional travel demand that outweighs the regional traffic capacity (Schrank & Lomax, 2009). In addition, this region still suffers from a lack of other options for transportation that are unable to fully accommodate regional travel demand. Since many other U.S. metropolitan areas are also in this transitional stage in which they put a lot of efforts into compact, mixed-use development, it is expected that the findings from this case study provide valuable lessons for other rapidly growing metropolitan areas in the. U.S.

RESEARCH DATA

2006 Austin Travel Survey (ATS)

This study utilized the 2006 ATS, which is part of a series of comprehensive Travel Surveys conducted by the Capital Area Metropolitan Planning Organization (CAMPO). CAMPO cooperated with the Texas Department of Transportation (TxDOT), the Texas Transportation Institute (TTI), and the Capital Metropolitan Transportation Authority (CMTA). This survey covers five counties in Central Texas, including Travis, Williamson, Hays, Bastrop, and Caldwell Counties. Similar to the 2009 NHTS, it consists of four files—household, person, vehicle, and trips. Table 7-1 illustrates the variables included in each file of the survey.

File	Variable	Description
HOUSEHOLD	Sample Number	Unique non-zero number assigned to each household participating in survey
	HH Zone	TAZ number where household is located
	Longitude	Longitude of household address
	Latitude	Latitude of household address
	Number Persons	Number of persons living in residence
	Number of Employed	Number of persons in household that are employed either full or part time
	Vehicle Available	Number of cars, vans, light trucks, motorcycles owned or leased by members of the household
	Income	Combined annual income of all household members
	Total HH Trips	The total combined number of all trips made by all persons in the household on the travel day
PERSON	Sample Number	Unique non-zero number assigned to each household participating in survey
	Person Number	Number assigned to each person in the household with 0 assumed to be the head of household
	Sex	Sex of person
	Ethnicity	Race or ethnicity of person
	Age	Age of person
	Licensed Driver	If person is a licensed driver
	Employment	If person is employed in a paying or volunteer job
	Employment Status	If person is employed, this is a code number indicating the person's employment status
	Longitude	Longitude of workplace location
	Latitude	Latitude of workplace location
	Person trips	The total number of trips the person made on his/her travel day
VEHICLE	Sample Number	Unique non-zero number assigned to each household participating in survey
	Vehicle Number	Unique non-zero number assigned to vehicle
	Type of Vehicle	Type of Vehicle
	Year	Year vehicle was manufactured
	Make	Make of vehicle
	Model	Model of vehicle
	Type of Fuel	Type of Fuel

Table 7-1 is continued on next page

TRIPS	Sample Number	Unique non-zero number assigned to each household participating in survey
	Month	Month of survey day
	Day	Day of the month of the survey
	Person Number	Number assigned to the person doing this activity
	Activity/Trip Number	The first trip/activity for each person will be recoded as 0 for where their day began. Each subsequent trip/activity should be numbered sequentially as 1, 2, 3, etc.
	Activity Description	Description of Activity
	Location	Name of location where activity took place
	Longitude	Longitude of location
	Latitude	Latitude of location
	Purpose	Purpose of trip
	Mode of Travel	Mode of travel used in travelling to this location
	Number of People	If travel was by private vehicle, this is the number of persons in the vehicle, including the driver
	HH Vehicle	Was a HH vehicle used to make this trip?
	Vehicle Used	If household vehicle was used for travel, this is the vehicle number
	Arrival Hour	Hour that person arrived at this location
	Arrival Minute	Minute that person arrived at this location
	Departure Hour	Hour that person departed this location
	Departure Minute	Minute that person departed this location

Table 7-1: Variables in the 2006 Austin Travel Survey.

In the household and person files, the demographic and socio-economic characteristics of either household or person are available, and the location information about each household is given. The trip file includes the location of each activity, the purpose of the trip, mode of transportation, and time of arrival and departure at the location. This 2006 ATS was incorporated with other land-use and transit related data from regional and local agencies. Four household socio-economic characteristics, including household size, workers, vehicle availability, and household income, were directly derived from the household file of the 2006 ATS. The process of database construction, other than household variables, will be illustrated in the following sections.

Travel Variables

For travel analysis, trip lengths were re-estimated. Using the TransCAD, all trips were geocoded based on the coordinates given in the trip file in the survey. Based on the assumption that a surveyed traveler took the shortest path from each origin to each destination, network distance for each trip was re-estimated (Zhang, Pang, & Kone, 2014). Afterwards, travel speed was computed by dividing trip length by reported trip time.

Throughout the cleaning process, trips without trip length or speed information were excluded. As a result of the cleaning process, 13,155 trips were considered in this study. Since the primary focus of this study was transportation GHG emissions, it was critical to determine which trips generated emissions. All trips made by automobiles for personal use were considered emission generators. These trips were aggregated at the household level for the analyses.

Three D Variables

To derive land use variables of the neighborhood for each surveyed household, a 1-mile buffer for each household based on the street network was first created (Figure 7-1). Using the Arc GIS software, these household buffer shapefiles were combined with census data and land-use data from local and regional agencies. Three original D-variables were derived and considered in this study: density; diversity; design (Cervero & Kockelman, 1997).

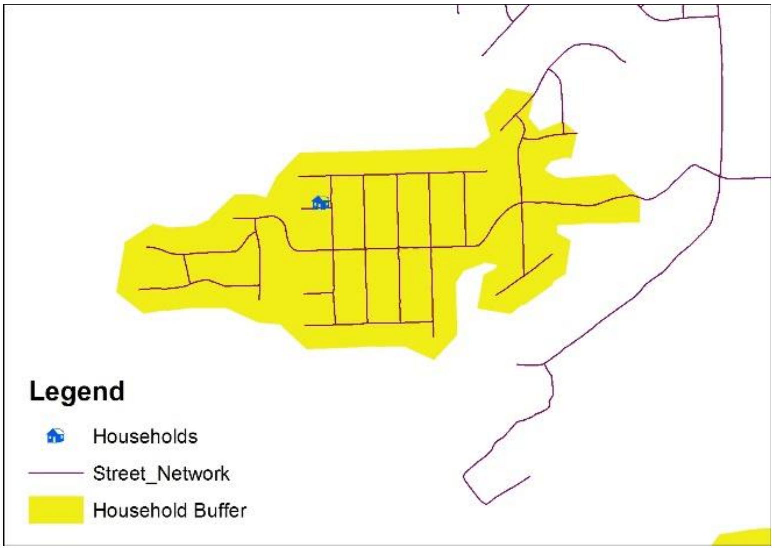


Figure 7-1: Household Buffers.

Table 7-2 illustrates how each D variable was computed. The density measures the prorated sum of the population for the 2000 census block groups which intersect the buffer. Prorating was done by calculating the density of population per residential acre (i.e., lots designated as single-family or multi-family) for the entire census block group, then multiplying the density by the amount of residential acreage within the block group contributing to the buffer, and finally, summing over all block groups intersecting the buffer area. Using the prorated population, population density per residential square mile was calculated. The diversity index represents the entropy score proposed in Cervero and Kockelman (1997) using the five land use categories, including single-family, multi-family, commercial, industrial, and institutional (public). The design was calculated as density of the number of 4 or more way intersections per square mile of gross land area within the buffer.

Variable	Measurement
Density	$\frac{Prorated\ sum\ of\ population}{Residential\ land\ area\ in\ the\ buffer}$
Diversity	$\frac{-[\sum_{i=1}^{n} P_i \times ln\ P_i]}{\ln(n)}$
Design	$\frac{Number\ of\ 4\ or\ more\ way\ intersections}{Gross\ land\ area\ in\ the\ buffer}$

Table 7-2: 3D Measurement.

Transportation GHG Emission estimation by MOVES

The estimation process is detailed in the *Motor Vehicle Emissions Simulator (MOVES)* section in Chapter Three.

Mixed-Use Development (MXD) Identification

To examine the local effects of land use on transportation GHG emissions, a special type of geography was considered in this study: mixed -use development (MXD). This is not a novel concept in the field of urban planning. MXDs are described as any developments that blend a combination of land-uses (i.e., residential, commercial, institutional, or industrial, etc.), and in which different functions are integrated.

In the Austin region, the selection of MXDs took a 'bottom up' approach, also taken by another study (Ewing et al., 2011), based upon the local knowledge of city officials, professional planners, staff of the CAMPO, and academic experts. The research team defines MXD as "a development or district that consists of two or more land uses between which trips can be made using local streets, without having to use major streets." Land use here includes residential, retail, office, and/or entertainment, and there may be walk trips between the uses. Throughout the sampling process, the research team at the University of

Texas at Austin identified and finalized the boundaries of 42 MXDs in the Austin area (Figure 7-2a) (Zhang, Pang, & Kone, 2014).

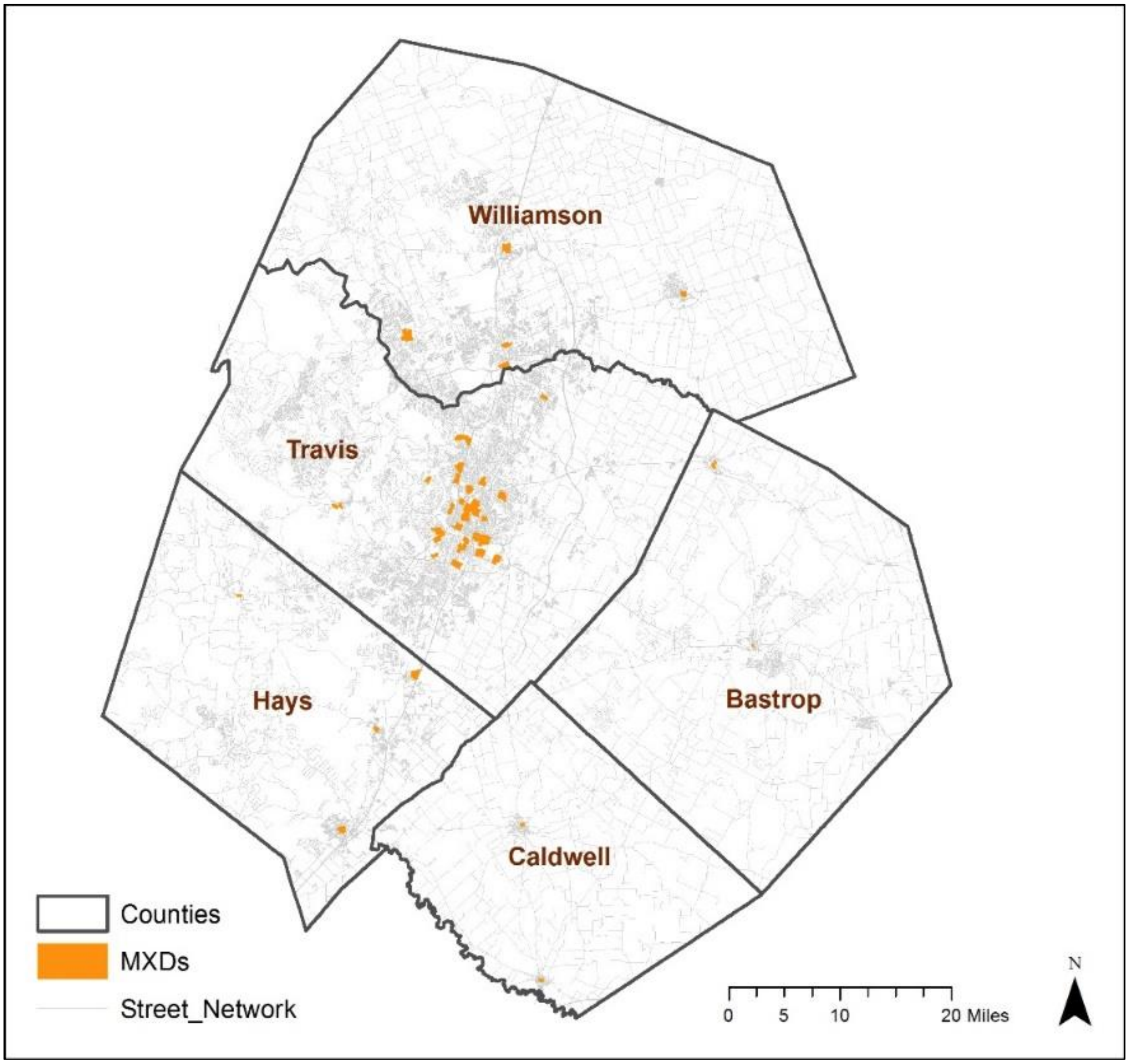


Figure 7-2a: MXDs in the Austin Metropolitan Area.

Consistent with the generally recognized definition of MXD, these Austin MXDs are characterized by compact, mixed-use (e.g., mixture of residential and commercial uses), and well connected developments (Figure 7-2b), which later became a basis for the

Activity Centers in the CAMPO 2035 LRTP (Zhang & Kone, 2009). Most MXDs, especially those located in Travis County, are served by public transportation. In this study, households living within these pre-defined MXD boundaries were considered MXD residents.

Crest View

Old West

River City North; South Congress; South 1st

Figure 7-2b: Examples of Austin MXDs.

ANALYSIS AND RESULTS

Path Analysis using Mplus

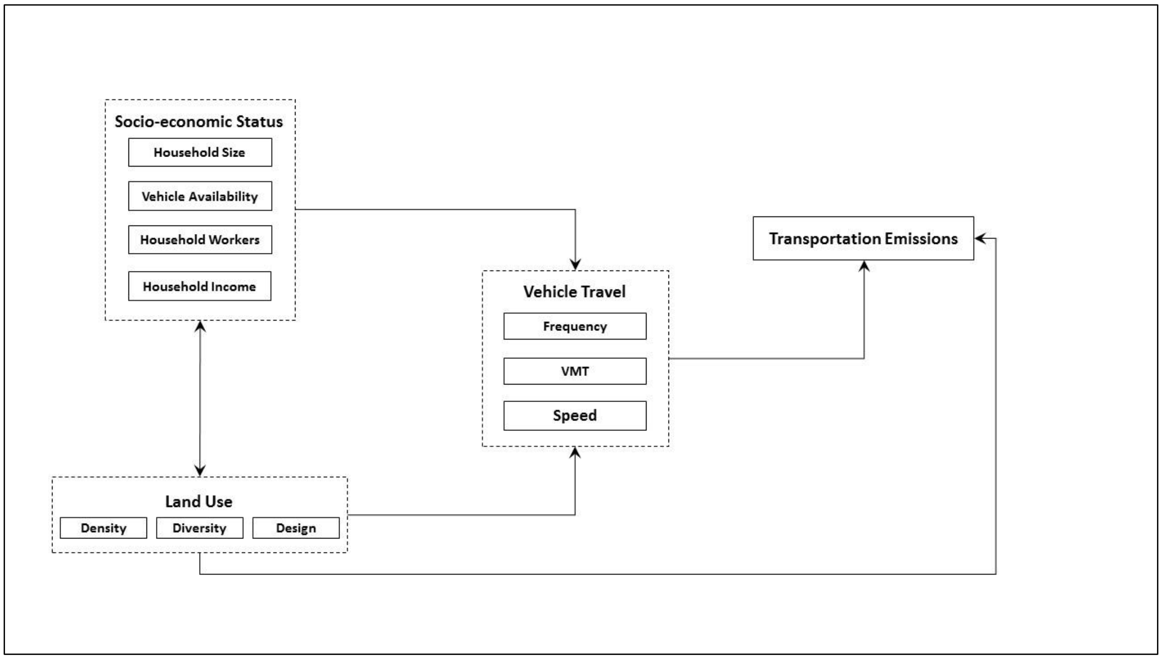


Figure 7-3: Conceptual Structural Model of Austin Case Study.

Since one objective of this study is to examine the effect of land use on transportation GHG emissions through various channels (Figure 7-3), the following set of equations were formulated:

$$VMT = \beta_1 SES + \beta_2 LU + e$$

$$VOS = \beta_1 SES + \beta_2 LU + e$$

$$VTF = \beta_1 SES + \beta_2 LU + e$$

$$CO2e = \beta_1 LU + \beta_2 VMT + \beta_3 VOS + \beta_4 VT + e$$

It was assumed that the three land use characteristics (LU) would be correlated to each other, and each land use attribute would affect the household vehicle travel distance

(VMT), average vehicle operating speed (VOS), and vehicle trip frequency (VTF). In addition, these three household vehicle travel characteristics determine how much each household generates transportation GHG emissions (CO2e) from vehicle-related activities. Moreover, the land use attributes influence transportation GHG through the type of vehicles owned and used by households. As control variables, four household socio-economic characteristics (SES) were considered in this study.

It is expected that a household would engage in more automobile-related activities and generate more emissions if household income is higher, household size is larger, vehicles are more available to household members, or more workers are in the household. Table 7-2 illustrates a more detailed descriptions of variables used in the study.

Category	**Name**	**Description**	**Transformation**
Control	HHSIZE	Household size	Continuous
	VEHICLE	Household vehicles divided by household size	Continuous
	WORKER	Number of household workers	Continuous
	INCOME	Household income in 2005 $	Continuous
Exogenous	DENSITY	Population per square mile	Ln (x)
	DIVERSITY	Land use mix entropy	Ln (x)
	DESIGN	Number of 4+way intersections per square mile	Ln (x+1)
	VMT	Total daily household vehicle miles traveled (population in vehicle taken into account)	Ln (x+1)
	VOS	Average household vehicle operating speeds	Ln (x)
	VTF	Total daily household trips by automobile	Ln (x+1)
	CO2e	Total daily household carbon dioxide equivalent in gram	Ln (x+1)

Table 7-3: Study Variables.

All variables, except for the control variables, were logarithmically transformed to improve multivariate normality and to make it easier to interpret the results of path analysis (elasticities). Since the natural logarithm function is undefined for zero values, a constant value of 1 was added to the original values of the variables (DESIGN, VMT, VTF and CO2e) that include zero values before the natural logarithm transformation.

Descriptive Statistics

Along with the path model for the entire Austin region, the same path models for two types of areas (MXD vs. non-MXD) were specified based on household locations to see whether the land use characteristics have a different influence on transportation GHG emissions locally. Table 7-4 below portrays a general picture of household characteristics by residential location. According to the t-test results, these characteristics are significantly different between those living in and outside MXDs.

In this sample, a household, on average, drives 42 miles at 22.45 miles per hour and emits 50.18 pounds (22761.62 grams) of carbon dioxide equivalent from a household's daily vehicle travel activities. The description statistics for the overall sample show that the Austin residents tend to heavily rely on the automobile as a primary mode of transportation because a household, on average, made less than one non-motorized trip on the travel day. Furthermore, only 14 out of 1331 households (1.1%) emit zero transportation GHG emissions on their travel day (data not shown). This implies that the rest of households were (98.9%) engaged in any vehicle related activities that generated transportation GHG emissions.

Variable	Overall (N=1,331) Min.	Max.	Mean	Std. Dev.	Non-MXD (N=1,269) Min.	Max.	Mean	Std. Dev.	MXD (N=62) Min.	Max.	Mean	Std. Dev.	Between t-test
Travel variables													
PMT	0.01	838.30	59.39	61.05	0.01	838.30	60.45	61.77	0.53	208.96	37.59	37.88	4.471
VMT	0.00	321.62	42.05	37.02	0.00	321.62	42.70	37.28	0.00	137.86	28.66	28.50	3.727
HBW	0.00	188.51	15.98	22.74	0.00	188.51	16.15	22.72	0.00	134.66	12.47	22.89	1.236
HBNW	0.00	162.49	16.90	19.90	0.00	162.49	17.17	20.11	0.00	61.88	11.38	13.89	3.127
NHBW	0.00	266.75	4.76	13.31	0.00	266.75	4.88	13.56	0.00	30.48	2.28	5.75	3.163
NHBO	0.00	106.23	4.41	10.15	0.00	106.23	4.50	10.29	0.00	36.21	2.54	6.47	2.535
SPEED	0.003	76.26	22.45	10.82	0.00	76.26	22.67	10.81	0.00	48.84	17.85	10.14	3.643
HBW	1.32	82.63	25.64	11.98	1.35	82.63	25.91	11.93	1.32	48.84	20.26	11.97	2.840
HBNW	0.00	81.36	22.22	12.54	0.00	81.36	22.44	12.57	4.20	71.10	17.52	10.99	3.136
NHBW	1.24	75.48	22.46	12.52	1.24	75.48	22.87	12.50	1.73	39.61	14.46	10.19	3.731
NHBO	0.12	81.60	20.51	13.01	0.12	81.60	20.52	12.97	0.70	56.02	20.18	14.43	0.099
VT	0	64	8.79	7.21	0	64	8.83	7.24	0	32	7.79	6.39	1.247
NVT	0	16	0.81	1.96	0	16	0.81	1.9	0	8	0.65	1.55	0.823
CO2e	0.00	171866.55	22761.62	18507.59	0.00	171866.55	23069.54	18623.08	0.00	78010.66	16459.22	14719.44	3.405
Household variables													
HHSIZE	1	13	2.84	1.54	1	13	2.87	1.55	1	5	2.32	1.21	3.413
VEHICLE	0	5	0.80	0.41	0	5	0.79	0.40	0	3	0.89	0.46	-1.708
WORKER	0	6	1.21	0.92	0	6	1.21	0.92	0	3	1.16	0.93	0.395
INCOME	2500	200000	56466.94	44803.60	2500	200000	56798.66	44703.95	2500	200000	49677.42	46653.33	1.176
Land use characteristics (1 mile buffer)													
DENSITY	3.20	14243.00	3493.34	2543.44	3.20	13670.71	3402.76	2500.15	767.30	14243.00	5347.45	2729.20	-5.499
DIVERSITY	0.02	0.86	0.58	0.15	0.02	0.86	0.57	0.15	0.33	0.81	0.66	0.10	-7.108
DESIGN	0.00	196.10	30.05	25.56	0.00	196.10	28.61	24.49	8.95	123.59	59.67	29.02	-8.286

Table 7-4: Descriptive Statistics.

Compared to non-MXD residents, a household living in MXDs, on average, travel and drive less. An MXD household, on average, travels 37.59 miles, which is about 23 (22.86) miles less than those living outside MXDs. In terms of VMT, a household living outside MXDs drives 42.70 miles, which constitute 14.04 miles (32.9%) more than those living in MXDs. However, outside MXD residents generate 28.7% more transportation GHG emissions than MXD residents. This is partly due to the fact that a household living outside MXDs drives on average at higher speed than those living in MXDs.

In general, lower levels of driving and associated transportation emissions from MXD households are due in part to the difference in household sizes. Since the average household size of MXDs is significantly smaller than that of households outside MXDs, MXD residents can travel less for household duties. Thus, the total amount of emissions from trips using automobiles may be smaller.

In terms of land use characteristics, these two groups are visibly different. MXD residents tend to live a denser, more diverse and better-connected neighborhood. Based on the empirical result in the existing studies, it is expected that these land use features will influence not only how much people drive but also how much transportation emissions they generate.

Model Results

Since almost all possible paths were being estimated, many fit indices in Table 7-5 show perfect fit (either zero or 1.0). As shown in Figure 7-3, models in this study assume that the variables under one category have a direct effect on those of another category. In addition, each variable under the same category correlates to one another. Thus, the "perfect fit" indices here do not mean that the model actually fits the data perfectly. These statistics cannot be used to determine how well the model fits.

Model Fit Information		**Overall**	**Non-MXD**	**MXD**
Number of Free Parameters		73	73	73
Loglikelihood	H0 Value	-19930.561	-19023.783	-753.725
	H1 Value	-19914.597	-19007.072	-752.565
Information Criteria	Akaike (AIC)	40007.122	38193.565	1653.450
	Bayesian (BIC)	40385.544	38568.528	1807.544
	Sample-Size Adjusted BIC (n* = (n + 2) / 24)	40153.657	38336.647	1577.901
Chi-Square Test of Model Fit	Value	31.928	33.421	2.321
	Degrees of Freedom	4	4	4
	p-value	0.0000	0.0000	0.6770
RMSEA (Root Mean Square Error Of Approximation)	Estimate	0.073	0.076	0.000
	90 Percent C.I.	0.051,0.097	0.054,0.101	0.000,0.150
	Probability RMSEA <= .05	0.046	0.028	0.736
CFI / TLI	CFI	0.994	0.993	1.000
	TLI	0.945	0.939	1.049
Chi-Square Test of Model Fit for the Baseline Model	Value	4374.976	4153.363	326.063
	Degrees of Freedom	34	34	34
	P-Value	0.0000	0.0000	0.0000
SRMR (Standardized Root Mean Square Residual)	Value	0.010	0.011	0.004

Table 7-5: Model Fit Indices.

Table 7-6 presents the estimates of all direct paths in three model specifications with their corresponding standard errors.

Endogenous variables	Overall				Non-MXD				MXD			
	VMT	**VOS**	**VTF**	**CO2e**	**VMT**	**VOS**	**VTF**	**CO2e**	**VMT**	**VOS**	**VTF**	**CO2e**
Household socio-economic status												
HHSIZE	0.165** (0.021)	-0.011 (0.017)	0.230** (0.013)		0.163** (0.021)	-0.015 (0.018)	0.229** (0.014)		0.302* (0.124)	0.082 (0.088)	0.303** (0.070)	
VEHICLE	0.446** (0.072)	-0.038 (0.061)	0.139** (0.046)		0.486** (0.074)	-0.052 (0.064)	0.153** (0.047)		0.085 (0.293)	0.226 (0.209)	-0.019 (0.165)	
WORKER	0.287** (0.031)	0.084** (0.025)	0.052** (0.020)		0.284** (0.031)	0.086** (0.026)	0.051* (0.020)		0.369** (0.140)	0.049 (0.101)	0.055 (0.079)	
INCOME	0.004** (0.001)	0.000 (0.000)	0.003** (0.000)		0.004** (0.001)	0.000 (0.000)	0.003** (0.000)		0.001 (0.003)	0.000 (0.002)	0.003 (0.002)	
Built environment characteristics												
Density	-0.149** (0.029)	-0.022 (0.025)	-0.004 (0.019)	-0.074** (0.018)	-0.144** (0.029)	-0.023 (0.026)	-0.003 (0.019)	-0.072** (0.018)	0.124 (0.251)	-0.105 (0.180)	0.072 (0.142)	-0.026 (0.074)
Diversity	-0.066 (0.086)	0.031 (0.071)	-0.038 (0.055)	-0.187** (0.051)	-0.046 (0.086)	0.031 (0.072)	-0.036 (0.055)	-0.168** (0.050)	-2.323** (0.838)	0.491 (0.671)	-0.213 (0.473)	-0.737* (0.329)
Design	-0.015 (0.027)	-0.126** (0.028)	0.077** (0.017)	0.206** (0.018)	-0.013 (0.027)	-0.118** (0.028)	0.077** (0.017)	0.196** (0.018)	0.130 (0.160)	-0.626** (0.168)	0.130 (0.090)	0.217** (0.090)
Household vehicle travel characteristics												
VMT				1.150** (0.026)				1.139** (0.026)				1.284** (0.070)
VOS				-0.328** (0.045)				-0.299** (0.046)				-0.982** (0.104)
VTF				0.138** (0.032)				0.145** (0.032)				-0.088 (0.079)

** significant at 0.01 level; * significant at 0.05 level

Table 7-6: Estimates and Standard Errors.

DISCUSSION

This section first discusses the results of the overall model specification. Next, the outcomes from the non-MXD and the MXD model specifications will be compared.

Overall Model

As expected, household characteristics strongly influence the vehicle travel behavior. A household with more workers, more members, more vehicle available, and more income tends to drive more and make more vehicle trips. Interestingly, a positive and statistically significant relationship between household worker and average vehicle travel speed was found. This result can be explained by recognizing that it is very likely that a higher income household (because of more workers) lives in the suburbs where their residents are provided with a more auto-friendly environment.

As expected, all land use variables are inversely related to household daily VMT, but only density dimension appears to have a significant direct influence on household daily VMT in the overall sample. Each coefficient of D variables presented in Table 7-6 represents an elasticity, which is a measure of effect size equal to the percentage change in an outcome variable with respect to a 1% increase in an explanatory variable. Table 7-6 suggests, for example, that a 1% increase in density will lead to a 0.15% decrease in household daily VMT. These findings support the previous argument that a compact development is likely to reduce household VMT. In terms of vehicle trip frequency, the socio-economic characteristics are more strongly related than land use factors as demonstrated in other studies (Ewing & Cervero, 2010; 2001). The positive coefficient of design to vehicle trip frequency (0.077) in the overall sample is due in part to frequent short distance vehicle trips.

As demonstrated in the previous chapters, land use also influences household vehicle travel speed in the case of Austin. In the overall model specification, two land use variables appear to reduce travel speed, but only the design dimension is statistically significant. The coefficient of -0.126 suggests that doubling the number of 4+ way intersections in a given area will reduce the average vehicle travel speed by about 13%. This result seems very reasonable and indicates that people driving in a well-connected area are more likely to make frequent stop-and-go movements than those living in a less-connected area, which consequently leads to slower vehicle movements.

The direct effect of any land use factors on transportation GHG emissions is assumed to be due to the choice of vehicle type a household owns and uses. In the overall model, all three dimensions seem to influence the type of vehicle. The negative coefficients of the density and diversity dimensions with respect to CO2e suggest that a household living in a more dense and diverse neighborhood is likely to own a vehicle that is more fuel efficient (i.e., generating less emissions), such as a passenger car rather than a truck. The design dimension has a positive direct effect on CO2e in the model, which may be partly due to the strong correlation with other land use factors. Overall, three dimensions have a very modest effect on the choice of vehicle (-0.074 + (-0.187) + 0.206 = -0.055) in the model.

Table 7-6 also presents the direct effects of the three vehicle travel characteristics on transportation GHG emissions. As expected, VMT is a primary determinant of the amount of transportation GHG emissions (CO2e), followed by VOS and VTF. However, they work in different directions. Larger VMT leads to higher levels of transportation emissions produced. The result, however, suggests that a slower vehicle is likely to produce more emissions than a faster vehicle. The result also suggests that more vehicle trips generate more emissions.

Besides the direct effects of three land use variables on vehicle travel characteristics, the total effects of each of land use variables on transportation GHG emissions were quantified (i.e., how much each built environmental characteristic influences household transportation GHG emissions through all different channels). Total effects simply include direct effects and indirect effects.

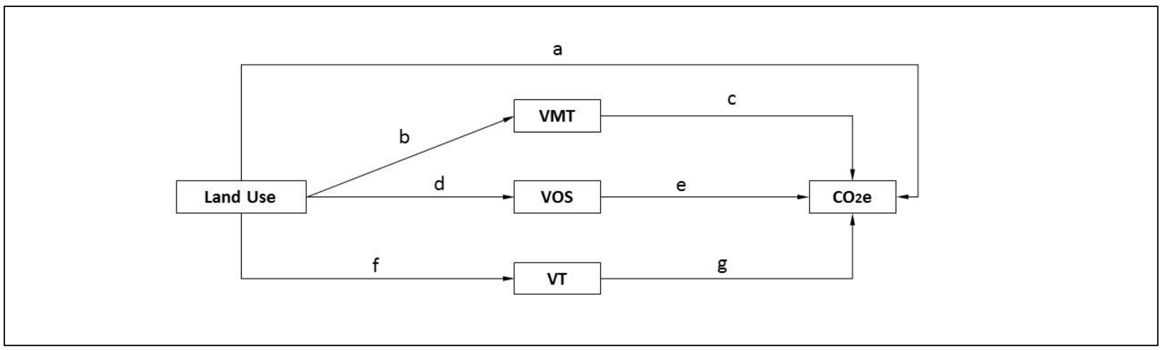


Figure 7-4: Total Effect of Land Use on Transportation GHG Emissions.

Figure 7-4 illustrates how land use influences transportation GHG emissions through various channels. First, each land use attribute directly influences household transportation GHG (a). This direct effect is mainly associated with the choice of vehicle households own and use. Second, each land use attribute is supposed to be negatively associated with household vehicle travel distance (b), and total household VMT is positively associated with household transportation GHG emissions (c). This is an indirect effect on transportation GHG emissions through changes in household daily VMT (b×c). Then, land use also influences vehicle travel speed (d), but there is a negative association between vehicle travel speed and transportation GHG emissions (e). As a vehicle moves faster, it generates less emissions per mile than a slower vehicle. This is an indirect effect on transportation emissions through changes in vehicle operating speeds (d×e). Lastly, land use characteristics also influence vehicle trip frequency (f), and the number of vehicle starts is also positively associated with transportation GHG emissions (g). This is an indirect effect on transportation emissions through changes in vehicle trip frequency. Therefore, the total effect of each land use attribute on transportation emissions is the sum of the direct effect (a) and the three indirect effects: (b×c), (d×e) and (f×g). This study, however, focused on the sum of the three indirect effects because, in the case of Austin, the sum of the direct effects of three land use characteristics seems to be marginal.

Table 7-7 presents the total effect of each land use variable on transportation GHG emissions for three model specifications. There are only a few studies reporting the elasticities of transportation GHG emissions by accounting for the indirect effects of land use. The overall results here generally suggest that simply translating VMT reduction into environmental benefits can overestimate the effect of land use policies, even in a specific region. This is mainly because of the secondary effect, the indirect effect land use has on transportation GHG emissions through the decrease in vehicle travel speed.

Variable	Path(s)	Overall		Non-MXD		MXD	
		Estimate (S.E.)	Total	Estimate (S.E.)	Total	Estimate (S.E.)	Total
Density	Density→VMT→CO2e	-0.171** (0.034)	-0.164** (0.033)	-0.164** (0.034)	-0.158** (0.033)	0.160 (0.323)	0.256 (0.288)
	Density→VOS→CO2e	0.007 (0.008)		0.007 (0.007)		0.103 (0.176)	
	Density→VT→CO2e	-0.001 (0.003)		0.000 (0.003)		-0.006 (0.014)	
Diversity	Diversity→VMT→CO2e	-0.075 (0.099)	-0.091 (0.095)	-0.052 (0.098)	-0.067 (0.095)	-2.982** (1.088)	-3.446** (0.982)
	Diversity→VOS→CO2e	-0.010 (0.024)		-0.009 (0.022)		-0.482 (0.643)	
	Diversity→VT→CO2e	-0.005 (0.008)		-0.005 (0.008)		0.019 (0.045)	
Design	Design→VMT→CO2e	-0.017 (0.031)	0.035 (0.031)	-0.015 (0.031)	0.032 (0.031)	0.167 (0.206)	0.770** (0.199)
	Design→VOS→CO2e	0.041** (0.013)		0.035** (0.012)		0.614** (0.139)	
	Design→VT→CO2e	0.011** (0.003)		0.011** (0.004)		-0.011 (0.013)	

Table 7-7: Elasticities of CO2e with respect to Land Use Changes.

Non-MXDs vs MXDs

Similar to the overall model, household characteristics are strongly associated with vehicle travel characteristics, specifically vehicle travel demand in both MXD and non-MXD models. Table 7-6 suggests that a household with more workers, members, vehicles, and income tends to use their automobile more.

In the non-MXD model, only the density dimension appears to have a significant direct influence on household daily VMT although the signs of all direct effects of land use variables are as expected (-). The design dimension, on the other hand, seems to be inversely related to average vehicle travel speed. These results together suggest that densification in less developed areas may lead to a reduction in household VMT, while increasing connectivity can cause slower vehicle movements in the areas.

In the MXD model, the larger coefficient of diversity shows that the efforts of mixing land uses function properly. What this means is that mixture of land-use seem to play a role in reducing vehicular travel within the MXDs as it was planned. However, it is worth noting that increasing density or connectivity may work in an opposite direction in MXDs: the elasticities of VMT with respect to density and design in the MXD model (0.124 and 0.130, respectively) suggest that a 1% increase in the density and design of MXDs is likely to lead to a 0.12% and 0.13% increase in VMT among the MXDs residents. Interestingly, these results show that a household living in MXDs is likely to drive more as the density or design of their residential area increases.

Based on the result, it can be inferred that the level of density (or connectivity) of these areas may reach the “saturation point,” at which increasing density (or connectivity) does not play a significant role in vehicle travel reduction. One explanation could be the difficulty in completely eliminating vehicle travel. As shown in Table 7-4, MXD households still drove a similar (or statistically not different) distance for home-based work trips (HBW) just as non-MXD households did. This implies that households have to drive to work regardless of their residential locations. Another explanation can support these results. The differences in density or design will be absorbed by the effect of the diversity feature of the areas. The significant VMT reduction among MXD households seems to be made by reducing vehicle travel for home-based non-work trips (HBNW). In this sense, the diversity attribute of MXDs may work in a desirable direction by making origins and destinations closer together and by providing favorable environments to non-motorized travelers.

However, the coefficient of design in the MXD model shows that improving connectivity in the MXDs is likely to reduce vehicle travel speed in the areas, to an even more serious extent than in the non-MXD region. The MXD model suggests that a 1% increase in design will likely lead to a 0.7% decrease in vehicle travel speed. The walkable features of the areas with diverse land-uses may attract people from outside. On the one hand, people are encouraged to walk from one place to another place within the areas, but on the other hand, they have to drive in and out (or even within the areas), which results in slower vehicle movements around the areas. The positive effect of the diversity dimension on vehicle travel speed in the MXD model is partly due to the faster vehicle travel speed for work trips. The results from Table 7-6 indicate that land use not only influences vehicle travel distance, but also vehicle operating speed.

However, Table 7-7 shows that land-use based strategies, such as densification, land-use mixture, and increasing road connectivity, can still potentially reduce household transportation GHG emissions through VMT reduction for areas with relatively lower levels of density, diversity, and design, even though these interventions may cause slower traffic flows in the area. However, the elasticities in MXDs imply that increasing road connectivity for the already dense area may be a challenge unless a meaningful modal shift from driving occurs. The promising finding for this type of area is the larger elasticities of VMT with respect to the diversity dimension although this feature seems to significantly decrease vehicle operating speeds in the area.

SUMMARY

As expected at the beginning of this study, the case study of the Austin, TX region reveals a very complex picture of the relationship between land use, vehicle travel, and transportation GHG emissions. The path models show how each land use attribute influences transportation GHG emissions through different channels. The study findings suggest that the influence of land use on VMT reduction appears to be meaningful even though the environmental benefits can be diminished by the secondary effect of reduced vehicle travel speed.

In general, the results of this case study suggest that region-wide, land use based strategies, such as densification, land-use mixture, and increasing connectivity, seem to play a meaningful role in regional transportation emission reduction. Although these interventions potentially cause slower vehicle movements in the region, the negative impact of land use changes (through a decrease in vehicle operating speeds) is not so large as to offset the environmental benefits through a VMT reduction in the region. These findings support the existing evidence that a compact, mixed-use, and well-connected development reduces transportation GHG emissions in the region (Ewing et al., 2008). Locally, however, higher population density and better connectivity can be associated with higher transportation emissions generation. While land-use mixture helps to reduce VMT and transportation GHG emissions in MXDs, densification and improving connectivity in this type of area may work in an undesirable direction. This poses a challenge to the land-use based strategies for reducing transportation GHG emissions. Some land-use strategies function like a double-edged sword in terms of their effects on VMT, vehicle operating speeds, and GHG emissions. However, the effects of land-use mix in this area are much larger than those of non-MXD areas. This implies that there could be possible synergy impacts among other land-use interventions for this area (Hong & Goodchild, 2014).

Several implications can be drawn from the findings. One implication of the study results is that land use based strategies for achieving the goal of reducing transportation GHG emissions should be carefully implemented depending on the level of development in areas. While it is practically unfeasible to eliminate vehicle travel entirely throughout the area, it is worth asking whether there exists an optimal level of development density and land use mix for a given level of vehicle ownership. For example, the findings show that the efforts on compact development still have potential in less developed areas while the efforts on mixture of land use look promising in MXDs in the case of Austin. However, improving connectivity can cause slow vehicle movements in the areas unless a meaningful modal shift occurs. Another implication of the study is that one land use based strategy alone may not work well in achieving the regional environmental goal (Zhang, 2010). The results suggest that land-use mixture is the most promising strategy to encourage non-motorized travel that emits zero emissions in the region. The effectiveness of land-use mixture in MXDs is even larger. However, land-use mixture should be coupled with densification and non-motorized traveler friendly design. Furthermore, it is essential to provide environmental friendly modes of transportation in the region.

Chapter Eight: Conclusions and Future Research

PRIMARY FINDINGS AND CONTRIBUTIONS

This dissertation research focuses on the link between land use measures at multiple geographic levels and household transportation GHG emissions. This research contends that land use based policies for reducing transportation GHG emissions require dealing with traffic congestion and should be practiced at an appropriate spatial scale as well as development stage to maximize the effectiveness of those policies. This research concentrates on the three following research questions: 1) how land use attributes relate to vehicle travel characteristics, 2) to what extent land use changes influence transportation GHG emissions through changes in vehicle travel, and 3) how land use at multiple geographic scales influence household daily transportation GHG emissions.

VMT reduction through land use changes may not necessarily lead to proportional GHG reduction because those land use changes may affect household vehicle travel in different ways or directions. This dissertation research finds that land use attributes influences not only household VMT but also vehicle travel speed and vehicle trip frequency, which in turn affect transportation GHG emissions. In addition, the relationship between land use and vehicle travel as well as transportation GHG emissions seems very complicated when land use policies are practiced in different spatial scales and different development stages.

While much literature recognizes VMT reduction as transportation GHG emissions reduction, less explores how land use changes influence transportation GHG emissions through changes in vehicle travel characteristics as intervening effects. Moreover, few studies address the spatial scale sensitive relationship between land use and transportation GHG emissions. This dissertation research bridges these gaps by applying two advanced modeling techniques (i.e., HLM and SEM). The following sections summarize the primary findings from this dissertation research.

Impact of Land Use on Vehicle Travel Speed and Frequency

The findings from Chapters Four and Six suggest that land use changes influence not only how many miles households drive, but also how fast and how frequent they drive. As demonstrated, these three vehicle travel (operating) characteristics that in turn determine transportation GHG emissions are influenced by the neighborhood land use in a very sophisticated way. While higher density, heterogeneous land use, better connected road network, provision of transit, and easy access of a given neighborhood are negatively associated with household VMT, which leads to reduction in transportation GHG emissions, most of these land use features are likely to reduce vehicle travel speed in the area, which produces more GHG emissions than under the free-flow situation. Moreover, the relationship between land use and vehicle trip frequency seems rather mixed. In other words, there exist some trade-offs between the benefits and risks of implementing land use policies in terms of reducing household transportation GHG emissions. From the modeling standpoint, inclusion of vehicle travel aspects, other than VMT, such as travel speed and trip frequency will provide a more comprehensive picture of the relationship between land use and transportation GHG emissions.

Scale-sensitive Effects of Land Use

The findings from Chapters Five and Six show that vehicle travel characteristics are influenced not only by neighborhood-level land use measures but also by those at higher geographic levels. These chapters also demonstrate that the effects of similar land use strategies can vary when they are practiced at different geographic levels. For instance, increasing connectivity of a given neighborhood may reduce vehicle travel in the area by encouraging use of sustainable transportation modes such as walking, biking, and transit. However, the existence of more roads in a given region may induce more vehicle travel thanks to the auto-friendly environment. Furthermore, the findings also suggest that land use policies should be implemented at an appropriate geographic level. For example, mixing residential and commercial use is a proper strategy for the neighborhood level, whereas balancing jobs and housing should be considered at the regional level. Restricting outward growth should be discussed at the metro level.

From the local perspective, the findings from Chapter Seven suggest that land use based strategies may be relatively more effective in less developed areas while the effectiveness of land use policies can be diminished if areas are already compact, mixed, and well-connected. Hence, other policies, rather than land use policies, should also be considered in these developed areas. For example, introducing policies in favor of carpooling and telecommuting or investing in infrastructure for public transportation and non-motorized travel, such as walking and bicycling, can help reduce per capita transportation emissions in these areas.

POLICY IMPLICATIONS

Travel Demand and Mobility Management

The findings from Chapters Four, Five, and Seven suggest that land use based policies, such as densification or road network design improvement in a given area, inevitably increase the congestion level of the area unless appropriate traffic mobility focused policies are simultaneously practiced. From the planning perspectives, providing other options to travel in the area will encourage travelers to switch from automobiles to sustainable modes of transportation. Increasing transit ridership and use of non-motorized travel will reduce transportation GHG emissions not only through reducing automobile use, but also alleviate traffic congestion. It is also possible to regulate vehicle trips in the area where high traffic demand and congestion are expected. From the engineering perspectives, improving traffic signals or road design may reduce traffic congestions even if the level of automobile use of the area remains the same.

Expansion of Authority of MPOs

The findings from Chapters Five and Six suggest that the same or similar land use policies can work differently depending on which geographic level those policies are implemented. For example, the densification efforts at the neighborhood and metro levels will reduce transportation GHG emissions, while the same effort at the county level may induce more automobile use, resulting in more emissions. This implies the importance of the role of metropolitan planning organizations (MPOs) in controlling development of an overall region. The expansion of authorities and responsibilities of MPOs may enable the region at all levels (i.e., neighborhood, city, and metro) to be developed more sustainably.

Land use based policies should be redesigned according to the geographic level to be implemented. At the neighborhood level, placing daily destinations such as grocery shopping or recreations closer to residential areas work well, while spatially evenly distributed regional employment centers may work better at the city or county level. In these situations, regional and local agencies should closely work together in order to achieve the environmental goal of the region. Also, several departments should collaborate when dealing with issues regarding travel demand and mobility.

Consideration of the Level of Development

Prior to implementing land use policies, it may be important to understand the current level of development of a given area. Developing a strong center, such as a central business district, would be a good strategy for small metropolitan areas without sufficient public transit system. In terms of population and land area, developing activity centers may work better for mid-size metropolitan areas. Increasing transit service may be effective for large metro areas where are already well-served by public transit. These areas are already compact, well connected enough, and has transit service that will help its residents shift to other modes of transportation.

Increasing connectivity (more intersections), however, can act as a double-edged sword. In mid-size metros, increasing the number of intersection may provide shorter routes without serious traffic congestion. On the other hand, increasing connectivity may cause serious traffic delay while reducing household VMT in a large metro area unless the area is well served by public transit.

LIMITATIONS

A better understanding of how land use influence individuals' or households' transportation GHG emissions is critical for designing efficient policies to achieve environmental goals of the region. The empirical analyses in this dissertation research have investigated the efficiency of land use policies in reducing transportation GHG emissions. There, however, exist some limitations, which can present further opportunities to extend this research.

First, real transportation GHG emissions rather than estimated emissions based on the trip distance and times from the travel survey datasets would have made the model specifications more accurate and reliable. Trip distances and times used in this dissertation research were based on the self-reported values of the surveyed individuals. Thus, reporting errors are highly likely to exist and affect VMT and speed estimates. Moreover, travel speed estimates for trips were aggregated into the household level, which may not reflect the actual driving conditions that influence emissions.

Secondly, the land use measures could have been improved. Even though the Smart Location Database enabled this study to consistently compare the location efficiencies across the entire study area, some variables may fail to capture all key dimensions of the built environment of a given area. Moreover, including only one variable for each category of land use is unlikely to capture the complexity of the D-variables. For instance, the design variable, *intersection density*, does not show the quality of the built environment, and distance to transit was estimated based on weighted population, which can differ from the actual household locations.

Thirdly, the 2009 NHTS add-on datasets considered in this study may not represent the entire U.S., and the analytic results in this study are exploratory. In other words, the findings from the analyses are valid to the sample of this study, but the external validity of the results is unknown. Consideration on households from other regions as well as weights of the sample may change the study results and increase the external validity of this study.

Lastly, the models specified in this study may not consider explanatory variables that should have been included. For example, variables that can explain the cultural variations by region were not considered. In addition, personal attitudes towards not only automobile use but also consideration for travel in general were limited.

FUTURE WORK

Future studies, therefore, can be further developed from these points. To be specific, the final model specifications in Chapter Five assumed that the effects of land use variables along with household socio-economic status were identical regardless of region while there were mean differences in household daily VMT and transportation emissions across the regions. In reality, however, it is very likely that the magnitude of those effects can vary from place to place because of several other observed (e.g., quality of pedestrian facilities, climate, crime rates, etc.) or unobserved factors (e.g., social/cultural norms, efficiency of planning process, etc.) that have not been considered in the analyses in this chapter. Thus, the model specification can be further developed by 1) specifying the random intercept and slope models can capture the variation in the effects of land use measures as well as socio-economic factors, and 2) including more observed or unobserved variables can increase the capacity of the model to explain the variation in the level of household automobile use and associated transportation GHG emissions.

The final model specification in Chapter Six can be developed further as well. First, household daily gasoline consumption, which was estimated based on other fuel related variables such as miles per gallon and fuel cost, is an alternative measure of transportation GHG emissions. Actual transportation GHG emissions from a tailpipe can more accurately capture the effect of changes in vehicle travel speed. Second, city-level land use measures, rather than the county-level ones, may increase the capacity of the model to explain the link between land use measures of multiple geographic levels and household transportation GHG emissions. Lastly, the model specification can be developed by accounting for the nested structure of multiple geographic levels.

Appendices

A1-1: Descriptive Statistics of Population by State

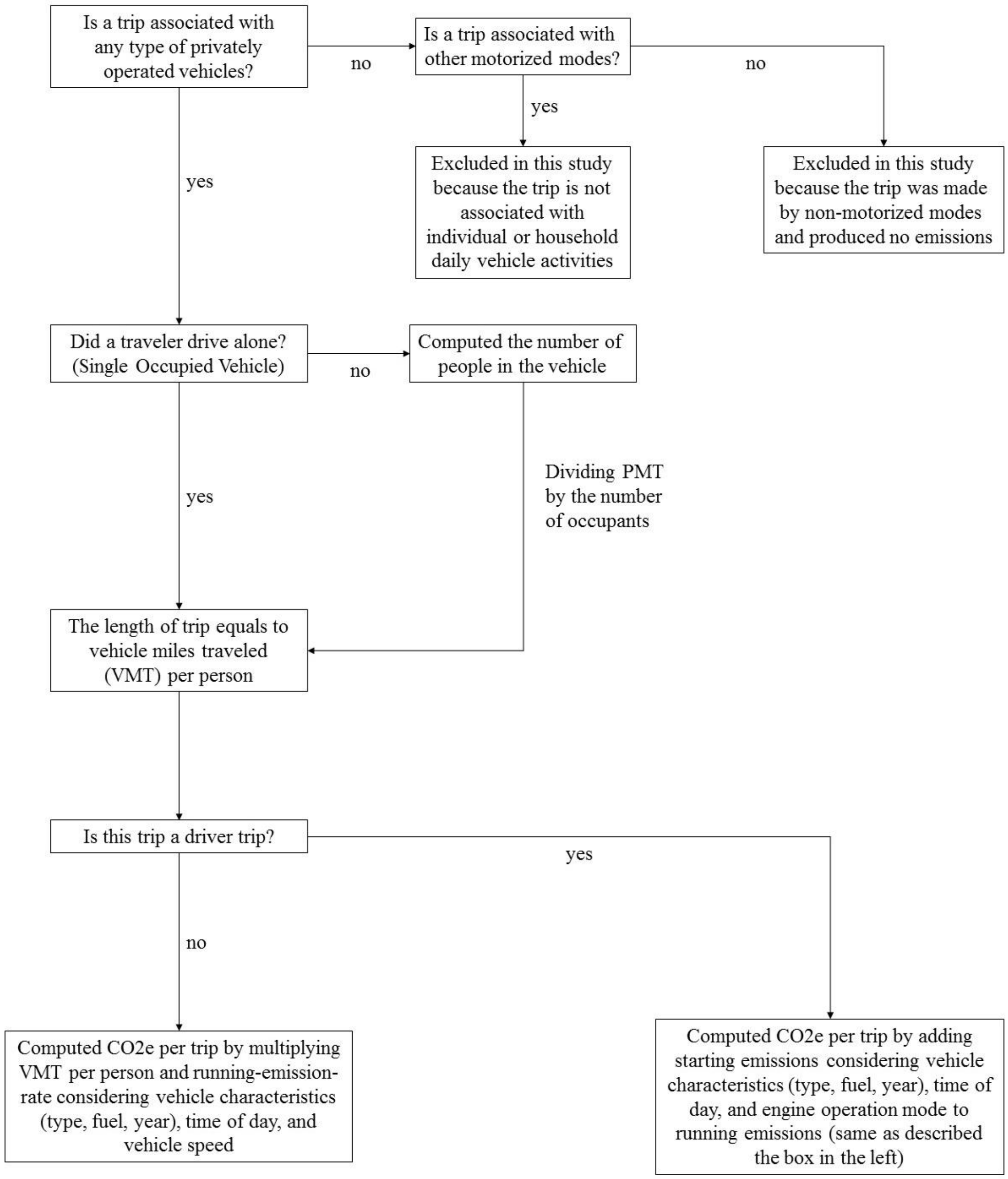
Variable	U.S.	CA	FL	GA	SC	TN	TX	VT	VA	WI
Household demographic and socio-economic characteristics										
Household size[1]	2.58	2.90	2.48	2.63	2.49	2.48	2.75	2.34	2.54	2.43
Household vehicle[2]	1.14	1.57	1.01	1.14	1.09	1.14	0.98	1.13	1.21	1.10
Household worker[3]	1.06	1.15	0.95	1.03	0.99	1.00	1.14	1.13	1.13	1.16
Household income[1]	70.88	83.48	66.32	66.62	58.94	59.21	68.70	65.89	82.58	65.27
Household travel characteristics										
Vehicle miles traveled[6]	69.41	70.68	72.50	83.48	74.73	77.16	70.62	81.69	72.55	69.89
Vehicle operating speed	-	-	-	-	-	-	-	-	-	-
Vehicle trip frequency	-	-	-	-	-	-	-	-	-	-
Household daily CO2e	-	-	-	-	-	-	-	-	-	-
Household daily gasoline consumption (gallons)[5]	3.15	3.18	3.02	3.68	4.09	3.41	3.65	3.48	3.47	2.97
CBG-level land use										
Activity density (per acre)[4]	5.48	5.82	6.15	2.75	1.97	2.45	4.59	2.12	5.27	4.84
Jobs and housing entropy[4]	0.45	0.46	0.45	0.48	0.47	0.42	0.46	0.58	0.46	0.46
Intersection density (per square mile)[4]	71.23	90.97	94.78	50.05	44.19	49.26	80.40	25.00	66.56	67.05
Distance to transit (meters)[4]	505.9	482.9	477.6	468.9	639.4	690.3	448.4	866.4	464.2	316.8
Regional centrality[4]	0.40	0.49	0.49	0.43	0.43	0.44	0.46	0.33	0.40	0.47
County-level land use										
Activity density (per acre)[4]	0.46	1.31	0.68	0.25	0.20	0.20	0.14	0.12	1.46	0.25
Jobs and housing balance[4]	0.81	0.92	0.78	0.71	0.78	0.68	0.77	0.93	0.97	0.94
Road network density (miles/acre)[4]	2.61	3.03	3.53	2.80	2.73	2.65	1.76	2.00	5.30	2.46
CBSA-level land use										
Unprotected land area (mi^2)[4]	1285.8	2019.89	988.91	975.22	967.3	845.61	1665.98	735.38	1368.19	923.93
Activity density (per acre)[4]	0.25	0.55	0.66	0.19	0.21	0.18	0.14	0.18	0.21	0.30
Road network density (miles/acre)[4]	2.45	2.33	3.38	2.64	2.90	2.71	1.91	1.89	2.43	2.65

[1] 2010 Decennial Census: http://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml#
[2] Derived from dividing the number of registered vehicles from 2009 State Motor-Vehicle Registrations in the 2009 edition of *Highway Statistics* from http://www.fhwa.dot.gov/policyinformation/statistics/2009/pdf/mv1.pdf by the number of households from 2010 Decennial Census
[3] Derived from dividing the number of workers from the Smart Location Database by the number of household from 2010 Decennial Census
[4] Smart Location Database
[5] Derived from 2009 Motor Fuel Use (Highway and non-highway use for private and commercial) in the 2009 edition of *Highway Statistics* from http://www.fhwa.dot.gov/policyinformation/statistics/2009/mf21.cfm
[6] Derived from 2009 Vehicle-miles of travel, by functional system in the 2009 edition of *Highway Statistics* from http://www.fhwa.dot.gov/policyinformation/statistics/2009/vm2.cfm

A1-2: DESCRIPTIVE STATISTICS OF SAMPLE BY STATE

Variable	Entire	CA	FL	GA	SC	TN	TX	VT	VA	WI
Household demographic and socio-economic characteristics										
Household size	2.45	2.59	2.28	2.44	2.37	2.41	2.54	2.37	2.46	2.51
Household vehicle	2.23	2.27	1.97	2.32	2.22	2.31	2.12	2.21	2.39	2.31
Household worker	1.03	1.1	0.88	1	0.94	1.03	1.11	1.22	1.11	1.21
Household income	69.41	76.28	66.42	61.31	61.08	60.24	78.79	65.68	69.68	70.27
Household travel characteristics										
Vehicle miles traveled	42.12	41.07	38.59	46.02	42.79	46.41	45.33	44.87	43.99	42.33
Vehicle operating speed	24.54	23.38	23.1	26.71	25.99	26.76	27.02	25.71	25.31	25.98
Vehicle trip frequency	5.86	5.97	5.59	5.87	5.96	5.86	5.87	5.86	5.93	6.09
Household daily CO2e	21130.2	20667.7	19821.0	22883.5	21562.7	22597.6	22195.2	21731.9	21862.7	20584.8
Household daily gasoline consumption (gallons)	3.2	3.09	2.83	3.59	3.32	3.58	3.35	3.19	3.44	3.27
CBG-level land use										
Activity density (per acre)	3.99	6.76	4.16	1.53	1.57	1.8	3.27	1.62	2.54	3.27
Jobs and housing entropy	0.46	0.46	0.44	0.47	0.48	0.42	0.48	0.56	0.46	0.49
Intersection density (per square mile)	69.95	103.95	78.93	36.24	40.7	41.48	56.7	20.62	49.32	58.14
Distance to transit (meters)	541.7	526.84	575.07	544.16	646.23	716.54	526.32	812.5	573.67	393.68
Regional centrality	0.46	0.47	0.46	0.47	0.5	0.42	0.37	0.4	0.46	0.51
County-level land use										
Activity density (per acre)	1.79	2.64	1.99	0.69	0.54	0.81	1.02	0.27	1.73	1.22
Jobs and housing balance	1.05	1.13	0.93	0.95	1.05	1.04	1.14	1.18	1.06	1.18
Road network density (per square mile)	5.06	4.91	5.33	4.17	4.2	4.47	4.41	2.26	6.14	4.81
CBSA-level land use										
Unprotected land area (mi^2)	2448.74	2908.58	1694.95	2685.56	1627.2	2922.28	3963.34	1288.82	2725.73	1529.36
Activity density (per acre)	1.19	2.12	1.48	0.36	0.38	0.36	0.54	0.2	0.55	0.71
Road network density (per square miles)	3.82	4.31	4.48	3.1	3.67	3.14	3.28	2.03	3.16	3.75

A2: MOVES EMISSIONS ESTIMATION



A3: PATH MODEL (MPLUS) RESULTS FOR US METROS

	Estimate	S.E.	Est./S.E.	P-Value
URBAN BY				
D1D	1.000	0.000	999.000	999.000
D2AEPHHM	0.038	0.002	16.731	0.000
D3B2	0.754	0.002	352.508	0.000
D4A	-0.345	0.010	-34.369	0.000
D5CRI	0.227	0.003	75.086	0.000
URBAN ON				
INC1000	-0.002	0.000	-32.736	0.000
HHSIZE	-0.085	0.002	-34.770	0.000
WRKCOUNT	-0.191	0.004	-52.227	0.000
HHVEH	-0.222	0.003	-75.976	0.000
LVMT ON				
URBAN	-1.230	0.005	-260.354	0.000
LVOS ON				
URBAN	-0.305	0.002	-167.779	0.000
LVT ON				
URBAN	-0.372	0.002	-161.830	0.000
LGASDAY ON				
URBAN	2.498	0.063	39.738	0.000
LVMT ON				
C_D1D	0.038	0.006	6.427	0.000
C_D2AJPH	0.022	0.007	3.043	0.002
C_D3A	-0.040	0.010	-3.913	0.000
S_SIZE	0.006	0.002	2.774	0.006
S_D1D	-0.014	0.006	-2.313	0.021
S_D3A	0.020	0.012	1.659	0.097
LVOS ON				
C_D1D	-0.085	0.007	-12.333	0.000
C_D2AJPH	0.019	0.008	2.256	0.024
C_D3A	0.071	0.012	5.926	0.000
S_SIZE	0.000	0.003	0.076	0.940
S_D1D	0.020	0.007	2.760	0.006
S_D3A	-0.039	0.014	-2.738	0.006
LVT ON				

C_D1D	0.061	0.009	6.977	0.000
C_D2AJPH	0.064	0.011	5.909	0.000
C_D3A	-0.054	0.015	-3.491	0.000
S_SIZE	-0.009	0.003	-2.683	0.007
S_D1D	-0.032	0.009	-3.390	0.001
S_D3A	0.021	0.018	1.124	0.261
LGASDAY ON				
LVMT	3.678	0.065	56.848	0.000
LVOS	-1.512	0.021	-73.132	0.000
LVT	-1.084	0.015	-71.032	0.000
INC1000 WITH				
HHSIZE	14.022	0.270	51.940	0.000
WRKCOUNT	15.784	0.202	78.021	0.000
HHVEH	15.749	0.245	64.407	0.000
HHSIZE WITH				
WRKCOUNT	0.508	0.005	98.256	0.000
HHVEH	0.535	0.006	85.846	0.000
WRKCOUNT WITH				
HHVEH	0.407	0.005	89.668	0.000
D1D WITH				
D2AEPHHM	0.182	0.007	27.880	0.000
D3B2	3.144	0.021	149.391	0.000
D4A	-1.397	0.039	-35.493	0.000
D5CRI	0.931	0.010	96.161	0.000
D2AEPHHM WITH				
D3B2	0.030	0.005	5.917	0.000
D4A	-0.055	0.005	-12.152	0.000
D5CRI	0.061	0.002	25.205	0.000
D3B2 WITH				
D4A	-1.056	0.032	-33.156	0.000
D5CRI	0.708	0.008	92.813	0.000
D4A WITH				
D5CRI	-0.397	0.013	-30.028	0.000
Means				
INC1000	69.195	0.213	324.625	0.000
HHSIZE	2.452	0.005	466.945	0.000
WRKCOUNT	1.035	0.004	272.663	0.000
HHVEH	2.231	0.005	475.984	0.000

Intercepts				
LVMT	2.019	0.022	90.438	0.000
LVOS	2.717	0.023	116.382	0.000
LVT	1.319	0.030	44.093	0.000
LGASDAY	-2.328	0.122	-19.146	0.000
D1D	1.407	0.013	108.403	0.000
D2AEPHHM	-0.889	0.004	-250.311	0.000
D3B2	4.391	0.010	425.421	0.000
D4A	6.192	0.009	676.856	0.000
D5CRI	-0.747	0.005	-140.272	0.000
Variances				
INC1000	2489.562	15.065	165.253	0.000
HHSIZE	1.535	0.009	166.828	0.000
WRKCOUNT	0.802	0.005	166.828	0.000
HHVEH	1.222	0.007	166.828	0.000
Residual Variances				
LVMT	-0.282	0.006	-46.710	0.000
LVOS	0.156	0.001	174.190	0.000
LVT	0.260	0.001	177.530	0.000
LGASDAY	2.560	0.056	46.046	0.000
D1D	4.182	0.027	155.942	0.000
D2AEPHHM	0.385	0.002	165.238	0.000
D3B2	2.697	0.018	151.733	0.000
D4A	1.049	0.027	38.606	0.000
D5CRI	0.739	0.005	152.656	0.000
URBAN	1.000	0.000	999.000	999.000

References

Anderson, D. (2012). *Hierarchical Linear Modeling (HLM): An Introduction to Key Concepts Within Cross-Sectional and Growth Modeling Frameworks*.

Badoe, D. A., & Miller, E. J. (2000). Transportation - Land Use Interaction: Empirical Findings in North America and their Implications for Modeling. *Transportation Research Part D: Transport and Environment*, *5*, 235–263. http://doi.org/10.1016/S1361-9209(99)00036-X

Bagley, M. N., & Mokhtarian, P. L. (2002). The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *Annals of Regional Science*, *36*(2), 279–297. http://doi.org/10.1007/s001680200083

Bailey, L., Mokhtarian, P. L., & Little, A. (2008). *The Broader Connection between Public Transportation, Energy Conservation and Greenhouse Gas Reduction*. *ICF International*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.169.5911&rep=rep1&type=pdf

Barla, P., Miranda-Moreno, L. F., Savard-Duquet, N., Thériault, M., & Lee-Gosselin, M. (2010). Disaggregated Empirical Analysis of Determinants of Urban Travel Greenhouse Gas Emissions. *Transportation Research Record: Journal of the Transportation Research Board*, *2156*, 160–169. http://doi.org/10.3141/2156-18

Barth, M., & Boriboonsomsin, K. (2008). Real-World Carbon Dioxide Impacts of Traffic Congestion. *Transportation Research Record: Journal of the Transportation Research Board*, *2058*, 163–171. http://doi.org/10.3141/2058-20

Bento, A. M., Cropper, M. L., Mushfiq, M., & Vinha, K. (2005). The Effects of Urban Spatial Structure on Travel Demand in the United States. *The Review of Economics and Statistics*, *87*(3), 466–478.

Bhat, C., Paleti, R., Pendyala, R., Lorenzini, K., & Konduri, K. (2013). Accommodating Immigration Status and Self-Selection Effects in a Joint Model of Household Auto Ownership and Residential Location Choice. *Transportation Research Record: Journal of the Transportation Research Board*, *2382*, 142–150. http://doi.org/10.3141/2382-16

Bhat, C. R., Astroza, S., & Bhat, A. C. (n.d.). Incorporating a Multiple Discrete-Continuous Outcome in the Generalized Heterogeneous Data Model: Application to Residential Self-Selection Effects Analysis in an Activity Time-use Behavior

Model. *Transportation Research Part B*. http://doi.org/10.1017/CBO9781107415324.004

Bhat, C. R., Astroza, S., Sidharthan, R., Alam, M. J. Bin, & Khushefati, W. H. (2014). A joint count-continuous model of travel behavior with selection based on a multinomial probit residential density choice model. *Transportation Research Part B: Methodological*, *68*, 31–51. http://doi.org/10.1016/j.trb.2014.05.004

Bhat, C. R., & Guo, J. Y. (2007). A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. *Transportation Research Part B: Methodological*, *41*(5), 506–526. http://doi.org/10.1016/j.trb.2005.12.005

Bhat, C. R., Sen, S., & Eluru, N. (2009). The Impact of Demographics, Built Environment Attributes, Vehicle Characteristics, and Gasoline Prices on Household Vehicle Holdings and Use. *Transportation Research Part B*, *43*, 1–18. http://doi.org/10.1017/CBO9781107415324.004

Boarnet, M., & Crane, R. (2001). The influence of land use on travel behavior: Specification and estimation strategies. *Transportation Research Part A: Policy and Practice*, *35*(9), 823–845. http://doi.org/10.1016/S0965-8564(00)00019-7

Boarnet, M. G. (2011). A Broader Context for Land Use and Travel Behavior, and a Research Agenda. *Journal of the American Planning Association*, *77*(3), 197–213. http://doi.org/10.1080/01944363.2011.593483

Boarnet, M. G., & Sarmiento, S. (1998). Can Land-use Policy Really Affect Travel Behaviour? A Study of the Link between Non-work Travel and Land-use Characteristics. *Urban Studies*, *35*(7), 1155–1169. http://doi.org/10.1080/0042098984538

Brownstone, D. (2008). *Key Relationships Between the Built Environment and VMT*. *Transportation Research*. Retrieved from http://onlinepubs.trb.org/Onlinepubs/sr/sr298brownstone.pdf

Brownstone, D., & Golob, T. F. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics*, *65*(1), 91–98. http://doi.org/10.1016/j.jue.2008.09.002

Brundell-Freij, K., & Ericsson, E. (2005). Influence of street characteristics, driver category and car performance on urban driving patterns. *Transportation Research Part D: Transport and Environment*, *10*(3), 213–229. http://doi.org/10.1016/j.trd.2005.01.001

CAMPO. (2010). *CAMPO 2035 Regional Transportation Plan Appendices*. Retrieved from www.campotexas.org

Cao, X. (Jason), Mokhtarian, P. L., & Handy, S. L. (2009). Examining the impacts of residential self selection on travel behaviour: A focus on empirical findings. *Transport Reviews*, *29*(3), 359–395. http://doi.org/10.1080/01441640802539195

Cervero, R., & Duncan, M. (2006). 'Which Reduces Vehicle Travel More: Jobs-Housing Balance or Retail-Housing Mixing? *Journal of the American Planning Association*, *72*(4), 475–490. http://doi.org/10.1080/01944360608976767

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, *2*(3), 199–219. http://doi.org/10.1016/S1361-9209(97)00009-6

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: Evidence from 370 US urbanized areas. *Environment and Planning A*, *42*(2), 400–418. http://doi.org/10.1068/a4236

Chen, C., Gong, H., & Paaswell, R. (2008). Role of the built environment on mode choice decisions: Additional evidence on the impact of density. *Transportation*, *35*(3), 285–299. http://doi.org/10.1007/s11116-007-9153-5

Cox, W. (2003). How Higher Density Makes Traffic Worse. *The Public Purpose*. Retrieved from http://publicpurpose.com/pp57-density.htm

Crane, R. (2000). The Influence of Urban Form on Travel : An Interpretive Review. *Journal Of Planning Literature*, *15*(1), 3–23. http://doi.org/10.1177/08854120022092890

De Abreu e Silva, J., Goulias, K., & Dalal, P. (2012). Structural Equations Model of Land Use Patterns, Location Choice, and Travel Behavior in Southern California. *Transportation Research Record: Journal of the Transportation Research Board*, *2323*, 35–45. http://doi.org/10.3141/2323-05

Eisele, W., Fossett, T., Schrank, D., Farzaneh, M., Meier, P., & Williams, S. (2014). Greenhouse Gas Emissions and Urban Congestion. *Transportation Research Record: Journal of the Transportation Research Board*, *2427*(2427), 73–82. http://doi.org/10.3141/2427-08

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., & Chen, D. (2008). *Growing Cooler: The Evidence on Urban Development and Climate Change*. Washington, D.C.: Urban Land Institute.

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, *1780*, 87–114.

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, *76*(3), 265–294. http://doi.org/10.1080/01944361003766766

Ewing, R., Greenwald, M., Zhang, M., Walters, J., Feldman, M., Cervero, R., … Thomas, J. (2011). Traffic Generated by Mixed-Use Developments—Six-Region Study Using Consistent Built Environmental Measures. *Journal of Urban Planning and Development*, *137*(September), 248–261. http://doi.org/10.1061/(ASCE)UP.1943-5444.0000068

Ewing, R., Hamidi, S., Gallivan, F., Nelson, a. C., & Grace, J. B. (2014). Structural equation models of VMT growth in US urbanised areas. *Urban Studies*, *51*(14), 3079–3096. http://doi.org/10.1177/0042098013516521

Fang, H. A. (2008). A discrete–continuous model of households' vehicle choice and usage, with an application to the effects of residential density. *Transportation Research Part B: Methodological*, *42*(9), 736–758. http://doi.org/10.1016/j.trb.2008.01.004

FHWA. (2011). 2009 National Household Travel Survey User's Guide.

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2007). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, *35*(1), 37–54. http://doi.org/10.1007/s11116-007-9136-6

Frank, L. D., Greenwald, M. J., Winkelman, S., Chapman, J., & Kavage, S. (2010). Carbonless footprints: Promoting health and climate stabilization through active transportation. *Preventive Medicine*, *50*(SUPPL.), S99–S105. http://doi.org/10.1016/j.ypmed.2009.09.025

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality. *Journal of the American Planning Association*, *72*(1), 75–87. http://doi.org/10.1080/01944360608976725

Frank, L. D., Stone, B., & Bachman, W. (2000). Linking land use with household vehicle emissions in the central puget sound: Methodological framework and findings.

Transportation Research Part D: Transport and Environment, *5*(3), 173–196. http://doi.org/10.1016/S1361-9209(99)00032-2

Garson, G. D. (2013). Introductory Guide to HLM with HLM 7 Software. In *Hierarchical Linear Modeling: Guide and Applications* (pp. 55–96). Los Angeles: Sage.

Glaeser, E., & Kahn, M. (2008). The greenness of cities. *Cambridge, MA*, (617). http://doi.org/Cited By (since 1996) 1\rExport Date 25 September 2012

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological*, *37*, 1–25. http://doi.org/10.1016/S0191-2615(01)00046-7

Handy, S. (2005). Smart Growth and the Transportation-Land Use Connection: What Does the Research Tell Us? *International Regional Science Review*, *28*(2), 146–167. http://doi.org/10.1177/0160017604273626

Handy, S., Cao, X., & Mokhtarian, P. L. (2006). Self-Selection in the Relationship between the Built Environment and Walking. *Journal of the American Planning Association*, *72*(1), 55–74.

Heres-Del-Valle, D., & Niemeier, D. (2011). CO2 emissions: Are land-use changes enough for California to reduce VMT? Specification of a two-part model with instrumental variables. *Transportation Research Part B: Methodological*, *45*(1), 150–161. http://doi.org/10.1016/j.trb.2010.04.001

Holtzclaw, J. (1994). Using Residential Patterns and Transit To Decrease Auto Dependence and Costs, (June), 51. Retrieved from http://docs.nrdc.org/smartGrowth/files/sma_09121401a.pdf

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., & Haas, P. (2002). Location efficiency: Neighborhood and socio-economic characteristics determine auto ownership and use-studies in Chicago, Los Angeles and San Francisco. *Transportation Planning and Technology*, *25*(1), 1–27.

Hong, J., & Goodchild, A. (2014). Land use policies and transport emissions: Modeling the impact of trip speed, vehicle characteristics and residential location. *Transportation Research Part D: Transport and Environment*, *26*, 47–51. http://doi.org/10.1016/j.trd.2013.10.011

Hong, J., & Shen, Q. (2013). Residential density and transportation emissions: Examining the connection by addressing spatial autocorrelation and self-selection.

Transportation Research Part D: Transport and Environment, *22*, 75–79. http://doi.org/10.1016/j.trd.2013.03.006

Hong, J., Shen, Q., & Zhang, L. (2014). How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. *Transportation*, *41*(3), 419–440. http://doi.org/10.1007/s11116-013-9462-9

Karathodorou, N., Graham, D. J., & Noland, R. B. (2010). Estimating the effect of urban density on fuel demand. *Energy Economics*, *32*(1), 86–92. http://doi.org/10.1016/j.eneco.2009.05.005

Kitamura, R., Mokhtarian, P. L., & Laidet, L. (1997). A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. *Transportation*, *24*(2), 125–158. http://doi.org/10.1023/A:1017959825565

Kwan, M. P., & Weber, J. (2008). Scale and accessibility: Implications for the analysis of land use-travel interaction. *Applied Geography*, *28*(2), 110–123. http://doi.org/10.1016/j.apgeog.2007.07.002

Lee, S., & Lee, B. (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy*, *68*, 534–549. http://doi.org/10.1016/j.enpol.2014.01.024

Litman, T. (2015). *Smart Transportation Emission Reduction Strategies* (Vol. 47).

Liu, C., & Shen, Q. (2011). An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems*, *35*(5), 347–357. http://doi.org/10.1016/j.compenvurbsys.2011.05.006

Mokhtarian, P. L., & Cao, X. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. *Transportation Research Part B: Methodological*, *42*(3), 204–228. http://doi.org/10.1016/j.trb.2007.07.006

Nasri, A., & Zhang, L. (2015). Assessing the Impact of Metropolitan-Level, County-Level, and Local-Level Built Environment on Travel Behavior : Evidence from 19 U . S . Urban Areas. *Journal of Urban Planning and Development*, *141*(3), 1–10. http://doi.org/10.1061/(ASCE)UP.1943-5444.0000226.

Newman, P., & Kenworthy, J. (1989). Gasoline Consumption and Cities. *Journal of the American Planning Association*, *55*(1), 24–37. http://doi.org/10.1080/01944368908975398

Newman, P., & Kenworthy, J. (1999). *Sustainability and cities: Overcoming automobile dependence*. Washington, D.C.: Island Press.

Pinjari, A. R., Pendyala, R. M., Bhat, C. R., & Waddell, P. a. (2011). Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions. *Transportation*, *38*(6), 933–958. http://doi.org/10.1007/s11116-011-9360-y

Ramsey, K., & Bell, A. (2014). *Smart Location Database: Version 2.0 User Guide*.

Reyna, J. L., Chester, M. V, Ahn, S., & Fraser, A. M. (2015). Improving the Accuracy of Vehicle Emissions Profiles for Urban Transportation Greenhouse Gas and Air Pollution Inventories. *Environmental Science and Technology*, *49*, 369–376. http://doi.org/dx.doi.org/10.1021/es5023575

Salon, D., Boarnet, M. G., Handy, S., Spears, S., & Tal, G. (2012). How do local actions affect VMT? A critical review of the empirical evidence. *Transportation Research Part D: Transport and Environment*, *17*(7), 495–508. http://doi.org/10.1016/j.trd.2012.05.006

Schrank, D., & Lomax, T. (2009). *2009 Urban Mobility Report*. *Texas Transport Institute*. Retrieved from mobility.tamu.edu

Schwanen, T., & Mokhtarian, P. L. (2007). Attitudes toward travel and land use and choice of residential neighborhood type: Evidence from the San Francisco Bay Area. *Housing Policy Debate*, *18*(1), 171–207. http://doi.org/10.1080/10511482.2007.9521598

Stone, B., Mednick, A. C., Holloway, T., & Spak, S. N. (2007). Is Compact Growth Good for Air Quality? *Journal of the American Planning Association*, *73*(4), 404–418. http://doi.org/10.1080/01944360708978521

Systematics, C. (2009). *Moving Cooler: An analysis of transportation strategies for reducing greenhouse gas emissions*. Urban Land Institute.

Taylor, B. D. (2002). Rethinking Traffic Congestion. *ACCESS Magazine*, *1(21)*, 8–16. Retrieved from http://www.escholarship.org/uc/item/2fb4t8wd

The Louis Berger Group Inc. (2004). *Emissions Benefits of Land Use Planning Strategies*. Cary, North Carolina. Retrieved from http://www.fhwa.dot.gov/environment/air_quality/conformity/research/benefits.pdf

TRB. (2009). *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions*. Washington, D.C. Retrieved from www.TRB.org

U.S. EIA. (2011). *Emissions of Greenhouse Gases in the United States 2009*. Washington, D.C.

Van Acker, V., Mokhtarian, P. L., & Witlox, F. (2014). Car availability explained by the structural relationships between lifestyles, residential location, and underlying residential and travel attitudes. *Transport Policy*, *35*, 88–99. http://doi.org/10.1016/j.tranpol.2014.05.006

Van Wee, B. (2009). Self-Selection: A Key to a Better Understanding of Location Choices, Travel Behaviour and Transport Externalities? *Transport Reviews*, *29*(3), 279–292. http://doi.org/10.1080/01441640902752961

Vance, C., & Hedel, R. (2007). The impact of urban form on automobile travel: disentangling causation from correlation. *Transportation*, *34*(5), 575–588. http://doi.org/10.1007/s11116-007-9128-6

Wang, K. (2013). Causality Between Built Environment and Travel Behavior. *Transportation Research Record: Journal of the Transportation Research Board*, *2397*(2397), 80–88. http://doi.org/10.3141/2397-10

Wang, X., Liu, C., Kostyniuk, L., Shen, Q., & Bao, S. (2014). The influence of street environments on fuel efficiency: insights from naturalistic driving. *International Journal of Environmental Science and Technology*, *11*(8), 2291–2306. http://doi.org/10.1007/s13762-014-0584-1

Woltman, H., Feldstain, A., Mackay, J. C., & Rocchi, M. (2002). An introduction to hierarchical linear modeling. *Tutorials in Quantitative Methods for Psychology*, *8*(1), 52–69. http://doi.org/10.2307/2095731

Zahabi, S. A. H., Miranda-Moreno, L., Patterson, Z., & Barla, P. (2015). Spatio-temporal analysis of car distance, greenhouse gases and the effect of built environment: A latent class regression analysis. *Transportation Research Part A: Policy and Practice*, *77*, 1–13. http://doi.org/10.1016/j.tra.2015.04.002

Zegras, C. (2010). The Built Environment and Motor Vehicle Ownership and Use: Evidence from Santiago de Chile. *Urban Studies*, *47*(July), 1793–1817. http://doi.org/10.1177/0042098009356125

Zhang, K., Batterman, S., & Dion, F. (2011). Vehicle emissions in congestion: Comparison of work zone, rush hour and free-flow conditions. *Atmospheric Environment*, *45*(11), 1929–1939. http://doi.org/10.1016/j.atmosenv.2011.01.030

Zhang, M. (2010). Can Transit-Oriented Development Reduce Peak-Hour Congestion? *Transportation Research Record: Journal of the Transportation Research Board*, *2174*, 148–155. http://doi.org/10.3141/2174-19

Zhang, M., & Kone, A. (2009). *CAMPO Transit-Oriented Development Study*.

Zhang, M., Pang, H., & Kone, A. (2014). Bridging the Gap Between the New Urbanist Ideas and Transportation Planning Practice. *Transportation Research Record: Journal of the Transportation Research Board*, *2453*, 109–117. http://doi.org/10.3141/2453-14