Effects of Built Environments on Travel Behavior and Emissions: A Reexamination by Addressing Methodological Issues

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Abstract

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Urban transportation researchers have been studying the relationship between land use policy and travel behavior for several decades due to the topic's great importance in public policy-making. Because of the improvements in energy efficiency, large reductions in emissions have been achieved for a given amount of travel. Unfortunately, the rapid growth in total travel distance over the past several decades, especially for light duty vehicles, has reduced the benefits from technological improvements. Therefore, many urban planners have suggested land use planning as an alternative and fundamental way to reduce auto dependency and thereby, transportation emissions.

However, several empirical studies about the linkage between built environments and travel behavior produced mixed results. In light of the inconsistent findings, research efforts to reconcile the discrepancy among different studies are required. Several methodological issues are found based on the previous literature and four main challenges are addressed in this study: self-selection, spatial autocorrelation, trip-interdependency, and geographic scale.

In addition, two key methodological issues in modeling transportation emissions are found and addressed. First, transportation emissions per person are often estimated by using vehicle miles traveled (VMT) and emissions factors, but these emissions factors do not fully consider variations in travel speed and vehicle characteristics. Second, VMT and emissions factors are associated with travel characteristics, implying that the same methodological challenges existing in the land use-travel behavior analysis can exist in the land use-transportation emissions analysis.

This research obtained several important results. First, increasing residential density can reduce VMT and emissions significantly. In addition, the impact of residential density on VMT is higher than that on transportation emissions, indicating that negative externalities such as congestion generated from compact developments should be considered in the land use-transportation emissions analysis. Second, analyses show that the effects of land use factors on VMT and emissions are different according to tour types and geographic scales. These results imply that different land use policies should be implemented according to neighborhoods characteristics. Finally, the sensitivity analyses of built environment factors show that ignoring trip and vehicle characteristics in the emissions calculation can inflate the influences of built environments on emissions.

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DEDICATION

To Jesus, my parents, brother’s family, lovely wife and son

CHAPTER 1: INTRODUCTION

Global warming has become a key challenge to humankind for decades. It is found that if we fail to reduce the annual emissions, the probability of global average temperature rising by over 2 Celsius degrees will range from 77 to 99 percent by 2035, depending on the climate models used (Stern, 2006). It implies that humankind will face serious problems in many different areas such as food shortage, natural disaster, weather pattern changes, and public health issues. Because of its critical influences on our lives, diverse policies have been implemented around the world in several fields.

In the urban planning field, a lot of effort has been put into the transportation sector because it is the largest source of carbon dioxide (CO_2) emissions in the United States, responsible for about 28 percent of nation's total greenhouse gas emissions in 2011 (EPA, 2013). Due to improvements in fuel efficiency, large reductions in emissions have been achieved for a given amount of travel. Unfortunately, the rapid growth in total travel distance over the past several decades, especially for light duty vehicles, has substantially reduced the benefits of technological improvements (EPA, 2006). To resolve this problem, urban planners have proposed land use planning such as growth manage and smart growth to reduce auto dependency and thereby, transportation emissions.

A large volume of literature has been dedicated to the study of the effects of built environment factors on travel behavior, including mode choice, trip frequency, and travel distance, to assess whether land use planning can be an effective policy instrument (Boarnet & Crane, 2001; Cao, Mokhtarian, & Handy, 2006; Frank, 2000; Kitamura, Mokhtarian, & Laidet, 1997; Shen et al., 2011). Moreover, some recent studies have focused on the direct linkage between built environments and transportation emissions calculated based on vehicle miles traveled (VMT) and emissions factors (Barla, Miranda-Moreno, Savard-Duquet, Theriault, & Lee-Gosselin, 2010; Frank et al., 2006; Frank, Stone, & Bachman, 2000). However, empirical studies show that the connections between land use, transportation, and transportation emissions are complicated and more in-depth analyses are required.

1.1. Debates about the effects of built environments on transportation

Many planners consider land use policy as a long-term and fundamental way for relieving the harmful environmental impacts of transportation in contrast to other policies including gasoline tax and congestion pricing since it establishes the spatial environments for human activities. However, the relationship between land use and transportation is not that simple, and several empirical studies based on theoretical reasoning have been conducted to reveal its complexity.

Urban economics has served as a useful tool to explain how cities were formed based on the relationship between land use and transportation. Von Thunen’s isolated state model simply explains how different land uses are determined based on the tradeoff between land rent and transportation costs. It delineates that land rent decreases as the distance from a central city increases due to increased transportation costs. Later, this model was extended by economist William Alonso by adopting its main idea to urban setting with a bid rent theory (Levinson & Krizek, 2008). His model assumes that people have different levels of preferences for space and time with constant utility. Here, constant utility means that people like less space with lower transportation costs or more space with higher transportation costs. The same idea can be applied to business firms or industries. Based on these assumptions, market determines different types of land use and the level of densification to maximize its utility (Levinson & Krizek, 2008). For example, taller buildings will be built in downtown where transportation costs are low to compensate its expensive land price while more single family homes appear in suburban areas where transportation costs are high and land rent is lower.

Even though these simple models cannot comprehensively reflect the complexity of city structure, a certain level of the spatial form of current cities can be well explained with them. The main reason that people or firms are willing to pay high rents in the central city is accessibility which represents the ease of access to many destinations. As one can easily imagine, accessibility is mostly determined by transportation facilities. For example, building a highway, in general, will reduce travel time and thereby increase accessibility. This implies that development patterns are largely dependent on accessibility that is determined by transportation investments. As an example, several empirical studies find new developments around light rail transit stations or new highways (Cervero, 1984; Hansen, Gillen, & Puvathingal, 1998).

Handy (2005) further examined the connection between transportation and land use by answering four propositions with comprehensive empirical studies. She focuses on two different linkages between them: transportation policy and investments change land development patterns by improving accessibility and reducing transportation costs; and land development patterns influence travel behavior. As well discussed in her paper, there have been a lot of debates on the linkage between transportation and land use among researchers since increased accessibility and reduced travel costs compared to the past have weakened their connection. Based on results from several empirical studies, she concludes that the connection between transportation and land use is much more complicated (i.e., endogenous). That is, all three elements (i.e., transportation policy and investments, land use developments, and travel patterns) have reciprocal relationships.

Since emissions from vehicle usage are mostly determined by travel patterns, the main focus of this dissertation is the connection between land use and travel behavior. The proponents of new urbanism or smart growth advocate that increasing density and mixing different land uses can improve the service of public transit and reduce auto dependency, resulting in less transportation emissions. In addition, these developments can encourage people to participate in social exchanges (Neuman, 2005). If so, building compact cities will result in more energy efficient and environment friendly spatial structure. There are, however, other possible costs that we need to consider. For example, compact cities can reduce travel cost by distributing diverse activities around people's homes, and reduced travel cost may produce more trips, resulting in more transportation emissions. Moreover, as Handy (2005) mentions, there is an endogenous relationship between them. Therefore, in-depth studies are required to fully evaluate the influences of land use policy on travel behavior and transportation emissions.

Several empirical studies have produced mixed results during the past decades. These confusing results are likely due to the different methods, data, and geographic resolutions (Crane, 2000; Van Acker & Witlox, 2011). For example, Boarnet and Crane (2001) find significant influences of land use on travel speed and distance with San Diego data but their results show no significant association between them using data for Los Angeles. Boarnet and Sarmiento (1998) investigated the influences of built environments on non-work automobile trip generation with various socio-economic factors of travelers. In addition, they employed an instrumental variables (IVs) approach to control the self-selection impact. Their results show that the land use variables have negligible impacts on non-work travel.

There are also more complicated methodological problems, including self-selection and spatial autocorrelation that may affect the estimates of built environments. Handy, Cao, and Mokhtarian (2005) performed different types of analysis (simple comparison, multivariate analysis, and quasi-longitudinal analysis) with their own survey. Interestingly, their results show that the variations in levels of driving are mostly explained by attitude factors and the influences of built environment factors disappear in their multivariate analysis. However, they also find significant associations between changes in built environments and driving level in their quasi-longitudinal analysis, showing contradictory results caused by different types of analysis.

In the meantime, several empirical studies find a very significant relationship between built environments and travel behavior (Cevero, 1996; Frank, 2000; Frank, Saelens, Powell, & Chapman, 2007). Shen (2000) identifies regional accessibility as the most important factor influencing commuting duration. Similarly Ewing and Cervero (2001) show that regional accessibility is a key determinant of vehicle hours traveled (VHT) and VMT. In addition, mode choice is mostly influenced by both land use factors and socio-economic characteristics of travelers while trip frequencies are mainly dependent on socio-demographic characteristics of travelers. Based on their meta-analysis, they find that cumulative effects of land use factors on travel behavior are fairly large and significant. The National Research Council

(2009) conducted a comprehensive literature review on the linkage between built environments and travel behavior. They find that most studies show statistically significant influences of land use on VMT however, these effects are modest. In addition, empirical evidence suggests that even though reduced travel cost due to high density developments can increase vehicle trip frequencies, the overall reduction in VMT is still valid.

Even though significant effects of built environments on travel patterns are found, the effectiveness of land use planning should be further investigated since changing built environments requires considerable time and cost. That is, the magnitude of land use impacts is important when assessing land use planning as a good policy instrument. Bento, Cropper, Mobarak, and Vinha (2005) simulated the potential impacts of changing urban structure from Atlanta to Boston on annual VMT. They find a 25 percent reduction in VMT based on their simulation results and conclude that urban form has a significant effect on the commuting mode choice and annual VMT. There are also several recent studies pointing out the infeasibility of land use policy due to the small magnitude of its impact on travel behavior. Brownstone and Golob (2009) note that, even though density influences both vehicle usage and fuel consumption, it is difficult to increase the density of developed cities.

Furthermore, a number of studies conducted a sensitivity analysis, calculating the elasticities of built environment factors (Bento et al., 2005; Ewing & Cervero, 2001, 2010; Heres-Del-Valle & Niemeier, 2011; Zegras, 2010). Ewing and Cervero (2010) surveyed the literature and calculated weighted average elasticities of VMT, walking, and transit use with respect to land use variables to compare the strength of the relationship between built environments and travel behavior directly. Their findings show that the greatest elasticity is 0.39 while others are much smaller. In addition, among five built environment variables (i.e., density, diversity, design, destination accessibility and distance to transit), the elasticity of destination accessibility is nearly as large as the sum of the elasticities of other land use factors in VMT analyses. Bhat and Guo (2007) also estimated elasticity effects of diverse exogenous variables including demographic, transportation network, and density variables on car ownership. Their results reveal the important influences of household and employment densities on car ownership even though they are inelastic. Finally, Fang (2008) find that the effect of residential density on vehicle ownership is statistically significant however, it is economically insignificant due to its small magnitude. These studies also show that estimating the elasticities of built environment measures on travel behavior is a good way to gauge the feasibility of land use policy as an effective instrument tool to reduce VMT and transportation emissions.

There are also several empirical studies that analyze the influences of built environments on transportation emissions and energy consumptions (Frank et al., 2006; Frank et al., 2000; Susilo & Stead, 2007). For example, Liu and Shen (2011) examined the effects of built environments on VMT and transportation energy consumption. Interestingly, they find that built environments influence VMT and energy consumption indirectly. That is, urban form (population density) affect travel behavior and energy consumption through other channels such as travel speed. As an another example, Barla et al. (2010) find significant effects of land use characteristics and transit supply on CO_2equivalent even though they are marginal.

In sum, empirical studies show mixed results, requiring well-designed analyses. Moreover, one should also take into account the additional effects of land use policy on health and environment to compare more comprehensive costs and benefits of land use policy. These extra benefits may overwhelm the cost of changing urban structure even though the effects of built environments on travel outcomes are small.

1.2. Dissertation objectives and hypotheses

As seen above, most studies focus on the relationship between land use and travel behavior to assess whether land use policy can be a good instrument to improve our environment. This is because transportation emissions are closely associated with travel outcomes and researchers can easily use existing travel survey. However, empirical land use-travel studies show inconsistent results, requiring research efforts to reconciliate these confusing outcomes. The contradictory findings seem to be by-products of the different methods, data (i.e., diverse travel outcomes and land use measures), geographic resolutions employed by researchers, and other modeling issues including spatial autocorrelation and self-selection.

As will be discussed in the following literature review chapter, various approaches have been developed to address each of these methodological issues. However, these issues should be considered simultaneously to obtain more reliable estimates of the influences of built environments on travel behavior and emissions.

There are also a few studies that analyze the direct effects of built environments on transportation emissions. Most of these studies employ statistical models and estimate overall average impacts. There are, however, two key methodological challenges in modeling transportation emissions. First, VMT and emissions factors are two main components used in the emissions calculation, but these emissions factors do not fully consider variations in travel speed and vehicle characteristics. Emissions are very sensitive to these characteristics, and these factors are also associated with urban form. For example, people living in urbanized areas are likely to experience severe congestion and own smaller vehicles compared to residents in suburban areas. Therefore, they should be considered in the transportation emissions calculation. Second, most statistical models developed to evaluate the effects of land use on transportation emissions ignore possible confounding effects. Since transportation emissions are measured by VMT and emissions factors which are associated with travel activities, similar methodological challenges found in the land use-travel analysis can arise in the land use-transportation emissions analysis. Unfortunately, little efforts have been made to relieve these methodological issues in the land use-transportation emissions analysis. Therefore, the objective of this dissertation is three-fold: (1) to examine possible methodological issues existing in the land use-transportation analysis, (2) to reexamine the influences of land use factors on VMT and transportation emissions by incorporating recently developed methodological approaches into a unified analytical framework , and (3) to assess the importance of the consideration of travel speed and vehicle characteristics in the transportation emissions calculation by measuring transportation emissions with different assumptions and comparing the influences of built environments on them. In this study, transportation emissions indicate CO_2 equivalent and will be used for the rest of dissertation.

The case area, the Puget Sound region, is surrounded by many mountains and waters, and these geographic characteristics with a moderate marine climate can cause serious air pollution problems by trapping pollutants. Moreover, it is noted that about 50 percent of emissions in the Puget Sound region come from transportation sources, showing the importance of managing travel demand (Puget Sound Region Council, 2010). It also has several unique land use policies such as growth management and urban centers. Washington state adopted the Growth Management Act (GMA) in 1990 and has made several amendments to create a better environment (Puget Sound Region Council, 2009). There are several goals of GMA including the sprawl reduction, good regional transportation, environmental protection and quality of life. In particular, all jurisdictions with over 50,000 population or more than 20 percent population increase during the past decade should develop and adopt comprehensive plans under GMA requirements (Bassok, 2009). In addition to GMA, several urban centers have been developed to keep the growth of neighborhoods. The basic concepts of urban centers are compact and mixed developments. They are also intended to support public transit and non-work travel, therefore reducing congestion (Bassok, 2009).

Having the Puget Sound region as a case area, three hypotheses are tested to meet the above objectives:

(1) Land use policy can be a good instrument for improving GHGs emission levels by decreasing VMT, thus reducing transportation emissions. In addition, confounding effects caused by spatial autocorrelation and self-selection are influential in estimating the effect of residential density on VMT and transportation emissions.

(2) Tour concepts and geographic scale issues should be taken into account in analyzing the effects of built environments on VMT and transportation emissions

to better represent travel behavior and understand the effects of diverse built environment factors at multiple scales, respectively.

(3) Ignoring travel speed and vehicle characteristics in the transportation emissions calculation can generate significantly different effects of built environments on transportation emissions.

CHAPTER 2: LITERATURE REVIEW

2.1. Land use and travel behavior

Several studies have conducted a comprehensive review of the literature on the linkage between land uses and travel behavior (Crane, 2000; Ewing & Cervero, 2001, 2010; National Research Council, 2009). They range from simple analyses such as comparisons to complicated analyses such as model estimation biases and modeling approaches. Generally speaking, the majority of studies found statistically significant influences of land use factors on travel patterns. However, some studies cast doubts about the feasibility of land use strategy for changing travel behavior due to its small magnitude or the lack of statistical significance. Further, important methodological issues are often acknowledged but not effectively addressed. These methodological issues, which are a major source of conflicting empirical results and conclusions in the existing literature, are the primary focus of this literature review.

2.1.1. Self-selection

Smart growth advocates claim that by creating compact and well-mixed urban settings, we can change the way people travel to reduce the negative influences of auto usage. Many empirical studies find a significant association between urban form and travel behavior but most of them have failed to show a causal relationship between them. Association is still valuable however, it is vital to understand the causal impacts of built environments on transportation since changing built environments requires great cost. In the scientific practice, four criteria should be satisfied to establish a causal relationship: association, time order, non-spuriousness, and causal mechanism (Handy et al., 2005). It indicates that there should be a significant statistical association between the cause and the effect, having the cause preceding the effect. Moreover, there should be no spurious effect between them. Due to the data limitation, it is very hard to consider the time order in the land use-travel analysis. Further, attitudes toward transport modes or neighborhoods can create spurious influences on the relationship between built environments and travel behavior if they are ignored.

Self-selection problem arises when individuals select themselves into preferred groups, resulting in a non-randomness issue. This can create bias in the statistical models when establishing behavioral relationships. In the land use-travel analysis, people's residential location choice and their travel behavior can be correlated due to personal attitudes. For example, people who dislike driving may choose to live in urban areas where other transit modes are well provided. If this is the case, personal attitudes are the main determinants of people's choice of their current residential locations that are related to more or less driving. Then, it is not clear to what extent built environments influence people's travel behavior. Therefore, if we ignore the self-selection impact, it will give us mis-estimated influences of land use factors on transportation. It is found that considering a rich set of socio-demographic factors of travelers could address the self-selection issue (Bhat & Guo, 2007; Brownstone & Golob, 2009), but other empirical studies also show that significant associations between built environment factors and travel patterns disappear when the influence of self-selection is controlled in their analyses. Several statistical approaches have been employed to resolve the self-selection problem and six most frequently used approaches (i.e., direct questioning, statistical control, IVs models, sample selection models, other joint models (discrete choice models and structural equations models), and longitudinal models) are well discussed in Mokhtarian and Cao (2008)' paper.

The classic way to estimate a causal impact would be to conduct a before-after controlled experiment with random samples. However, there are ethical concerns and political barriers so it is very hard to implement it in the real world. A more practical way is to conduct a longitudinal analysis with panel data. It means analyzing the changes in travel patterns of the same people over time. Krizek (2003b) utilized the Puget Sound Transportation Panel data to analyze the influences of neighborhood accessibility (NA) and regional accessibility (RA) on four different kinds of travel behavior. His results show that moving to a neighborhood with a higher NA and RA is associated with the reduction in VMT and the number of trips per tour and the increase in the number of tours. In particular, if households move to a suburban area from a traditional neighborhood, they will drive 5 miles more per day.

A second approach is to use attitudinal information from travel surveys and control its impact directly. Many researchers have carried out their own survey since most travel surveys conducted by Metropolitan Organizations (MPOs) do not include attitudinal questions. Data reduction approaches, such as the factor analysis, are often employed to find out common attitudinal factors from various questions, and those factors are used in the regression models to relieve the self-selection impact. As an application example, Frank et al. (2007) analyzed the effects of built environments on travel behavior and obesity by controlling the influences of neighborhood selection and preference. Their results show significant impacts of both attitudinal predisposition and the neighborhood characteristics on walk trips and VMT. In particular, people who prefer and live in the walkable areas tend to walk more and drive less than those who like and reside in the auto-oriented areas.

Kitamura et al. (1997) examined the effects of built environments on mobility in the San Francisco Bay Area with subjective factors as well as objectively measured variables. Their regression models find that some neighborhood characteristics are significantly related to trip generation. However, attitudes are certainly more strongly and perhaps more directly associated with travel behavior.

Hickman and Banister (2007) tried to figure out what are the possible reasons for the mixed empirical results in land use-travel analyses. Based on their findings, they used diverse land-use factors, socio-economic variables, and attitudinal variables to control possible spurious effects. They also developed the energy consumption index with the diverse types of information including journey length, time, mode choice, and occupancy, and estimated the impacts of built environment variables on the energy consumption. Their results show that land use factors have critical influences on energy consumption, explaining about 10 percent of the variation in the energy consumption.

Third, an IVs approach is frequently used to solve the endogeneity problem in the land use-travel relationship (Grazi, van den Bergh, & van Ommeren, 2008; Vance & Hedel, 2007). If we can find IVs that are not correlated with attitudes toward travel but related with built environments, these IVs can be used instead of actual land use factors to estimate unbiased coefficients. Heres-Del-Valle and Niemeier (2011) employed three instruments (i.e., % of units built before 1939, % of non-white population, and % of family HH) to predict residential density and investigated its influence on VMT. Their results show that a 10 percent increase in residential density generates a 1.9 percent reduction in VMT holding all things equal. Grazi, van den Berge, and van Ommeren (2008) employed the IVs approach to estimate the impact of urban form on transport induced level of CO_2 emissions through commuting behavior. They employed same gender of children, number of children, number of adults, and characteristics of the partner's employment as IVs and analyzed the influence of urban density on commuting behavior and emissions. Their results show that urban density more negatively influences auto use compared to slow transit modes. In addition, the magnitudes of IV estimates and Ordinary Least Squares (OLS) estimates for mode choice are significantly different, indicating that ignoring the endogenous problem will lead to biased estimates.

Fourth, several studies have jointly modeled residential location choice and travel behavior (Bhat & Guo, 2007; Cervero & Duncan, 2002; de Abreu e Silva, Golob, & Goulias, 2006). For example, Brownstone and Golob (2009) employed 2001 National Household Travel Survey data (NHTS) and analyzed the relationship between residential density, total annual miles, and total annual household fuel usage by adopting structural equation models. In their model, people were assumed to first choose their neighborhoods and decide their travel patterns based on their residential location choice. Their results show that households living in denser areas tend to drive fewer miles and consume fewer fuels compared to residents in less dense areas.

de Abreu e Silva and Goulias (2009) compared people living in the Seattle metropolitan area and the Lisbon metropolitan area by employing structural equations models. They, however, couldn't perform a direct comparison of results in terms of the magnitude due to different data sources and the geographic scales of land use measures. Nevertheless, both results reach to similar conclusions in that land use patterns still have significant influences on commuting distance and other travel related choices after controlling for the self-selection impact. In addition, they find that even though both results have a lot of commonalities, they also include several differences in the effects of built environments, implying that the influences of land use policies can be different depending on the local circumstances.

Fifth, some studies employed a sample selection approach to estimate the separate influences of urban form and self-selection. In the experimental environment, we can assess the causal impact by comparing control and treatment groups. This idea can be adopted in the land use-travel analysis by creating two different groups, that is, people living in urban areas and living in suburban areas. By comparing the average travel patterns of two groups, we can identify the causal effect of urban form. One problem is that these samples are not random but they intentionally select their residential locations. To solve this problem two models are often used: Heckman's selection model and the propensity score matching. Cao, Xu, and Fan (2010) used the distance between household's residential locations and city center to create four different groups (i.e., living in urban, inner-ring suburbs, suburbs, and exurbs). They also employed the propensity score matching approach and estimated the effects of urban form on vehicle miles driven (VMD). Their results indicate that there is a significant impact of residential location, accounting for 13 to 81 percent of VMD.

In sum, diverse statistical approaches have been developed to relieve the self-selection impact by removing spurious relationship between built environments and travel behavior. However, researchers should acknowledge each model's weakness and strengths before adopting them since they have certain conditions that need to be satisfied.

2.1.2. Spatial autocorrelation

If observations are located nearby, they are more likely to have similar characteristics, and this dependency is called spatial autocorrelation. It is a very common feature in spatial analysis, and requires special care since the assumption of the independence of observation in classic regression models is no longer met. For example, if there is a non-zero spatial autocorrelation, it can result in mis-estimated standard errors in linear regressions, possibly producing incorrect inference of significance (LeSage, 1997).

In the field of spatial econometrics, diverse strategies have been developed and applied to spatial data. For example, a spatial contiguity matrix that represents the relationships between neighbors (i.e., whether they share geographic boundaries or not) is constructed and included in the linear regression to obtain correct estimates. Furthermore, more complicated spatial relationships are modeled by incorporating distances between neighbors with diverse functional forms.

Many researchers also have employed the multilevel modeling framework to analyze spatial data (Antipova, Wang, & Wilmot, 2011; Bhat & Zhao, 2002; Bottai, Salvati, & Orsini, 2006; Chaix, Merlo, Subramanian, Lynch, & Chauvin, 2005; Duncan & Jones, 2000). In the land use-travel analysis, travelers are clustered into geographic units such as census block, tract, and zip code. Since travelers living in the same area share many common aspects, their behaviors are more likely to be similar in some ways. If we can control all relevant factors in the model, there will be no dependency among travelers. However, some variables such as the social norm are hardly measurable and cannot be controlled in the model. Multilevel models are useful when data have more than one level, and it can consider spatial autocorrelation among elementary units in the same group by introducing varying coefficients. Furthermore, it can explicitly model heterogeneities among groups and among elementary units (Bhat & Zhao, 2002; Duncan & Jones, 2000). Specifically, multilevel models have different levels of variances (i.e., between individual and between groups) that can be modeled by several predictors with different functional forms. This characteristic allows researchers to distinguish heterogeneities among both individuals and groups.

There are many reasons why spatial autocorrelation matters in the land use-transportation analysis. For example, Bhat (2000) investigated the clustering influences of residential and work places through the commuting mode choice behavior by developing multi-level cross-classified model. After comparing different results from diverse models, he concludes that spatial context should be considered to obtain more reliable results. As another example, most travel behavioral studies used residential density or accessibility as land use variables, but these measures cannot cover a whole spectrum of built environments, and therefore, unmeasured confounding factors such as pedestrian friendliness design can cause some correlation among people residing nearby.

Goetzke (2003) theoretically explained a potential bias that may be caused by spatial autocorrelation in the mode choice model. Neighborhoods have similar spatial structure and this homogeneity can lead to biased estimates of the influences of built environments on mode choice by violating the basic assumption of statistical models. For example, transit ridership can be over-estimated in suburban areas while underestimated in urban areas. Even though transit friendly environments can be measured by residential density or distance to bus/train stations, due to their inaccuracy there may be an omitted effect that can cause bias in estimates and forecasts.

Bhat and Zhao (2002) analyzed the spatial issues in activity stop generation by using a multilevel analysis framework. Three different spatial elements are thoroughly discussed in their paper: spatial dependency, spatial heterogeneity, and spatial heteroscedasticity. By employing varying intercepts and slopes structures, this model can consider spatial heterogeneity between zones (that is associated with the correlation among people living in the same zone). In addition, they specified the variance of varying intercepts as a function of zonal attributes to incorporate spatial heteroscedasticity in their analysis. They find that the effect of accessibility on the shopping stop decision is only influential to people living in rural areas. They also compared the results from aspatial ordered response logit (ORL) and spatial mixed ordered response logit (MORL). Generally, ORL underestimates the number of shopping stops by 50 percent and 63 percent as they increase the number of couple family households and rural accessibility, respectively.

Bottai et al. (2006) employed a multilevel model to analyze the impacts of gender and age of travelers on travel distance and trip generation. In addition, they tested for the homogeneity of travelers across families and geographic areas. Their results show that travel distances of people living in the same family and area are more similar than those from other families and areas. Especially, they find that any two families living in the same area have a modest level of similarity (6%) in the measured travel outcomes.

Moreover, there is another possible confounding effect due to the spatial location that has never been discussed in the land use-travel analysis. It is called “confounding by location” and thoroughly explained in Clayton and his coauthor’s paper (1993). Location itself can act as a confounder if the spatial patterns of the variations of dependent and independent variables are similar (Clayton, Bernardinelli, & Montomoli, 1993). In other words, unmeasured factors that vary smoothly with location may exist and affect to the regression coefficient. Therefore, if this confounding effect exists in the analysis then the coefficient of covariate can change significantly when the effect of location is considered.

2.1.3. Trip-interdependency

A trip-based modeling approach has been employed for most studies of travel behavior. In general, this approach ignores the interdependency between trips and considers each trip separately. That is, it overlooks the importance of trip chaining in explaining travel behavior by isolating each trip from a complete tour. Krizek (2003a) also indicates that the fundamental forces that are related to people’s travel choice cannot be satisfactorily explained with the trip-based analysis.

The sequence and combinations of trips are often the crucial determinants of individual’s travel decision; therefore, researchers should consider the influence of inter-trip dependency in travel behavior modeling. For example, a person who plans to pick up her children on her way home from work is more likely to drive than take public transit. To take inter-trip dependency into account, two different methods are generally used in the empirical land use-built environment link studies.

First, simple tour and complex tour are defined based on the number of connected trips, and their characteristics are analyzed using socio-economic information of travelers and built environment factors. The connection between tour complexity and travel behavior is well discussed in several studies. For instance, people living in rural areas will make more complex tours by delaying their needs rather than making simple trips to satisfy them instantly. Hanson and Schwab (1987) find a significant influence of accessibility on trip complexity for women who do not have access to automobiles. In addition, the superior aspects of automobile to public transit in terms of time flexibility and ease to carry cargo make people use more private vehicles. Chen, Gong, and Paaswell (2008) investigated the influence of density on mode choice decisions with the consideration of self-selection and tour complexity. Their results show that as the number of stops in a tour increases more people use auto, indicating the importance of tour characteristics in understanding actual travel choices.

Second, trip purposes/activities are used to classify tour types. Recker and Schuler (1982) identified activity pattern profiles based on information of activity type, time and space. A similarity index was developed to create seven activity pattern profiles and the impacts of household characteristics and built environments on activity profiles were investigated. Thill and Thomas (1987) reviewed a body of early works that focused on the treatment of trip chaining. Several classification schemes were employed in the empirical analyses to conceptualize and model trip chaining. Pas (1984) defined travel activity patterns by using stops made in a day with four different activity types and time: subsistence (work or school), maintenance, leisure, and return home. His results show that lifestyle and lifecycle have very significant influences on travel activity behavior, and residents in low-density neighborhoods are more likely to make complex tours. Frank and his co-authors (2008) and Krizek (2003a) analyzed the influences of land use factors by incorporating information about predetermined tour types in the analysis. Their results show a statistically significant association between travel outcomes such as trip/tour frequencies, mode choice and VMT, and built environment factors.

2.1.4. Geographic scale

Scale effects and modifiable areal unit problem (MAUP) have been analyzed for decades, especially in geography (Fotheringham & Wong, 1991; Jelinski & Wu, 1996). Using spatial data measured at different geographic scales can result in inconsistent empirical results. Several recent studies have incorporated MAUP into the land use and travel behavior analysis. For example, Kwan and Weber (2008) find the scale invariant property of accessibility with space-time measures, and Horner and Murray (2002) analyzed the influences of zonal aggregation and geographic scale on the estimation of excess commuting.

In general, census block, tract or TAZ are employed as the geographic unit of analysis in the land use-travel behavior analysis. Due to different geographic scales, it is not often feasible to directly compare the influences of land use factors on travel patterns from different case studies. For example, Boarnet and Crane (2001) employed two different levels of geographic scale, that is, census block group and census tract to measure built environments in their analysis. Specifically, population density was measured at the census block group level while retail and service densities were calculated at the census tract level, mainly due to data limitation. Even though using different levels of geographic detail can make data analysis and interpretation more difficult, it should be noted that land use factors measured at different scales are still valid since land use practice can be implemented at multiple scales. In addition, some land use factors are only influential in travel choices at a certain geographic resolution. Therefore, the main challenge is how to use available data appropriately and interpret the empirical results.

Conceptually, the type of travel outcomes analyzed is closely relevant to geographic scale. For example, trips related to work will be more likely associated with larger geographic scales, such as regional geography, than neighborhood levels. On the other hand, the neighborhood design will more heavily influence non-work trips, especially made by non-motorized modes (Handy, Boarnet, Ewing, & Killingsworth, 2002). Boarnet and Sarmiento (1998) attempted to test the impacts of land use factors on the trip generation of non-workers with a behavioral framework and different levels of geography such as census group, tract, and zip codes. They conclude that controlling the residential location choice and different geographic resolutions is necessary when analyzing the relationship between the built environment and travel behavior. Krizek (2003a) calculated both neighborhood accessibility and regional accessibility by using a gravity model. He notes that using a different scale is important since these factors have their own influence on residential location choice and travel behavior. Frank and his co-authors (2008) measured land use variables around a traveler’s residential and work places at the 1-km network buffer since they find a quarter mile buffer is not appropriate for their study.

2.1.5. Auto ownership: Indirect impacts of built environments on VMT

Auto ownership is a very important factor that affects other travel outcomes such as VMT, mode choice, and trip generation. In many empirical studies, it is treated as an exogenous variable (for example, see Cervero & Kockelman, 1997; Brownstone & Golob, 2009). A few studies, however, find that neighborhood design around the home location is associated with household's choice of auto ownership. Hess and Ong (2002) estimated the effects of neighborhood characteristics and urban design characteristics on auto ownership. Their results show that only mixed land use has a significant impact. Specifically, households living in well-mixed neighborhoods have a 31 percent higher probability of being carless. Kockelman (1997) tested the influences of diverse built environment factors on travel outcomes including auto ownership. The results in her study reveal that people's choice of automobile ownership is affected by local attributes such as population density and land use balance. That is, as population density and the levels of mixed land uses increase, people tend to own fewer cars.

There are also a few studies that consider the self-selection impact. de Abreu e Silva and his co-authors (2006, 2009) estimated the influences of built environments on car ownership while controlling for the self-selection effect. They find that living in more traditional and urbanized zones and working in central areas lower car ownership. Bhat and Guo (2007) developed a joint mixed multinomial logit-ordered response structure that can address residential location choice and auto ownership simultaneously. They conclude that household density and employment density are negatively related to car ownership marginally.

In addition, several empirical studies have investigated the vehicle type choice that is highly related to energy saving and transportation emissions. Peoples' preference for vehicle type has been changing and the number of light duty trucks has increased rapidly compared to others. The problem is that vehicles such as SUVs and pick-up trucks produce more transportation emissions and consume more energy per travel distance compared to passenger cars. They consist of 16.2 percent and 15.8 percent of the total in-use vehicle population, respectively and together are responsible for approximately 40 percent of total transportation emissions in 2004 (DeCicco & Fung, 2006). Generally speaking, higher density and well-mixed neighborhoods are associated with lower levels of owning trucks and higher levels of buying smaller cars.

Fang (2008) developed a discrete-continuous model to analyze the impacts of density on vehicle choice and usage with the 2001 National Household Travel Survey data. The results show that density has a significant impact on the number of trucks owned. Specifically, increasing density by half will raise the probability of not possessing trucks by 1.2 percent. It is acknowledged, however, that the use of density as a policy tool seems to be irrational due to its small impacts within feasible ranges. Cao et al. (2006) also examined the relationship between choices of both neighborhood types and vehicle type with a sample from Northern California. They included travel attitude and perceived and preferred neighborhood characteristics in their analysis to relieve the self-selection impact. Based on their findings, they conclude that neighborhood design has a strong influence on the vehicle type choice. In particular, people residing in more spacious areas and farther from workplaces tend to own pick-up trucks and SUVs rather than passenger cars. In contrast to Fang's conclusion, they indicate that land use policies have some effects on people's choice for light duty trucks.

In addition, some empirical studies have analyzed both the direct and indirect impacts of built environments on VMT through auto ownership with the consideration of endogeneity. Similar to the self-selection problem, unobserved household characteristics or preferences may influence auto ownership and VMT choices simultaneously (West, 2004; Zegras, 2010). Therefore, households with several vehicles may prefer auto travel rather than other transit modes because they like driving. In this case, the impact of auto ownership on VMT can be biased due to the omitted variables. Shay and Khattak (2005) employed a quasi-experimental design and compared two different communities (neo-traditional vs. conventional neighborhoods) to identify the effects of built environments on automobile ownership, total trips, travel time, and auto distance. They find that neighborhood design is associated with all travel outcomes and their results show that auto ownership has very significant impacts on trip generation, auto time, and auto distance, implying possible indirect influences of built environments on travel outcomes through auto ownership.

Sample selection bias is another problem that may occur in this analysis. Auto usage can only be noticed when people choose to drive. Therefore, using this sub-sample can result in biased estimates. Zegras (2010) tried to solve both the sample selection bias and endogeneity problem by employing a selectivity bias correction and an IVs approach, respectively. His result shows that there is no significant selectivity bias but a strong positive effect of auto ownership on VMT exists, indicating that the indirect influences of built environments on VMT should be considered in the land use-travel analysis. He also finds that several micro-level design factors, e.g., dwelling unit density, mixed use, and four-way intersection density, are not significant in the VMT model but influence VMT indirectly through auto ownership.

2.2. Land use and transportation emissions

Greenhouse gases (GHGs) are the fundamental cause of global warming. Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases are the main components of GHGs, and they are also generally referred to as CO_2 equivalent. A body of recent literature related to GHGs focuses on the transportation sector due to the rapid growth of transportation GHGs. The total GHGs in 2003 from all other sectors increased by 9.5 percent compared to those in 1990 while GHGs from the transportation sector grew 24 percent over the same time period (EPA, 2006). In addition, several types of air pollutants from transportation have been identified with their harmful influences on human health. For example, Carbon monoxide (CO) is often generated because of incomplete combustion, causing headache, reduced mental acuity, and for the worst case, death. Particulate matter (PM) and Nitrogen dioxide (NO_2) have been found to increase lower respiratory symptoms and reduce lung function of children. Ozone formed in the upper atmosphere protects people from harmful ultraviolet radiation but ozone in the lower level (ground level) causes breathing difficulty and heart disease. The precursors of ozone, which are nitrogen oxides (NO_x) and volatile organic compounds (VOC_s), are generated from diverse activities including transportation, industry, and wood burning (Puget Sound Region Council, 2010; Turco, 2002).

Two factors are mainly responsible for the significant increase in GHGs from the transportation sector, especially for light-duty vehicles. First, VMT has increased rapidly compared to other demographic and economic factors. For example, 35 percent and 15 percent increases were found in VMT by households and the total number of households, respectively between 1990 and 2001 (EPA, 2006). Second, the preference of people toward auto vehicles has changed. Many people have bought more energy consuming vehicles such as SUVs and pick-up trucks that produce more GHGs into air instead of small passenger cars.

Therefore, a three-legged stool strategy is suggested to reduce transportation GHGs (DeCicco & Fung, 2006; Ewing, Bartholomew, Winkelman, Walters, & Chen, 2008). It includes vehicle fuel economy, carbon content of the fuel itself, and the amount of driving or VMT. Among those, the last one has been brought to planners' attentions. Even though the technological approaches such as new substitutes of fuel and vehicle are more politically accepted, people generally agree that land use policy and transportation planning aimed at reducing travel demand are crucial to reach the goal. In this section, diverse literature related to emissions models and connection between built environments and transportation emissions are reviewed.

2.2.1. Emissions models

Several models are developed by U.S. government agencies to evaluate various policies aiming at the reduction of transportation air pollutions. They vary according to the purpose, input data details, spatial and temporal resolution, and so forth. Those models range from mobile source emissions estimation tools such as MOBILE, Emission FACtors (EMFAC), and Motor Vehicle Emission Simulator (MOVES) to integrated models with economy, energy, and environment. National Energy Modeling System (NEMS) and MiniCAM, are the examples of integrated models frequently used in the estimation of GHGs by the U.S. government (Chien, 2005). However, these models are complicated, often requiring substantial amounts of data and understanding of other sub-models such as macro-economic models and energy demand/supply models. There are also several studies that employed Geographic Information System (GIS) to integrate land use, transportation, and air quality analyses. Travel demand forecasting modelers have been using GIS for decades and many applications of GIS in air quality modeling have been conducted. However, those comprehensive analysis frameworks need to be further developed since their estimated emissions factors and spatial allocation of emissions are coarse (Wu, 2008).

Many research teams distinguish mobile source emissions models according to their main components, functions, and outputs. Two main approaches employed in the mobile source emissions analysis are found based on existing literature: average speed emissions models and modal emissions models. The majority of empirical studies have used average speed emissions models due to their simplicity and relatively fewer requirements for input data compared to modal emissions models. There are two processing steps in a common transportation emissions modeling approach. First, it estimates emissions factors based on predefined driving patterns such as Federal Test Procedure (FTP). Secondly, vehicle activities (speed and VMT) are estimated and the results from these two steps are combined to calculate the emission inventory. As the name represents, average speed emissions models statistically connect emission rates to average vehicle speeds, smoothing the effects of driving modal characteristics such as acceleration and deceleration (Barth, An, Norbeck, & Ross, 1996). Therefore, this approach has been criticized in that it cannot represent real driving patterns, underestimating actual transportation emissions.

EMFAC and MOBILE models are the average speed emissions models frequently employed by U.S. government agencies. They have a very similar basic concept. They simulate typical trips with predefined driving cycles to estimate emissions in the laboratory. They also make several adjustments to account for local conditions such as temperature, air conditioning, speed, and vehicle fuel specification since base emissions rates estimated under the lab conditions cannot reflect variations in those factors (Barth et al., 1996; Claggett & Houk, 2008; Smith, 2006). By combining adjusted base emissions rates and travel activities these models calculate several types of emissions. However, there are some differences in the two models. EMFAC is specially designed for air quality planning in California regions. It means that all input data such as geography and vehicle standards are California-specific. Moreover, this model, like other average speed models, is designed for regional- and statewide-level analyses rather than local-level analyses. The following primary pollutants are generated through EMFAC 2007: Hydrocarbons (HC), Carbon monoxide (CO), Nitrogen oxides (NO_x), Carbon dioxide (CO_2), Particulate matter ($\mathrm{PM}_{10,2.5}$), Oxides of sulfur (SO_2), and Lead (Pb). In addition, the EMFAC produces fuel consumption by using the carbon balance equation.

MOBILE has been widely used due to its application ability for other regions. It is primarily designed to generate emissions inventories for State Implementation Plans (SIPs) and conformity determinations. It also estimates emissions rates for all vehicles in the traffic and has been validated by several studies (EPA, 2004; Pierce, Isakov, Haneke, & Paumier, 2008). Even though it is very similar to EMFAC, there are significant differences in estimated emissions factors due only to the information related to regions, that is, California versus other states (Claggett & Houk, 2008).

One of the most critical issues for average speed emissions models is the consideration of congestion. Transportation emissions are associated with VMT, trip frequency, and speed. As the speed decreases due to traffic congestion, more emissions will be generated from more stop and go driving patterns. Since average speed emissions models do not consider modal characteristics it is very hard to find out whether the effect of congestion can be considered in the calculation process. However, it is certain that they do include certain levels of congestion effects. For example, MOBILE6 uses congestion and road type specific driving patterns during the lab test so it implicitly includes some portion of congestion effects (Smith, Brown, & Chan, 2008).

A modal approach is, on the other hand, constructed based on different speeds and various driving modes. As mentioned, the primary critique on average speed emissions models is that they cannot handle the effects of different operating modes on total emissions. A body of literature finds that pollutants such as carbon monoxide (CO) and hydrocarbons (HC) are greatly affected by driving patterns such as acceleration, deceleration, idling, and cruising (Barth et al., 1996; Esteve-Booth, Muneer, Kubie, & Kirby, 2002; Smith, 2006). Therefore, to estimate more accurate emissions, especially for a micro-scale analysis, diverse operation modes should be taken into account in the estimation process. However, it is noted that researchers can still receive benefits from using average speed models to estimate emissions inventories at a regional level in a simple way. That is, these two approaches conform to each other and researchers can choose according to their purposes.

The U.S. National Academy of Science (NAS) recommended that Environmental Protection Agency (EPA) improve their emissions programs by allowing a multiple scale analysis and users to easily update new information. EPA has put their efforts into developing this new generation and recently released MOVES2010. MOVES follows a modal approach and replaces MOBILE 6.2. It allows users to calculate emissions rates over diverse driving patterns and estimate not only the exhaust and evaporative emissions but also brake/tire wear emissions. In addition, it can generate emissions inventories or factors at multiple geographic scales, ranging from an individual transportation project to a national level (Bai, Eisinger, & Niemeier, 2009; EPA, 2009; Koupal, Beardsley, Brzezinski, Warila, & Faler, 2010). With these benefits, MOVES can be used for SIPs and a project level transportation conformity analysis. In addition to MOVES, there are several useful modal approaches for the micro-scale analysis (Barth et al., 1996; Lin & Niemeier, 2003). For example, Barth et al. (1996) employed the power-demand modeling approach based on the connection between vehicle operation and emissions production. These approaches can better reflect actual driving behavior however, they require more specific data which are often not available for researchers.

2.2.2. Relationship between land uses and transportation emissions

A few existing works have focused on how urban form influences VMT and transportation emissions that are fundamentally associated with climate changes. Even though several useful implications are discussed in the literature, the direct link between urban form and transportation emissions is not clear due to the similar methodological issues existing in the land use-travel analysis. In addition, most empirical studies employed a simple emission factor that does not fully consider variations in travel speed and vehicle characteristics. These two factors are closely associated with urban form and greatly affect subsequent transportation emissions estimates. Therefore, research on the direct influences of land uses on transportation emissions with the consideration of both methodological issues and appropriate emissions factors is necessary.

Two different approaches are found in the land use, transportation, and air quality link literature. The first focuses on the relationship between built environments, transportation, and regional air quality with directly measured emissions. For example, Friedman, Powell, Hutwagner, Graham, and Teaque (2001) analyzed the effects of transportation changes due to The 1996 Summer Olympic Games on air quality and childhood asthma. The primary pollutants and ozone data were directly collected from air quality monitoring sites in Atlanta. Their results show significant reductions in ozone pollution and childhood asthma events during the Olympic Games and these results are associated with reduced traffic density. As another example, Stone (2007) investigated the effects of land use characteristics on ozone precursor emissions provided by government agencies and ozone exceedances.

Secondly, several studies have analyzed the direct impacts of built environments on emissions from vehicle usage through travel activities. For instance, Frank, Greenwald, Kavage, and Devlin (2011) analyzed the effects of sidewalk connectivity, urban form, quality of transit services, and demand manage policies on VMT and $\mathrm{CO_2}$ emissions in King County. They estimated link-based $\mathrm{CO_2}$ emissions by using the shortest time path analysis with a regional travel survey and emissions factors provided by the California Air Resources Board. Their results indicate that a more pedestrian-friendly urban form is correlated with lower VMT and associated $\mathrm{CO_2}$. VandeWeghe and Kennedy (2007) investigated the effects of urban form on GHGs from buildings and transportation. They calculated transportation

GHGs from private auto and public transit by combining trip counts, average distances, average vehicle occupancy, and conversion factors (emissions factors). Their results reveal that high levels of GHGs are found in suburban areas, mostly due to automobile usage.

In addition, several studies have identified influential factors that are related to transportation emissions such as type of fuel, vehicle characteristics, trip distance, frequency of acceleration and deceleration, and engine temperature (Frank & Engelke, 2005; Frank et al., 2000). Speed is found to be especially important since it is directly associated with both urban form and the rate of release for different types of emissions. Frank and Engelke (2005) point out that even though a positive influence of compact developments on transportation emissions is found in the literature, CO and VOC can highly concentrate in compact neighborhoods due to congestion.

Most land use-transportation link analyses have followed the second method but used different approaches to measure transportation emissions. These methods can be broadly categorized in three ways; use emissions factors provided by government agencies or other studies, employ mobile source emissions models, and integrate future travel demand with emissions models. First, a few empirical studies do not use any typical emissions models but try to measure transportation emissions directly with different public data sources and formulations (Barla et al., 2010; Norman, Heather L. MacLean, & Kennedy, 2006). Several government agencies provide data required to calculate the quantity of emissions such as average fuel consumption rates and emissions factors. For example, Barla et al. (2010) calculated transportation emissions from disaggregated survey data by using average fuel consumption rate, average speed correction, VMT, emissions factors, and vehicle occupancy information. Fuel consumption rate and emissions factors are provided by National Resources Canada and Environment Canada, respectively.

Second, the majority of studies employ average speed emissions models like MOBILE and EMFAC to calculate nationally regulated pollutants such as NOx, VOCs, and CO (Frank et al., 2006; Frank et al., 2000; Henderson & Mokhtarian, 1996). One of the benefits of using these models is that we can estimate more accurate emissions compared to using public data since specific local data can be employed and several emissions factors according to speed, vehicle characteristics, and road characteristics can be estimated. Frank, Greenwald, Winkelman, Chapman, and Kavage (2010) analyzed the influences of urban form on health and GHGs. For this analysis, CO_2 emissions were calculated for each link of each trip by using emissions factors from MOBILE. In addition, they also considered the effect of cold starts on the CO_2 emissions estimation since emissions rates are sensitive to the temperature of engine. As an example of other countries outside the U.S., Susilo and Stead (2007) calculated CO_2 per person by using emissions factors from COPERT (average speed emissions model developed by the European Environment Agency) and travel information including mode, distance, fuel type, vehicle age, occupancy, and speed.

Lastly, a few empirical studies combine predicted travel activities based on different transportation and land use scenarios (simulation approach) with emissions models (MacDonald-Buller, Webb, Kockelman, & Zhou, 2010; J. Song, Webb, Parmenter, Allen, & Mcdonald-Buller, 2008). First, they predict future travel demand based on several scenarios and assumptions. Later, these outputs are combined with emissions factors from emissions models or previous studies. For example, Stone, Mednick, Holloway, and Spak (2007) integrated three modeling components, that is, population projection techniques, household vehicle activity framework, and emissions model to compare future air quality depending on two different land development scenarios (business as usual (BAU) vs. compact growth (CG)). Mobile 6 was employed to estimate emissions of CO, NOx, PM, and VOC. They find a 6 percent lower median VMT in the CG scenario than the BAU scenario by 2050 but lower median reduction in CO_2 emissions due to the influences of travel speed and cold starts. Their elasticity analysis shows that the median elasticity of VMT across 11 metro areas is -0.35, indicating that compact growth strategy can lead to a significant reduction in VMT in the long term. In addition, they find that the effects of density on travel and emissions are different according to community types, and compact growth strategy can be more effective in urban areas rather than rural areas. Hankey and Marshall (2010) estimated GHGs from passenger vehicles with predicted future VMT according to six policy scenarios and emissions factors. Future VMT per person per day was calculated based on population density and the equation based on 2000 Department of Transportation data. Emissions factors with different transportation technologies, such as hybrid electric vehicles and energy intensive fuels were derived from other previous studies.

In sum, most studies that investigate the relationship between built environments and transportation emissions employ statistical models to estimate the effects of the former on the latter with different measuring approaches. However, as mentioned, more in-depth analyses are required due to the usage of a simple emission factor and the possible existence of methodological challenges similar to land use-travel behavior analyses.

CHAPTER 3: METHODOLOGY

3.1. Research design and data

This dissertation aims at reexamining the direct effects of built environments on VMT and transportation emissions (see Figure 1). Indirect impacts through auto ownership are also very important but they are left for the future study since there are several modeling complexities such as endogeneity. This analysis proceeds by addressing four indentified methodological issues (i.e., self-selection, spatial autocorrelation, trip-interdependency, and geographic scale) by adopting and incorporating several innovative approaches identified in the literature review into an integrated framework for empirical analyses. First, an IVs approach and the joint model of residential location and transportation are employed to address the self-selection problem. In addition, models include a rich set of socio-economic factors to further relieve the self-selection problem.

Second, Bayesian multilevel models combined with spatial random effects are developed to more fully address spatial autocorrelation. As shown in Chapter 2, multilevel models do not consider the spatial relationship between higher groups (Chaix et al., 2005). Since the spatial autocorrelation can result in mis-estimated standard error in linear regression models and spatial location itself can act as a confounder if independent variable is spatially structured, incorporating spatial relationship between higher groups in the multilevel framework will provide more reliable results. Therefore, spatial random effects that use conditional autoregressive (CAR) specification as a prior are included in the Bayesian hierarchical model. This model has been frequently applied in epidemiology (Lawson, 2008), and can take into account both uncorrelated heterogeneity and correlated heterogeneity by including varying intercepts and spatial random effects, respectively.

Third, trips are redefined by work tours and non-work tours to incorporate tour concept into the travel behavioral modeling. In general, if a tour entails work or school related trips, the whole trip chain is defined as a work tour. For instance, if a person drives to a workplace and picks up her children on her way home, all trips are defined as a work tour.

Fourth, diverse built environment factors are calculated at two different geographic details (1-km buffer and TAZ): residential, non-residential, and four-way intersection densities; land use mix index (entropy); and distance from Central Business District (CBD). Their influences on VMT and transportation emissions are examined and compared.

Lastly, transportation emissions are estimated based on four different assumptions. These assumptions include the consideration of:

1. Link-speed and vehicle characteristics
2. Average travel speed and vehicle characteristics
3. Vehicle characteristics
4. None (single generalized emission factor)

In addition, the sensitivity of the effects of land use factors measured at two different scales (1-km buffer and TAZ) on transportation emissions are investigated through elasticities. The comparison between the results from different transportation emissions will show the importance of considering travel speed and vehicle characteristics in the land use-transportation emissions analysis and provide useful policy implications.

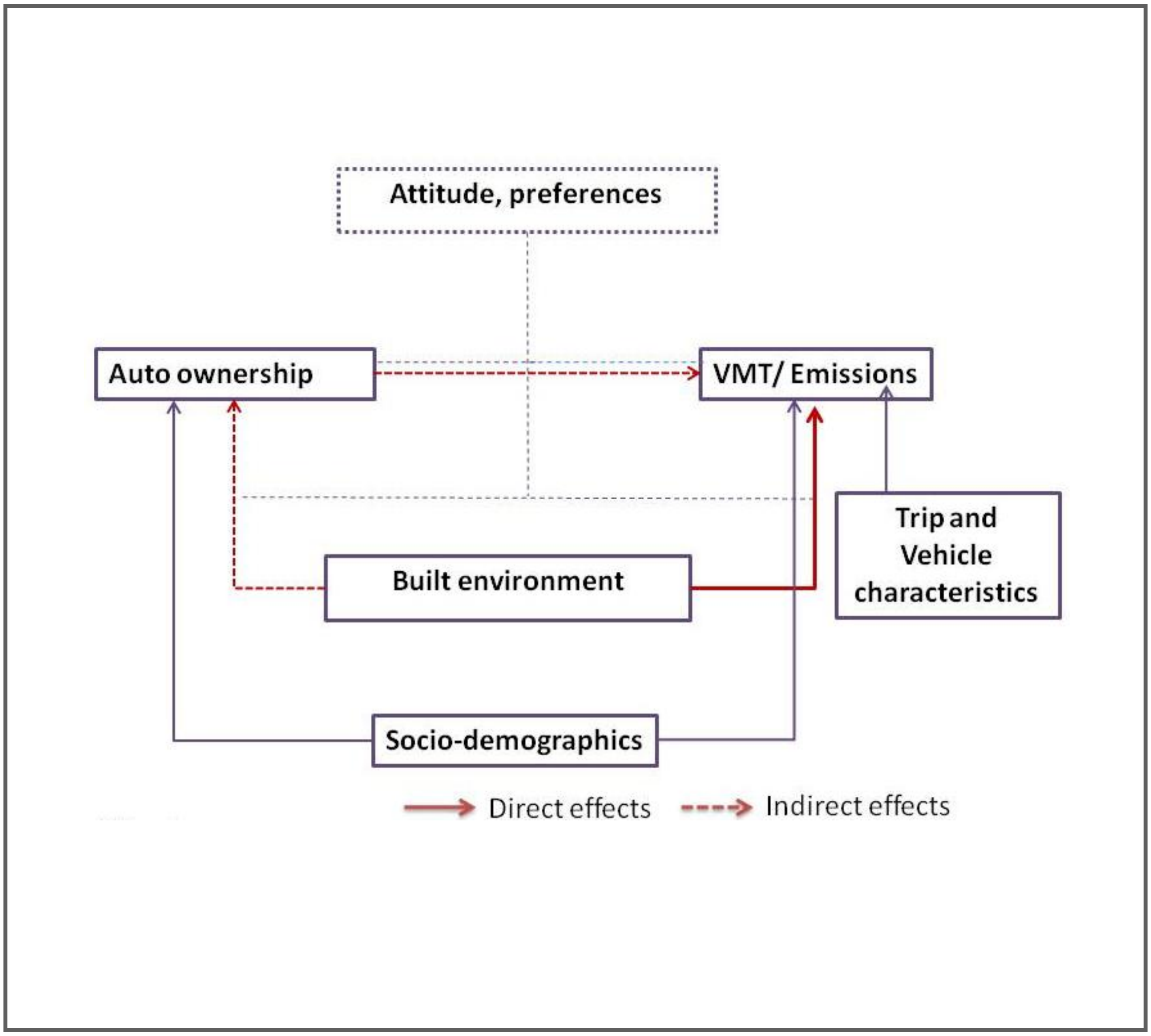


Figure 1. Framework

An original data set is created by combining several different existing data sources. The Puget Sound Regional Council (PSRC) has conducted travel surveys to obtain information of residents in the Puget Sound region (i.e., King, Kitsap, Pierce, and Snohomish Counties), their activities, and travel behavior. There are 4,746 households in the most recent 2006 Household Activity Survey and all members of these households reported their socio-economic information, activity participations, and trips occurred over two days. The survey includes exact home location information of households and this information is matched with land use characteristics by using GIS.

Built environment factors are calculated based on 2005 parcel-level land use data and building data collected by PSRC. These datasets include land use types, area, and total building floor area, allowing measurements of diverse land use factors at different geographic details.

Finally, some local data required to estimate emissions factors through MOVES are collected and used to obtain the most realistic estimates possible. The MOVES includes default databases such as vehicle fleet, vehicle activity, fuel, and meteorology. However, these default databases are not ideal for a particular place because they cannot represent local condition well enough (EPA, 2010), requiring using local data. Figure 2 shows how final data is processed.

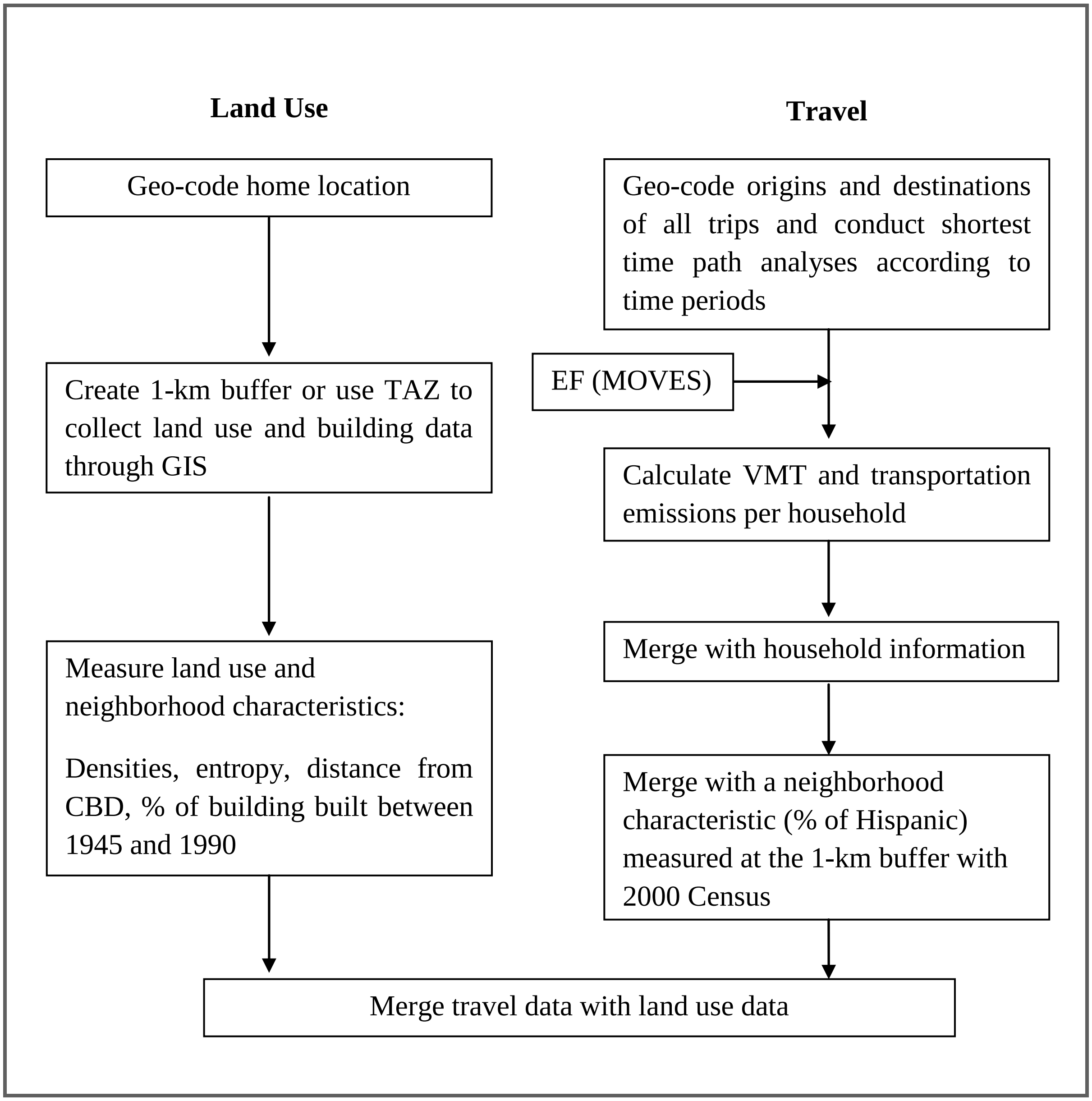


Figure 2. Data processing

3.2. Built environment measures

To evaluate the influences of built environments on transportation emissions or travel outcomes we first need to know how to measure built environments. There are a few studies focusing on measuring urban structure. Y. Song and Knaap (2004) evaluated development patterns of two different neighborhoods in Washington County, Oregon through quantitative measures of urban form. They categorized them into five features: street design and circulation systems, density, land use mix, accessibility, and pedestrian access. For the calculation they used several types of information such as number of intersections, block size, length of cul-de-sacs, lot size, dwelling units, land areas, and distances to different sources.

Sprawl is a general spatial pattern in the U.S. and the degree of it cannot be measured in a simple way. It is a complex phenomenon that can only be explained through several dimensions of urban structure. Ewing, Pendall, and Chen (2003) developed a comprehensive sprawl index by combining density, land use mix, centeredness, and street accessibility. More than ten measures were used to make this single index through the reduction technique. Stone (2007) employed this index and investigated the impacts of sprawl on emissions from the transport sector. He finds that as the degree of sprawl increases, emissions and annual ozone exceedances also increase.

Moreover, diverse characteristics of built environments have been developed in the land use-transportation analysis. Ewing and Cervero (2001) summarized a large body of literature and listed several land use variables that have significant effects on travel behavior. Most studies focused on measures that were easy to achieve, and density was generally used as the representative of built environments. Based on their literature review, land use patterns were characterized by various densities, mixed use, and accessibility. Transportation networks and urban design features were also reviewed in their paper.

Kockelman (1997) developed density, accessibility, land use balance, and dissimilarity index to operationalize complex descriptors of land use patterns. For the accessibility variable, she employed a gravity model with information about the total jobs per traffic analysis zone (TAZ). She also distinguished land use types as residential, commercial, public, offices, industrial, and parks recreation to calculate a land use balance index (entropy). Besides entropy, a dissimilarity index was estimated to consider how well different land uses come into contact with others. Her results show that accessibility is a more effective factor than density on both vehicle kilometers traveled (VKT) and mode choice. In addition, mixed land use indices (entropy and dissimilarity) have significant influences on VKT. Density and tract-confined entropy also influence auto ownership significantly.

Cervero and Kockelman (1997) characterized built environments by three main dimensions, i.e., density, diversity, and design (3Ds). Diverse land use variables were employed and two factors – intensity and walking quality - were extracted by using a factor analysis to capture the complex dimensions of built environments. Their results indicate that land use density, diversity, and design factors have fairly marginal influences on travel outcomes. Later, these 3Ds were expanded to 5Ds by including destination accessibility and distance to transit (Ewing & Cervero, 2001; National Research Council, 2009). Table 1 shows the examples of the 5D measurements.

Table 1. Built environment measures (5Ds)

5D	Definition	Some examples of measures
Density	Population, dwelling unit and employment by geographic area	• Population density (population per developed area, dwelling units per area, building floor area per area) • Employment density (Jobs per area Office & industrial floor space per area)
Diversity	The balance of different land uses, mix of land use.	• Dissimilarity index • Entropy • Commercial intensity • Job-housing balance • Distance to the nearest store
Design	Neighborhood layout and pedestrian environments	• Presence of sidewalk, sidewalk coverage • Street patterns (grid vs. Cul-de-sacs) • Average block size or intersection density
Destination accessibility	Ease of access to other destinations	• Gravity model with travel time and number of jobs • Distance from CBD
Distance to transit	Ease of access to public transit facilities	• Distance to bus or rail stops • # of bus stops per area • Transit route density

Based on the previous literature, several densities, land use mix, and the distance from CBD are calculated to represent the built environments for analyses. All these variables, described in Table 2, are measured at the two geographic scales: a 1-km buffer and the TAZ based on respondent's home location.

Table 2. Built environment factors

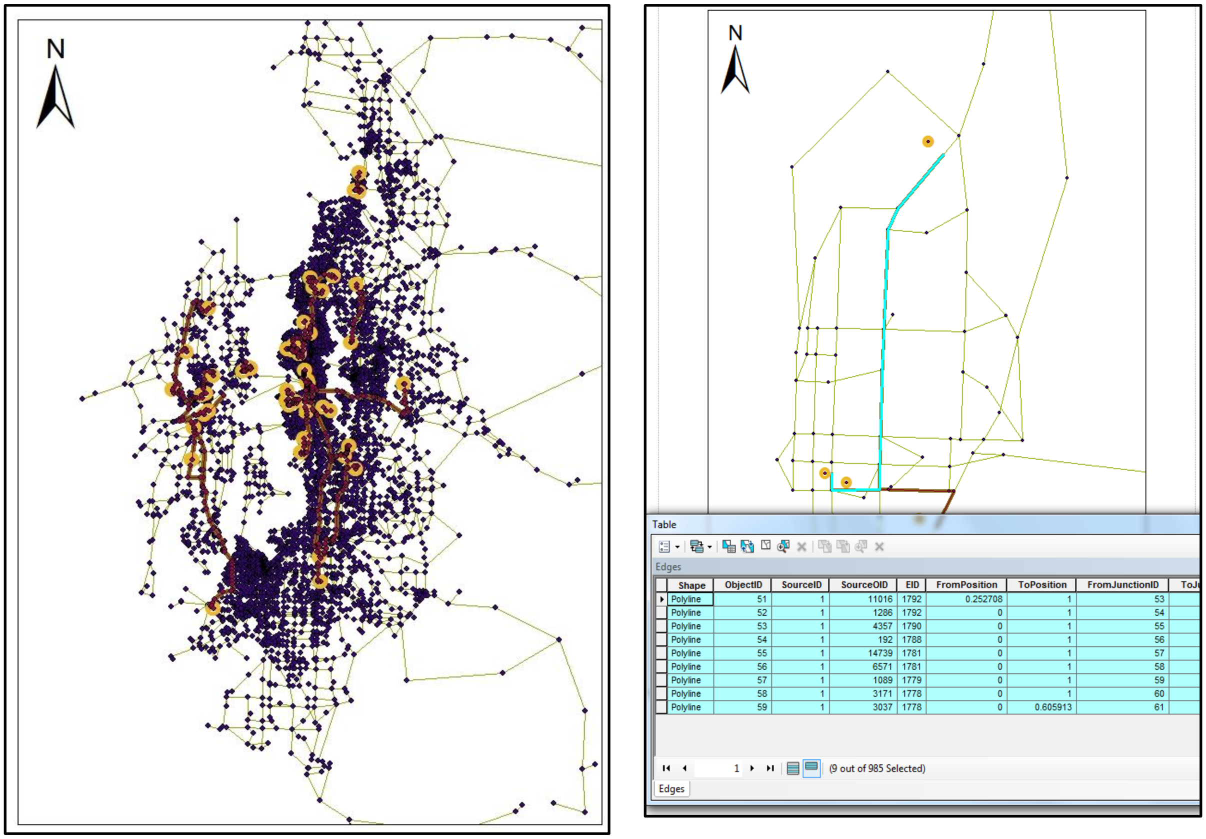
Measure	Aggregated within 1-km buffer and TAZ
Densities	▪ Net residential housing unit density (# of dwelling units within 1-km buffer/residential land area within 1-km buffer) ▪ Net residential density (residential building floor area/residential land area) ▪ Net non-residential density (the sum of commercial, office, industrial, and government buildings floor areas/ the sum of land areas of all four uses) ▪ Intersection density (# of four-way intersections/area)
Land use mix (Entropy)	Entropy = $-\sum_j \frac{P_j{}^{*} * \ln(P_j{}^{*})}{ln(J)}$
Distance from CBD	Straight line distance from CBD

$*$ P_j is the proportion of building sqft of the jth use type. The six (J=6) land use types considered are residential, commercial, industrial, office, government, and others.

3.3. Estimating transportation emissions

Transportation emissions are estimated based on VMT and emissions factors. Here, transportation emissions indicate CO_2 equivalent. As shown in Chapter 2, emissions factors are sensitive according to vehicle and travel characteristics. Therefore, using a single generalized emission factor for all trips can generate significantly different emissions. For this research, emissions factors for Pierce County, Washington State, U.S. are estimated by using the MOVES according to the speed (16 categories), vehicle types (motorcycle, passenger car and truck, school bus, and transit bus), vehicle age, and road types (highway and local roads).

In addition, using the average speed to estimate transportation emissions can be inaccurate since emissions are very sensitive to speed. To relieve this problem, link-based transportation emissions are calculated. First, all trips are grouped into five different time periods (am-peak, mid-day, pm-peak, evening, and night) because link speeds vary by time of the day due to the traffic volume. Second, shortest time path analyses are conducted for all trips according to each time period. Link speeds under congested conditions provided from PSRC are estimated by regional transportation modeling. Third, all route information is merged with the number of passengers, link speed, vehicle characteristics, and road type. The number of passengers for bus users is controversial, so 11.29 and 12.59 passengers are assumed for off-peak and peak periods, respectively based on the ridership data provided from King County Metro Transit (Frank et al., 2011). Fourth, this data is connected to emissions factors estimated by MOVES, and transportation emissions for links of all routes are calculated by multiplying link lengths per passengers and emissions factors. Finally, link-based transportation emissions are calculated by adding the estimates up for each trip, person, and household. Figure 3 shows the result of the shortest time path analysis for 50 samples and one detailed example.



	Shape	ObjectID	SourceID	SourceOID	EID	FromPosition	ToPosition	FromJunctionID	ToJ
▸	Polyline	51	1	11016	1792	0.252708	1	53	
	Polyline	52	1	1286	1792	0	1	54	
	Polyline	53	1	4357	1790	0	1	55	
	Polyline	54	1	192	1788	0	1	56	
	Polyline	55	1	14739	1781	0	1	57	
	Polyline	56	1	6571	1781	0	1	58	
	Polyline	57	1	1089	1779	0	1	59	
	Polyline	58	1	3171	1778	0	1	60	
	Polyline	59	1	3037	1778	0	0.605913	61	

(9 out of 985 Selected)

Figure 3. Shortest time path analyses

Besides link-based transportation emissions, three different emissions are estimated based on different assumptions about emissions factors. First, average speeds for all trips are calculated and merged with emissions factors instead of using link speeds. Second, emissions factors for different vehicle types from the EPA are employed to estimate transportation emissions. The EPA (2008) provides methodologies for estimating GHGs from different modes of transportation based on CO_2, CH_4, N_2O, and global warming potential (GWP). Different formulas are used to estimate GHGs for each vehicle type:

Motorcycle: VMT * (EF_{CO2} (0.167) + EF_{CH4} (0.070) * 0.021+ EF_{N2O}(0.007)*0.310))

Passenger car: VMT * (EF_{CO2} (0.364) + EF_{CH4} (0.031) * 0.021+ EF_{N2O}(0.032)*0.310))

Truck: VMT * (EF_{CO2} (0.519) + EF_{CH4} (0.036) * 0.021+ EF_{N2O}(0.047)*0.310))

Bus: PMT * (EF_{CO2} (0.107) + EF_{CH4} (0.0006) * 0.021+ EF_{N2O}(0.0005)*0.310))

Finally, a single generalized emission factor (0.435 kg CO_2 per passenger mile for SOV trip) measured through diverse types of data from government agencies is employed to estimate transportation emissions (Federal Transit Administration, 2010). This estimate compared to others only accounts for CO_2 not CO_2 equivalent.

3.4. Bayesian multilevel model with spatial random effects (BMSR)

Bayesian inference is distinct from classical inference (Frequentist inference) in that it uses data to update prior knowledge or belief about parameters. Specifically, a Frequentist approach is based on the likelihood function and estimates parameters that give the highest probability to the observed data. Bayesian inference uses Bayes's rule that provides a rational method for updating prior information with data (Lawson, 2008). The Bayes's Theorem can be written as below:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \tag{1}$$

Here, $p(y|\theta)$ is the likelihood, representing the probability of y given θ is true and $p(\theta)$ is the prior distribution. The prior should be assigned before seeing data and it represents knowledge or belief about the parameters (θ). Lastly, $p(\theta|y)$ indicates the posterior distribution that reflects the behavior of parameters that we are interested in. As the formula represents, the posterior distribution is proportional to the product of the likelihood and the prior. In other words, the likelihood through data and the prior through prior belief or knowledge inform the parameters in which we are interested (Lawson, 2008). This posterior distribution can be employed as the prior for future analyses.

Priors should be assigned for all parameters in the Bayesian Framework. However, in many cases, no prior information is known, and several empirical studies employ the non-informative prior. It has a relatively flat distribution, having little influence on the posterior distribution. Using non-informative priors can weaken the strength of a Bayesian approach. However, there are still great benefits that can compensate for its complexity. First, it can be more flexible for building a complicated model with diverse variables. For instance, an IVs approach and spatial random effects are incorporated into a unified analytical framework in this research to consider both self-selection and spatial relationship. This can be easily implemented by using a Bayesian approach. Second, it simulates the posterior distribution of a parameter based on the likelihood and prior, therefore, we can use the simulated distribution to directly assess the significance of the parameter. For example, if zero is not included in the 95% credible interval (CI) of the posterior mean of the parameter, it implies that this parameter is statistically significant at the 0.05 level of significance.

When the data is spatially clustered, the multilevel/hierarchical modeling is frequently employed. This model can consider the correlation among element units in the same group by estimating different coefficients for each group. That is, it can be viewed as a compromise of two extreme models (i.e., one that excludes all group indicators and one that builds a model for each group) (Gelman & Hill, 2007). In general, the variation between groups is ignored in the former model while overestimated in the latter model. Technically, a multilevel model sets different levels of variances. For example, if there are two different levels (i.e., individuals and areas), between-individuals and between-areas variances can be modeled by diverse covariates with different functional forms. Because of this characteristic, researchers can explicitly model the heterogeneities between individuals and between groups. (Duncan & Jones, 2000). For this research, varying intercept models are used for empirical analyses. Assuming a simple case without any other predictors, the varying intercepts (α_j)

can be approximated by the mean of observations in a group and the mean over all groups with weights.

$$\hat{\alpha}_j \approx \frac{\frac{n_j}{\sigma_y^2}\bar{y}_j + \frac{1}{\sigma_\alpha^2}\bar{y}}{\frac{n_j}{\sigma_y^2} + \frac{1}{\sigma_\alpha^2}} \tag{2}$$

where n_j is the sample size in area j, σ_y^2 is the within-area variance in the dependent variable (log VMT or transportation emissions), σ_α^2 is the variance among the mean of dependent variable of different areas (groups), $\bar{y}_j$ is the mean of the dependent variable in area j, and $\bar{y}$ is the mean of the dependent variable over all areas. The equation 2 shows that both individual and group information influence the estimate of varying intercepts. The model with land use variables measured at the TAZ level and its posterior density can be expressed as follow:

$$y_i \sim N(\alpha_{j[i]} + \beta_{SES}^{\intercal} X_{iSES} + \beta_{PTA} X_{iPTA}, \sigma_y^2), \text{ for i= 1, … , n.}$$

$$\text{and} \tag{3}$$

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

$$\mathrm{P}(\alpha, \beta_{SES}^{\intercal}, \beta_{PTA}, \gamma_{BE}^{\intercal}, \sigma_y, \sigma_\alpha | y, X_{SES}, X_{PTA}, X_{BE}) \propto \tag{4}$$

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

where, y represents VMT or transportation emissions, and X_{SES}, X_{PTA}, X_{BE} represent various socio-economic factors, public transit accessibility (distance to the nearest bus stop), and built environment variables, respectively. Varying intercepts, α_j, are normally and independently distributed with the mean ($\gamma + \gamma_{BE}^{\mathrm{T}} X_{jBE}$) and the standard deviation σ_α. Here, X_{jBE} are calculated at the TAZ level (group predictors) and σ_α is the variance between TAZs.

In the classical ordinary least squares (OLS) regression, R^2 is often used to summarize how well a regression fits. It is defined by the proportion of variation explained.

$$R^2 = 1 - \frac{\Sigma(\hat{y}_i - y_i)^2}{\Sigma(y_i - \bar{y})^2} = 1 - \frac{RSS}{TSS} \tag{5}$$

where RSS and TSS refer to the residual sum of squares and the total sum of squares, respectively. However, a multilevel model does not have exactly the same R^2 because it explains data at different levels. Gelman and Pardoe (2006) explained how to calculate the R^2 of a multilevel model for different levels to assess the goodness of fit of the model in their study. Different R^2 is defined as follow:

$$\mathrm{Y_i} = \mathrm{u_i^T} + \epsilon_\mathrm{i}, \text{ for i = 1,…, I} \tag{6}$$

$$\mathrm{R}^2 = 1 - \frac{\mathrm{E}\left(\mathrm{V}_{\mathrm{i=1}}^{\mathrm{I}} \epsilon_\mathrm{i}\right)}{\mathrm{E}\left(\mathrm{V}_{\mathrm{i=1}}^{\mathrm{I}} \mathrm{Y_i}\right)}$$

where, $\mathrm{u_i^T}$ refers the linear predictors and ϵ_i represents the errors. $\mathrm{Y_i}$ are data points in the individual level or batches of coefficients at the higher level. E and V represent the posterior distribution mean and the finite-sample variance operator, respectively. As the posterior mean of error (ϵ_i) becomes large, the R^2 is close to 0. In contrast, R^2 is pulled toward 1 when $\mathrm{u}_\mathrm{i}^\mathrm{T}$ is getting close to Y_i. The R^2 is calculated as follow in the simulation process:

1. Calculate the difference between Y_i and $\mathrm{u}_\mathrm{i}^\mathrm{T}$ in the simulation routine.
2. Estimate the variances of the difference (ϵ_i) and Y_i with sample draw.
3. Calculate R^2 based on Equation 6.

Diverse empirical studies related to travel behavior have employed the multilevel modeling framework to consider spatial issue (Schwanen, Dieleman, & Dijst, 2003; Snellen, Borgers, & Timmermans, 2002). A varying intercept model can consider the possible correlation among residents in the same area but not the spatial relationship between areas. For example, the correlation between two residents in the same area is defined by intraclass-correlation (ICC) calculated by $\sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_y^2)$ while two residents in different areas are assumed to be independent in the multilevel framework. In sum, a multilevel model hypothesizes that within neighborhood correlation can explain all spatial correlation (Chaix et al., 2005). Therefore, spatial random effects (s_j) calibrated based on a CAR model are incorporated in the Bayesian multilevel framework to take the spatial relationship between groups into account. That is, this modified model can take both uncorrelated and correlated heterogeneities into account by introducing varying intercepts and spatial random effects, respectively. Another benefit of the model is that the effect of location can be modeled by incorporating spatial random effects (Clayton et al., 1993; Wakefield, 2003). As discussed briefly in Chapter 2, one should remember that if the spatial patterns of the variations of a built environment factor and VMT or transportation emissions are similar after controlling for other covariates, this is the case that the location may act as a confounder. This problem also could be minimized if one can reduce the systematic geographical variation in either independent or dependent variables by integrating regions into broader areas (Clayton et al., 1993).

The BMSR with TAZ level land use variables can be written as follows:

$$y_i \sim N(\alpha_{j[i]} + s_{j[i]} + \beta_{SES}^{\intercal} X_{iSES} + \beta_{PTA} X_{iPTA}, \sigma_y^2), \text{ for i= 1, … , n.}$$

$$\text{and} \tag{7}$$

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

$$s_j \sim N\left(\overline{s_j}, \frac{\sigma_s^2}{n_j}\right)$$

$$\overline{s_j} = \sum_{k \in neigh(j)} w_{j,k} s_j / n_j$$

where, $w_{j,k}$ refers to the weight between region j and k, and n_j is the number of neighbors for area j. The neigh(j) includes the first neighbors only and all weights set to 1.

3.4.1. Hypothesis 1 test: Instrumental variables (IVs) approach

Hypothesis 1: Land use policy can be a good instrument for improving GHGs emission levels by decreasing VMT, thus reducing transportation emissions. In addition, confounding effects caused by spatial autocorrelation and self-selection are influential in estimating the effect of residential density on VMT and transportation emissions.

Several approaches have been employed to relieve the self-selection issue. The IVs approach is one of the most frequently used methods and is well explained in several papers (Kitamura et al., 1997; Mokhtarian & Cao, 2008; Vance & Hedel, 2007). If IVs that are correlated with land use factors without significant associations with travel attitudes or preferences exist, we can use the predicted estimates of built environment factors based on these IVs to obtain unbiased results. Specifically, a built environment measure is modeled with covariates and IVs, and a predicted value is calculated based on the model parameters in the first step. Then, this predicted value is used in the main model instead of the original built environment measure to obtain an unbiased estimate in the second step. In the land use-transportation analysis, neighborhood amenity factors are often employed as instruments, and two instruments (percentage of buildings built between 1945 and 1990 and percentage of Hispanic) are used in this analysis. As explained in Introduction, Washington State adopted GMA in 1990, and many suburban cities were developed between 1945 and 1990. Therefore, there are common characteristics among neighborhoods built between 1945 and 1990. These two IVs are also selected based on the Sargan test which shows the appropriateness of IVs.

The BMSR model combined with the IVs approach is used to examine the first hypothesis. For this test, net residential housing unit density within a 1-km buffer of traveler's home locations is measured as the representative of built environments.

However, more care should be taken when modeling residential density with the IVs approach. First, the standard error will be mis-estimated if a conditional two step approach is adopted, requiring correction. The problem is that the predicted value of residential density is used at the second step (main model) in an isolated manner. This issue can be easily solved by estimating two models simultaneously in the Bayesian framework. Second, residential density is spatially correlated. For example, residential density is likely to be positively associated with closer neighboring densities. Therefore, it would be necessary to include spatial components to obtain the more accurate prediction of residential density. Unfortunately, previous empirical studies ignored this spatial influence and employed simple OLS. Therefore, a multilevel model and a BMSR are employed to build the residential density model in this analysis. A BMSR with IVs can be expressed as follows:

$$\binom{y_i}{R_i} \sim N\left(\begin{pmatrix} \alpha_{j[i]} + s_{1j[i]} + \beta_{SES}^{\intercal} X_{iSES} + \beta_R R_i \\ \gamma_{j[i]} + s_{2j[i]} + \beta_{ivSES}^{\intercal} X_{iSES} + \beta_{INS}^{\intercal} X_{iINS} \end{pmatrix}, \begin{pmatrix} \sigma_y^2 & \rho_{yR}\sigma_y\sigma_R \\ \rho_{yR}\sigma_y\sigma_R & \sigma_R^2 \end{pmatrix}\right), for\ i = 1, \dots, n,$$

and (8)

$$\alpha_j \sim N(\mu_\alpha, \sigma_\alpha^2), \text{ for j=1, …, J,}$$

$$\gamma_j \sim N(\mu_\gamma, \sigma_\gamma^2), \text{ for j=1, …, J,}$$

$$s_{kj} \sim N\left(\overline{s_{kj}},\ \sigma_{ks}^2 / n_{kj}\right), \text{ k=1, 2}$$

$$\overline{s_{kj}} = \sum_{l \in neigh(j)} w_{j,l} s_{kj} / n_{kj}$$

where R is net residential housing unit density and X_{INS} is two IVs. Since net residential housing unit density is measured at the individual level, random effects (α_j and γ_j) are modeled without group variables.

3.4.2. Hypothesis 2 test: Joint model of residential location and transportation

Hypothesis 2: Tour concepts and geographic scale issues should be taken into account in analyzing the effects of built environments on VMT and transportation emissions to better represent travel behavior and understand the effects of diverse built environment factors at multiple scales, respectively.

In this analysis, diverse built environment variables are included. Since the IVs approach requires more, or at least the equal number of IVs than endogenous variables (here, build environment variables) it is difficult to employ it if we do not find enough IVs. Therefore, the joint model of residential location and transportation is developed for this analysis.

People make choices in everyday life. For example, people choose what types of activities to participate or which transportation mode to use for their travel. To analyze these kinds of choice behavior, utility maximization theory has been often adopted in diverse fields. It means that people will choose an alternative that maximizes their utility. Several economists have contributed to apply this theory in the land use-travel analysis and employed qualitative models including Logit and Probit models (McFadden, 1974; Train, 1986). In general, utility function has two basic components, that is, observed factors and random errors. The fundamental difference between Logit and Probit models is the assumptions about error terms. While a Logit model assumes the logistic distribution for errors, a Probit model assumes that errors are normally distributed. Due to the different scales of variance of errors, the estimates of a Logit model is approximately 1.81 times greater than those of a Probit model.

In this analysis, it is assumed that the residential location choice and travel behavior are correlated. Specifically, people who prefer public transit may choose to live in urban areas rather than suburban areas where public transit is widely available. Therefore, if residential location is controlled in the VMT and transportation emissions models with the correlated error structure and a rich set of socio-economic characteristics of travelers, it will reduce the self-selection impact. A similar idea has been applied in the Greenwald (2003) paper.

Let U_i represent the choice of individual i; U_i =1 refers to living in urban areas and U_i =0 indicates residing in suburban areas. Then, the Probit model with a binary choice can be written as follows:

$$\Pr\,(U_i = 1\ (urban) | X_i) = \Phi(X_i \beta) \tag{9}$$

Here, $X_i\beta$ is the linear predictor and Φ is the cumulative distribution function of the normal distribution. The residential location choice is often expressed as a function of individual and neighborhood characteristics (Boarnet & Sarmiento, 1998) and it can be written as below:

$$\Pr(U_i = 1) = \Phi(\alpha + \beta_S^{\intercal} X_{SES} + \beta_N^{\intercal} X_N\ ) \tag{10}$$

where X_{SES} and X_N represent socio-economic status characteristics and neighborhood characteristics around traveler’s home locations, respectively. Now, we need to make a correlated error structure between the residential location choice and VMT or transportation emissions. However, it is difficult to make a correlated error structure between binary and continuous variables. Therefore, the latent variable U* ($\alpha + \beta_S^{\intercal} X_{SES} + \beta_N^{\intercal} X_N$ + ε) from a Probit model is used instead of the residential location indicator to make this relationship easier. The equation 11 shows a simple linear regression with a correlated error structure.

- Probit model for the residential location choice: U = 1 if U* > 0 & U = 0 if U* < 0
- Suppose y and U* follow the bivariate normal distribution with a correlation matrix like below.

$$\Sigma = \begin{pmatrix} \sigma_y^2 & \rho\sigma_y\sigma_{U^*} \\ \rho\sigma_y\sigma_{U^*} & \sigma_{U^*}^2 \end{pmatrix} \tag{11}$$

Then, y|U* ~ N($u_y + \frac{\sigma_y}{\sigma_{U*}} * \rho * \left(U^* - \ mean(U^*)\right), (1-\rho^2)\sigma_y^2$)

Here, ρ can be considered as a correlation coefficient between y and U^*. The variance of the residential location model, σ_{U*}, equals to 1 since a Probit model is employed. This model implies that the effect of residential location on dependent variables (VMT and transportation emissions) can be estimated with a dichotomous variable U while considering the correlated errors between U* and dependent variables. Then the final VMT or transportation emissions models can be expressed as follows:

$$y_i \sim \mathrm{N}(\alpha_{j[i]} + s_{j[i]} + \beta_{SES}^{\intercal} * X_{SES} + \beta_U * U + \sigma_y * \rho * \left(U^* - mean(U^*)\right), (1-\rho^2)\sigma_y^2)$$

$$\alpha_j \sim N(\gamma + \gamma_{BE}^{\intercal} * X_{BE}, \sigma_\alpha^2)$$

$$s_j \sim N\left(\overline{s_j}, \frac{\sigma_s^2}{n_i}\right) \tag{12}$$

$$\overline{s_j} = \sum_{k \in neig\,h(j)} w_{j,k} s_j / n_i$$

where y is VMT or transportation emissions and U is residential location (urban vs. suburban).

3.4.3. Hypothesis 3 test: Transportation emissions with different assumptions

Hypothesis 3: Ignoring travel speed and vehicle characteristics in the transportation emissions calculation can generate significantly different effects of built environments on transportation emissions.

As mentioned, transportation emissions are very sensitive to travel speeds and vehicle characteristics. In addition, these characteristics are associated with urban form. For example, residents in urban areas will experience more severe congestion and may buy smaller cars or fewer cars due to parking space and good public transit services compared to suburbanites. Therefore, it is valuable to see how the effects of built environments on transportation emissions can vary according to different assumptions. This will also provide possible explanations for why the effects of built environments on transportation emissions and VMT are different. For this analysis, built environment factors are measured at the two different geographic scales (1-km buffer and TAZ), and the elasticities of these measurements are calculated. As described in Chapter 3.3, four transportation emissions are estimated.

1. Emissions with link speed and vehicle characteristics
2. Emissions with average speed and vehicle characteristics
3. Emissions with different types of vehicles
4. Emissions with a single generalized emission factor

CHAPTER 4: EMPIRICAL RESULTS

4.1. The effect of residential density on VMT

Table 3 shows the basic statistics for selected variables in 2006 Household Activity Survey data. Average household size is 2.28 people, and the mean household income is between \$60,000 and \$80,000. More than 40 percent of households are one worker household and 35 percent of households have two or more workers. Nearly 90 percent of households have more or equal number of cars to drivers.

Table 3. Basic statistics

Variable	N	Mean	SD	Minimum	Maximum
Household size	3830	2.28	1.23	1	8
Household annual income	3830	7.66	3.94	1	16
1 worker	3830	0.42	0.49	0	1
2 or more workers	3830	0.35	0.48	0	1
Vehicle availability	3830	0.89	0.3	0	1

The calculated mean VMT and transportation emissions per TAZ are visually presented with data plots. Figure 4 presents the estimates ± standard errors for the ordered mean VMT and transportation emissions per household by TAZ. We can see that each TAZ has the different mean value and variation, showing the possibility that travelers residing in the same TAZ have a certain level of correlation.

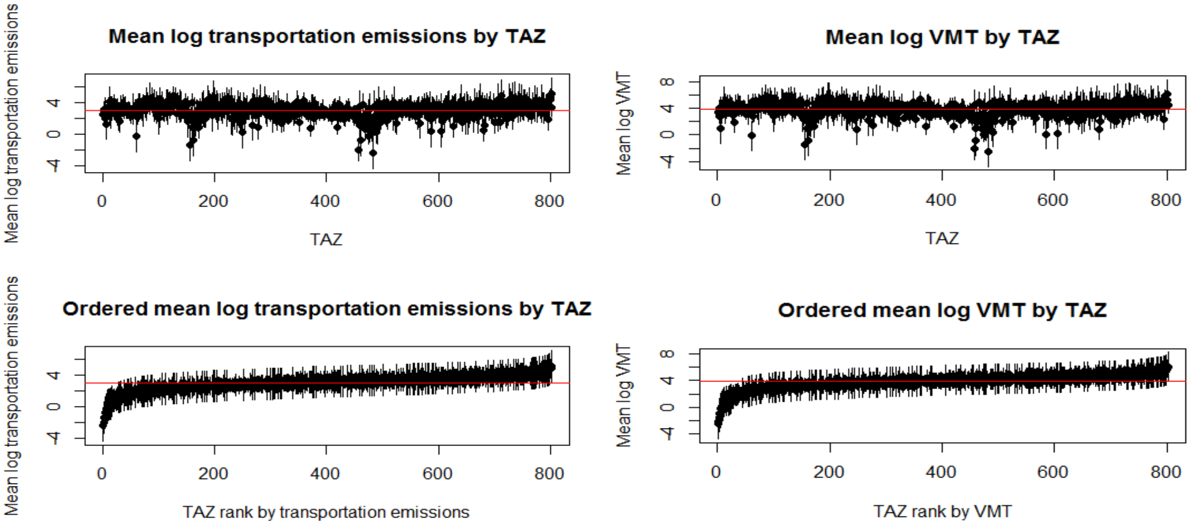


Figure 4. Estimates of VMT and transportation emissions per household by TAZs

First, the influences of spatial issues (i.e., spatial autocorrelation and confounding by location) on the estimate of *Residential density* are examined by comparing the results from the OLS, the multilevel model, and the BMSR. The results are presented in Table 4. The multilevel model assumes that all spatial autocorrelation is captured within neighborhood correlation while spatial relationship between TAZs is considered in the BMSR. The mean of coefficients and 95% CI are presented. If zero is not included in the 95% CI, it means that this variable has a significant impact on VMT at the 0.05 level of significance.

Residential density and VMT are transformed by taking log because of their skewed distributions, and also to estimate the elasticity directly. Furthermore, all continuous variables (i.e., household size, household income, and distance to bus stop) are standardized to compare the magnitude of coefficients. The result indicates that the effects of socio-economic factors are consistent across three models and are very significant.

Table 4. Comparative results from OLS, multilevel model, and BMSR (VMT)

	OLS		**Multilevel model**		**BMSR**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	0.139	0.163 (-0.172, 0.464)	0.212	0.175 (-0.105, 0.577)	1.219	0.206 (0.730, 1.575)
Household size	0.273	0.019 (0.234, 0.313)	0.271	0.020 (0.234, 0.312)	0.259	0.020 (0.220, 0.297)
Household income	0.184	0.019 (0.146, 0.219)	0.188	0.019 (0.148, 0.225)	0.207	0.019 (0.168, 0.242)
Vehicle availability	0.764	0.058 (0.652, 0.877)	0.735	0.055 (0.632, 0.838)	0.692	0.056 (0.581, 0.800)
Number of workers 1	0.298	0.048 (0.204, 0.395)	0.288	0.046 (0.199, 0.376)	0.278	0.045 (0.188, 0.372)
Number of workers 2+	0.662	0.055 (0.555, 0.765)	0.654	0.053 (0.551, 0.755)	0.640	0.053 (0.536, 0.745)
Distance to bus stop	0.068	0.019 (0.031, 0.106)	0.072	0.021 (0.030, 0.113)	0.044	0.021 (0.028, 0.111)
Residential density(log)	-0.292	0.017 (-0.326, -0.259)	-0.289	0.018 (-0.324, -0.253)	-0.185	0.022 (-0.232, -0.145)
σ_y			0.985	1.034	1.001	0.013
σ_α			0.182	0.297	0.062	0.045
σ_s					0.425	0.057
R^2	0.341		0.376		0.386	

Household size is positively associated with VMT. If more persons are in the same household, their cumulated VMT will increase. Specifically, the result shows that one standard deviation (SD) increase in household size is associated with approximately 27 ($\beta_{\text{household size}} * 100$) percent increase in VMT (Technically, it is a 31 percent: [(exp(0.273)-1) *100] percent). In addition, rich households are likely to drive more, probably due to their insensitivity to travel cost. If households own more or an equal number of cars compared to drivers, VMT increases. It implies that vehicle availability is highly correlated with driving. *Number of workers* has a positive impact on VMT. Work trip is the prevailing transportation activity during a day and more workers imply more commuting trips, therefore increasing auto usage. As the *Distance to bus stop* increases VMT also increases. It indicates that people living in neighborhoods where the accessibility to public transit is poor tend to drive more, increasing VMT.

Residential density is negatively associated with VMT and significant changes are found in the magnitude of coefficient and standard error when spatial issues (spatial autocorrelation and the effect of location) are considered. Households residing in denser areas drive less. For example, the result shows that a 1 percent increase in residential density will reduce VMT by 0.29 percent. However, its magnitude reduces to -0.185 percent when the spatial random effects are incorporated. It indicates a 0.185 percent reduction in VMT as *Residential density* increases by 1 percent. This significant difference occurs because the distribution of *Residential density* has a spatial pattern (e.g., local zoning restrictions), and the variability in VMT can be attributed to either the effect of location, or *Residential density* itself.

Table 5. Comparative IVs results from OLS, multilevel model, and BMSR (VMT)

	OLS		**Multilevel model**		**BMSR**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-1.052	0.489 (-2.030, -0.157)	-0.321	0.189 (-0.674, 0.027)	0.218	0.295 (-0.344, 0.766)
Household size	0.243	0.024 (0.197, 0.288)	0.260	0.019 (0.223, 0.299)	0.252	0.019 (0.214, 0.287)
Household income	0.177	0.019 (0.140, 0.216)	0.184	0.019 (0.148, 0.221)	0.195	0.019 (0.159, 0.234)
Vehicle availability	0.692	0.062 (0.579, 0.813)	0.714	0.056 (0.602, 0.824)	0.686	0.057 (0.417, 0.612)
Number of workers 1	0.340	0.046 (0.244, 0.429)	0.302	0.045 (0.218, 0.389)	0.296	0.043 (0.212, 0.384)
Number of workers 2+	0.701	0.053 (0.596, 0.807)	0.667	0.052 (0.565, 0.766)	0.660	0.052 (0.560, 0.764)
Distance to bus stop	0.010	0.029 (-0.049, 0.070)	0.045	0.020 (0.005, 0.084)	0.044	0.021 (-0.001, 0.085)
Residential density(log)	-0.426	0.055 (-0.537, -0.328)	-0.348	0.020 (-0.388, -0.308)	-0.293	0.032 (-0.353, -0.233)
σ_y	1.048	0.015	1.011	0.013	1.008	0.013
σ_R	0.998	0.012	0.447	0.006	0.447	0.006
σ_α			0.238	0.029	0.106	0.056
σ_γ			1.085	0.030	0.090	0.054
σ_{s1}					0.335	0.068
σ_{s2}					1.085	0.041
ρ_{yR}	0.140	0.052	0.116	0.020	0.106	0.025
Sargan test	4.067		3.701		0.757	
Hausman t statistic	-2.561		-6.767		-4.648	
R^2	0.327		0.374		0.379	

In addition, the SD of *Residential density* increases from 0.017 to 0.022. This indicates that if we ignore positive spatial autocorrelation, it could produce an underestimated SD which is associated with the level of significance. The R^2s of models are 0.341, 0.376, and 0.386, showing that they explain about 34, 38, and 39 percent of the variation in VMT.

The results with IVs are compared in Table 5 to examine the effect of self-selection. First, a Sargan-test is performed to check the appropriateness of IVs. It is often used to check the over-identification restriction in the model, that is, whether the IVs are truly exogenous or not. A Sargan-test is based on the chi-square distribution with i (number of IVs) - e (number of endogenous variables) degree of freedom. Since two IVs are used for one endogenous variable the degree of freedom is 1 and the statistic of 95% value is 3.84. A Sargan-test shows that IVs are truly exogenous except the OLS model, and statistically significant effects of IVs are found in three residential density models, proving strong associations between IVs and *Residential density*. In addition, R^2s of the OLS, multilevel model, and the BMSR for residential density are 0.27, 0.85, and 0.85, respectively (Results from these analyses are not presented here). This also indicates that a large amount of variations in the residential density model can be explained by spatial components, and therefore they should be incorporated in the estimation to obtain accurate predicted values.

All estimates are not significantly different from those from the previous results. However, IVs estimates of *Residential density* increase significantly. The result shows that a 1 percent increase in *Residential density* will result in 0.426, 0.348, and 0.293 percent reductions in VMT across models. The magnitude of IVs coefficients is greater than that from the previous outcomes and different from what we expect, but several empirical studies also found similar results (Grazi et al., 2008; Ewing and Cervero, 2010).

The Hausman test is conducted to examine whether the IVs estimates are statistically different from the coefficients of *Residential density* from models without IVs. Instead of comparing the linear combinations of estimates from models, only the estimates of *Residential density* are compared. If there is only one endogenous variable, The Hausman t statistic can be calculated as follow:

$$(\beta_{r,IV} - \beta_{r,P})/[se\left(\beta_{r,IV}\right)^2 - se\left(\beta_{r,P}\right)^2]^{1/2} \quad (13)$$

Here, $\beta_{r,IV}$, $\beta_{r,P}$ are the coefficients of *Residential density* from models with and without IVs, respectively. If the null hypothesis is rejected it indicates that these two estimates are statistically different. The tests show that the endogeneity problem should be taken into account in this analysis.

4.2. The effect of residential density on transportation emissions

Since transportation emissions are sensitive to travel speed and vehicle characteristics, the influence of *Residential density* on transportation emissions can be different from that on VMT. The same models are employed to analyze the effect of *Residential density* on transportation emissions (CO_2 equivalent), and the results from the OLS, the multilevel model, and the BMSR are shown in Table 6. The differences between results indicate the impacts of spatial issues in land use-transportation emissions analyses.

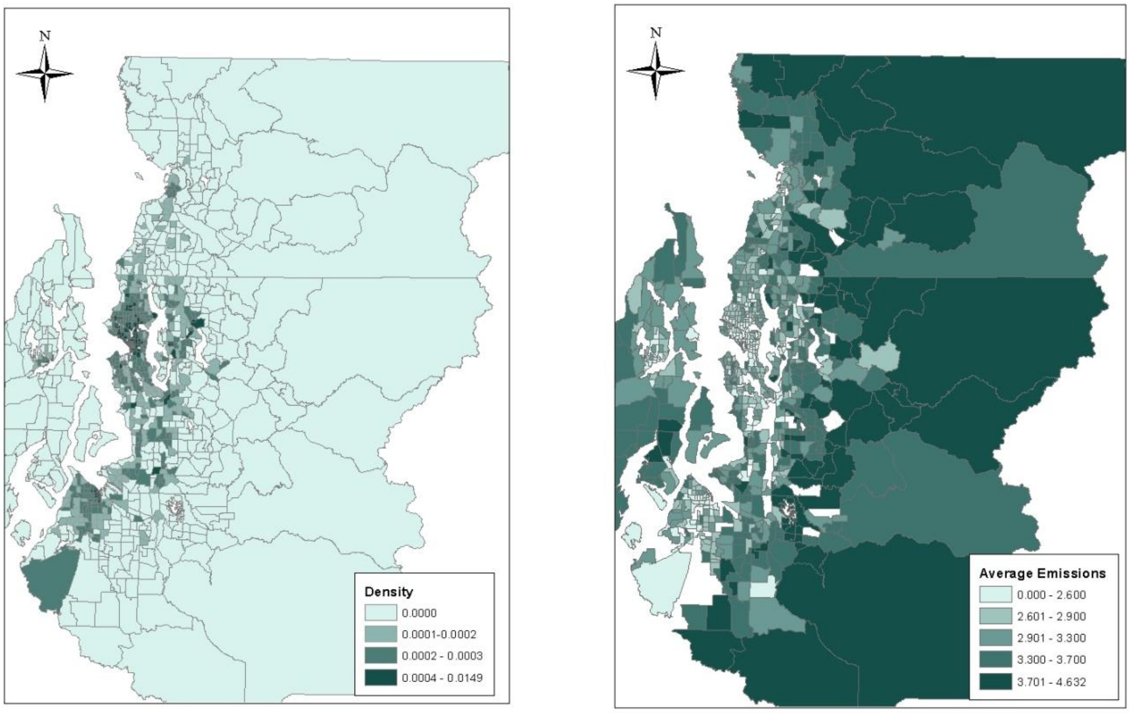
The results are very similar to those from VMT analyses. *Household size* is positively associated with transportation emissions. For example, the result of OLS shows that one standard deviation (SD) increase in household size will reduce transportation emissions by 32.3 ((exp(0.28)-1) *100) percent. In addition, *Household income* has a positive influence on transportation emissions, indicating that rich households are likely to produce more transportation emissions, probably due to their economic capacity. *Vehicle availability* and *Number of workers* also have significant effects on transportation emissions, implying that vehicle accessibility and commuting trips are positively associated with transportation emissions. Moreover, as the *Distance to bus stop* increases transportation emissions increase. It indicates that improving public transit accessibility can reduce transportation emissions while holding other variables constant.

Table 6. Comparative results from OLS, multilevel model, and BMSR (Transportation emissions)

	OLS		**Multilevel model**		**BMSR**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-0.159	0.138 (-0.418, 0.117)	-0.086	0.153 (-0.389, 0.214)	0.787	0.236 (0.347, 1.284)
Household size	0.280	0.017 (0.248, 0.312)	0.277	0.017 (0.242, 0.310)	0.265	0.017 (0.232, 0.298)
Household income	0.162	0.017 (0.129, 0.195)	0.166	0.017 (0.133, 0.200)	0.182	0.017 (0.147, 0.216)
Vehicle availability	0.582	0.049 (0.489, 0.683)	0.550	0.047 (0.462, 0.639)	0.516	0.050 (0.417, 0.612)
Number of workers 1	0.312	0.04 (0.239, 0.389)	0.303	0.039 (0.225, 0.379)	0.297	0.039 (0.219, 0.376)
Number of workers 2+	0.650	0.044 (0.565, 0.738)	0.644	0.046 (0.552, 0.734)	0.633	0.045 (0.547, 0.723)
Distance to bus stop	0.077	0.016 (0.045, 0.107)	0.078	0.018 (0.040, 0.112)	0.070	0.020 (0.031, 0.110)
Residential density(log)	-0.253	0.014 (-0.279, -0.225)	-0.249	0.016 (-0.281, -0.217)	-0.159	0.025 (-0.205, -0.109)
σ_y			0.881	0.011	0.875	0.011
σ_α			0.225	0.025	0.065	0.042
σ_s					0.380	0.051
R^2	0.366		0.404		0.413	

The key finding in this analysis is that the effects of *Residential density* on transportation emissions are smaller than those on VMT. In addition, significant changes are found in the magnitude of coefficient and standard error when spatial issues (spatial autocorrelation and the effect of location) are incorporated. In general, households residing in denser areas generate fewer transportation emissions. For example, the result shows that a 1 percent increase in residential density will reduce transportation emissions by 0.25 percent. However, its magnitude reduces to -0.159 percent when the spatial random effects are introduced. Again, this significant difference may occur because the distribution of *Residential density* has a spatial pattern, and the variability in transportation emissions can be attributed to either the effect of location or *Residential density* itself.

Comparing the geographical distributions of *Residential density* and predicted values of transportation emissions will make it clear whether this difference is caused by the confounding effect due to location or not. Figure 5 shows *Residential density* and the mean fitted values of transportation emissions per household calculated based on results from the BMSR without the *Residential density* variable according to quantiles. It is obvious that there is a great level of inverse relationship between two spatial patterns, showing the possibility that the location is acting as a confounder. That is, there are unmeasured factors related to the spatial variation in transportation emissions, inflating the influence of *Residential density* on transportation emissions.



Residential unit density for each TAZ

Average predicted value of emissions for each TAZ

Figure 5. Spatial patterns of the variations of residential density and transportation emissions for TAZs

As mentioned before, controlling the confounding effect by location may result in an overly conservative coefficient of *Residential density*. However, when we think about the monetary costs and time required to change built environments, this conservative effect would be safer for planners or policy makers compared to an over-estimated result. Furthermore, when the spatial autocorrelation is considered, the SD of *Residential density* increases from 0.014 to 0.025. This also shows that an underestimated SD can be generated if a positive spatial autocorrelation is ignored in linear regressions. The calculated ICC based on the outcome from the multilevel model is 0.061, showing that the correlation among residents in the same TAZ is approximately 6 percent.

Table 7. Comparative IVs results from OLS, multilevel model, and BMSR (Transportation emissions)

	OLS		**Multilevel model**		**BMSR**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-1.193	0.425 (-2.014, -0.240)	-0.587	0.170 (-0.911, -0.249)	-0.037	0.275 (-0.545, 0.483)
Household size	0.254	0.020 (0.214, 0.295)	0.267	0.018 (0.234, 0.303)	0.260	0.018 (0.224, 0.297)
Household income	0.156	0.017 (0.123, 0.192)	0.164	0.016 (0.132, 0.194)	0.173	0.017 (0.140, 0.205)
Vehicle availability	0.519	0.057 (0.413, 0.631)	0.529	0.051 (0.429, 0.631)	0.508	0.049 (0.415, 0.609)
Number of workers 1	0.348	0.042 (0.270, 0.429)	0.315	0.040 (0.240, 0.396)	0.309	0.040 (0.229, 0.387)
Number of workers 2+	0.681	0.049 (0.588, 0.777)	0.654	0.046 (0.563, 0.739)	0.644	0.044 (0.560, 0.734)
Distance to bus stop	0.025	0.026 (-0.023, 0.079)	0.052	0.018 (0.017, 0.087)	0.051	0.019 (0.015, 0.089)
Residential density(log)	-0.369	0.048 (-0.463, -0.264)	-0.305	0.018 (-0.339, -0.266)	-0.250	0.031 (-0.308, -0.189)
σ_y	0.918	0.012	0.882	0.011	0.879	0.011
σ_R	0.999	0.011	0.448	0.006	0.448	0.006
σ_α			0.225	0.025	0.091	0.056
σ_γ			1.083	0.029	0.082	0.055
σ_{s1}					0.312	0.061
σ_{s2}					1.086	0.040
ρ_{yR}	0.138	0.054	0.120	0.021	0.108	0.025
Sargan test	2.229		1.725		0.366	
Hausman t statistic	-2.527		-6.791		-6.124	
R square	0.356		0.402		0.406	

The results with IVs are compared in Table 7 to assess the effect of self-selection. Again, since two IVs are used for one endogenous variable the degree of freedom is 1 and the statistic of 95% value is 3.84. A Sargan-test shows that IVs are truly exogenous for all models.

All estimates are not significantly different from those from the previous results. However, IVs estimates of *Residential density* increase significantly. The result shows that a 1 percent increase in *Residential density* will result in 0.369, 0.305, and 0.250 percent reductions in transportation emissions across models. In addition, the Hausman tests show that estimates with IVs and without IVs are statistically different therefore, the endogeneity problem should be considered in this analysis.

In conclusion, empirical results from VMT and transportation emissions models imply that *Residential density* has a very significant and moderate influence on VMT and transportation emissions. In addition, confounding effects caused by spatial autocorrelation and self-selection should be considered in the analysis of land use and transportation to obtain more reliable results. The BMSR produces the most conservative elasticities, ranging from 19 percent to 29 percent for VMT and 15 percent to 25 percent for transportation emissions, respectively when doubling *Residential density,* and these are slightly higher than what has been reported in most previous studies. Therefore, it is reasonable to say that land use policy has a potential to be an effective instrument for reducing VMT, and thereby transportation emissions in the Puget Sound region. In addition, improving transit accessibility also has a significant impact on individuals' travel choices.

4.3. The effects of built environment factors measured at two geographic scales on tour based VMT

Two separate models based on tour purposes - work and non-work tours - are built to incorporate trip-interdependency into analyses. In this research, a tour is defined as a chain of trips that begins and ends at home. If a tour includes work-related or school-related activities, it is classified as a work tour. In addition, five different land use variables measured at the two different geographic scales (1-km buffer and TAZ) are used to obtain a more specific effect of each land use characteristic on VMT and transportation emissions. VMT and transportation emissions are transformed by taking log because of their skewed distributions, and all continuous variables are standardized. Finally, the correlated error structure is integrated into the BMSR framework to consider both self-selection and spatial issues.

The regression analyses with two different tour types produce some significantly different results and generally provide richer information. Additional insights are obtained by examining these differences. As seen in Table 8 and 9, all variables have the expected signs and effects. The R^2 of a work-tour VMT model is about 0.32, and the key results are as follows:

- **Work-tour VMT**

Residential location choice model

First, residential location (urban vs. suburban) is modeled with a rich set of socio-economic factors (i.e., household size, household income, number of vehicles, and number of workers) and two neighborhood characteristics (% of buildings built between 1945 and 1990 and % of Hispanic). Then, location information is included with a correlated error structure in the VMT models.

Household size has a statistically significant negative influence, indicating that larger households tend to live in suburban areas than urban areas. Houses in suburban areas are more spacious and inexpensive compared to those in urban areas, thus they become more attractive to larger households. In addition, rich people tend to reside in urban areas rather than suburban areas. This is consistent with previous studies of gentrification. Seattle's Central District has experienced racial shift. That is, a more educated and rich white and Asian population has moved in while black people have moved out (McGee, 2007). As households own more cars, they are more likely to live in suburban areas, as shown by the negative coefficient. An automobile provides flexibility in terms of mobility, and it is one of the most important driving forces of suburban developments. On the other hand, densely developed urban areas often encourage people to own fewer cars by providing alternative transportation modes. As the *Number of workers* increases households prefer living in urban areas compared to suburban areas. It is plausible because work location is a predominant factor influencing the residential location choice, and more jobs are generally located in urban areas. *Home ownership* also shows a significant negative association. That is, people living in urban areas are more likely to rent homes rather than owning them. In general, homes in urban areas are expensive, and there are many duplexes or apartments in urban areas compared to suburban areas. Households who want to buy single family homes, therefore, tend to live in suburban areas. Two IVs have very significant associations with the residential location choice. More buildings were built between 1945 and 1990 in suburban areas than urban areas. The Washington's Growth Management Act was enacted in 1990 and before that time, suburban developments were continued mainly due to the increased automobile ownership. Finally, more Hispanic population tends to live in urban areas, mostly due to job opportunities.

VMT model

Since VMT is transformed by taking log and all continuous variables are standardized, the coefficient can be simply interpreted that VMT changes by 100*coefficient percent when the independent variable increases by one SD while holding all other variables constant.

The influences of most socio-economic status variables are consistent with previous studies. *Household size* has a negative influence on work-tour VMT. It is plausible in that members of a large household can reduce the intermediate trips per work-tour by coordinating activities. As the household annual income rises, VMT also increases, perhaps because they are less sensitive to travel cost. *Number of vehicles* is one of the most influential factors for work-tour VMT, showing that increasing vehicle accessibility tends to increase vehicle uses. Moreover, *Number of workers* is the most influential and significant factor for work-tour VMT. It shows that as the *Number of workers* increases work-tour VMT increases. The result also indicates that public transit accessibility measured by *Distance to bus stop* is not statistically associated with work-tour VMT. In addition, neither residential location nor the correlation between residential location and VMT shows a significant impact on work-tour VMT. However, additional analyses show that failing to consider a rich set of socio-economic factors in the VMT model can increase the level of significance of correlation. This result is consistent with previous empirical studies, showing the importance of controlling diverse socio-economic characteristics of travelers in the land use-transportation analysis to relieve the self-selection impact.

All built environment variables have significant effects on work-tour VMT. Households living in denser areas tend to drive less. Specifically, one SD increase in Residential density in the 1km model will reduce VMT by about 12 percent. Especially, increasing *Non-residential density* decreases work-tour VMT significantly. This variable is associated with job opportunities around home locations and it supports the claim of compact city supporters. In addition, *Entropy* has a negative influence on work-tour VMT, indicating that increasing accessibility to other activities can reduce VMT. Four-way intersection density around traveler's home location has a significant negative effect on work-tour VMT only at the TAZ level. It often represents walkability and the result shows that improving walkability at the TAZ level can reduce work-tour VMT.

Finally, *Distance from CBD* has a highly significant impact on VMT. This is consistent with previous studies, indicating the importance of accessibility to jobs and services. Overall, built environments have very significant effects on work-tour VMT, especially, at the TAZ level.

Table 8. Results for residential location choice and work-tour VMT

	Work tour					
	Residential location		VMT (1km)		VMT (TAZ)	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-0.027	0.068 (-0.159, 0.109)	3.616	0.098 (3.431, 3.800)	3.641	0.097 (3.458, 3.837)
Household size	-0.123	0.028 (-0.175, -0.068)	-0.095	0.025 (-0.145, -0.044)	-0.093	0.025 (-0.141, -0.045)
Household income	0.057	0.028 (0.004, 0.113)	0.160	0.024 (0.113, 0.208)	0.160	0.024 (0.114, 0.207)
Number of vehicles	-0.194	0.031 (-0.254, -0.136)	0.206	0.032 (0.143, 0.269)	0.209	0.032 (0.145, 0.268)
Number of workers	0.116	0.029 (0.062, 0.175)	0.324	0.025 (0.278, 0.372)	0.324	0.025 (0.275, 0.373)
Distance to bus stop			0.013	0.026 (-0.037, 0.065)	0.019	0.026 (-0.033, 0.070)
Urban			-0.030	0.229 (-0.489, 0.401)	-0.036	0.229 (-0.480, 0.404)
Correlation			-0.045	0.126 (-0.196, 0.279)	0.047	0.126 (-0.199, 0.287)
Residential density			-0.121	0.031 (-0.183, -0.059)	-0.157	0.043 (-0.241 -0.067)
Non- residential Density			-0.090	0.032 (-0.149, -0.025)	-0.136	0.043 (-0.221, -0.057)
Entropy			-0.079	0.026 (-0.128, -0.030)	-0.070	0.026 (-0.121 -0.019)
Intersection density			-0.029	0.035 (-0.096, 0.035)	-0.088	0.034 (-0.155, -0.022)
Distance from CBD			0.219	0.058 (0.104, 0.335)	0.182	0.052 (0.079, 0.280)
Home ownership	-0.233	0.076 (-0.377, -0.074)				
Building built 1945 & 1990	-0.381	0.026 (-0.432, -0.328)				
% of Hispanic	0.137	0.025 (0.086, 0.185)				
σ_α			0.083	0.051	0.082	0.052
σ_s			0.295	0.062	0.256	0.062
$(1-\rho^2)\sigma_y^2$			1.188	0.037	1.189	0.037
$R^2\ for\ data\ level$			0.315		0.312	
$R^2\ for\ group\ level$			0.000		0.959	

- **Non-work tour VMT**

Significant differences in results compared to those from work-tour VMT analyses are found and discussed in this section. For non-work tour models, two dummy variables that represent the number of workers are used instead of one continuous variable to assess the differences between groups. The R^2 of a non-work tour VMT model is about 0.25. This is relatively smaller than that of the work tour VMT model but still shows a moderate goodness of fit. The key results are as follows:

Residential location choice model

Again, most socio-economic factors of travelers show the expected effects on residential location choice. *Household size* has a negative impact on residential location choice, indicating that larger households tend to live in suburban areas than urban areas. Rich households are likely to live in urban areas than suburban areas, and households with more cars tend to live in suburban areas. In addition, households with more workers tend to live in urban areas. However, households with one worker compared to those with no worker are likely to live in suburban areas (This variable is significant at the 0.10 level of significance). Generally, households with no worker are the elders, students, or the welfare recipients and they are more likely to live in urban areas due to their physical conditions and socio-economic status. *Home ownership* has a negative coefficient, indicating that households living in suburban areas tend to buy their own homes than urbanites. Finally, neighborhood characteristics show similar influences on the residential location choice compared to the previous analysis.

Table 9. Results for residential location choice and non-work tour VMT

	Non-work tour					
	Residential location		VMT (1km)		VMT (TAZ)	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-0.029	0.088 (-0.205, 0.136)	3.604	0.079 (3.446, 3.754)	3.664	0.084 (3.500, 3.832)
Household size	-0.135	0.030 (-0.190, -0.074)	0.190	0.025 (0.141, 0.238)	0.190	0.026 (0.139, 0.239)
Household income	0.056	0.030 (-0.007, 0.113)	0.132	0.024 (0.085, 0.180)	0.139	0.023 (0.094, 0.182)
Number of vehicles	-0.143	0.031 (-0.200, -0.083)	0.210	0.026 (0.158, 0.259)	0.213	0.026 (0.164, 0.266)
Worker 1	-0.116	0.064 (-0.239, 0.010)	-0.355	0.049 (-0.453, -0.255)	-0.371	0.050 (-0.472, -0.271)
Worker 2	0.141	0.074 (-0.003, 0.289)	-0.615	0.056 (-0.728, -0.501)	-0.625	0.061 (-0.738, -0.501)
Distance to bus stop			0.095	0.023 (0.050, 0.139)	0.098	0.023 (0.052, 0.144)
Urban			-0.242	0.172 (-0.556, 0.111)	-0.366	0.172 (-0.690, 0.014)
Correlation			0.064	0.099 (-0.141, 0.238)	0.132	0.100 (-0.077, 0.311)
Residential density			-0.109	0.027 (-0.163, -0.052)	-0.166	0.043 (-0.253, -0.083)
Non residential density			0.009	0.028 (-0.047, 0.063)	0.042	0.049 (-0.050, 0.141)
Entropy			-0.125	0.025 (-0.174, -0.079)	-0.099	0.024 (-0.146, -0.047)
Intersection density			-0.071	0.028 (-0.126, -0.016)	-0.085	0.031 (-0.146, -0.028)
Distance from CBD			0.044	0.032 (-0.019, 0.113)	0.053	0.040 (-0.025, 0.139)
Home ownership	-0.247	0.078 (-0.394, -0.093)				
Building built 1945 & 1990	-0.364	0.027 (-0.416, -0.312)				
% of Hispanic	0.126	0.024 (0.079, 0.172)				
σ_α			0.130	0.063	0.151	0.058
σ_s			0.086	0.062	0.126	0.072
$(1-\rho^2)\sigma_y^2$			1.055	0.032	1.046	0.036
R^2 $for\ data\ level$			0.243		0.250	
R^2 $for\ group\ level$			0.000		0.727	

VMT model

The effects of socio-economic factors on non-work tour VMT are quite different from those on work-tour VMT. First, larger households tend to produce more non-work tour VMT. Specifically, one SD increase in household size will increase non-work tour VMT by 21 percent. *Household income* and *Number of vehicles* have similar influences on non-work tour VMT compared to those on work-tour VMT. That is, rich households or households with more vehicles tend to produce more non-work tour VMT, mainly due to their economic capacity. In addition, as households have more workers, non-work tour VMT decreases. Workers have time constraints for their daily activities so they are less likely to participate in diverse activities than non-workers. This effect becomes larger when there are more workers in the household.

Distance to bus stop has a significant and positive effect. It means that as the accessibility to public transit decreases, non-work tour VMT increases. This result implies that public transit accessibility matters more for non-work related activities than commuting. *Urban* has a significant negative influence on non-work tour VMT with TAZ level land use factors at the 90% CI, indicating that households living in urban areas tend to drive less. However, the empirical results show that there is no significant correlation between the residential location choice and VMT when including a rich set of socio-economic factors of travelers and land use characteristics.

There are also some significant differences in the effects of built environments. The influences of *Non-residential density* and *Distance from CBD*, mostly associated with job opportunities, are no longer significant. This indicates that job opportunities are not related to non-work tour VMT. In addition, the effects of *Entropy* and *Intersection density* become stronger compared to those from work-tour VMT models. This shows that improving the accessibility to other activities and walkability can reduce VMT significantly through the reduction in non-work related trip distances and vehicle usage.

In sum, built environments have highly significant impacts on VMT from both work and non-work tours. However, there are significant differences between the two tour types and these should be considered when making plans or policies.

4.4. The effects of built environment factors measured at two geographic scales on tour based transportation emissions

Table 10 and 11 show the results from transportation emissions models with the same covariates as VMT models. Here, transportation emissions indicate $\mathrm{CO_2}$ equivalent. All variables are standardized and log transformation is taken for the transportation emissions variable. The results are consistent with previous VMT analyses. The R^2s of transportation emissions models are about 0.32 and 0.25 for work and non-work tour, respectively. The key results are as follow:

- **Work-tour transportation emissions**

Residential location choice model

The result from the residential location choice model is the same as that from the work-tour VMT model since the same data is used. Larger households are likely to live in suburban areas than urban areas. Houses in suburban areas are more spacious and inexpensive compared to those in urban areas, thus they become more attractive to larger households. Moreover, rich people tend to live in urban areas rather than suburban areas. This is consistent with previous studies of gentrification. That is, a more educated and rich population has moved into the central districts of Seattle. As households own more cars, they are likely to live in suburban areas, mainly due to increased mobility. In addition, households with more workers tend to live in urban areas and this is associated with job opportunities. *Home ownership* has a negative coefficient, indicating that people living in urban areas are likely to rent their homes. Finally, two IVs show that fewer buildings were built between 1945 and 1990 and more Hispanic population lives in urban areas than suburban areas. It implies that the Washington's Growth Management Act approved in 1990 affected development patterns in the Puget Sound region.

Transportation emissions model

The influences of most socio-economic status factors are consistent with previous VMT models. *Household size* is negatively associated with work-related transportation emissions. Again, it is plausible in that members of a large household can coordinate activities to save their trips. Rich people are more likely to produce more transportation emissions, probably due to their insensitivity to travel cost. Households with more vehicles also produce more transportation emissions. It implies that increasing vehicle accessibility tends to increase vehicle uses. In addition, *Number of workers* has the largest impact on work-tour transportation emissions, showing that as the *Number of workers* increases work-tour transportation emissions increase.

On the other hand, the results indicate that public transit accessibility (*Distance to bus stop*), residential location (*Urban*), and the correlation between residential location choice and emissions (*Correlation*) do not have significant influences on work-tour transportation emissions. However, additional analyses show that failing to consider a rich set of socio-economic factors in the transportation emissions model can increase the level of significance of *Correlation*. Several previous empirical studies also find that including diverse socio-economic characteristics of travelers in analyses can relieve the impact of self-selection.

Significant effects of built environment factors on work-tour emissions are found. For example, *Residential density* is negatively associated with transportation emissions at both geographic scales, implying that households living in denser areas produce less transportation emissions. In addition, land use factors associated with job opportunities such as *Non-residential density* and *Distance from CBD* have very significant impacts on work-tour transportation emissions, supporting the claim of compact city supporters.

Entropy has a negative influence on work-tour transportation emissions, indicating that increasing accessibility to other activities can reduce transportation emissions. In addition, *Intersection density* has a significant negative effect on work-tour transportation emissions only at the TAZ level. It implies that increasing four-way intersection density at the TAZ level can reduce work-tour transportation emissions by creating more walkable and pro-transit environments. Overall, built environments have very significant effects on work-tour transportation emissions, especially, at the TAZ level.

Table 10. Results for residential location choice and work-tour transportation emissions

	Work-tour					
	Residential location		**Emissions (1km)**		**Emissions (TAZ)**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-0.039	0.06 (-0.173, 0.093)	2.776	0.081 (2.632, 2.935)	2.800	0.083 (2.630, 2.965)
Household size	-0.122	0.028 (-0.175, -0.068)	-0.047	0.021 (-0.092, -0.008)	-0.044	0.022 (-0.085, -0.001)
Household income	0.057	0.028 (0.004, 0.113)	0.137	0.021 (0.096, 0.180)	0.139	0.020 (0.102, 0.177)
Number of vehicles	-0.195	0.033 (-0.262, -0.130)	0.142	0.027 (0.088, 0.197)	0.143	0.027 (0.090, 0.198)
Number of workers	0.118	0.028 (0.062, 0.175)	0.311	0.021 (0.272, 0.354)	0.311	0.021 (0.271, 0.354)
Distance to bus stop			0.023	0.024 (-0.026, 0.069)	0.029	0.023 (-0.016, 0.074)
Urban			0.065	0.187 (-0.316, 0.408)	0.066	0.195 (-0.335, 0.442)
Correlation			-0.011	0.117 (-0.211, 0.232)	-0.011	0.124 (-0.243, 0.241)
Residential density			-0.096	0.026 (-0.147, -0.046)	-0.121	0.040 (-0.196, -0.040)
Non- residential density			-0.077	0.027 (-0.131, -0.023)	-0.118	0.040 (-0.197, -0.041)
Entropy			-0.072	0.023 (-0.116, -0.028)	-0.064	0.021 (-0.104, -0.022)
Intersection density			-0.028	0.031 (-0.086, 0.034)	-0.084	0.030 (-0.146, -0.024)
Distance from CBD			0.203	0.055 (0.097, 0.314)	0.167	0.048 (0.080, 0.261)
Home ownership	-0.219	0.074 (-0.365, -0.066)				
Building built 1945 & 1990	-0.383	0.025 (-0.432, -0.335)				
% of Hispanic	0.138	0.023 (0.092, 0.186)				
σ_α			0.081	0.055	0.085	0.056
σ_s			0.281	0.058	0.246	0.061
$(1-\rho^2)\sigma_y^2$			0.888	0.026	0.888	0.028
$R^2\ for\ data\ level$			0.324		0.322	
$R^2\ for\ group\ level$			0.000		0.938	

- **Non-work tour transportation emissions**

Significant differences in results compared to those from work-tour transportation emissions analyses are found and discussed in this section. For non-work tour models, two dummy variables that represent the number of workers are used instead of one continuous variable to assess the differences between groups. The $R^2$of a non-work tour transportation emissions model is about 0.25. This is relatively smaller than that of the work-tour transportation emissions model but still shows a moderate goodness of fit. The key results are as follows:

Residential location choice model

Table 11 shows the results of residential location choice and non-work tour transportation emissions models. Again, most socio-economic factors of travelers have expected influences on residential location choice. *Household size* has a negative impact, implying that larger households tend to living in suburban areas, due to the housing characteristics. As the household's annual income increases, they tend to live in urban areas. In addition, households with more automobiles are more likely to live in suburban areas because of the increased mobility.

Households with more than one worker (*Worker2*) tend to live in urban areas due to the job opportunities. However, households with one worker compared to those with no worker are likely to live in suburban areas. In general, students and the elders do not have jobs and they are inclined to live in urban areas due to their physical conditions and socio-economic status. *Home ownership* has a negative impact, indicating that suburbanites have a tendency to buy their homes then renting them. Finally, neighborhood characteristics show similar influences on the residential location choice compared to the work-tour models.

Transportation emissions model

There are significant differences in the effects of socio-economic factors of travelers on non-work tour and work-tour transportation emissions. First, *Household size* is positively related to non-work tour transportation emissions. It implies that more people in the same household can translate into more motorized non-commuting trips, thereby increasing non-work tour transportation emissions. In addition, rich people or households with more cars are inclined to drive more to participate in non-work related activities, increasing non-work tour transportation emissions. As households have more workers, non-work transportation emissions decrease significantly. Because of worker's time constraints for their daily activities, they are less likely to participate in diverse activities than non-workers.

Distance to bus stop has a significant and positive effect. It indicates that households living in neighborhoods with poor public transit accessibility tend to produce more non-work tour transportation emissions. This result implies that public transit accessibility matters more for non-work related activities than commuting. Moreover, residential location (*Urban*) is negatively associated with non-work tour transportation emissions and its impact is significant at the 90% CI. It indicates that households living in urban areas tend to produce fewer emissions while holding other factors constant. However, the correlation between residential location choice and non-work tour transportation emissions (*Correlation*) has no significant impact, showing that the self-selection impact can be relieved when including a rich set of socio-economic factors of travelers and land use characteristics in this model.

There are also some significant differences in the effects of built environments on transportation emissions. First of all, the effects of *Non-residential density* and *Distance from CBD* are no longer significant. It indicates that job opportunities are not associated with non-work tour transportation emissions. On the other hand, the influences of *Entropy* and *Intersection density* become stronger compared to those from work-tour transportation emissions models. This indicates that improving the accessibility to other activities and walkability can reduce transportation emissions significantly through the reduction in non-work related trip distances and vehicle usage.

In sum, built environments have very significant impacts on transportation emissions from both work and non-work tours. However, there are significant differences in the effects of built environments on transportation emissions according to tour types and geographic scales.

Table 11. Results for residential location choice and non-work tour transportation emissions

	Non-work tour					
	Residential location		**Emissions (1km)**		**Emissions (TAZ)**	
	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Intercept	-0.046	0.086 (-0.212, 0.127)	2.759	0.082 (2.585, 2.915)	2.799	0.077 (2.654, 2.950)
Household size	-0.134	0.031 (-0.193, -0.071)	0.235	0.023 (0.191 0.279)	0.236	0.023 (0.190, 0.282)
Household income	0.054	0.030 (-0.006, 0.111)	0.130	0.021 (0.087, 0.172)	0.135	0.022 (0.095, 0.181)
Number of vehicles	-0.143	0.031 (-0.198, -0.079)	0.166	0.025 (0.119, 0.213)	0.171	0.025 (0.121, 0.221)
worker 1	-0.114	0.066 (-0.241, 0.016)	-0.373	0.050 (-0.471, -0.279)	-0.390	0.048 (-0.490, -0.296)
worker 2	0.144	0.076 (-0.009, 0.287)	-0.647	0.057 (-0.760, -0.537)	-0.663	0.057 (-0.783, -0.552)
Distance to bus stop			0.099	0.022 (0.057, 0.141)	0.102	0.022 (0.057, 0.142)
Urban			-0.193	0.170 (-0.508, 0.155)	-0.260	0.163 (-0.565, 0.054)
Correlation			0.026	0.105 (-0.193, 0.230)	0.065	0.101 (-0.123, 0.254)
Residential density			-0.084	0.025 (-0.131, -0.038)	-0.138	0.042 (-0.217, -0.055)
Non residential density			0.009	0.028 (-0.049, 0.061)	0.048	0.046 (-0.039, 0.142)
Entropy			-0.111	0.023 (-0.155, -0.067)	-0.098	0.024 (-0.144, -0.053)
Intersection density			-0.067	0.027 (-0.117, -0.014)	-0.087	0.028 (-0.144, -0.030)
Distance from CBD			0.039	0.029 (-0.016, 0.100)	0.042	0.034 (-0.021, 0.112)
Home ownership	-0.227	0.077 (-0.378, -0.080)				
Building built 1945 & 1990	-0.362	0.025 (-0.410, -0.313)				
% of Hispanic	0.127	0.024 (0.079, 0.178)				
σ_α			0.135	0.054	0.154	0.050
σ_s			0.072	0.050	0.089	0.061
$(1-\rho^2)\sigma_y^2$			0.931	0.028	0.924	0.028
R^2 *for data level*			0.246		0.250	
R^2 *for group level*			0.000		0.672	

4.5. The sensitivity analyses of built environment measures on different transportation emissions through elasticities

Four transportation emissions are calculated and compared to see how travel speed and vehicle characteristics affect total transportation emissions and the effects of built environments. For this analysis, BMSR models with diverse types of travelers' information and built environment measures are employed.

As mentioned, travel speed and vehicle characteristics are very influential components in estimating transportation emissions and are considered in the previous analyses. To see the relationship between urban form and these factors, simple frequency and correlation analyses are conducted. First, the relationship between urban form (urban vs. suburban) and vehicle types (motorcycle, passenger car, light duty truck, and transit bus) used for people's trips is shown in Table 12.

Table 12 Frequency analysis for vehicle types according to urban form

Vehicle type	**Urban form**		
	Suburban	**Urban**	**Total**
Motorcycle (Frequency)	96	77	173
Percent	0.18	0.14	0.32
Row percent	55.49	44.51	
Column percent	0.3	0.37	
Passenger car (Frequency)	16444	11831	28275
Percent	30.79	22.15	52.95
Row percent	58.16	41.84	
Column percent	50.76	56.31	
Light duty trucks (SUV, minivan, pickup truck) (Frequency)	15247	7841	23088
Percent	28.55	14.68	43.23
Row percent	66.04	33.96	
Column percent	47.07	37.32	
Transit bus (Frequency)	607	1260	1867
Percent	1.14	2.36	3.5
Row percent	32.51	67.49	
Column percent	1.87	6	
Total (Frequency)	32394	21009	53403
Percent	60.66	39.34	100

Households living in urban areas tend to use more passenger cars (56%) for their trips than light duty trucks (37%). In addition, households living in suburban areas use relatively more light duty trucks for their daily trips than households living in urban areas. About 47 percent of trips are made by using light duty trucks for households living in suburban areas whereas only 37 percent for households living in urban areas. Moreover, urbanites take public transit buses more frequently than suburbanites. 6 percent of total trips by urbanites are made by public transit while suburbanites made only 1.87 percent of their total trips by public transit. This result shows that urban form has a strong correlation with travelers' mode choice and thereby, transportation emissions. Specifically, households living in urban areas tend to use more energy efficient and low emission vehicles than suburbanites.

Table 13 shows the relationship between urban form and average speeds of trips. For this analysis, average speeds for all trips are averaged by households. The mean speeds of trips made by urbanites and suburbanites are 33.8 miles per hour and 35.9 miles per hour, respectively. It shows that households living in urban areas have lower average trip speeds, mainly due to congestion. The result also indicates that there is a significant negative correlation (-0.09) between the average speeds of trips and residential density. This implies that both travel speeds and urban form have a strong association and people living in urban areas tend to produce more transportation emissions per mile due to lower travel speeds.

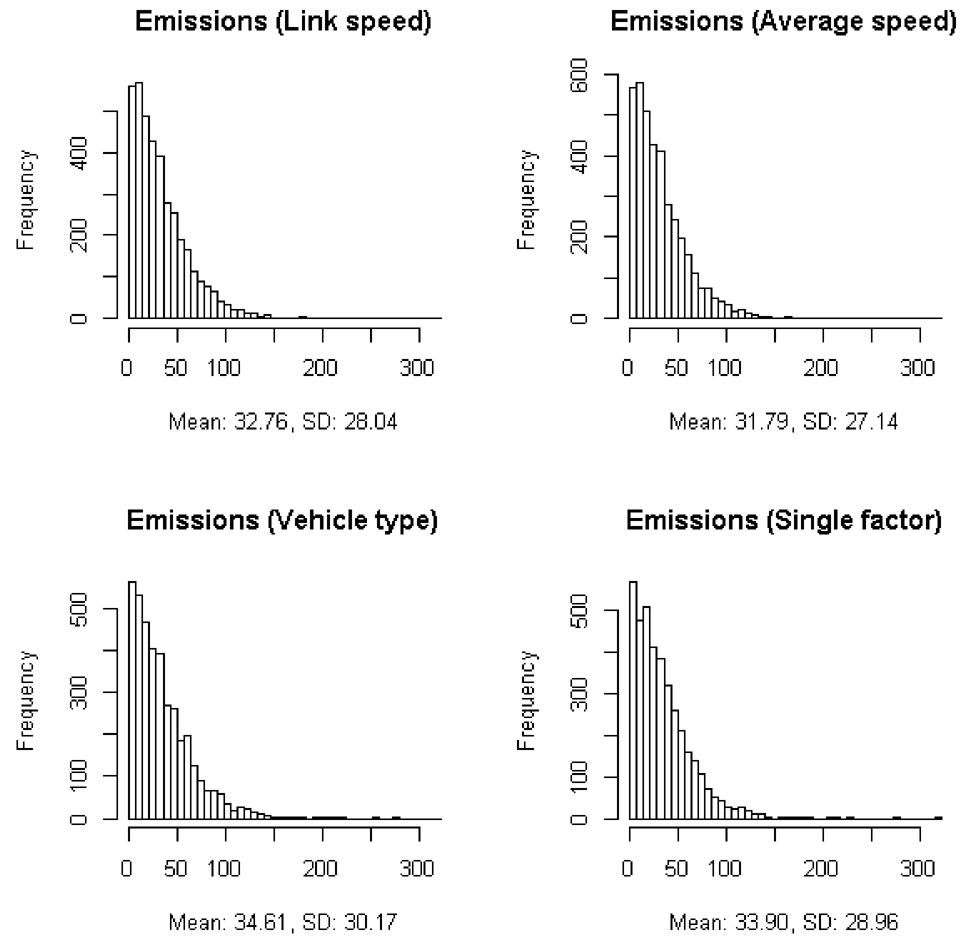
Table 13. Relationship between urban form and average travel speeds

	Analysis Variable : Average travel speeds			
Urban form	**Mean**	**Std Dev**	**Min**	**Max**
Suburban	35.868	5.920	15	57.896
Urban	33.807	5.794	15	54.413
	Correlation (Residential density & Average travel speeds)			
	Pearson correlation -0.09 (<.0001)			

Total transportation emissions per household for two days calculated based on different assumptions are compared in Figure 6. It shows that the differences in total transportation emissions are not big but marginal. Employing the average travel speed with vehicle characteristics in the estimation process generates the smallest average transportation emissions, showing about 2.1kg smaller compared to those calculated based on a single emission factor. Since this single emission factor only accounts for CO_2, the actual transportation emissions (CO_2 equivalent) will be a little bit bigger. However, one should remember that since emissions factors for vehicle types and a single emission factor are from other sources, it is not easy to compare or interpret the absolute values of total transportation emissions and their differences directly. Further correlation analyses are conducted to assess the relationship between residential density and differences in total emissions. First, link-based emissions are set as a reference and the differences with other two transportation emissions (vehicle types and single emission factor) are calculated. Transportation emissions with the consideration of vehicle types ignore the influence of the variation of trip speeds, therefore it could produce relatively less emissions for people living in denser areas. In that case, the correlation between residential density and the difference between link-based emissions and emissions with different vehicle types should be positive. The correlation is

0.067, showing that the difference becomes larger as residential density increases. There are also similar relationships between other built environment measures and their differences.

The relationship between residential density and the difference between link-based emissions and emissions without the consideration of both the variations of trip speeds and vehicle characteristics shows the similar trend. The correlation between residential density and the difference is 0.024. In conclusion, these analyses indicate that if we ignore the effects of the variations of travel speeds and vehicle characteristics in the transportation emissions process, it can underestimate or overestimate emissions generated from certain groups of people.


Emissions (Link speed)

Mean: 32.76, SD: 28.04

Emissions (Average speed)

Mean: 31.79, SD: 27.14

Emissions (Vehicle type)

Mean: 34.61, SD: 30.17

Emissions (Single factor)

Mean: 33.90, SD: 28.96

Figure 6. Histograms of total transportation emissions based on different assumptions

The results from simple analyses provide evidences that there is a connection among urban form, travel speed, vehicle characteristics, and transportation emissions. However, the changes in the effects of built environments on different transportation emissions cannot be identified with simple analyses. Therefore, BMSR models are employed to analyze the effects of land use factors measured at the two geographic scales (1-km buffer and TAZ) on different transportation emissions. In addition, the elasticity of each built environment measure is calculated to assess how the effects of built environments change according to different assumptions. Besides five land use variables, *Distance to bus stop* is included to consider the influence of the accessibility to public transit. The results of six measures are presented in Table 14 and 15. It turns out that the estimates of built environments for different transportation emissions vary but the differences are modest. As expected, the estimates of *Residential density, Entropy,* and *Intersection density* for transportation emissions with a single emission factor are slightly larger than those from other models, indicating that ignoring travel speed and vehicle characteristics could inflate the influences of built environments on transportation emissions. However, the empirical results indicate that there is no significant difference in results from link-based transportation emissions and vehicle type emissions models when considering diverse types of travelers' information.

Table 14. Results from BMSR models for different transportation emissions (1KM)

	Link speed		Average speed		Vehicle types		Single factor	
	Mean	SD (95%CI)	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Residential density	-0.197	0.043 (-0.278, -0.113)	-0.195	0.043 (-0.281, -0.115)	-0.188	0.042 (-0.273, -0.106)	-0.259	0.048 (-0.357, -0.168)
Non residential density	-0.017	0.059 (-0.134, 0.099)	-0.023	0.058 (-0.133, 0.097)	-0.029	0.060 (-0.141, 0.090)	-0.031	0.065 (-0.161, 0.093)
Entropy	-0.529	0.082 (-0.689, -0.361)	-0.528	0.082 (-0.693, -0.381)	-0.525	0.081 (-0.685, -0.368)	-0.602	0.092 (-0.782, -0.417)
Intersection density	-0.192	0.088 (-0.358, -0.004)	-0.189	0.087 (-0.357, -0.017)	-0.212	0.084 (-0.372, -0.037)	-0.228	0.098 (-0.412, -0.026)
Distance from CBD	0.015	0.005 (0.006,0.025)	0.015	0.005 (0.006,0.024)	0.016	0.004 (0.008,0.025)	0.015	0.005 (0.005, 0.026)
Distance to Bus stop	0.046	0.017 (0.013, 0.080)	0.045	0.017 (0.010, 0.078)	0.046	0.018 (0.012, 0.082)	0.039	0.019 (0.002, 0.077)
R^2 for data level		0.422		0.422		0.419		0.398
R^2 for group level		0		0		0		0

Table 15. Results from BMSR models for different transportation emissions (TAZ)

	Link speed		**Average speed**		**Vehicle types**		**Single factor**	
	Mean	SD (95%CI)	Mean	SD (95% CI)	Mean	SD (95% CI)	Mean	SD (95% CI)
Residential density	-0.171	0.044 (-0.251, -0.082)	-0.163	0.047 (-0.252, -0.071)	-0.168	0.048 (-0.261, -0.077)	-0.225	0.053 (-0.329, -0.120)
Non residential density	-0.069	0.056 (-0.186, 0.047)	-0.074	0.062 (-0.197, 0.049)	-0.069	0.061 (-0.186, 0.052)	-0.084	0.071 (-0.222, 0.048)
Entropy	-0.403	0.084 (-0.567, -0.249)	-0.417	0.084 (-0.584, -0.254)	-0.414	0.089 (-0.591, -0.226)	-0.436	0.096 (-0.623, -0.243)
Intersection density	-0.630	0.131 (-0.888, -0.377)	-0.610	0.141 (-0.886, -0.336)	-0.619	0.136 (-0.865, -0.346)	-0.682	0.154 (-0.966, -0.392)
Distance from CBD	0.011	0.004 (0.003,0.019)	0.011	0.004 (0.002,0.019)	0.012	0.004 (0.004,0.021)	0.012	0.005 (0.003, 0.022)
R^2 for data level		0.419		0.420		0.417		0.394
R^2 for group level		0.918		0.912		0.916		0.936

The relative effects of built environments on transportation emissions can be identified through the elasticities of built environment factors. They are calculated as follows:

1. Calculate base transportation emissions based on model coefficients and information of individual and built environment measures.
2. Select built environment measures that have significant effects on transportation emissions and increase them by 10 percent.
3. Calculate new transportation emissions based on regression coefficients and new built environment measures.
4. The elasticity of each variable is estimated by: $[Emissions_{base} - Emissions_{new})/Emissions_{base}]/[(100-110)/100]$

Table 16 presents the relative influences of four land use factors and public transit accessibility on different transportation emissions. Similar to the previous results, elasticities of built environments calculated with a single emission factor are greater than those from other models. Here, I will focus on the results from 1km models for the interpretation. The result of link-based transportation emissions shows that doubling *Residential density* will reduce transportation emissions by 3.6 percent. Entropy has a stronger effect, indicating an 8.7 percent reduction in transportation emissions when doubling *Entropy*. These results are very similar to elasticities estimated by Ewing and Cevero (2010) with a meta-analysis based on multiple emprical studies.

Table 16. Elasticities of built environment measures

	Link-speed		Average speed		Vehicle types		Single factor	
Built environments	1KM	TAZ	1KM	TAZ	1KM	TAZ	1KM	TAZ
Residential density	-0.036	-0.030	-0.036	-0.028	-0.035	-0.029	-0.046	-0.037
Entropy	-0.087	-0.119	-0.087	-0.123	-0.087	-0.122	-0.095	-0.128
Intersection density	-0.028	-0.061	-0.028	-0.059	-0.030	-0.060	-0.031	-0.063
Sum of 3Ds	-0.151	-0.210	-0.151	-0.210	-0.152	-0.211	-0.172	-0.228
Distance from CBD	0.278	0.196	0.276	0.198	0.301	0.227	0.285	0.214
Distance to bus stop	0.037		0.035		0.037		0.031	

Among the built environment variables, destination accessibility measured by *Distance from CBD* has the strongest influence on transportation emissions, which is larger than the sum of other three variables (3Ds – Density: residential density, Diversity: entropy, Design: intersection density). It implies that infill development policies could play a critical role in reducing GHGs, and thereby meeting region's environmental goals.

The sum of the elasticities of three land use variables, represented by "3Ds", from 1km models are 0.151, 0.151, 0.152, and 0.172 for link speed, average speed, vehicle types, and single factor models, respectively. It indicates that doubling 3Ds will reduce transportation emissions by 15.1, 15.1, 15.2, and 17.2 percent depending on models. This comparison also shows that there is a 2.1 percent difference between the lowest and the highest ones. The absolute difference is modest but relatively significant. Finally, doubling all land use factors simultaneously will reduce link-based transportation emissions by about 47 percent. In sum, the results show that built environments have significant impacts on transportation emissions and ignoring the trip and vehicle characteristics in the land use-transportation emissions analysis can result in over-estimated influences.

4.6. Policy implications

The empirical results produce several policy implications.

- Built environments have significant influences on VMT and transportation emissions, and their magnitudes are not small. Therefore, a smart growth strategy and Growth Management Act can be good policy instruments for the Puget Sound region. However, improving only a particular land use characteristic such as residential density and mixed use will not produce a significant change.
- Infill redevelopments can result in significant positive impacts on our environment. Destination accessibility, measured by *Distance from CBD*, has a large influence on both VMT and transportation emissions. This implies that suburban developments should be controlled with well designed plans and more efforts should be put into redevelopments inside urban areas. Washington State has adopted Growth Management Act since 1990 and controlled sprawl by adopting urban growth boundary. This policy effort needs to be continued. In addition, creating a polycentric spatial structure combined with a good public transit system can be a good way to reduce transportation emissions by improving destination accessibility. As an existing example, regional growth center policy has been proposed by PSRC and adopted as a core strategy in a regional plan. (Bassok, 2009). In the long run, this plan can be very effective in improving our environment.
- Land use factors have different effects on VMT and transportation emissions according to tour types. It implies that different land use strategies should be

applied depending on neighborhoods' goals. For example, improving 3Ds will be especially effective in decreasing non-work VMT and transportation emissions by creating more activities near people's homes and encouraging people use more non-motorized modes. On the other hand, land use plans integrating jobs and housing can reduce commuting-related transportation emissions. Each community has its own functions and relationships with other surrounding neighborhoods; therefore, it would be more desirable to concentrate different land use strategies to meet their own goals.

- Improving the accessibility to public transit has a modest influence on individuals' travel behavior. In addition, the empirical results show that its effect is more influential for non-work tours. Compared to the early 1990s, accessibility to non-work related activities has become a key factor in deciding residential location, and more non-work related trips have been made during a day. Therefore, improving public transit quality will become more important in the future, and to secure the economic costs of public transportation system, a certain level of compactness is necessary.
- Even though a compact development has a positive influence on our environment by reducing vehicle usage, it should be noted that there are by-products such as congestion that could produce harmful effects. Comparing results from link-based transportation emissions and transportation emissions calculated based on a single emission factor shows that slow travel speeds due to congestion could reduce the benefits of compact developments on our environment. It indicates the importance

of monitoring the diverse effects of smart growth strategies on our environment to maximize its benefits.

CHAPTER 5: CONCLUSION

In this dissertation, existing methodological issues, including self-selection, spatial autocorrelation, trip-interdependency, and different geographic scales issues are taken into account to analyze the relationship between built environments, VMT, and transportation emissions. In addition, transportation emissions are measured under several assumptions and the sensitivities of built environment measures on them are analyzed.

Several data sources are employed to estimate the effects of built environments on transportation. Travel information is obtained from the 2006 Household Activity Survey and built environment factors are measured based on the 2005 parcel-level land use data and building data provided by PSRC. Finally, the 2000 census data and spatial data are used to obtain neighborhood characteristics and match travelers' home locations with land use data.

The results from hypothesis test 1 show that increasing *Residential density* can reduce VMT and transportation emissions significantly, thus can be a good policy instrument. Specifically, when doubling *Residential density*, VMT are reduced between 18.5 percent and 42.6 percent depending on different models. Moreover, IVs estimates are larger than those from models without IVs. This indicates the importance of considering an endogeneity problem in the land use-travel behavior analysis.

The impact of *Residential density* on transportation emissions is smaller than that on VMT. This is because the effects of travel speed and vehicle characteristics are considered in the transportation emissions models. The calculated elasticities from different models range from 15.9 percent to 36.9 percent when doubling *Residential density*, indicating that land use policy can be a good policy tool for improving the environment by reducing vehicle usage.

Moreover, incorporating spatial random effects causes the significant change of the influence of *Residential density* due to the confounding effect by location. The resulting coefficient of *Residential density* is smaller than those from other models, suggesting the necessity of correcting spatial effects. In addition, positive spatial autocorrelation underestimates the standard error of the coefficient of *Residential density*.

In sum, confounding effects caused by spatial autocorrelation and self-selection should be taken into account to obtain the reliable estimate of the influence of *Residential density* on VMT and transportation emissions. The BMSR produces the most conservative elasticities, ranging from 18.5 percent to 29.2 percent and 15.9 percent to 25.3 percent for VMT and transportation emissions, respectively when doubling *Residential density*.

Second, analyses show that the effects of land use factors on VMT and transportation emissions are different according to tour types and geographic scales. For the work tour, job related land use measures such as *Non-residential density* and *Distance from CBD* are strongly associated with VMT and transportation emissions. On the other hand, those factors do not show significant influences in the non-work tour analyses. In addition, *Entropy* and *Intersection density* have stronger effects on non-work VMT and transportation emissions compared to those from the work tour analyses. These results imply that different land use policies should be implemented for different purposes. Specifically, improving pedestrian-friendly environment and encouraging mixed land uses will be useful for neighborhoods where non-work related activities are predominant. Furthermore, some built environment measures have greater effects on VMT and transportation emissions at the TAZ level. For instance, *Non-residential density* and *Intersection density* measured at the TAZ level have stronger influences compared to those from the 1km model in the work tour analyses.

Finally, different transportation emissions are compared and the sensitivity of built environment factors is analyzed through elasticities. The results indicate that the total transportation emissions vary according to different assumptions, and ignoring trip and vehicle characteristics can inflate the influences of built environments on transportation emissions. It shows that doubling 3Ds in the 1km model will reduce link-based transportation emissions and emissions with a single emission factor by 15.1 and 17.2 percent, respectively. Among the built environment measures, the accessibility to destination measured by the *Distance from CBD* has the biggest influence on transportation emissions, indicating that improving accessibility to jobs and other activities is crucial.

In sum, the empirical analyses indicate that four methodological challenges should be taken into account in the land use-transportation analysis, and there are significant influences of land use factors on VMT and transportation emissions. Even though the cumulated effects are quite big, some people may cast doubts about the effectiveness of land use policy since changing built environments in existing cities is very difficult and costly. People may think land use planning is not a cost-effective policy tool for improving our environment. However, as mentioned in the beginning of this dissertation one should consider not only the estimated influences of land use factors on transportation emissions but also their possible monetary benefits on the environment and peoples' health. Many research teams have tried to identify the monetary value of air pollution on human's lives. For example, Stern (2006) find that the economic costs of extreme weather could reach 0.5-1 percent of world GDP per year by the middle of the century if current trend continues. They also employed several complicated models and conclude that the costs of climate change will continue to rise if the earth becomes warmer, and the benefits of taking early actions will be much higher than the costs.

Weisbrod, Lynch, and Meyer (2009) compared several monetary values of air pollution and health from different research teams and countries, showing the considerable effect of air quality on health. In addition, one should also remember that land use policy such as smart growth is a long-term strategy and it changes the spatial structure in a way that support public transit and non-motorized transportation modes by increasing accessibility to other activities. This fundamental change can provide people a chance to change their behavior in a favor way to our environment without any enforcement. Therefore, it is reasonable to say that land use policy is a good policy instrument for improving our environment.

This research has several limitations. First, network data do not fully cover all roads in the Puget Sound region. Some minor roads are excluded and it can affect the estimated VMT and transportation emissions. In addition, link speeds are estimated through regional transportation modeling, therefore the estimated transportation emissions do not fully consider real trip speeds. Second, auto ownership should be further analyzed to estimate more comprehensive impacts of built environments on transportation. Several empirical studies have identified the potential indirect impacts of built environments on VMT and transportation emissions through auto ownership. However, more care should be taken since there are also complicated methodological problems such as endogeneity and self-selection. Third, even though empirical analyses show very significant impacts of built environments on transportation, this result cannot be generalized since only the Puget Sound region is investigated. It would be useful to apply the same approach to other cities and compare empirical results to generalize the influences of built environments. Finally, only linear effects of built environments are analyzed in this dissertation. There could be non-linear relationships between land use characteristics and transportation outcomes, therefore more in-depth analyses will provide richer information.

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Zegras, C. (2010). The built environment and motor vehicle ownership and use: Evidence from Santiago de Chile. *Urban Studies, 47*(8), 1793-1817.

Curriculum Vitae

EDUCATION

University of Washington **Seattle, WA**
Ph.D., Urban Design and Planning 2013
Statistics Track in the interdisciplinary Ph.D. program 2011
Dissertation: "Effects of Built environments on Travel Behavior and Emissions: A Reexamination by Addressing Methodological Issues"
Committee chair, Prof. Qing Shen

Seoul National University **Seoul, Korea**
Master, City Planning 2007
Thesis: "The influence of compact and mixed land use on transit modal choice"

University of Seoul **Seoul, Korea**
BEngr, Urban Planning and Design 2005
Final project: "Redevelopment plan for Ahyundong"

PUBLICATIONS

- **Jinhyun Hong,** Qing Shen, & Lei Zhang. How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales. *Transportation.***(forthcoming)**

- **Jinhyun Hong** & Qing Shen (2013). Residential density and transportation emissions: Examining the connection by addressing spatial autocorrelation and self-selection. *Transportation Research Part D*, 22, 75-79.

- Zhang, L.**, Hong, J.,** Nasri, A., & Shen, Q (2012). How built environment affects travel behavior: A comparative analysis of the connections between land use and vehicle miles traveled in U.S. cities. *Journal of Transport and Land Use*, 5(3), 40-52.

- Shen, Q., Zhang, L., **Hong, J**., Nasri, A., He. X., Lu, Y., Krause, C., and Ferrari, N. (2011). Statistical analysis of the impact of land uses on vehicle miles traveled. Final Report, Prepared for Federal Highway Administration, U.S. Department of Transportation.

CONFERENCE PRESENTATIONS

Jinhyun Hong & Qing Shen (2013). *How does residential density affect transportation emissions: A reexamination by addressing spatial autocorrelation and self-selection*. Paper presented at the WRSA 2013 52st Annual Conference, Santa Barbara, CA, February 24-27.

Jinhyun Hong & Qing Shen (2012). *Analyzing land use effects on vehicle emissions: Addressing self-selection and spatial autocorrelation*. Paper presented at the ACSP 2012 53st Annual Conference, Cincinnati, Ohio, November 1-4.

Jinhyun Hong (2012). *Multilevel analysis of land use, VMT, and auto ownership*. Paper presented at the WRSA 2012 51st Annual Conference, Kauai, HI, February 8-11.

Jinhyun Hong & Qing Shen (2011). *Effects of the built environment on motorized travel: A comparative analysis of Seattle and Phoenix*. Paper presented at the ACSP 2011 52st Annual Conference, Salt Lake City, UT, October 13-16.

Lei Zhang, **Jinhyun Hong**, Arefeh NAsri, & Qing Shen (2011). *How built environment affects travel behavior: A comparative analysis of the connections between land use and vehicle miles traveled in U.S. cities*. Paper presented at the WSTLUR 2011 Annual Conference, Whistler, BC, Canada, July 28-30.

Jinhyun Hong, Qing Shen, & Lei Zhang (2010). *How do built-environment factors affect travel behavior? A multilevel analysis of their effects*. Paper presented at the ACSP 2010 51st Annual Conference, Minneapolis, MN, October 7-10.

PROFESSIONAL EXPERIENCE

University of Washington **Seattle, WA**
Pre-Doctoral Research Assistant 2008 to 2013

- Led and contributed to multiple research projects incorporating land use policies, transportation, and air quality
- Developed Bayesian multilevel models incorporating self-selection problem and spatial autocorrelation, with a goal of investigating the connection between built environments and vehicle miles traveled
- Collaborated on an innovative survey design with a Civil Engineering and Geography research teams
- Partnered with research teams at the University of Maryland for analyzing the effects of built environments on travel behavior and the University of Idaho for investigating an innovative travel survey design

University of Washington **Seattle, WA**

Pre-Doctoral Teaching Assistant (Urban Economics and Public Policy) 2012

- Helped master's level students understand class materials and homework
- Taught concepts and theoretical background related to homework during office hours
- Created homework and exam
- Evaluated homework assignments, mid-term exam, and final paper

REPRESENTATIVE PROJECTS

PacTrans: Region 10 University Transportation Center 2012 to 2013

An innovative survey design to understand sustainable travel behavior

- Objective of project is to understand problems existing in a present household travel survey and provide recommendations for a future household travel survey with rolling samples
- Completed a literature review related to rolling sample design and continuous travel surveys
- Compared the benefits and costs of rolling sample design with one-time cross-sectional surveys
- Investigated how to use rolling sample surveys for inference
- Studied existing rolling sample surveys related to transportation
- Analyzed the administration process of a travel activity survey in the Puget Sound region
- Investigated relevant theories in the behavioral modeling including utility maximizing theory, theory of planned behavior, and social cognitive theory
- Built hypotheses for our pilot survey and created survey instruments

Federal Highway Administration and U.S. Department of Transportation 2009 to 2011

Development of "What if" Scenario Models and "Seed Value" data for the FHWA Multimodal Passenger Travel Modeling Program

- Objective of project is to establish mathematical formulas and analytical models linking passenger vehicle miles traveled to various land use policies
- Completed a literature review related to built environments and travel behavior, specifically methodology works and empirical research
- Collected travel survey data, parcel level land use data, building data, and census for two different metropolitan areas, Seattle and Phoenix
- Produced maps and processed land use and travel survey data through the ArcGIS, SAS, and R
- Measured built-environment factors and developed analytical models incorporating self-selection, spatial autocorrelation, trip-interdependency, and geographic scales issues
- Wrote a final report

HONORS AND AWARDS

CSSS Grad Student Research and Presentation Training Grant Award, University of Washington, 2013
GPSS Travel Grant, University of Washington, 2012
Best Overall Paper (Team), World Symposium on Transport & Land Use Research, 2011
GSFEI Graduate Student Travel Award, University of Washington, 2010, 2011
Outstanding Paper Award, Korean Planners Association (KPA), 2006
Award for Environmental Planning and Design Work, Seoul National University, 2005
Certificate of Urban Planning, Human Resources Development Service of Korea, 2004
Fellowship based on the GPA, University of Seoul, 1998, 2003 to 2004
Global Leadership Program, University of Seoul, 2003