HOW THE BUILT ENVIRONMENT INFLUENCES DRIVING: INSIGHTS FROM GLOBAL POSITIONING SYSTEM DATA

by
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To my family, with love

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Table of Contents

List of Tables

List of Figures

List of Appendices

Abstract

The sprawling low-density car-dependent urban developments in many metropolitan areas in the United States have contributed to severe transportation consequences in the last five decades. These urban developments demand intensive automobile travel which exacerbate the nation's oil dependency and increase greenhouse gas (GHG) emissions which in turn contribute to global warming. While automobile travel patterns have been related to the built environment in current literature, few studies have made the direct connections between the built environment and vehicle fuel consumption and emissions. This dissertation establishes a methodology for understanding the relationships between specific attributes of the built environment, people's driving behavior, and the associated vehicle fuel consumption and emissions.

This dissertation applies a disaggregated analysis scheme, through which an individual driver's travel behavior and travel outcomes are related to the built environment. In addition to the built environment near drivers' home and work places, this dissertation provides detailed examinations on the urban corridors along drivers' commuting routes, an important and yet understudied urban space. A rich global positioning systems (GPS) dataset collected from 73 automobile drivers over 30 days on a second-by-second basis in the Detroit metropolitan region is used to quantify driving behaviors and to estimate fuel consumption and major tailpipe emissions. Multivariate statistical techniques are applied to test the influences of the built environment on driving outcomes, controlling for other factors.

The results of this dissertation demonstrate that built environment features near home and work locations do not have significant associations with total vehicle miles traveled (VMT) and total fuel consumption and emissions on non-work travel. Rather, the influences of built environment along commuting routes on these travel outcomes are

statistically significant. Denser and more diverse non-work destination choices are associated with lower levels of driving, less fuel consumption and less air pollution. This research also indicates that denser and more diverse land-use patterns near drivers' homes lead to lower vehicle fuel efficiency with higher emissions per mile.

Chapter 1
Introduction

In the last five decades, the urbanized area of the United States has grown more than twice as fast as metropolitan population (HUD 2000). The United States is sprawling, as urban development spreads outwards to urban fringes in a low-density, scattered, discontinued, and car-dependent manner (Galster et al. 2001; Ewing, Pendall and Chen 2002; Hayden and Wark 2004). Urban sprawl has caused severe transportation consequences, as it demands intensive automobile travel which exacerbates the nation's oil dependency and increases greenhouse gas (GHG) emissions that contribute to global warming. The goal of this dissertation is to examine the relationships between the built environment (land development and road configuration) and the automobile travel outcomes and to assess *the potential of reducing fuel consumption and emissions through changes in land-use patterns and roadway designs*. This study acknowledges that to save energy and limit greenhouse gas emissions two distinct but interrelated factors have to be addressed simultaneously: the fuel consumption and emission rate, and vehicle miles traveled (VMT). Although technology advancements (such as fuel-efficient vehicles) are capable of improving the former factor significantly, alternative built environment patterns (the opposite of urban sprawl) are of particular importance to combat global warming by reducing the need of automobile travel.

Two approaches to the same problem

Scientific findings have demonstrated that the global environment is becoming warmer as a consequence of human activities. The Intergovernmental Panel on Climate Change (IPCC) reported that global surface temperature increased 0.74 ± 0.18 °C (1.33 ± 0.32 °F) during the last century, and that most of the temperature increase over the past 50 years was caused by increased concentrations of greenhouse gas (GHG) emissions resulting from human activities such as fossil fuel burning (IPCC 2007). This notion was supported by 40 scientific societies and academies of science.

To slow down or stop global warming and to avoid dangerous climate change damages, scientific evidences show that a reduction of global GHG emissions by as much as 60% to 80% by 2050 is required (compared to the 1990 level) (Ewing et al. 2008). Only by such dramatic reduction could it be possible to limit the global warming within 2 °C or below (relative to pre-industrial levels), a threshold which is believed to bring relatively stable climate outcomes (Schnellnhuber, Cramer and Great 2006; IPCC 2007; Ewing et al. 2008; Meinshausen et al. 2009). The task of reducing fuel consumption and GHG emissions is more challenging and urgent than ever.

The United States, as the biggest emitter of greenhouse gas (emitting 19% of the world total in 2000 followed by China emitting 14% of the world total) (World Resources Institute 2000), has reached agreements with 180 nations to stabilize greenhouse gas concentrations (UNFCCC, 1992). To achieve this GHG stabilization goal, the transportation sector in the US, as the largest contributor to the total US CO_2 emission (33 % of all emissions in 2006), has an important role to play (Energy Information Administration 2009).

In theory, there are two approaches to achieve this goal from a transportation perspective: reducing energy consumption and emissions per mile (i.e. improve fuel efficiency), and reducing the total VMT. The first approach, focusing on improvements in the rate of fuel consumption and emissions, is promising because it requires no modification on people's automobile travel behaviors. It is the approach which receives the most publicity and political attention. A landmark legislation passed by Congress and signed into law by President Bush (U.S. Congress 2007) established corporate average fuel economy (CAFE) standards of at least 35 miles per gallon (mpg) by 2020. The legislation was later surpassed by President Obama's new national policy which requires an average fuel efficiency standard of 35.5 mpg in 2016 (The White House 2009). These actions signaled the US government's resolve to tackle its oil-dependency and to reduce GHG emissions. However, a group of scholars question whether fuel efficiency alone can achieve the climate stabilization goal (Ewing et al. 2008).

If cars were more efficient, would we use less fuel and emit less? The answer to this question relies on another determinant of total fuel consumption and emissions: total distance travelled by cars. For instance, a Prius[1] driver who conducts more automobile trips with longer distances is not "greener" than a SUV driver who drives less.

Studies have shown that increases in fuel efficiency in fact induce more driving due to the decline of the cost of driving per mile. This is called *rebound* or *takeback effect* (Greening, Greene and Difiglio 2000). Greening et al. reviewed 22 studies on this issue and concluded that estimates of the elasticity of annual VMT with respect to per-mile costs range from about –0.1 to –0.3 *(Greening, Greene and Difiglio 2000)*, meaning that a 100 percent decrease in price corresponds to a 10 to 30 percent increase in total VMT. A more recent paper by urban economists Kenneth A. Small and Kurt Van Dender found that the rebound effect is diminishing over time, but that there is still 10.7% for the period of 1997 to 2001 (Small and Dender 2007). As a consequence, partial energy savings brought by improved fuel efficiency could be canceled out by the rebound effect.

A steady increase in total VMT in US has been observed over the last several decades (the black solid line in Figure 1-1). Despite the increase in fuel efficiency (the dash line), more gasoline was consumed (the grey solid line) because increases in VMT have historically overtaken improvements in fuel efficiency (National Transportation Statistics 2009). The VMT increase is in part caused by population increase. However, it is shown that VMT has grown three times faster than population (FHWA 2003). Another large portion of VMT increase is attributable to longer vehicle trip length, higher number of trips per capita, and mode shift, all of which are mostly results of low-density and car-oriented land use development patterns (Ewing et al. 2008).

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[1] Toyota prius is the most efficient vehicle in the US EPA (2009). "Fuel Economy Leaders: 2010 Model Year ". The vehicle is sometimes referred to as a combined hybrid, a vehicle that can be propelled by gasoline (petrol) and/or electric power. The mpg for city driving is 48 and 45 for highway driving.

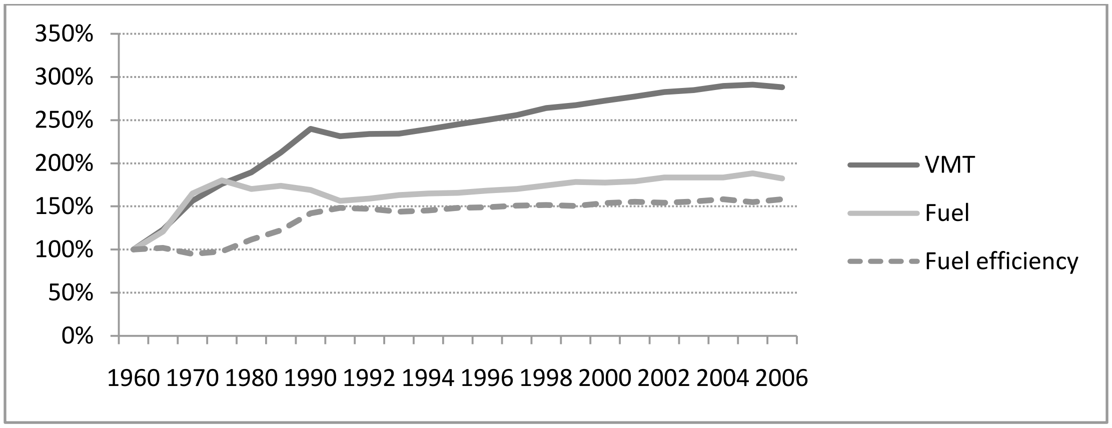

Figure 1-1 The increase of fuel efficiency, VMT, and total fuel consumption, 1960-2006

Source: National Transportation Statistics, 2009

In a recently released book *Growing Cooler*, a group of scholars argued that the United States cannot meet its climate stabilization target through vehicle and fuel technology alone and that we have to stop urban sprawl and significantly reduce vehicular travel (Ewing et al. 2008). By promoting compact development, mixed land use, and urban design improvements, residents can work and shop closer to their homes, to travel by non-motorized means, and thus, to drive fewer miles. Popular land use strategies for reducing drive-alone travel include new urbanism, transit-oriented development, and traditional neighborhood design or pedestrian pockets (Duany and Plater-Zyberk 1991; Calthorpe 1993).

Numerous studies have been conducted to examine relationships between various dimensions of the built environment (density, diversity, and design) and different aspects of travel behavior and outcomes (trip generation, trip length, travel mode, and VMT). Many of these studies have shown significant associations between the built environment and travel behavior (Frank and Pivo 1995; Cervero and Kockelman 1997; Kockelman 1997) while others failed to observe any significant relationships (Ewing, Deanna and Li 1996; Boarnet and Sarmiento 1998). Empirical evidence of the impact of the built environment on energy consumption and emissions is far from conclusive. What is not certain is how much, by which mechanisms, and under which conditions land use strategies can effectively reduce automobile mileages, energy consumption, and emissions. There are two main limitations of the prior research work: incomplete data and insufficient research frameworks.

Limitations of prior research

Due to the scarcity of the real-time fuel consumption and emission data and the lack of reliable methods for estimations, there are only a handful of studies that directly draw connections between the built environment, energy consumption, and emissions. In these studies, researchers commonly make a set of simplified assumptions which translate total VMT into the amount of fuel consumed or emissions generated. However, it often results in inaccurate estimations of fuel consumption and emissions, which harms the credibility of the research.

Newman and Kenworthy's study is one of the first attempts to explore the relationships between density and energy use (Newman and Kenworthy 1989). They concluded that density of development is the most important single determinant of energy consumption, although their research data and methodology was criticized as over-aggregated by Gordon and Richardson (1989). A study by Frank and James et. al. (2006) showed that mixed land uses, higher density, and greater street connectivity are associated with significantly lower per capita emissions of oxides of nitrogen (NOx) and volatile organic compounds (VOC) when controlled for household income, age, vehicle ownership, and household size. However, the authors acknowledged in the paper that their estimations of emissions have wide confidence bands, meaning the true values may differed significantly from what they estimated.

The recent development in global positioning system (GPS) technology provides unprecedented opportunities for researchers to study travel behavior and its energy and environmental consequences. Collecting travel data with GPS receivers and recorders has several advantages compared to the collection of traditional trip diary data. It does not rely on the memory or subjective estimates of a survey respondent. It imposes less burden on respondents. The recorded distance and time information have much higher accuracy. Travel survey conducted by GPS methods often has better trip reporting rates. GPS data can be collected over much longer periods of time than the traditional travel survey. GPS data also provide detailed spatial-temporal information such as chained trips and tours.

The use of GPS receivers and recorders poses several challenges to transportation professionals. The amount of data is massive. Converting points of GPS data into a meaningful travel behavior database requires substantial effort. The fuel consumption and emissions monitored and measured by GPS technology has never been linked with the built environment before, possibly due to the lack of appropriate methods. A mature methodology could advance our understandings on the links between the built environment and travel outcomes.

Besides the data constraints, the lack of a sound theoretical framework is another limitation of the current travel behavior and the built environment literature. Most of the built environment-travel behavior studies have focused on determinants at the neighborhood level (the residential setting), with the assumption that the surroundings near a person's home would have the most influence on travel behavior. This assumption is valid in that a portion of people's daily activities do happen in urban space adjacent to homes. However, there are still a large number of trips located outside the neighborhood (Handy 1992; Krizek 2003). A notable gap in the literature is the consideration of the effect of the built environment on travel behavior at scales larger than the neighborhood (Handy 1992; Boarnet and Crane 2001; TRB 2005).

Beyond home, which part of the urban space has the most influential impacts on travel outcomes? Due to the lack of theoretical basis to identify these urban spaces, the current literature provides no answers. Theories borrowed from other disciplines may provide some guidance for answering this question. Anchor point theory proposed by behavioral geographers is one of them. The theory depicted that a set of frequent-visited nodes and corridors anchored people's activity space (the space that support normal activities of individuals). Based on this theory, urban space near work locations and the major urban corridors connecting home and work could be of particular importance to travel behavior.

The importance of urban corridors has been highlighted by scholars in the field of urban design as well. Two books from Allan Jacobs, *The Boulevard Book* and *Great Streets* explicitly outlined the history, evolution, and design of the multiway boulevards and "great streets", which are considered to be the "monumental links between important destinations" (Jacobs 1995; Jacobs, Macdonald and Rofé 2002). Using a qualitative approach, these books made observations on more than fifty boulevards and hundreds of streets around the world and suggested that a functional multiway boulevard should serve both the through traffic and the slow-paced vehicular-pedestrian movement, and that "great streets" can take people "from one part of the city to another, whether on foot or in a vehicle, with grace and at a reasonable pace". Great streets should encourage socialization and participation of people in the community (Jacobs 1995).

How and how much would the built environment in these spaces influence energy consumption and emissions? Expanding research to nonresidential settings would broaden our knowledge on the influence of various built environments on travel behavior (TRB 2005).

In September 2009 US National Academy of Sciences released a special report, entitled *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions*. In response to the request by the Energy Policy Act of 2005 (Section 1827), a committee consisted of 12 experts in transportation planning, energy conservation, and economics, conducted a thorough literature review and a scenario analysis to identify the potential impact of compact development on automobile travel. Their results suggested that significant increases in more compact, mixed-use development will result in only modest short-term reductions in energy consumption and CO_2 emissions, but these reductions will likely grow over time (National Research Council Committee 2009). The committee acknowledged that their analysis result "does not have as much verifiable scientific evidence to support this recommendation (compact development) as it would like" (National Research Council Committee 2009). In the end, this special report was calling for more carefully designed studies of the effects of land use patterns and the form and location of more compact, mixed-use development on travel outcomes so that compact development can be implemented more efficiently. This dissertation work was designed to fills such a gap by providing a detailed study with a sound theoretical framework and based on a complete empirical data.

New perspectives from this dissertation

The primary goal of this dissertation is to examine the relationships between the built environment (defined as land use development patterns and road configurations) and automobile travel and to assess *whether and to what extent compact and mixed use development patterns can be associated with reduced fuel consumption and emissions*. This study demonstrates that the built environment influences the ultimate economic and environmental consequences of automobile travel by influencing how much people travel (VMT) as well as the way they travel (translated into energy consumption and emissions per mile). It also hypothesizes that the urban space along major commuting corridors, in addition to the built environment near home and work, is critically important in influencing fuel consumption and emissions.

Commuting routes have traditionally been regarded by transportation engineers and planners as single-purpose routes, with a main purpose to deliver commuters to work or home. Commuting trips are viewed as an obligatory type of travel with fewer choices on the time of the travel and the routes of the trips. Major commuting corridors were designed and constructed in such manner that people can get to work or back home as quickly as possible. To fulfill this purpose, a typical commuting route is consisted of limited access highways. This study argues that the urban space along commuting routes matters. A carefully-designed corridor that provides easy access to non-work destinations for commuters will likely bring desirable travel outcomes.

This dissertation formulated six research hypotheses to be tested as follows. The first three hypotheses are related to the built environment near home and work while the latter three are regarding the built environment along commuting corridors.

Built environment near home or work places

1) Compact and mixed-use developments near home or work places are associated with less total amount of driving on non-work activities (such as eating or shopping). In such environment, drivers can take advantage of the close destinations near home or work and travel shorter distance per trip. This type of built environment near home or work may also provide alternative transportation means such as walking, biking, or public transit, all of which will reduce the number of private automobile trips.

2) Compact and mixed-use developments near home or work places are associated with lower fuel efficiency and higher emission rates. In such an environment, drivers are inclined to change speed more often, to make stop-and-go movements more frequently, and to cruise at extremely low speed. All these behavior will lead to higher energy consumption and emission rates.

3) For the built environment near home and work, savings in the total amount of driving can offset the lower fuel efficiency and higher emission rates, and thus produce beneficial energy consumption and emission outcomes.

Built environment along commuting corridors

4) Compact and mixed-use developments along commuting routes are associated with less total amount of driving on non-work travel, because commuters may chain various non-work activities on their way to or from work, at locations adjacent to or close to commuting routes. Compared to single-purpose travel centered at home/work places, this type of multi-purpose/multi-activity travel is likely to reduce total distance travelled by vehicles through reducing VMT per activity.

5) Compact and mixed-use developments along commuting routes are associated with lower fuel efficiency and higher emission rates for the same reasons listed for the built environment near home/work: more densely-built urban settings induce frequent stops and low-speed driving, especially for travel connecting home and work locations.

6) Compact and mixed-use developments along commuting routes are associated with lower fuel consumption and emissions, as the reduced vehicle mileages could offset the lower fuel efficiency and higher emission rates.

There are a number of studies which focused on testing the first hypothesis. A limited number of studies addressed hypothesis number three. To the author's knowledge, no previous study has tested the other four hypotheses formulated in this dissertation.

This dissertation focuses on the Detroit metropolitan area and on non-work travel. Low-density subdivisions, strip malls, physical separation of land uses, and limited access roads and freeways are the norms of the land use developments in the study area. At the urban fringes, agricultural land and open space are rapidly transformed to low density residential, commercial, or business development, despite an urban center that is losing population (Norris 2002; Southeast Michigan Council of Governments 2003). The Detroit urbanized area ranked the third highest in the degree of sprawl measured by Galster et al (Galster et al. 2001)[2], following Atlanta (the highest) and Miami (the second highest). Residents in the region are relying on automobiles to meet their daily needs, with 90% of all trips made by private vehicles in the Detroit metropolitan in 2001 (NHTS 2001).

In the past, studies were traditionally conducted to examine the connections between the compact, mixed-use developments and travel outcomes in regions that are less sprawled, mostly because a certain level of variability in land use features have to exist in order to be related to different travel outcomes. Metropolitan areas that can be found at the other end of the spectrum (i.e. more sprawling regions) tend to be neglected in such discussions. Few land use and transportation studies were carried out for the Detroit metropolitan area. This dissertation has shown that pockets of compact mixed-use urban development exist even in such sprawling metropolitan area. Systematic studies on the ranges of built

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[2] Galster developed eight indices to measure sprawl, which is defined as "a pattern of land use in a UA (urbanized area) that exhibits low levels of some combination of eight distinct dimensions: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity."

environment features with their driving-related fuel consumption and emission outcomes in such regions will generate the much-needed knowledge to fight the “toughest” sprawl, and may gain the largest environmental benefits.

This study focuses on non-work vehicle travel, which constitutes about 60% of all vehicle trips in the Detroit region (NHTS 2001). Compared to work trips, non-work trips (such as shopping/eating/personal business trips) are more flexible in both location choices and timing of the travel. It is presumably more sensitive to different opportunities presented in various types of built environment. However, studies related to non-work travel have been scarce (Ewing and Cervero 2001).

Borrowing from the anchor point theory, this dissertation assumes that work travel structures non-work travel. The principle commuting routes, together with important nodes such as home or work places, are thought to “form a skeletal structure upon which additional node, path and areal information is grafted” (Golledge and Stimson 1987). Following this logic, the built environment features were evaluated along all commuting routes travelled by each driver in this study, in addition to those near home or work.

A disaggregated research approach was implemented in this study, through which an individual driver’s travel behaviors and outcomes are related to the built environment he/she experienced.

The built environment was characterized from four dimensions: business density (the amount of business establishments closely related to non-work activities), business diversity (the variety of business establishments), road connectivity (represented by intersection density), and road functionality (measured through the percentage of local roads). These dimensions, individually or collectively, are expected to have close relationships with VMT, fuel consumption, and emissions for non-work travels.

Capitalizing on the recent advances in the global positioning system (GPS), this study derived major travel attributes from an extensive GPS dataset which was collected for 78 drivers in the Detroit metropolitan area. Driving data from GPS records were part of the naturalistic driving data (NDD) collected by the University of Michigan Transportation Research Institute (UMTRI). The GPS dataset contains, among other information, speed, heading, location, and time information on a second-by-second basis, collected in consecutive four weeks for each driver. Considerable efforts have been executed to convert GPS traces into a comprehensive database which integrated trip characteristics (trip generation, duration, and trip purposes), demographic features of drivers, road network attributes of travel routes, and land use features of trip destinations. Fuel consumption and emissions (including carbon dioxide, carbon monoxide, hydrocarbon, and nitrogen oxides) were estimated by utilizing the newly-developed instantaneous models which can produce reliable estimations on a second-by-second basis.

In addition to trip-based analysis, this study applied a tour-based analysis scheme, in which continuous trips are combined into tours. The most important urban spaces which potentially have the most significant relationships with travel behavior and outcomes were identified based on the spatial analysis on tour-making patterns. Different types of tours were correspondingly linked to different types of urban spaces defined in this study.

Correlation and regression analysis were conducted to determine the directions and magnitudes of the connections between specific attributes of the built environment and the total VMT, fuel efficiency/emission rates, and total amount of fuel consumption and emissions.

The research results have shown that compact mixed-use developments near drivers' homes may not be associated with beneficial fuel consumption and emission outcomes. On the other hand, built environment along commuting routes matters. Compact and mixed-use developments along routes have statistically significant associations with beneficial energy and environmental outcomes. These results provide supportive arguments for "great streets" and "great boulevards". The research results also provide supportive evidence for policies that aim to reduce VMT, as a complement to improving fuel efficiency. It is shown that fuel consumption and emissions per capita is much lower if commuting corridors contain compact and mixed-use built environment features, even though vehicles operate less efficiently in such an area.

The policy implications from this dissertation are multiple and far-reaching. This study is rooted in the belief that preserving the benefits of driving while conserving energy and reducing air pollution can only be achieved when land use strategies (reducing how much people drive by bringing destinations closer), and advanced technology (reducing energy consumption/emission per mile) are appropriately combined. A package of well-balanced policies which limits total amount of vehicle travel and at the same time improves energy and emission rate is likely to help bring a more sustainable future.

Organization of the dissertation

Chapter 2 provides a critique on the existing empirical studies about the relationships between the built environment and travel outcomes, described the new method (rooted in behavioral geography) to understand the links, and introduced the GPS technology and its applications in transportation research. Chapter 3 illustrates the overarching research framework of this dissertation, and Chapter 4 lays out the research questions and hypotheses, the research design, and methodologies in details. Chapter 5 is devoted to the methodology development of deriving useful travel information from GPS data. To validate some of the methods used, a comparison is made between trip metrics derived from the NDD GPS dataset and from the 2001 National Household Travel Survey data (NHTS). Chapter 6 analyzes the trip/tour-making patterns in the study area and the energy consumption and emission outcomes. The built environment is characterized and visualized in Chapter 7. Chapter 8 brings its previous two chapters together by conducting correlation and regression analysis on the VMT, fuel and emission rates, and total fuel consumption and emissions for non-work travel, as functions of the built environment. The six research hypotheses are tested. Major conclusions, policy implications, research limitations, and a summary of future work are presented in Chapter 9.

Chapter 2
The State of Knowledge, New Framework, and New Technology to Understand the Built Environment and Travel Link

The purpose of this Chapter is to review what we do and do not know about the relationship between the built environment and travel, and to summarize the existing/new methods and tools to study this relationship. It focuses on three main topics: (1) the current state of knowledge about the links between the built environment, travel behavior, and energy and environmental outcomes, (2) new frameworks to understand the links including methods rooted in behavior geography with the focus of disaggregate behavioral processes, (3) new technology to study the relationships, which reviews GPS applications in transportation research.

The built environment, travel behavior, and energy consumption/emission: Current state of knowledge and research design issues

During the past decades, a considerable amount of research has been carried out on how the built environment influences travel behavior. Several dimensions of the built environment (land use patterns, transportation system, and micro-scale urban design features) have been connected to different aspects of travel outcomes (trip frequency, trip length, mode choice, VMT, and vehicle hours traveled). More extensive literature reviews from Crane (1999) and Ewing and Cervero (2001) provided comprehensive lists of these studies.

Because previous studies posed many different research questions and employed various research designs, it is difficult to compare and synthesize their results. The only agreement reached among researchers is that the existing literature has demonstrated an *association* between the built environment and travel behavior and little is known about the causal relationships between the two (Boarnet and Crane 2001; TRB 2005). It is difficult to investigate this causal relationship because researchers cannot simply set up a laboratory experiment and randomly assign their control/experimental groups to different neighborhoods and observe the impacts (Levine 2005). Instead, researchers tend to implement a cross-sectional or quasi-experimental design with statistical techniques to control variations. As a result, this method can only be used to demonstrate associations but not causality.

The following literature review will focus on how to conduct research which can provide more rigorous understanding of how the built environment is associated with travel outcomes. The importance of a well-structured theoretical framework is first discussed. Research design issues and challenges in understanding the connections between the built environment, travel behavior, and energy/emission are then summarized.

The role of theory

A theoretical framework that links the built environment to travel behavior is critical in understanding their associations. Theories provide the basis for formulating hypotheses and interpreting results. However, there has not been a coherent theory explaining the connections between built environment and travel behavior (Boarnet and Sarmiento 1998: 1155; TRB 2005).

A good portion of the research lies in traditional utility-based theories of urban travel demand. The theory of demand provides a straightforward way to understand and analyze travel behavior. This framework assumes that individuals make choices based on their preferences over different goods (travel choices), the relative costs of these goods (time or money cost), and the availability of resources (the budget). Individuals will make travel related decisions to maximize their utility while limiting the cost. Theoretically, if land use affects travel behavior, it does so by affecting the generalized price (time and money cost) of travel to various destinations.

Boarnet and Sarmiento provided several illustrations on how the built environment can be connected to travel behavior through the channel of travel cost. One classic example is their circulation pattern (i.e. grid-like streets) illustration. It is claimed by New Urbanists that a grid-like street network will shorten trip lengths. Boarnet and Sarmiento's illustration starts by assuming this claim is true and they use a comparative statics (an analysis method from microeconomics) to derive the effect of the shortened trip lengths on vehicle trip generation and total VMT. Their arguments are that if grid-like street shorten trip lengths, then trip cost for all modes (cars, transit, and walking) will be reduced and the demand for trips by each mode will likely rise. However, the total number of car trips may decrease if people substitute walking or transit for car trips and if car trips are insensitive to their length (the cost). In this case, total VMT may decrease. On the contrary, if few car trips are substituted by walking or transit trips and car trips are sensitive to trip length, the total number of car trips may increase and leave total VMT undetermined.

As shown in Boarnet and Sarmiento's analysis, with its explicit and simplified assumptions about how people make decisions about their travel behavior, the theory of demand provides a clear behavioral framework for linking the built environment and travel behavior. By doing so, it helps us to frame our research hypothesis. Boarnet and Sarmiento take one step further and apply this theoretical framework in their empirical study by assuming that land use affects travel behavior only through the cost of travel (Boarnet and Sarmiento 1998).

The theory of demand has several limitations as a result of its assumptions about the utility-maximization process. First of all, travelers are not always rational. With imperfect or incomplete information about destinations and traffic conditions, people often make travel decisions which do not appear to be utility-maximized. How do people make decisions with imperfect incomplete information? How do people learn about the surrounding built environment? How do individuals identify their own choice set? The theory of demand can only provide limited answers for these questions. The second limitation of the demand theory is that it ignores the complexity of the travel-related decision-making process. Travel behavior is a complex phenomenon which happens in time, in space, and with different travel modes. Travelers decide when, where, how to travel and even if to travel simultaneously or sequentially (or both). For example, decisions about when to travel may be tied to decisions of how to travel (travel during day time with walking vs. travel at night through driving); decisions about the choice of the next destination may be tied to the previous place visited. Travel decisions are also embedded in a larger decision-making process which involves both long term decisions (where to live or work) and short term decisions (where to eat or shop). Demand theory rooted in the utility-maximization assumption is not sufficient enough to explain the rationale behind all these complex decisions.

Despite the limitations mentioned above, the theory of demand is still the single most used theory in studies of the built environment and travel behavior. There are theories available from other fields focusing on the connections between environment and behavior, such as cognition theory from psychology and spatial behavior theory from behavioral geography. These theories explain how people acquire knowledge from space and how they navigate and make actions in space. However, mainstream built environment and travel behavior studies have not yet incorporated these theories into their research designs. More discussion will be provided in the second section of this literature review.

The following literature review will discuss several research design issues regarding the measures of the variables, level of aggregation of the unit of analysis, and geographic scale of the built environment to be studied.

Research Design Issues

Issue 1: Built Environment Variables

The built environment is a multi-dimensional concept which includes land use patterns, transportation network, and micro-scale design features (such as aesthetic appeal and the function of buildings, streetscapes, and public spaces). The existing literature focuses on aspects of land use patterns and their impact on travel behavior.

The density of population is a common measure of the built environment largely because of their simplicity. However, as many authors have argued, these densities have limited ability to explain travel behavior (Steiner 1994; Kockelman 1997; Ewing and Cervero 2001). For instance, individuals living in a place with higher population density may travel more. However, it is not because there are more people that makes individual travels more, but rather the lower travel cost from the closer origins and destinations (which are a property of higher density). Higher density might also mean more congested traffic, higher parking costs, higher level of transit services, and lower automobile ownership rates, all of which have more direct impact on travel behavior (Ewing and Cervero 2001). Kockelman's study supports this notion by showing that other built environment variables (such as accessibility to opportunities) are far better predictors of vehicle kilometers traveled (VKT) and mode choice than density (Kockelman 1997).

Over the past decade, advances in geographic information system (GIS) have provided new and innovative ways to document land use patterns and introduced measures to capture land use characteristics besides density.

Frank and Pivo (1995) used an entropy index as a measure of land use heterogeneity. The index, first used in a land use context by Cervero (1989), measures the evenness of the distribution of built land area among seven land use categories (single family residential, multifamily residential, retail and services, office, entertainment, institutional, and industrial). A geographic unit with all uses presented in the same area proportion will have the highest index value.

Cervero and Kockelman (1997) developed another measure of land use mix that they named as a dissimilarity index. Different from entropy index which only captures the degree of balance across distinct land uses, dissimilarity index reflects the integration of land uses. A dominant land use is assigned to each 1-hectare square of land. The dissimilarity index compares the land use of the central square to that of the adjoining squares. The number of adjoining squares with different land uses reflects the overall dissimilarity.

Both of the entropy and dissimilarity indexes showed a statistically significant relationship between land use and travel, which underscores the importance of refined land use measurements. However, Hess and Moudon (2001) argued that neither of the two indexes strengthens the significance of the relationship between land use and transportation, because they only capture land use heterogeneity and the degree of overall mixing, and do not distinguish between different types of mixed land use (office-industrial mix or housing-retail mix) and their travel implications. Hess and Moudon argue that land use complementarity is a more appropriate theoretical concept than land use mix or heterogeneity. However, their method of measuring land use functional complementarity has not been tested in land use and travel research.

Research interest in the impact of transportation infrastructure on travel is recent. Grid-like street networks are considered beneficial to all travel modes. Block size and intersection density are the commonly used variables to quantify the street pattern. Although several studies report statistically significant relationships between travel and transportation network design (Cervero and Kockelman 1997; Frank, Stone and Bachman 2000), the exact relationships are still under debate. In Cervero and Kockelman's study (1997), VMT for non-work travel was related to the proportion of four-way intersections and to the proportion of blocks with quadrilateral shapes. The two relationships turn out to have opposite directions. In the study by Kitamura et al. (1997), the frequency of walking/biking trips was shown to have a significant relationship with the presence of the sidewalks whereas the share of the walking/biking trips does not. Ewing and Cervero

(2001) consider the relationship to be inconclusive and they are calling for more studies that focus on road network design and travel.

Recent studies have applied statistical tools such as factor analysis and cluster analysis to choose the built environment measures to be incorporated in the empirical model which tests their relationships with travel behaviors. Cervero and Kockelman (1997) used factor analysis to combine a large number of built environment measures into composite measures which represent three dimensions of the built environment: density, diversity, and design. Song and Knaap (2007) used cluster analysis to translate multiple built environment measures into a neighborhood typology. However their derived factor scores and neighborhood types are more difficult to interpret than individual measures.

Issue 2: Travel Outcome Variables

Among the key travel outcome variables (trip frequency, trip length, mode choice and VMT), trip frequency has drawn a lot of attention. However, as pointed out by Ewing and Cervero (2001) based on their extensive literature review, trip frequency appears to be primarily a function of socioeconomic characteristics of travelers and secondarily a function of the built environment. Trip length, which has been less studied, is primarily a function of the built environment and secondarily a function of socioeconomic characteristics.

Energy consumption and emission are rarely included as travel outcomes in literature on built environment and travel behavior. It may be partially due to the difficulty of getting energy and emission data, and researchers simply assume that more automobile travel means higher energy consumption and emission. It may also be due to the lack of interest caused by the traditional separation between travel demand models and energy models. Regardless of the underlying reason, it is certain that there is a gap in knowledge between the built environment and its impact on energy consumption and emission. The distance that people drive cannot be directly translated into the amount of energy they consume. Energy consumption also depends on the way people drive. Thus, the built environment influences total energy consumption and emission through two channels: influences on the traditional travel behavior outcome (trip frequency, trip length, mode choice and VMT); and influences on the energy consumption/emission rate.

To the author's knowledge, there are only a few studies that explicitly evaluate the impact of the built environment on energy and emissions. Newman and Kenworthy's study (2001) is one of the first attempts of exploring the relationships between density and gasoline consumption. The authors compared fuel consumption across 32 cities around the globe and showed that "average gasoline consumption in U.S. cities was nearly twice as high as in Australian cities, four times higher than in European cities and ten times higher than in Asian cities." By controlling the variations in gas price, income, and vehicle efficiency, this study demonstrated that a city's population density/job density is the most important single determinant of gasoline consumption per capita. However, their research method of global comparison have been criticized as being over aggregated (Gordon and Richardson 1989).

A more recent study by Frank, James et. al (2006) showed that mixed land uses, higher residential density, and greater street connectivity are associated with significantly lower per capita emissions of oxides of nitrogen (NOx) and volatile organic compounds (VOC) (two important pollutants which form harmful ground-level ozone) when controlled for income, age, vehicle ownership, and household size. Due to the lack of individual data, the authors had to make uniform region-wide assumptions about environment conditions and vehicle age in order to estimate emissions using EPA's MOBILE 6.2 model. Lacking data on travel routes, they estimated and used the shortest path between origins and destinations, all of which make their estimations of emissions imprecise. The authors themselves acknowledged in the paper that their estimations of emissions have wide confidence bands, meaning that the true values may differ significantly from what they estimated.

A most recent special report entitled *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO_2 Emissions* was published in September 2009 by National Academy. In response to the request in the

Energy Policy Act of 2005 (Section 1827), the research committee conducted a thorough literature review and a scenario analysis at the national-level to estimate the potential impact of compact development on automobile travel, energy consumption, and CO_2 emissions. Key assumptions made in the scenario analysis include that 25 percent (lower bound) to 75 percent (upper bound) of new and replacement housing units are compact development in the future; residents of compact communities will drive 5 percent (lower bound), 12 percent, or 25 percent less (upper bound) relative to base case conditions. The analysis results show that the reductions in VMT, energy use, and CO_2 emissions resulting from compact, mixed-use development would be in the range of less than 1 percent to 11 percent by 2050. However, the committee disagreed on whether or not it is plausible to achieve development changes in the high end of the scenario (National Research Council Committee 2009).

In the end, the research committee concluded that significant increases in more compact, mixed-use development will result in only modest short-term reductions in energy consumption and CO_2 emissions, but these reductions will likely grow over time (National Research Council Committee 2009). This special report was calling for more carefully designed studies of the effects of land use patterns and the form and location of more compact, mixed-use development on travel outcomes so that compact development can be implemented more efficiently.

Brundell-Freij and Ericsson's study (2001; Brundell-Freij and Ericsson 2005) focuses on making connections between energy consumption/emission, street environment, characteristics of drivers, and traffic conditions. This research provides much more precise estimations of the fuel consumption and emission. However, the street type is the only built environment variable that this study considered. The experiment-like research design controls the variations among other built environment dimensions.

Issue 3: Level of Aggregation

Level of aggregation of the unit of analysis is another important issue which can influence the credibility of the analysis and validity of the research result. Many built environment and travel behavior studies implemented an aggregated research design. They compare aggregated travel behavior across different neighborhoods, represented by the immediate census block, census tract, zip code, or traffic analysis zone (TAZ).

This aggregated approach assumes behavioral similarity within each neighborhood, which obscures much detailed behavioral information (Ericsson 2001). Individuals living in the same neighborhood may experience the surroundings in different ways. Such differences can be caused by several factors such as individual demographic characteristics, and the locations of their residential parcels. Ignoring these differences makes it harder for researchers to fundamentally understand why travel decisions are made and how exactly the built environment influences travel behavior.

A shift from aggregate transportation studies to more disaggregated research has emerged, and this shift was in a large part motivated by a desire to get a better understanding on how travel decisions are made. Disaggregate studies which focus on how people make travel decisions are called as *behavioral* studies because they attempt to understand the attitudes and preferences that lie behind decision making (Lynch 1960; Golledge and Rushton 1976; Hanson and Schwab 1995). The unit of analysis of disaggregate studies is usually an individual, a driver, or a household. The built environment for each unit is measured and related to the travel behavior of that particular unit. More detailed survey (individual survey or household survey) are usually conducted to get information on individual's gender, age, income, attitudes, preferences, activities, and travel decisions so that the travel behavior of individuals can be explained by these factors.

Disaggregate research explicitly treats travel as a *derived* demand. Attention is focused on activity-related information such as the type of activities, the time/duration of activities, and the location of activities. Partitioning activity into various categories based on spatial and temporal characteristics allows researchers to break several traditional dichotomies embedded in the aggregate approach (work trips vs. non-work trips, peak vs. off peak, etc.). Because various categories of activities (with associated trips) may respond differently to environment factors, this disaggregate approach helps researchers sort out subtle and delicate connections between the built environment and travel behavior. More reviews on disaggregate research and activity-based analysis will be provided in the second section.

Issue 4: Geographic Scale

As noted by several authors (Boarnet and Crane 2001; TRB 2005), the issues of geographic scale of the built environment to be studied have been ignored in past and recent studies linking travel behavior to the built environment. Most of the literature has focused on environment determinants at the neighborhood level. However, a notable gap in the literature is the consideration of the effect of the built environment on travel behavior at scales larger than the neighborhood (Handy 1992). Good built environment features can draw residents out of the neighborhood and potentially provide activity opportunities. Handy shows that a large number of non-work trips are made outside the neighborhoods (TRB 2005). Boarnet and Crane's study varies the geographic scales by using both smaller neighborhood block group and also larger zip code areas (Boarnet and Crane 2001). However, the study focus is still centered around home location (the residential setting).

Does the built environment at work, at school, or the space in between home and work/school influence travel behavior? Expanding research to nonresidential settings would broaden our knowledge on an array of built environments on travel behavior (TRB 2005). Much of the work related to non-residential setting focuses on how the designs of large employment centers influence commute trips. In the study of 59 large employment centers in the U.S., Cervero (1989) found that a significant reduction in midday travel and overall automobile dependence could be achieved through the integration of retail services into office parks. Frank and Pivo have shown that a stronger relationship exists between mode choice and urban-form characteristics when they are measured at both trip origins and destinations than at one end (Frank and Pivo 1995). However, there are few studies which have tested the collective impacts of urban form at both trip ends none of the studies have tested the impacts of the space which connects the trip ends.

One obvious reason behind the lack of nonresidential setting research is data availability. Limited understanding of the behavioral theory and poorly constructed theoretical frameworks also contributed to the lack of nonresidential setting research. Why do people choose further destinations even if the close opportunities within the neighborhood were available? Which space other than the adjacent residential setting is important in influencing people's travel behavior? The traditional demand theory cannot provide the theoretical basis to identify and justify the geographic scale to be selected in the future studies. We have to look for other theories from other disciplines to fill in this gap. The following section summarizes these theories (spatial behavior theory and activity-based analysis), which can contribute to understanding the connections between the built environment, travel behavior, and energy consumption/emission.

Spatial behavior theory and activity-based analysis: the new way to understand the link

Spatial behavior theory

While the theory of demand draws insights from the field of economics, spatial behavior theory largely draws its theoretical underpinnings from both behavioral geography and environmental psychology. Spatial behavior theorists are interested in linking the environment and human behavior in general. This interest is quite similar to that of the mainstream built environment and travel behavior researchers. They argue that although researchers can objectively observe different design elements, they cannot easily evaluate the ways in which different individuals interpret and respond to those elements. The choices individuals make depend not on an objective evaluation of urban form but on their perceptions of and responses to urban form. As Goodwin precisely summarized, " it is generally accepted that an individual's perceptions of an event or attribute is the appropriate dimension for explaining behavior" (Goodwin 1978). With this belief, spatial behavior research focuses on the ways in which urban form shapes the perceptions of the physical environment and how perceptions of the physical environment shape activity within that environment.

Spatial behavior theory primarily deals with two questions: 1) how do people acquire knowledge and understand space; 2) how do people act in space. The following review will address each of them respectively.

Golledge and Stimson (1997) argued that traveling through an environment is the most common way of spatial learning and acquiring spatial expertise. His anchor point theory explicitly illustrates how people acquire knowledge in the spatial context (Goodwin 1978:17). In this theory, initially important locations such as home, work, and shopping places anchor the set of spatial information grasped by an individual. Individuals constantly search for paths by which the primary nodes or anchor points are connected. As more and more interactions occur along the paths between the primary nodes, there is a spillover or spread effect with which the areal concepts of neighborhood, community, and region develop. Primary nodes as well as primary paths connecting these nodes are forming a skeletal structure upon which additional node, path and areal information is grafted. The end result of this formation process is a map-like image formed in people's mind: a hierarchical ordering of locations, paths, and areas within the general spatial environment (Golledge and Stimson 1987). Researchers name this map as cognitive map or mental map.

Cognitive maps, constructed through people's constant spatial learning and knowledge acquiring, can help explain how people act or behave in space. The idea of activity space was introduced to comprehensively describe and understand people's spatial behavior. Activity space is the part of the environment which a traveler uses for his/her daily activities (Golledge and Stimson 1997). It consists of the locations, which the person has visited, and the routes and areas the person has travelled through, in particular those locations which have been registered and seen, but not necessarily visited yet. Activity spaces can be thought of as approximations of the cognitive or mental maps of the traveler.

Studies based on multi-day activity/travel surveys have shown that there are certain temporal and spatial regularities of people's activity space. The repetitive nature of people's activity was studied by Huff and Hanson by using 5-week travel diary data in Uppsala, Sweden. They found that core stops accounted for, on average, 57% of each person's total stops. Core stops, stops occurring with considerable frequency (four times in a five-week period), structure much of the rest of the individual's activity pattern (Huff and Hanson 1990: 233). Although Huff and Hanson did not explicitly mention Golledge's anchor point theory in their study, their findings provide strong support for Golledge's theory.

Other spatial and temporal regularities have also been noticed in activity space. The simplest and most universal is that of distance decay, which is an aggregate concept that indicates a tendency for people to take trips most frequently to places nearby and less frequently as distances from the origin of the trip increase (Jakle, Brunn and Roseman 1976: 99). It has been shown that activities with the greatest frequency of participation are generally located close to the home. An inverse relationship is found between the distance travelled to an activity and the frequency of participation in that activity, owing in part to the greater time or monetary cost of longer trips (Jakle, Brunn and Roseman 1976: 99)

In summary, spatial behavior theory, with its focus on how people understand and behave in space, provides a way to conceptualize the connections between built environment and travel behavior with more behavioral and psychological emphasis. Spatial behavior theory underscores the importance of individuals. It emphasizes that individuals are the most basic decision-making unit. They are learning the environment by travelling and acting in it. The spatial knowledge that they acquired, in turn, conditions their travel and activity decisions. Through this dynamic and repetitive process, each individual forms his/her own interpretation of the built environment, represented by a distinct cognitive map. Most importantly, spatial behavior theory tells us that spatial features located in different segments of space are not equally important to individuals. Rather, they are structured hierarchically in people's mind. Each individual, with his/her own cognitive map anchored by critical nodes (such as home and work locations) and primary paths (such as the road connecting home and work), centers their activities around these core nodes and paths. Traditional studies, which focus on the space near the residential settings, are over-simplified and omit a large portion of the built environment which could potentially influence people's behaviors.

Activity-based analysis

Activity-based analysis is not an easy subject to review because it covers a variety of fragmented topics and there is no identifiable and dominant theoretical basis that has emerged (Jones 1990). This literature review is not intended as a comprehensive review on all topics and methods in activity-based analysis; rather, it will emphasize the subjects that are particularly important to the debate about the relationship between the built environment and travel behavior.

Activity-based analysts share several common characteristics which define them as a school: they acknowledge and explicitly treat travel as a derived demand; they focus on sequences or patterns of behavior rather than on discrete trips; they focus on interactions between activity participation and travel behavior; they emphasis on detailed timing as well as the duration of activities and travel (Jones 1990).

Among many contributions that activity-based analysts have made, three are particularly important to the debate about the relationship between the built environment and travel behavior: longitudinal analysis (day-to-day variability or repetitive travel), trip chaining research, and the typology of activity/travel. Longitudinal analysis, featured by Huff and Hanson's study (1990) on repetitive travel mentioned in the previous section, will not be repeated here. Trip chaining and activity/travel typology are the focus of the following literature review.

Trip chaining is one of the most important investigation areas of activity-based researchers. A large portion of the studies focus on building the theoretical base and empirical model of trip chaining behavior (Kostyniuk and Kitamura 1984; Thill and Thomas 1987; Kitamura, Nishii and Goulias 1990; Golob 2000). These studies bring a good amount of knowledge on the key factors that influence the prosperity of the trip chaining behavior and also its spatial and temporal characteristics.

Mahmassani studied two-week diaries of commuting trips completed by a sample of auto commuters in Austin, Texas. The study shows that about 25% of all reported commutes contained at least one non-work stop, underscoring the importance of trip-linking in commuting behavior. It also shows that longer commute time is associated with more morning non-work stops; female and younger commuters tend to conduct more chained trips. From the spatial perspective, this study shows that most non-work stops in the morning commuting trips were made close to the shortest driven commuting path. Only 19.2% of all trips with stops take commuters more than three miles from their minimum-distance routes (Mahmassani, Hatcher and Caplice 1996). Kitamura's study explicitly focuses on the spatial aspects of trip chaining behavior of central-city workers in Japan (Kitamura, Nishii and Goulias 1990). Their results suggest that before-work stops tend to be made near the home base and after-work stops tend to be near the work base. Commuting distance is shown to be a principal determinant of the selection of non-work stop locations by commuters. Stop locations tend to scatter in every direction when commuting distance is short, but they tend to be located along the line segment that connects the home and work locations as commuting distance increases (Kitamura, Nishii and Goulias 1990: 153).

To summarize, the existing literature on trip chaining behavior clearly shows that trip chaining behavior (especially non-work stops chained in commuting trips) is common phenomenon which deserves much more academic attention. Also, it shows that chained stops won't deviate too much from the shortest commuting path and longer commute tends to create more chained stops.

The gap in the current literature is that most trip chaining research rarely made the connections between the built environment and chained trips. To the author's knowledge, there are only a few studies which either touch on the issue or explicitly examine this relationship.

Hanson's study on the multi-purpose journey to work was the first attempt to make the connections between land uses and trip chaining. Using the same 35 days travel diary data collected in Uppsala, Sweden, Hanson shows that there are certain land uses that are frequently visited on the way to work (public offices, insurance and other offices), some that are often visited an route from work to home (Kiosk, bank, auto repairs and service, and liquor store), and some (restaurant, photo store) that are visited during the work day. The study further proves that there is a group of urban functions that have stronger travel links with the workplace than with the home. Restaurant, kiosk, car repairs, bank, photo shop, liquor store, and grocery store (with the descending order) are usually visited on the first stop after the traveler leaves workplace (Hanson 1980: 230).

Despite the interesting and rich information Hanson's study provided on the connections between land uses and trip chaining, this study would have placed more emphasis on the availability of these businesses (how many businesses that are available) and the spatial locations of these businesses (whether they are close to the work place or home location).

Krizek's study is also worth mentioning in that he explicitly made the connections between neighborhood service (which is centered at home location) and tour-based travel in the U.S. context. He found that residents who moved to neighborhoods with better local accessibility, all else being equal, had significantly reduced their vehicle miles traveled (VMT) and number of trips per tour, but increased their average number of trips (Krizek 2003). The study shows that trip-based travel analysis is limited to a large extend because it does not consider the linked (chained) nature of most travel. Krizek introduced the tour-based analysis and developed the travel tour typology. The limitation of his study is that he focuses only on the built environment features around home (neighborhood) while maintenance-type activities are related to the work location and the journey-to-work as indicated in Hanson's study. As a result, Krizek's study could not explain why a large portion of household's maintenance travel is still pursued outside the neighborhood.

Trip chaining behavior, albeit a prevalent phenomenon, has long been ignored in the built environment and travel behavior research, except for the studies from researchers like Hanson and Krizek, Many authors have realized this gap and call for more studies on this subject (Ewing 1995; Ewing and Cervero 2001). As Handy argued, ignoring this phenomenon, planners might have missed an important link between the built environment and travel behavior.

The other major contribution that activity-based researchers made is to develop various typologies of activity/travel. Researchers realize that there are different types of activities which show significantly different characteristics. By grouping similar activities together and building a typology, researchers are able to better understand the mechanism behind each type of activity and its relationship to the corresponding built environment features.

Activity-based researchers have developed several typologies with various complexities. Some typologies are simpler than others. The simplest distinction was drawn between obligatory and discretionary activities based on the degree of elasticity of an activity (Chapin 1974). Obligatory acts, including sleep, work, and school, occur more or less in cycles with timed regularity. Discretionary acts, including recreation, shopping activities and leisure, have a greater degree of choice than constraint (Chapin 1974: 37-38). Reichman (1976) defines three major classes of travel-related activities in which he further separates discretionary activities into two categories: maintenance activities, consisting of the purchase and consumption of convenience goods or personal services needed by the individual or household; and leisure or discretionary activities, comprising multiple voluntary activities performed on free time, not allocated to work or maintenance activities. Using Reichman's classification scheme, activities for work, school or college trips are considered as subsistence (or work) activities. Activities can be further broken down into more categories. Golob defines six groups of activities (work, shop, school, personal business, serve passengers, and social recreational) (Golob 1986). Activity typology can be designed to be as detailed as possible, as necessitated by the research purpose. As activity-based researchers acknowledged, the coding scheme of a given typology needs to serve the purpose of a particular study. A clearly defined and carefully chosen activity/travel typology will strengthen the research design and better answer the research questions.

As mentioned earlier, trip chaining and activity/travel typology are the two major contributions from activity-based researchers, which are closely related to the discussions about the built environment and travel behavior. What is most valuable in these studies is that they call attention to the way in which people actually live in the urban environment. As concluded by King and Golledge, the rationale of activity-based approach to urban analysis is that by knowing how people use an urban area, how they sequence their activities, how they arrange different activities in the urban environment, we will be in a better position to understand the built environment as it is used by the people and in a better position to evaluate the policies which are designed to change the built environment (King and Golledge 1978).

GPS: the new technology to study the link

The Global Positioning System (GPS) is now increasingly utilized in transportation research as it becomes easier and less expensive to use. GPS is a global satellite navigation system. Utilizing a constellation of at least 24 satellites transmitting precise microwave signals, the system enables a GPS receiver to compute its position, velocity, direction, and time. Collecting travel data using GPS receivers and recorders has several advantages compared to the traditional trip diary data:

- They do not rely on the memory or estimates of a survey respondent, which places less burden on the respondents.
- The recorded distance and time information have much higher accuracy. Travel survey conducted by using GPS receivers and recorders results in better trip reporting rates.
- GPS data can be collected over much longer periods of time than the traditional travel survey. The Commute Atlanta instrumented vehicle GPS data covers for about

one-year travel period, which is currently the longest running GPS data source (Guensler et al. 2006). Traditional travel diaries rarely last longer than one week because of the burden on respondents and the cost of the survey (Wolf 2000).

- They provide detailed spatial-temporal information such as chained trips and tours.
- In normal household travel survey, trips are coded individually, making it difficult to identify where a trip chain began or ended (Hanson and Schwab 1995).

The use of GPS receivers and recorders poses several challenges to transportation professionals. The amount of data is massive, and converting points of GPS data into a meaningful travel behavior database requires significant effort and programming. The detailed description about respondents' activities, choices, and decisions cannot be directly obtained, such as what the travelers are doing at particular locations and why they decide to choose one location over another. Trip purposes, which can be easily derived from traditional travel survey, are difficult to obtain solely based on GPS data.

Most GPS-related literature focus on the feasibility of using GPS in transportation research. They attempt to answer the following questions: whether traditional travel survey can be completely replaced by GPS; whether it is feasible to perform multiple day survey by using GPS; and how can we derive the trip purpose and capture multi-stops trip chaining behavior (Yalamanchili, Pendyala, Prabaharan and Chakravarthy 1999; Wolf 2001; Wang, Dixon, Li and Ogle 2004; Wolf et al. 2004; Silva, Farias, Frey and Rouphail 2006).

The earliest proof-of-concept study about GPS application in travel data collection was conducted in 1996 in Lexington, Kentucky. This study examined the feasibility of using GPS equipment to supplement self-reported telephone-based travel behavior data collection. By comparing GPS-captured trips versus trips reported by CATI[3] recall interviews for same trips, the Lexington study demonstrated that recall data likely underestimates the total number of trips and overstates both travel time and travel

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[3] CATI stands for computer-assisted self-interviewing

distance. Moreover, GPS data are able to capture complex route choice decisions without adding burden to the survey respondents (Battelle 1997; Murakami and Wagner 1999).

The Lexington GPS dataset was analyzed by other groups through different perspectives. A group from University of Wisconsin evaluated the use of GPS-based dataset to capture the variations in route choices. Their study showed that real travel paths selected by drivers are often different from the shortest paths and only GPS can capture the variations (Jan, Horowitz and Peng 2000). A group from University of Connecticut further developed methods to identify trip ends by using passive GPS data traces (Du and Aultman-Hall 2007). Their results showed that the success of identification of trip ends with GPS data depends on carefully selected criteria including not only dwell time but also heading changes and others.

The success of Lexington GPS data in improving travel behavior data collection led to several other efforts to apply and evaluate the feasibility and performance of GPS data relative to traditional survey method. Studies in Kansas City, U.S. and Toronto and Quebec City, Canada all demonstrated that GPS can be used to record people's travel behavior in one or multiple days (Pearson 2001; Nustats 2004; Roorda et al. 2005).

Several GPS datasets were collected in the Atlanta region including an early dataset with 30 participants and a large dataset collected in 2004 containing data for 487 vehicles from 268 representative households in the 13-county Atlanta metro area with around one-year worth of travel behavior data, the longest GPS survey period ever in the US. Research using Atlanta GPS data further confirmed the advantages of GPS technology and the feasibility of completely replacing traditional survey method with GPS data.

Detailed information on several existing studies on GPS applications can be found in Table 2-1, which compares these studies by their data sources, research goals, methodologies and key findings. Despite these tremendous efforts in applying GPS in transportation field, travel behavior researches, which used GPS as data collection methods are rare and to the best of our knowledge, no study has yet used GPS data to examine the relationship between the built environment and travel behavior.

Table 2-1 Comparisons of existing GPS studies

GPS data collection effort	Researchers	Research goal	Method used	Findings
100 households in Lexington, Kentucky participated between March 2002 and July 2003, for six days with each household; main equipments include a personal data assistant (PDA) and Garmin GPS receivers 	Battelle (Battelle 1997; Murakami and Wagner 1999)	Determine the feasibility of integrate GPS technology with self-reported travel behavior to improve travel behavior data and evaluated GPS data's accuracy and completeness.	Compared GPS-captured trips versus trips reported by CATI[4] recall interviews for same trips; elements analyzed include individual trips, travel times, and trip lengths; map matching software was used to identify trip links	Lexington respondents take more trips of shorter distances than past national estimates. The GPS data captures complex route choice decisions and reduce burden for respondents. Different trip start time and trip distance distribution by the GPS data vs. recall interviews Recall data likely underestimate the total number of trips and overstate both travel time and travel distance.
A subset of the above Lexington dataset; 12 participants	A group from University of Connecticut (Du and Aultman-Hall 2007)	Develop methods to identify trip ends by using passive GPS data stream	Compared the computer identified trip ends with the true trip ends identified by self-reported trip log. A heuristic model was developed.	A combination of a maximum and minimum dwell time, a heading change and a check for distance between the GPS points and the road network provides an improvement over dwell time alone in identifying trip ends in a passive GPS data stream. Trip reporting rate is sensitive to defining parameters which need to be cautiously selected.
The Lexington dataset	A group from University of Wisconsin (Jan, Horowitz and Peng 2000)	Evaluate the use of GPS-based data to capture the variations in route choices	Performed a map-matching procedure and determined the variations in paths from same drivers on multiple trips and	Path selected are often different from the shortest paths. Paths for trips made by the same driver were very consistent over time; paths by different drivers showed more deviations even when the trip ends were the same or very similar.

[4] CATI stands for computer-assisted self-interviewing

			across drivers through a path deviation index and the percentage of identical links.	
3049 households in Kansas city participated beginning from 2003 in the general one-day travel survey, among which 228 households participated in the GPS supplement (Geostats Geologger) installed in the vehicles 	Nustats company (Pearson 2001; Nustats 2004)	Compare passive GPS-collected data with travel diary/telephone interview reported travel data	Reviewed the CATI data as compared to the GPS data	The study found that 89% of all trips reported in both CATI and GPS matched. There are missed trips which are not reported through CATI.
In a data collection effort of travel/activity panel survey in the Toronto and Quebec city regions, 12 individuals outfitted with portable GPS units	A group from University of Toronto and Université Laval (Roorda et al. 2005)	Test the feasibility of recording multi-week activity patterns using GPS	Develop GIS algorithms to identify trip ends, travel times, road usage, and speed	It is feasible to automatically detect a person's underlying scheduling decisions (modifications and impulsive decisions only), something believed to be largely unobtainable except through self-reporting.
Several GPS datasets were collected in the Atlanta region including an early dataset with 30 participants and a large dataset collected in 2004 containing data for 487 vehicles from 268 representative households in the 13-county Atlanta metro area with around one-year worth of travel behavior data.	A group from Georgia Tech	Several studies have been conducted: 1) to test accuracy levels and performance characteristics of different GPS equipment on map matching (Wolf 1999) 2) to understand destination choice, route choices, and activity space by using GPS	Develop various algorithms to derive trip attributes such as route choice and trip purposes.	It is feasible to derive most trip attributes from GPS data which were found to match or exceed the reporting quality of the participants. It is feasible to derive trip purpose from the GPS data through combining with a spatially accurate and comprehensive GIS dataset. Li's study shows that minimizing travel time, although very important, is not the only factor impacting route choice. Work schedule flexibility and trip-chaining are important factors too.

		data (Li 2004; Li, Guensler and Ogle 2006) 3)to test the feasibility of deriving trip purpose from GPS data (Wolf 2000; Wolf 2001)		

Chapter 3
Conceptual Framework

This dissertation research intends to help understand the relationships between specific attributes of the built environment, driving behavior, and the associated vehicle fuel consumption and emissions. Drawing heavily on both demand theory and spatial behavior theory and implementing a tour-based approach, this study has developed a conceptual framework as shown in Figure 3-1.

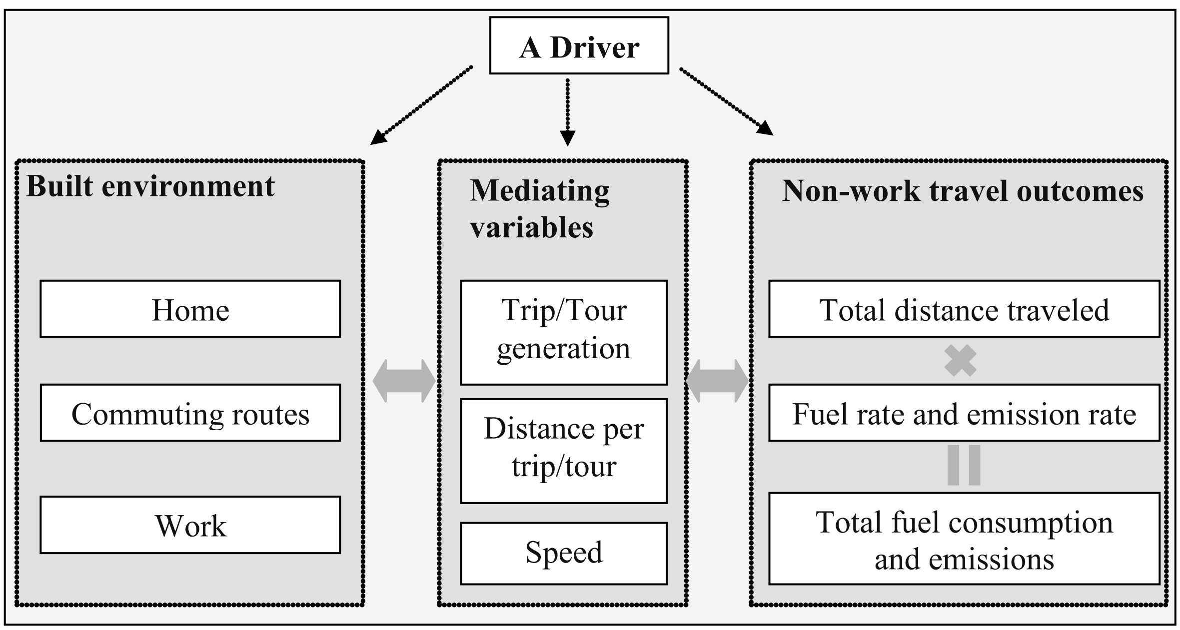

Figure 3-1 Conceptual research framework

In this framework a driver as a decision maker is the basic unit of analysis. Each driver experiences the built environment by living, working, and travelling through different urban spaces. The urban spaces centered at a driver' home, work places, and along commuting routes are assumed to be the most important urban spaces that have potential connections with the driver's travel behaviors related to non-work travel. Each driver's travel behavior and outcomes are evaluated along three perspectives: total distance travelled by automobiles (total VMT) for non-work activities, the rates of fuel consumption and emissions for these non-work travels, and consequently, non-work-related total amount of fuel consumption and emissions. The associations of the built environment and travel outcomes are assumed to channel through several mediating variables which are more detailed descriptors of drivers' travel and activities.

There are several key features involved in this conceptualization:

- Decomposing total energy consumption/emissions into total distance traveled and energy/emission rate

  This study considers total energy consumption/emissions as the product of two components: total VMT and energy consumption/emission rates. Neither component alone can determine the ultimate energy and environmental impacts. The relationships between the built environment and travel outcomes are specific to which components of the travel outcome are being studied. By decomposing total energy consumption/emissions into total distance traveled and energy/emission rate, this study provides an in-depth understanding about the inter-relationships between the built environment, travel behavior, and energy consumption/emission.

- Focusing on three urban spaces

  According to spatial behavior theory, urban spaces anchored by important nodes and corridors are particular important in influencing individuals' behavior. Such nodes include people's home location, schools, or work places. Such corridors include routes that connect core nodes. Moreover, distinct urban spaces may have different influences on different types of non-work travel. As shown in Figure 3-2, space near home locations may have more influences on non-work travel originated and ended at home (HNH tours) whereas space near work or along commuting routes travel may have closer relationships with non-work travel originated and ended at work places (WNW tours) or travels in-between home and work (WNH or HNW tours). Tours are composed of sequential trips. A detailed tour typology is developed in this study.

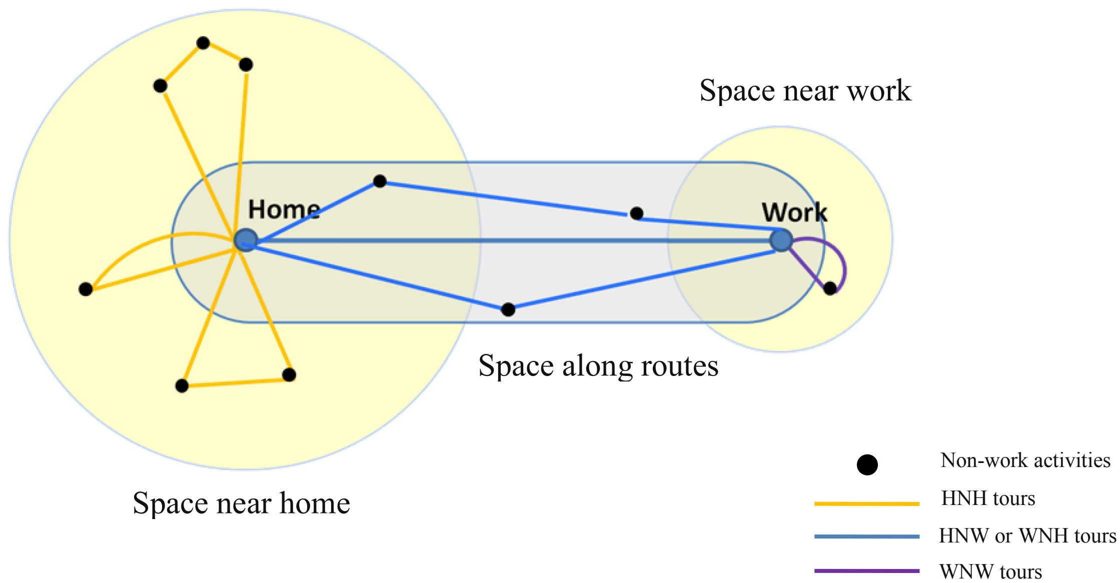

Figure 3-2 Illustration of three types of urban spaces and corresponding non-work travels

- Constructing mediating variables

The relationships between the built environment and energy/emission operate through many mediating variables (as shown in Figure 3-1). This study assumes that the total distance traveled and total energy consumed are not travel choices themselves, but rather derived from decisions related to participation in activities. These intermediate variables are more detailed descriptors of people's activity and travel behavior. Mediating variables included in this study range from attributes of trips or tours (number of trips/tours, average trip/tour length) to characteristics of driving (speed). Each mediating variable may have different influences on travel outcomes depending on different environmental factors.

Chapter 4
Research Questions and Methodology

Research questions and hypotheses

The overarching goal of this research is to gain an understanding of the effects of different aspects of the built environment on vehicle miles traveled (VMT), on vehicle energy consumption and emissions per distance traveled, and on the total energy consumption and emissions for non-work travel. The "built environment" studied here represents the physical features of the urban spaces, and includes the density and diversity of the land use as well as the connectivity and functionality of the roads.

Six main hypotheses are tested in this study with the former three focusing on the built environment near home/work and the latter three regarding the urban space along commuting routes:

About the built environment near home or work places

1) Compact and mixed-use developments near home or work places are associated with less total amount of driving on non-work activities (such as eating or shopping). In such environment, drivers can take advantage of the close destination choices near home or work and travel shorter distance per trip. This type of built environment near home or work may also provide alternative transportation means such as walking, biking, or public transit, all of which will reduce the number of private automobile trips.

2) Compact and mixed-use developments near home or work places are associated with worse fuel efficiency and emission rates. In such environment drivers are inclined to change speed more often, make stop-and-go movements more frequently, or cruise at

extremely low speed, all of which will lead to higher energy consumption and emission rates.

3) For the built environment near home/work, the worse fuel efficiency and emission rates can be compensated by the savings in the total amount of driving, and eventually produce beneficial energy consumption and emission outcomes.

About the built environment along commuting corridors

4) Compact and mixed-use developments along commuting routes are associated with less total amount of driving on non-work travel, because commuters may chain various non-work activities on their way to or from work, at locations adjacent to or close to commuting routes. This type of multi-purpose/multi-activity travel is likely to reduce total distance travelled by vehicles through reducing VMT per activity.

5) Compact and mixed-use developments along commuting routes are associated with worse fuel efficiency and emission rates, with the same reasons listed for the built environment near home/work: more densely-built urban settings mean more stops and low-speed driving, especially for travel connecting home and work locations.

6) Compact and mixed-use developments along commuting routes are associated with lower fuel consumption and emissions, as the reduced vehicle mileages could cancel out the worse fuel efficiency and emission rates.

Hypothesized directions of relationships between dimensions of built environments and three non-work travel outcomes can be summarized in Table 4-1.

Table 4-1 Summary of research hypotheses

	VMT	Fuel/emission rates	Total fuel/emissions
Compact and mixed-use developments near home/work	-	+	-
Compact and mixed-use developments along commuting routes	-	+	-

Research Design and Methodology

This study applies a disaggregated analysis scheme, through which an individual driver's travel behavior and travel outcomes are related to the built environment that he/she experiences. There are four key steps involved in this research: quantification of travel behavior, evaluation of energy and emission outcomes, characterization of the built environment, and determination of the relationships between the outcomes and the built environment. The following chapter first describes the study area and the research data and then explains the four key steps listed above.

Study Area and Data Description

The study area covers seven counties in the Southeast Michigan metropolitan area. Driving data from GPS records, which will be used in this study, were part of the naturalistic driving data (NDD) collected by UMTRI's Engineering Research Division between May 2004 and February 2005. Eleven identical instrumented vehicles were given to 78 drivers. Each driver was allowed to use the vehicle for one month period. Five drivers' driving activities occurred mostly outside the study area and they were excluded from this study. The drivers were randomly selected from licensed drivers from Southeast Michigan region. This sample of drivers was equally divided by age groups (20-40, 40-60, and 60-70) and by gender. The vehicle was equipped with multiple sensors which collected, among other information, vehicle speed, positions (in latitude and longitude), heading, and time. The resulting data captured a total of 9,582 trips over 83,000 miles of driving.

Through an extensive data processing procedure, the author converted the original GPS records into a comprehensive database from which travel behavior variables could be derived. The data processing procedure included deleting trips with GPS malfunction, aggregating trip ends into single destinations, identifying intermediate stops and sudden stops, etc.

The study area and key locations from the GPS data are shown in Figure 4-1

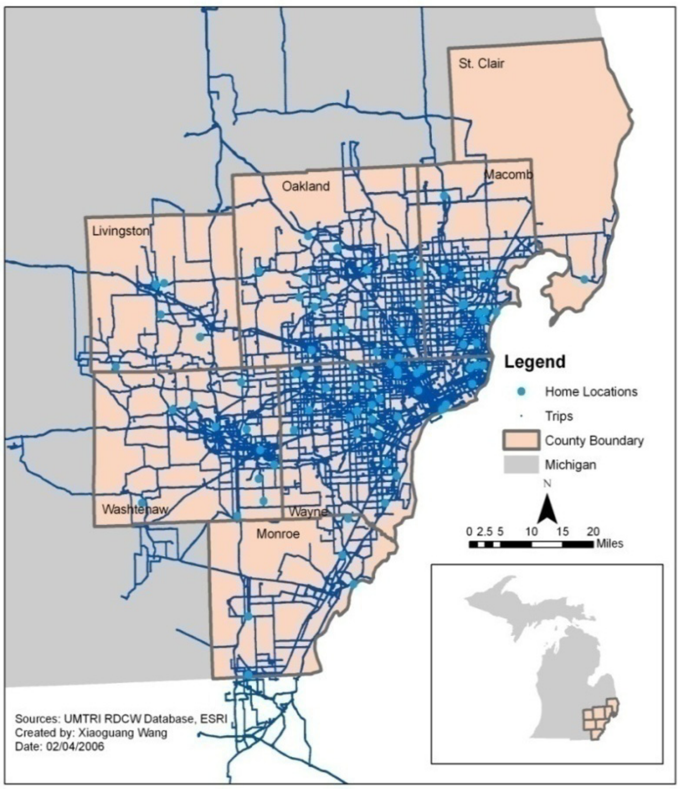

Figure 4-1 Study area, drivers' home locations, and travel routes

The advantage of using UMTRI naturalistic driving data (NDD) is that all drivers were given the same type of vehicles (Nissan Altima). Thus the vehicle type is controlled for, when using NDD to examine the relationships between the built environment and travel outcomes. However, one disadvantage is that travel behaviors and outcomes observed may deviate from drivers' normal travel behaviors/outcomes when they use their own vehicles. For instance, assume driver A lives at a compact environment and owns a compact car while driver B lives at a suburb and drives a van. When they are given the same Nissan Altima, driver A may drive less because of Altima's relatively low mileage per gallon (mpg) compared to the original compact car. Meanwhile driver B may drive more as a result of the Altima's better mpg. In this scenario the use of instrumented vehicles may introduce bias into this research. Drivers' driving habits may be modified by the instrumented vehicles as well. The vehicles were provided to drivers for free, though drivers need to pay the cost of gasoline. Some drivers may take advantages of the free cars and drive more. In addition, the recruited drivers were aware that their travel was being monitored. Some drivers may drive less aggressively under such circumstances, resulting in better fuel efficiency. Without proper methods to estimate the impacts of the instrumented vehicles, this study assumes that drivers did not change their behaviors significantly after they got the new vehicles.

In order to measure the built environment, detailed business data and precise road network data are required. This study uses the business establishment data bought from the private vendor InfoUSA. The data categorizes different business types based on six-digit Standard Industrial Classification (SIC) code. It also provides the location information, the number of employees, and sale records. The road network provided by the Center for Geographic Information in Michigan is used to derive all road network related variables.

Quantifying travel behavior and outcomes

Characteristics of non-work vehicle trips in terms of trip distances and trip durations are derived from the GPS dataset. In addition to the trip-based analysis, this study applies a tour-based analysis scheme in which trips are coded into tours. Tours are defined as a composition of series continuous trips. A tour always starts at home or a work site, stops at one or more non-work locations, and concludes with the next trip that ends at home or a work site.

Based on the relative locations of the starting and ending points of tours, this study groups tours into five categories as shown in Table 4-2. Other types of travel such as trips directly connecting home and work places were analyzed as well, but the results are not included as they are not the focus of this study.

Table 4-2 Tour typology

Sub-types of tours	Abbreviation
Home-to-home tour	HNH
Work-to-work tour	WNW
Home-to-work tour	HNW
Work-to-home tour	WNH
Work-to-another work tour	WNW'

The five types of tours include: tours originated and ended at homes (HNH), originated at homes and ended at work sites (HNW), originated at work sites and ended at homes (WNH), originated and ended at the same work sites (WNW), originated and ended at different work sites (WNW’). Each type of tour presumably has different relationships with the built environment in different urban spaces.

Multiple attributes of tours are derived from the second-by-second GPS points as well, which includes the number of tours, tour length, and number of non-work activities chained in a tour. Tour-related attributes are tabulated with tour types and drivers’ demographic features including age and gender. Tour-based analysis allows us to understand how non-work activities are chained into tours in relation to home and work locations. Spatial analysis on tour-making patterns reveals the most important urban spaces which potentially have the most significant relationships with travel behavior and outcomes.

Evaluating energy and emission outcomes

The Comprehensive Modal Emissions Model (CMEM), developed by a group in the University of California, Riverside (Barth 2001), is used to estimate the energy consumption and emissions for the non-work travel in this study. CMEM is a type of instantaneous model, with which fuel consumption and multiple emissions (including carbon dioxide, carbon monoxide, hydrocarbon, and nitrogen oxides) can be estimated on a second-by-second basis.

There are a variety of fuel consumption models which have been developed to date, ranging from instantaneous models to more aggregate, average speed models (summarized in Table 4-3). Environmental Protection Agency (EPA) MOBILE 6 is a type of average speed model, which is required by EPA to be used by all states in their State Implementation Plan and conformity emissions inventory development (except California, which has its own model). The estimation of EPA MOBILE 6 is based on facility-specific *driving cycles*. Representative driving cycles were developed for different road facilities with different level of service (LOS)[5]. This approach using facility-specific driving cycles assumes that the regional driving variability is insignificant when controlling for facility type and LOS.

Despite its easier implementations, MOBILE 6 has been widely criticized for its over-simplified estimation based on average speed and vehicle miles traveled (Murakami and Wagner 1999; Yalamanchili, Pendyala, Prabaharan and Chakravarthy 1999; Wolf 2000; Pearson 2001; Wolf 2001; Roorda et al. 2005). Researchers are calling for more microscopic models which take detailed driving variability into considerations (Gyo-Eon, Sung-Mo, Kun-Hyuck and Sung-Bong 2006).

The common characteristics of instantaneous models are that they estimate the second-by-second energy consumption and emission based on instantaneous speed and acceleration (commonly recorded in every one to ten seconds). The instantaneous models were usually constructed by monitoring laboratory energy and emissions and conducting a model-fitting procedure between speed/acceleration and energy consumption and emission by assuming a polynomial relationship between the two.

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[5] LOS is a measure of volume to capacity (i.e. a measure of traffic congestion) and is given a scale of A (free flow) to F (forced or breakdown flow).

This study chose to use CMEM because the model provides an alternative to the average speed model and presumably can produce better estimations of both energy use and emissions. Compared to other instantaneous models, CMEM has a wider application. It is capable of making predictions for a wide range of vehicle categories. The instrumented vehicle used in our study is included.

Using CMEM, the second-by-second fuel consumption and vehicle tailpipe emissions of carbon dioxide, carbon monoxide, hydrocarbon, and nitrogen oxides are estimated for each trip. Estimations are aggregated into tours which are further aggregated to represent all non-work travel by each driver throughout the four-week survey period. The rate of energy consumption and emissions are derived by dividing the total energy consumption and emissions by the total vehicle miles traveled on non-work trips.

Table 4-3 Fuel consumption model comparisons

Type	Name	Key inputs	Outputs	Application	Notes
Instantaneous models	Biggs' power-based model (Biggs and Akcelik 1986)	instantaneous acceleration, instantaneous speed, level of road , mass of the car	instantaneous energy consumption		This model separate consumption into three components. It requires model calibration.
	VT Micro model (Anh 2002)	instantaneous acceleration, instantaneous speed	instantaneous energy consumption and emission	five light-duty vehicles and three light-duty trucks	The model is shown to be highly accurate with coefficients of determination ranging from 0.92 to 0.99.
	Comprehensive Modal Emissions Model (Barth 2001)	instantaneous acceleration, instantaneous speed	instantaneous energy consumption and emission	about 400 different vehicles were tested	
Average speed model	Evans' simplified model (Evans and Herman 1976)	average speed	fuel consumption per distance		
	EPA MOBILE 6 (EPA 2003)	average speed	emission	can be applied to travel demand modeling result	

Characterizing the built environment

The built environment was measured along four dimensions including business density, business diversity, road connectivity, and road functionality, each at three urban spaces. This process results in a total of twelve built environment variables. Business density and diversity are designed to capture the quantity and variety of the non-work destination choices. Road connectivity and functionality measure the characteristics of the road systems which connect these non-work destinations.

Three criteria were used to guide the selection of built environment variables: 1) to capture various distinct dimensions of the built environment and at the same time minimize the likelihood of multicollinearity; 2) to avoid over-simplified variables while controlling the complexity of the measures; 3) to choose the variables that have direct impacts on peoples' travel behavior (either by affecting the cost of travel or the attractiveness of the destinations).

The current set of measurements covers the three dimensions of the built environment identified by Cervero and Kockelman (Cervero and Kockelman 1997): density, diversity, and design ("the 3Ds"). Street layouts and functions belong to the design dimension. A minimal number of measurements were selected to capture each of the three dimensions with the purpose of avoiding multicollinearity. Despite this effort, this study found that the twelve built environment variables are correlated with each other. These correlations indicate the co-existence of different built environment features at the same urban space (a dense neighborhood may have both higher business variety and higher road connectivity). In order to solve the multicollinearity problem, factor analysis was employed to combine the twelve variables into three composite variables, each representing the overall built environment at a single urban space (space near home, work, or along commuting routes). The composite measurements generated from the factor analysis allow us to study the collective impacts of the individual built environment variables.

Population density, a commonly-used measure in other studies, was not included in this research. The reason to exclude population density is that it is over-simplified and has limited ability to explain travel behavior, as argued by several scholars (Steiner 1994; Kockelman 1997; Ewing and Cervero 2001). Areas with higher population density may be associated with higher level of vehicle travel. However, it is not higher density of population that makes people drive more, but rather the shorter driving distance brought by closer destination choices (which is a property of higher population density).

The four measurements included in this study are measures that have direct impacts on or predictors of people's vehicle travel. A close proximity to a high density business setting containing not only shops but also banks, post offices, restaurants is likely to reduce total VMT by reducing total number of vehicle trips needed and reducing distance travelled per trip. A well-connected road system composited with easy-accessed streets is likely to reduce VMT by providing more route choices.

More complex measurements such as dissimilarity index, entropy index, or measures of land use complementarity were not selected because all these measures are relatively difficult to interpret and they require detailed land use data which were not readily available. Measures related to pedestrian or cycling provisions and parking facilities were not selected either for a lack of data.

A cell-based approach is implemented in measuring all built environment variables. The study area, Southeast Michigan metropolitan region, is equally divided into 200-by-200 meters grid cells, each of which represents a small portion of the land within the study area (an example is shown in Figure 4-2). The cell size was chosen because it is big enough to capture multiple built environment features on the ground including buildings and roads. At the same time this cell size is small enough to differentiate urban landscape with a fine resolution. Business density, business diversity, road connectivity, and road functionality are defined as follows:

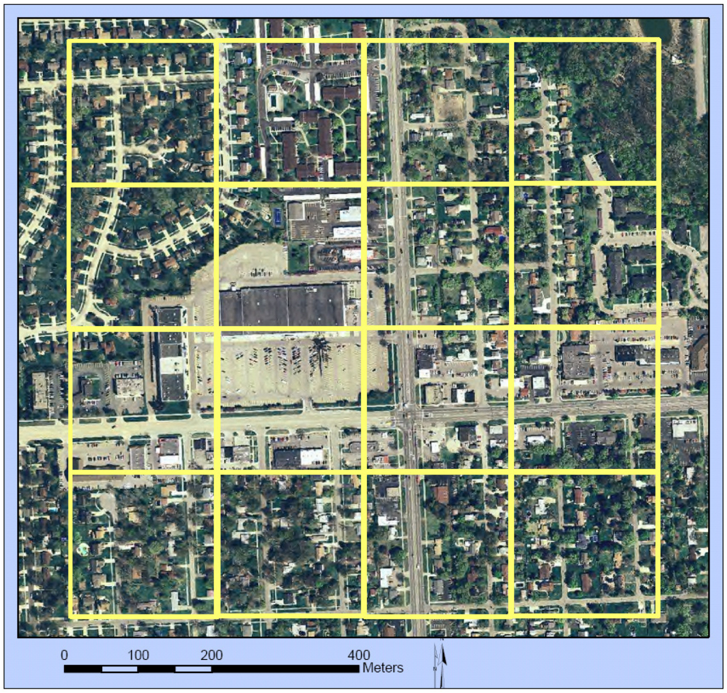

Figure 4-2 Example of cells with 200-by-200 meters cell size

1. Business density

   This measurement represents the total number of business employees divided by the area of a cell (40,000 m^2). Higher business density means that there are either more businesses or businesses with many employees located in one cell, providing more opportunities for non-work activities.

   Business types included in this measurement are carefully selected to reflect the opportunities for drivers' non-work activity (shown in Table 4-4). Only businesses that are likely to be visited by drivers for at least a few times in a year for non-work purposes are included in the measurements. Three categories of businesses are selected including: shops (super market, retail single use, convenient store, gas, and etc.), eating and drinking places (restaurants and fast food), and personal businesses (insurance carriers, real estate, hospitals, legal services, educational services, and membership organizations). Within the educational services, only elementary and secondary schools and libraries are included. Colleges, schools, and universities are excluded with the assumption that they are less likely to be visited as locations for non-work activities. For students, going to school is regarded as work-related activity.

Table 4-4 Business establishments used in the business density measure

Business Categories	First two digits of Standard Industrial Classification (SIC) code	Business types
Shop	52	Building materials, hardware, garden supply, & mobile home
	53	General merchandise stores
	54	Food stores
	55	Automotive dealers and gasoline service stations
	56	Apparel and accessory stores
	57	Furniture, home furnishings and equipment stores
	59	Miscellaneous retail
Eating and drinking	58	Eating and drinking places
Personal business	60	Depository institutions
	61	Nondepository credit institutions
	63	Insurance carriers
	64	Insurance agents, brokers, and service
	65	Real estate
	72	Personal services
	75	Automotive repair, services, and parking
	76	Miscellaneous repair services
	78	Motion pictures
	79	Amusement and recreational services
	80	Health services
	81	Legal services
	82	Educational services
	83	Social services
	84	Museums, art galleries, botanical & zoological gardens
	86	Membership organizations
	88	Private households
	89	Miscellaneous services

Note: certain business types are excluded from the above categories. Refer to Appendix 1 for more detailed information.

2. Business diversity

   The number of unique business types, out of the three categories of businesses identified above, is used to represent the business diversity. Based on this simplified scheme, the maximum business density is three. The higher the business density value of a cell, the more variety of businesses is mixed together in that location, providing more choices for various types of non-work activities.

3. Road connectivity

   Four-way intersection density is used to reflect the road connectivity. It is derived by dividing the total number of four-way intersections (excluding freeway intersections) by the land area excluding water. Higher road connectivity means that a grid-type of street network provides more direct routes and a greater choice of routes to destinations, which should reduce travel distance per destination. However, with more possibility of turns and stop-and-go situations, this grid-like street type might increase the rate of energy consumption and emissions.

4. Road functional class

   The ratio of the length of low function roads to all roads is used to reflect the overall road function in a cell. Based on road function classification defined by Federal Highway Administration and the Center for Geographic Information in Michigan, this study grouped roads into four main categories: arterials with limited access such as limited access interstates (A1), arterials without limited access such as US highways & state highways (A2), collectors and locals (A3), and other roads (A4-A9). Collectors and locals are considered as low function roads. Higher proportion of low function roads means lower speed limit and more speed variation which might increase energy consumption rate. Low function roads also provide more access to the surrounding lands. The relationships between road function and land access is discussed later in this chapter.

The above built environment features are measured at three types of urban spaces: space near a driver's home, work site, and along commuting routes. The sizes of the three urban spaces to be studied for all drivers are determined endogenously by the spatial distribution of the non-work activities from the 34 drivers who have one work locations. Euclidean distances between non-work activities (linked in different types of tours) and home locations, work sites, or straight lines connecting home and work are calculated. The results are shown in Table 4-5. The median distances between all non-work activities chained in HNH tours and home locations (4.6 miles), non-work activities chained in WNW tours and work locations (1.9 miles), and non-work activities chained in HNW or WNH tours and commuting routes (0.96 miles) are selected to represent the buffer sizes of the three urban spaces (highlighted in grey). The urban spaces defined in this manner could capture a significant amount of non-work activities (i.e. more than half of activities) and presumably have a closer relationship with drivers' travel decisions. Only the built environment features located in these spaces are studied for each driver.

Table 4-5 Distances between non-work activities and home, work, and commuting routes, by tour types, for drivers with only one work location

Types of tours which non-work activities belong	Number of non-work activities	Mean/Median	Distance to home (miles)	Distance to work (miles)	Distance to straight lines connecting home and work (Miles)
H-D...D-H	1772	Mean	14	17	6
		Median	5	10	1
H-D...D-W	238	Mean	6	5	2
		Median	5	3	1
W-D...D-H	470	Mean	12	11	4
		Median	6	5	1
W-D...D-W	152	Mean	11	5	3
		Median	10	2	1
Other	86	Mean	20	18	10
		Median	22	17	6
Total	2718	Mean	13	14	5
		Median	5	8	1

The cell-based built environment measurements (business density, business diversity, road connectivity, and road functionality) are weighted and aggregated to each of the three urban spaces, which results in twelve final built environment scores for each driver. The calculations of the built environment scores for home-related/work-related and route-related urban space are essentially the same, although with a few modifications. Weights for cells located in home-related and work-related urban spaces are determined by two factors: the closeness of cells to home or work locations and the visit frequency of home or work locations. The general rule is that farther cells have lower weights and frequently-visited home or work locations bring higher weights to all surrounding cells.

More specifically, the built environment measurements near home and work are determined by equation 1, where b_i represents one of the four built environment dimensions measured for cell *i,* and d_i is the distance between cell *i* and the key locations (either home or work). Corresponding annotations can be found in Figure 4-3. v represents the visit frequency of home or work.

$$B_{home/work} = v\sum_i \frac{b_i}{d_i^2} \qquad \textbf{Equation 1}$$

The above equation is essentially a gravity model, the most commonly known type of spatial interaction models. Gravity model, following the Newton's formulation of gravity, assumes that the interaction between two regions is a function of the properties of the regions and the distance between them. Similarly, equation 1 assumes that the interaction between home/work (where people live or work) and the surrounding built environment is a function of the property of the built environment and the distance between home/work and the built environment. It also assumes that the interaction is inversely proportional to the distance squared.

Ideally, the denominator (in this case, d_i^2) should reflect drivers' perceived impedance of having interactions with cell *i.* It can be specified in different ways. The specification can be guided by observing the actual interactions (trip-making pattern) or by studying drivers' perceptions. However, the actual trip-making behaviors may not reflect the perceived impedance as it may be constrained by the available built environment. And without in-depth study on drivers' perceptions, this study made a simple assumption that driver's perceived impedance is proportional to the distance squared. Compared to other impedance functions such as the inverse distance or exponential function, this specification places much more weights on the built environment in cells nearby and the weights decreases much faster as distance increases. Limitations of such selection are discussed in Chapter 7.

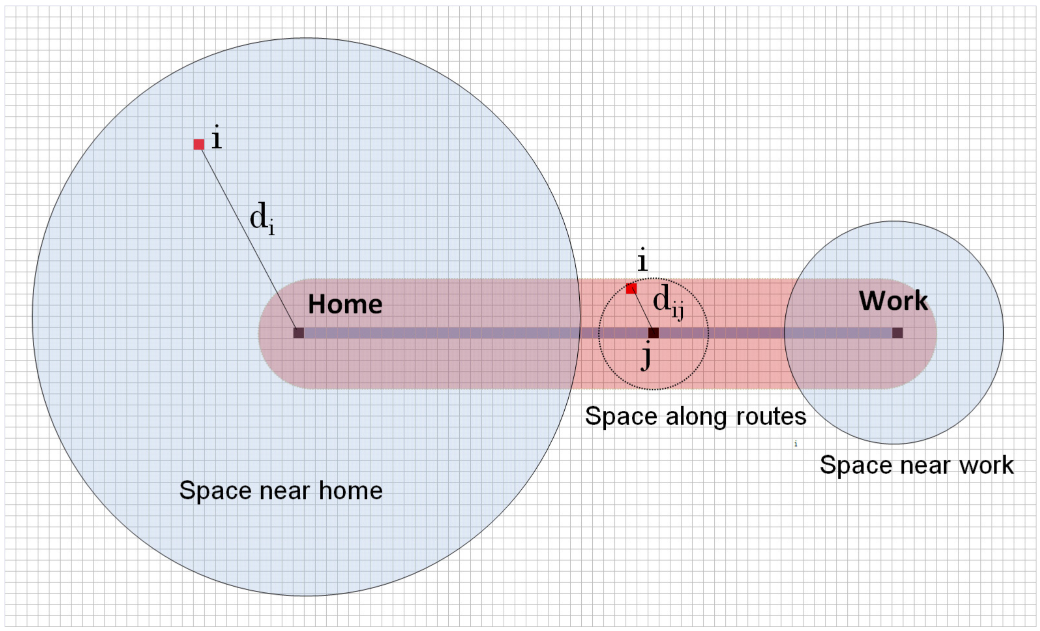

Figure 4-3 Illustration of geographic scale identification and cell weights

Note: refer to **Figure 3-2** for the conceptual geographic scale

Route-related built environment scores are calculated based on a two-step aggregation procedure as shown in equation 2. Imagine a driver moving along his/her commuting routes from one road segment to another. At each road segment (such as the road segment *j* in Figure 4-3), this driver experiences the surrounding built environment located at all directions. Farther built environment cells will have less influence on this driver at road segment *j*. Following this logic, the weighted average of the built environment measurements for all surrounding cells that are located within one-mile distance from the road segment *j* are calculated to reflect the built environment experienced by this driver at location *j*. The component of $\sum_i \frac{b_i}{d_{ij}^2}$ in equation 2 represents the first-level aggregation.

$$B_{route} = \frac{1}{n}\sum_j v_j a_j \left(\sum_i \frac{b_i}{d_{ij}^2} \right) \qquad \text{Equation 2}$$

In the second step, the built environment measurements for each road segment are further aggregated to represent the built environment characteristics for the entire commuting routes as a whole. In this step, road segments are weighted by their visit frequency in the one-month survey period (represented by v_j) and land access (represented by a_j). n represents the total number of road segments located on commuting routes. Frequently travelled road segments with unlimited access to the surrounding lands (e.g. residential roads) have higher weights. The underlying assumptions are that drivers experience, learn, and conceptualize the environment by travelling through it. The more frequently travelled road segments are likely to correlate with more spatial knowledge about the abutting opportunities. Also, limited access roads such as interstate highways are likely to block the spatial information otherwise perceivable by drivers.

The concept of land access is illustrated by the Federal Highway Administration (FHWA) on the following figure (Federal Highway Administration 1989):

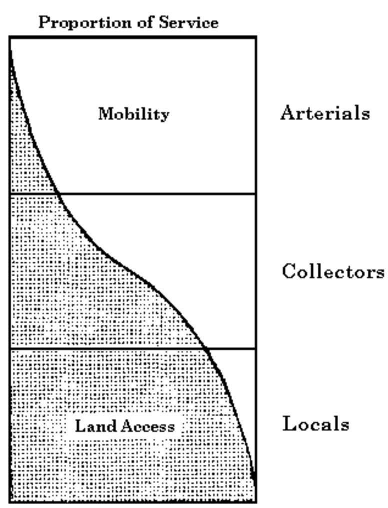

Figure 4-4 Relationship of functionally classified systems and land access

Source: Federal Highway Administration, FHWA Functional Classification Guidelines, 1989

Higher functional roads such as arterials serve primarily through traffic with higher mobility (i.e. higher operating speed or shorter trip travel time). However, land access decreases as mobility increases. Local roads which have the lowest mobility provide much more access to the surrounding properties.

Based on the above illustration, this study proposes the following weighting system on different classes of roads according to their level of land access. a_j in equation 2 represents land access weights.

Table 4-6 Weighting system for land access

Road functional class	Land access weights (a_j)
Arterials with limited access such as limited access interstates and freeways (A1)	0
Arterials with non-limited access such as US Highways & State Highways (A2)	1
Collectors and Locals (A3)	2
Other roads (A4-A9)	2

Note: the classification code is defined and used by the Center for Geographic Information in Michigan.

As defined, arterials with limited access have zero weights because drivers get limited information of and limited access to the surrounding lands when driving on these roads. Arterials with unlimited access have weight score of one as they provide better land access than arterials with limited access. Other roads which primarily serve local traffic have the highest weight with a score of two as they have the lowest speed limit and presumably drivers have more opportunities to learn and conceptualize the surrounding properties. The actual numbers of the weights are determined arbitrarily. They do not represent the absolute values of land accessibility; rather, they reflect the relative level of land access for one type of roads compared to other types. Representative images for each road category are shown in the following figures, all of which are generated from the Street View in Google maps[6].

[6] Street View was launched by Google Maps in May 2007 to allow users to explore the world through images. The feature provides users 360° horizontal and 290° vertical panoramic street level views within Google Maps.

Figure 4-5 Arterials with limited access: Interstate 696, Michigan

Source: Street View in Google map

Figure 4-6 Arterials with unlimited access: Woodward Ave., Michigan

Source: Street View in Google map

Figure 4-7 Collectors and locals: South main, Ann Arbor, MI

Source: Street View in Google map

Determining the connections

To answer the research questions and to test the six hypotheses, this study developed multiple regression models which consider travel outcomes as a function of the built environment by controlling for driver age and gender. The multivariate regression models take the following form:

$$D = \sum_{i=1}^{n} B_i \beta_i + \sum_{j=1}^{m} C_j \alpha_j + \varepsilon \qquad \text{Equation 3}$$

Where D represents one of three travel outcome variables, B_i represents the i^{th} built environment variable, β_i is the coefficient for B_i, C_j represents the j^{th} control variable, and α_j is the coefficient for C_j. Control variables include driver gender and age. ε represents the error term containing factors not controlled in the model.

The analyses use three sets of travel outcomes as dependent variables to test the research hypotheses. The travel outcomes include: 1) total VMT traveled for non-work purposes; 2) the rates of fuel consumption and emissions for non-work travel; 3) total fuel consumption and emissions for non-work travel. The third dependent variables are essentially the product of the previous two.

In the first step, simple linear correlation analysis is conducted to test for the existence of significant relationships between the built environment and travel outcomes. Multiple regression models are then constructed to test the directions and magnitudes of the relationships by controlling for other factors such as age and gender. Independent variables are entered into regression models in a stepwise manner in which, at each step, the variable with the lowest probability (or highest probability) of F statistic are added to (or removed from) models.

In addition to the three main dependent variables illustrated above, this dissertation also conducts similar correlation and regression analysis to examine several intermediate variables (tour generation or tour length by types of tours) as a function of the built environment features. These analyses on intermediate variables contribute to the understanding about interconnections between the built environment and travel outcomes.

Chapter 5
GPS Methodology Development

Introduction

This chapter summarizes the methods and algorithms developed to derive essential travel behavior attributes and outcomes based on tracks of GPS points.[7] Methods covered in this chapter include data preprocessing procedure which identifies valid/invalid trips, identification of intermediate stops (stops made in the midst of a trip), aggregation of trip ends into single destinations, home and work place identification, map matching which locates GPS traces to the underlying road networks, and the estimation of energy consumption and emissions through the application of the Comprehensive Modal Emissions Model (CMEM). This chapter illustrates these methods in the order given above, in comparison with existing methods used in other studies. To validate some of the methods used, a comparison is made between trip metrics derived from the NDD GPS dataset and from the 2001 National Household Travel Survey data (NHTS).

Preprocessing and trip definition

The original data consisting of second-by-second GPS coordinates require extensive preprocessing procedures before they can be further used to construct the comprehensive database of travel behaviors. The primary goal of preprocessing is to detect invalid trips, and to evaluate the accuracy of the GPS dataset in preparation of algorithms developed later.

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[7] Most of the results in this chapter have been published in Journal of Urban Technology Grengs, J., X. Wang and L. Kostyniuk (2008). "Using GPS Data to Understand Driving Behavior." Journal of Urban Technology **15**(2): 33 - 53.

A trip is defined as a vehicle movement which is initiated by a successful engine start and ended by an engine shut-down. Vehicle movement is the result of changes in vehicle positions. Based on this definition, the actions of engine turn-on and shut-downs without vehicle movements cannot be qualified as trips. On the other hand, a trip's origin and destination could be the same as long as there is vehicle movement in between.

A trip defined in this way represents vehicle travel only, and does not include travel by other means such as bus, bicycle, pedestrian, or on foot. Moreover, trips defined for one driver should contain all vehicle trips made by this particular person as the driver. In the NDD study from which the GPS data were obtained, all study subjects were asked to drive only the assigned instrumented vehicles for their normal everyday travel, and only the study subjects were to drive the instrumented vehicles. Thus, we are reasonably confident that the NDD GPS traces contain the records of all vehicle trips driven by the study subjects during the study period.

According to the trip definition, two types of invalid trips from the original dataset were identified and screened out: trips with zero distance and trips without geographic information (latitude and longitude). There are 921 trips in which drivers kept the engine running but did not make a move. There are 169 trips which lacked latitude and longitude information for the entire trips, and they were discarded.

Intermediate stops

One of the limitations associated with the trip definition outlined above is that some stops may not be recognized by the current procedure because an activity may occur when the engine is running. For example, when drivers visit drive-through of banks or fast food restaurants, pick up passengers, or drop-off mails, they usually leave their vehicle engine running. In conventional travel surveys these events are recognized as stops for activities. In this study, such stops will be referred to as *intermediate stops*.

To detect the intermediate stops from the GPS traces, both time and location information needs to be considered. Each trip in the NDD dataset is composed of continuous second-by-second GPS traces. For each second, GPS device record the time and the vehicle location. Whenever the location of a vehicle is stationary (engine idling) while time elapses, an intermediate stop might occur. The idling duration can be used as a key criterion to detect intermediate stops. If idling duration is longer, the likelihood of an intermediate stop to occur is higher.

Following Stopher et al.(2003), who conducted controlled experiments to test the success rate of different idling durations on detecting intermediate stops, a two minutes was selected as the threshold idling duration. If a vehicle is stationary for a period longer than two minutes in a trip, an intermediate stop is assumed to occur. More detailed criteria are as follows: the difference in successive latitude and longitude values is less than seven meters; the heading is unchanged or zero; speed is zero; and the elapsed time during which these conditions hold is equal to or greater than 120 seconds. A computer algorithm was developed to flags all points that meet these conditions as intermediate stops.

One drawback to this method of identifying intermediate stops is that it solely relies on idling duration without considering other information. In reality, vehicle might be idling for quite a long time when drivers are waiting for traffic light or making a left turn. The current program may incorrectly identify such cases as intermediate stops; it may also miss out real stops whose idling durations are less than two minutes. Figure 5-1 shows such an example. The driver shown in this map detoured from major travel routes to stop in front of a building structure for one and a half minutes. It is very likely that an intermediate stop occurs at this location since this driver made a detour; however, the algorithm fails to recognize it because the idling duration is less than two minutes. Spatial information such as the relative locations of these idling points in comparison with previous or sequencing points can help to make corrections on the current algorithm.

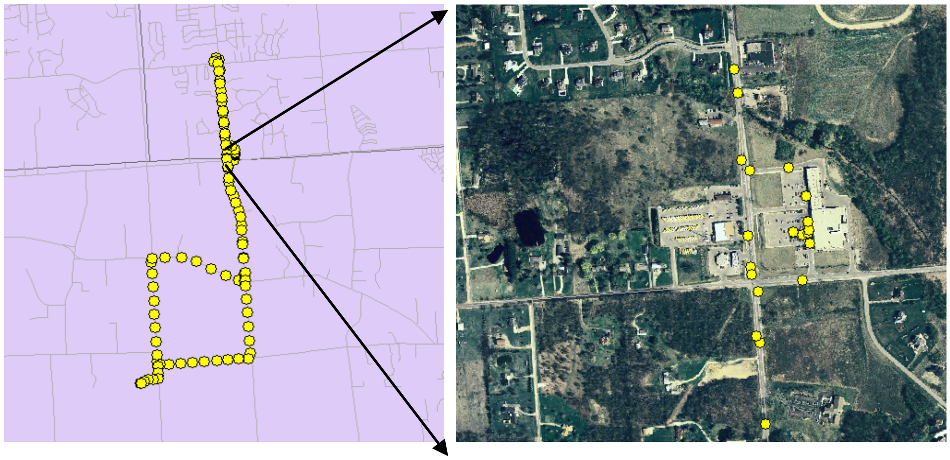

Figure 5-1 A stop with idle duration less than two minutes

Trip end aggregation and the clique concept

Quite often a driver's pattern may show trip ends that are located in close proximity to each other. The clustering of trip ends could indicate a single destination associated with these trips. An example is shown in Figure 5-2. Trip ends detected from the GPS points (shown in yellow dots) are overlaid with satellite images. It is shown that four trip ends are located at the same parking lot of a regional shopping center, suggesting that these four trips could be associated with a shopping activity at the same location.

Figure 5-2 An example of trip end aggregation

An aggregation algorithm was developed to analyze the clustering of points and merge points within a threshold distance. A threshold distance of 100 feet was selected and trip ends were aggregated whenever their distances among each other are less than 100 ft. The aggregation of trip ends into destinations is also an essential first step which helps to derive trip purpose later.

The choice of 100 feet as the threshold value is based on a sensitivity analysis which evaluates the effectiveness of trip end aggregation by testing various threshold distances ranging from 50 feet to 1000 feet (shown in Figure 5-3). As shown in the graph, the number of identified unique destinations decreases exponentially as the threshold distance increases. The trend line shown in Figure 5-3 has an "elbow" at the 100 feet distance, indicating that trip ends cannot be aggregated much further when threshold distance increases beyond 100 feet. With 100 feet threshold distance, trip ends can be aggregated by approximately 60% (12431 trip ends are aggregated to 4788 unique destinations).

There are several limitations to the current algorithm, because its performance heavily relies on the choice of the threshold distance. Trip ends might be mistakenly aggregated by current algorithm when they should not be (refer to as the *over-aggregation* problem); some trip ends are not aggregated when they should be (refer to as the *under-aggregation* problem). For instance, in a densely built urban setting where businesses are located close to each other, various trip destinations might be located within 100 feet from one another. The current program will consider these trip ends as associated with a single destination while they are not. In a more disbursed built environment with large parking spaces, trip ends which are farther apart (farther than 100 feet) may belong to the same destination. The current algorithm will incorrectly distinguish between them. In order to deal with this problem, threshold distances which are specific to different land uses need to be defined in the future. As shown in the following sections in this chapter, despite these limitations the 100 feet threshold is sufficient to help us identify potential trip destinations, especially the potential home and work locations and to help us discern a general pattern of travel activities.

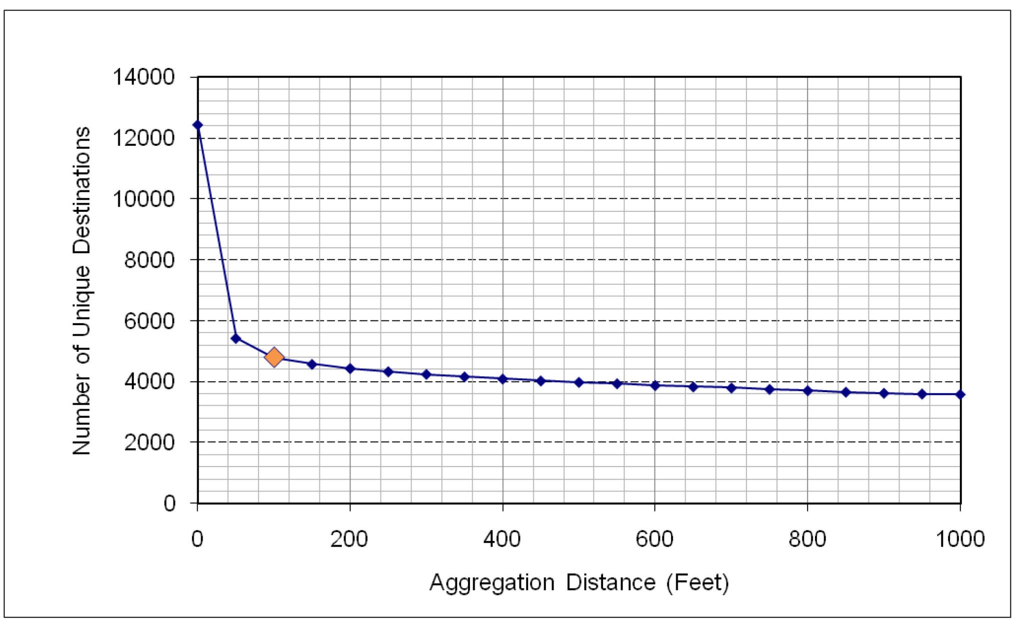

Figure 5-3 Sensitivity analysis of trip end aggregation

The algorithm to implement the aggregation described above with 100 feet threshold is what computer scientists refer to as *union-find algorithm* which solves *the maximum clique problem*. According to the graph theory, in a given graph containing vertices and edges (lines connecting vertices), a clique can be defined as a set of vertices each of which is connected with all other vertices in the same clique by edges (as shown in Figure 5-4). To solve the maximum clique problem is to find the largest clique in a graph. In this study, a graph contains nodes representing each latitude and longitude of a trip end for one driver. Edges are formed connecting nodes if and only if the edge length is less than the threshold distance (100 feet). This graph is then solved to find all maximal cliques, which represents a cluster of trip ends that are located within 100 feet from each other. The geographic center is then calculated for each maximum clique and the trip end closest to the geographic center will be assigned to represent the unique destination point.

Visit frequency for each unique destination was calculated by counting the related cliques. The average time that the driver spent at each destination was calculated as well. In the previous example shown in Figure 5-2, the orange triangle represents the identified single destination location (a clique) of these four separate trips.

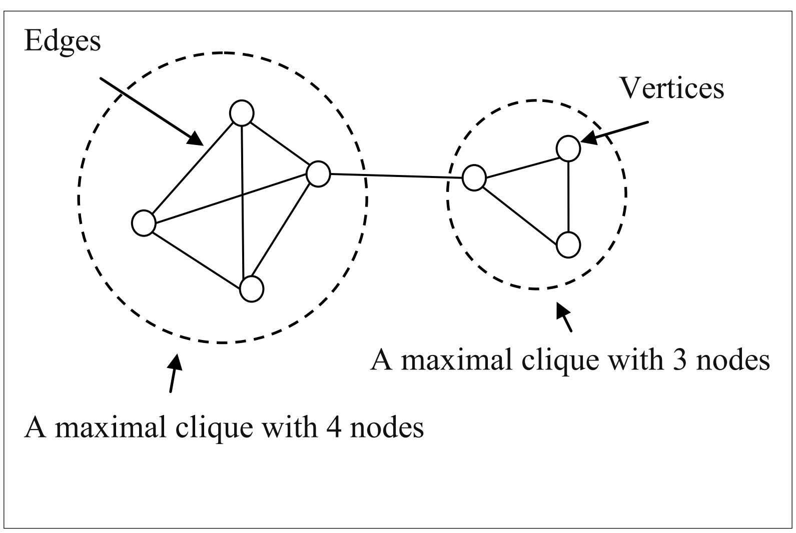

Figure 5-4 Examples of cliques

Trip Purpose Identification

Trip purpose is an important trip attribute which can often be easily collected by traditional self-reported travel diary. However, deriving trip purposes from GPS data poses a major challenge to this study. Successfully identifying trip purposes requires an innovative definition of different trip purposes, and a reliable process which capitalizes on the available information provided in the GPS dataset: location and time.

Where is home?

As required by the Institutional Review Board (IRB) for human subject research, the home address of each respondent was not available for this research. However, knowledge of home locations was critical for the analysis. To find drivers' home locations home must be defined first. Is home where we spend most of our time at? Is home the place we are most familiar with? In traditional transportation studies, survey respondents identify homes themselves. In comparison, in this study, homes are defined as places where drivers visit the most and spend most of their time at.

Based on this definition, home locations are identified for each driver through two steps. First, a set of destinations were chosen as a driver's potential home locations based on the following criteria: 1) the destination is visited at least 15 times in four weeks; 2) the average activity duration at the destination is more than six hours; and 3) the destination occurs within a land use category related to residential development.

Second, one and only one location among the potential homes was identified as the home. Based on the above criteria, most drivers had only one potential home location, and thus defined as the home. For drivers with more than one potential home locations, the destination with the highest visit frequency was defined as their home. For drivers without potential homes, the above criteria were relaxed until a single home location was reasonably assigned to this driver. Home identification process and results are summarized in Table 5-1.

Table 5-1 Home identification process and results

Number of Drivers	Identification Process
63	There is one and only one potential home following criteria.
5	more than one potential home, the clique with the highest visit frequency has the highest total activity duration, define the clique with the highest visit frequency as home
2	more than one potential home, the clique with the highest visit frequency do not have the highest total activity duration, define the clique with the highest visit frequency as home
6	no potential home, relax the activity duration criteria, choose the clique which the highest visit frequency when visit frequency>15times
2	no potential home, relax both the visit frequency and activity duration criteria, , choose the clique which the highest visit frequency

Note: 78 drivers in total

Where is work location?

Work or school location for each respondent was also not available directly for this research. Work/school location was identified in a way similar to home identification. The criteria to identify potential work locations for full-time workers working outside the home include: 1) destinations are not home locations; 2) destinations are visited at least eight times in four weeks; and 3) the average activity duration exceeds two hours.

Land use was not included as one of the criteria because jobs could be located in any type of land use categories. Drivers may have one or more work locations. Full-time students were not differentiated from workers as students are considered the same as workers with study as their job.

The above criteria produce a single work location for 36 drivers, two work locations for six drivers, and three work locations for five drivers. Thirty one drivers do not have work locations, who may be retirees, work-from-home workers, or part-time workers.

Manual checking and corrections of home and work identification

To further screen out identification errors, all identified home and work locations went through a manual checking process in which they were overlaid with land use data and aerial photographs.

Three types of identification errors were detected, all of which are due to the under-aggregation problem discussed previously (in the trip end aggregation section). Under-aggregation happens if trip ends were not aggregated when they should have.

Detailed identification errors and corresponding corrections include:

1. Multiple home and work locations which are falsely separated need to be further aggregated to produce a single home or work location. The indications of such errors are that the distances among identified home and work locations are close (slightly over 100 feet, but below 200 feet) and they appear to be on the same parking space.
2. Some trip ends are falsely separated from the identified home or work locations which need to be further aggregated to the identified home/work locations. The visit frequency of identified home and work locations should be increased.
3. Some home and work locations are omitted because trip ends associated with a single destination are mistakenly separated, which needs to be further aggregated to produce a new home or work location.

To correct these errors, the spatial distributions of important cliques (identified home and work cliques, cliques with large visit frequency, and cliques that are close together) were visually inspected as well. More detailed manual checking procedure is shown in Appendix 2: Manual checking procedure for home and work identification.

The manual correction results (summarized in Table 5-2) show that none of the home locations identified by previous criteria has aggregation errors and they are considered as the final home locations. However, a significant number of work locations are found to be in need of corrections. The number of work locations identified for 78 drivers before or after manual checking is shown in Table 5-2. Five out of the 78 drivers were excluded from this study because either their home/work places or commuting routes are located outside the study area.

Table 5-2 The number of work locations identified for 78 drivers, before or after manual checking

Number of Work Locations	Before Manual Checking	After Manual Checking
Driver without work location	31	29
Driver with one work location	36	36
Driver with two work location	6	10
Driver with three work locations	5	3
Total	78	78

Trip purpose identification for non-work trips

The above analysis demonstrates that, without self-reported travel survey information, it is feasible to identify drivers' home and work locations by using GPS data. The following section describes the effort which has been made to identify trip purpose for non-work trips. It can be concluded from this effort that non-work trip purposes such as shopping, eating, or personal businesses cannot be reliably identified by using GPS data alone. There are two factors which make this task difficult:

1) Non-work trips with different purposes may share similar characteristics. For instance, fast-food-meal trips may have similar time use patterns as convenient-store-shopping trips. They all require activity duration of about 20–30 minutes; both types of trips can occur at any time throughout the day; they may have similar visit frequencies.

2) It is difficult to associate single business establishment with a trip end. This difficulty results from the way business establishment data were geocoded. As shown in Figure 5-5, business establishment data obtained from the private business data vendor, InfoUSA, are geocoded along road networks (as shown in blue dots). The location of a business (recorded in the form of latitude and longitude) does not represent the geographic center of the actual building structure. In comparison, the latitude and longitude of trip ends provided by GPS data are much more precise (with the precision of 3 to 5 meters) (as shown in yellow dots). It is impossible to match a trip end with a single business.

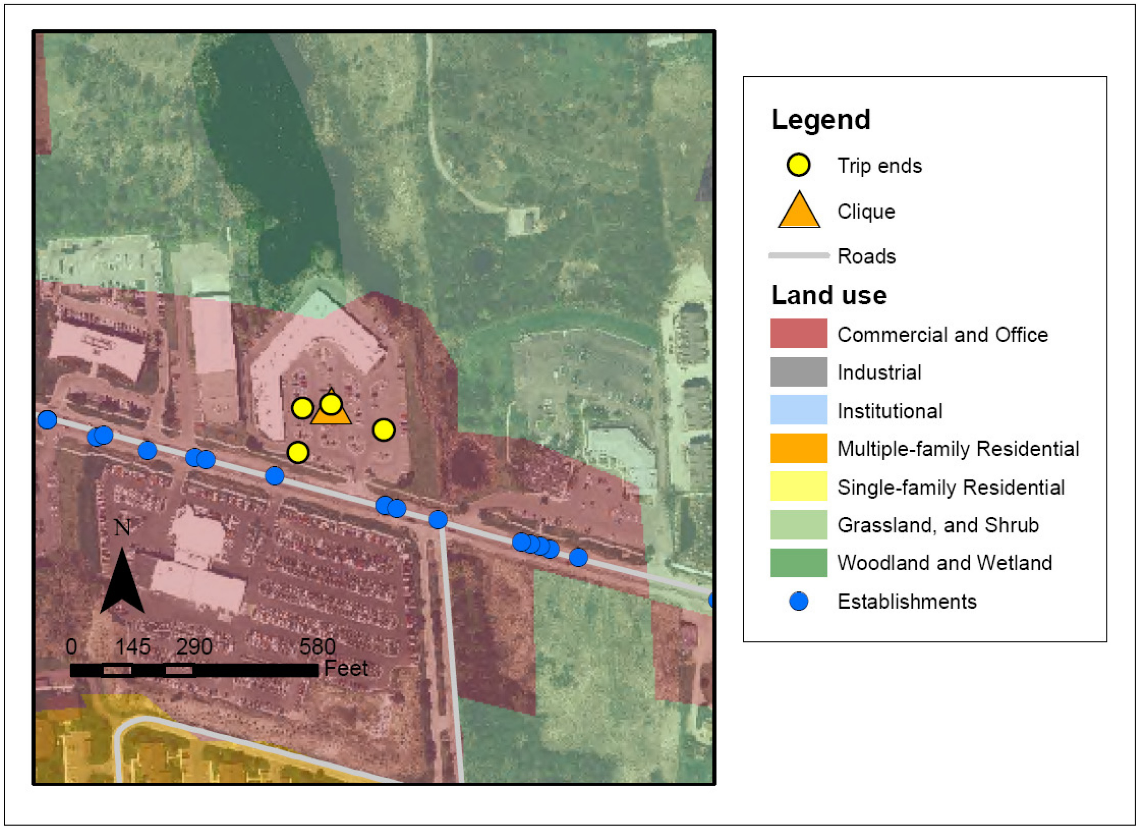

Figure 5-5 trip purpose identification for non-work travel

Existing literature has shown that deriving non-work trip purposes from GPS data requires acquiring precise and detailed land-use data such as parcel data and person-based rather than vehicle-based GPS data (Wolf 2000; Wolf 2001). Unfortunately, detailed land-use data cannot be obtained for all seven counties in the Southeast Michigan area and the GPS data were collected from the instrumented vehicles in this study. As a compromise, trip purposes for non-work trips were not further differentiated. Instead, all trips that are neither home trips nor work trips are grouped together as non-work trips.

Map Matching

To identify the routes that drivers used between home and work places, this study implemented a map matching procedure to match GPS points with the underlying digital road networks for commuting trips only.

Map matching, a common procedure to match two sets of spatial features, has been widely used in Vehicle Navigation Systems, in which the GPS-captured vehicle positions are matched with the road networks. There are a variety of map matching algorithms which have been developed, ranging from simple algorithms to more sophisticated ones. The basic types of map matching include point-to-point, point-to-curve, and curve-to-curve matching. The advantages and disadvantages of each method are thoroughly discussed in existing literature (Bernstein and Kornhauser 1996; White, Bernstein and Kornhauser 2000).

This study implemented a simple algorithm which the shortest paths run sequentially through all GPS points in a trip. The algorithm starts from the very first GPS point of a trip and evaluates the distances of all potential paths to the next GPS point. A path with the shortest distance is selected. Next, the algorithms moves on to the next GPS point and repeats the above process until all GPS points contained in one trip are visited and a travel route is generated.

The reason for choosing this algorithm is its simplicity and its capability of generating a topologically correct travel route (travel routes that are continuous and connected), which fulfills the need of this research. However, this simplified algorithm is less accurate than other more complicated methods because it does not consider the positional information of previous points; its performance is constrained by the accuracy of the digitization process of the current road network data which might be outdated or have missing road links; it does not consider signals lost at the beginning of a trip (consequently, there might be discrepancy between the trip end of a previous trip and the trip start of a next trip); and finally, it does not consider the turn restriction and one-way restriction.

The road network provided by the Center for Geographic Information in Michigan (CGIM) was selected to be matched with the NDD GPS dataset. It is shown in Figure 5-6 that, the CGIM road network data is as precise as the NDD GPS data and they can line up with each other properly.

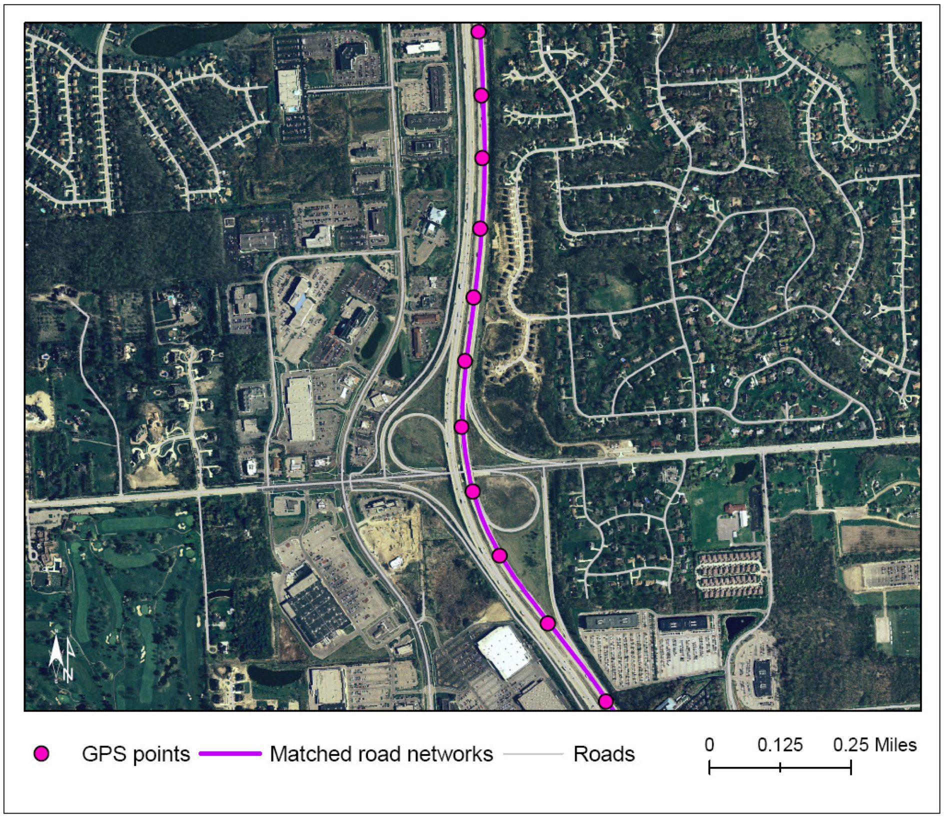

Figure 5-6 An example of map matching

CMEM model

The Comprehensive Modal Emissions Model (CMEM) developed by the University of California, Riverside is used to estimate the second-by-second fuel consumption and vehicle tailpipe emissions of carbon dioxide, carbon monoxide, hydrocarbon, and nitrogen oxides for the vehicle trips in this study.

The key inputs of CMEM model include the vehicle activity records (represented by second-by-second speed), the types of the vehicle (such as normal emitting cars or trucks, high emitting or low emitting vehicles), and soak time. Soak time, defined as the duration of time in which the vehicle's engine is not operating and which precedes a successful vehicle start (i.e. one that does not result in a stall)[8] has considerable influence on exhaust

[8] http://www.crwr.utexas.edu/gis/gishydro01/Class/trmproj/Sivakumar/Termproject.html

emissions. If a vehicle has been soaked for a long time (more than 12 hours), the first few minutes of driving of a new trip will result in higher emissions as the emissions-control equipment has not reached its optimal operating temperature (EPA 1994).

The second-by-second speed information contained in the NDD GPS dataset was used as inputs for the vehicle activity. Nissan Altima, a vehicle model used by all the drivers from our study, belongs to the normal emitting car category in CMEM[9]. The soak time was calculated for each trip by subtracting the trip start time from the end time of the previous trip[10].

CMEM generated the estimations of fuel consumption and emissions for every second in a trip, which were then aggregated to represent the overall level of fuel consumption and emissions for all non-work trips of each driver. The descriptive statistics of energy and emissions are provided in Chapter 8 Travel Behaviors and Outcomes.

Data validation and comparison

To determine if the trip characteristics of the study subjects were reasonable, trip metrics were derived from the NDD GPS data and compared against measures obtained from the 2001 National Household Travel Survey data (NHTS). NHTS is conducted periodically by US Department of Transportation, and collects data on daily travel patterns from a representative sample of people in the United States. For this comparison, trip data from the Detroit-Ann Arbor-Flint consolidated metropolitan statistical area (CMSA) was extracted from the NHTS database.

Table 5-3 to Table 5-7 shows the comparisons between NDD and NHTS data on trip generation, trip distances, and travel duration for trips traveled by privately-owned

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[9] CMEM model has tested Nissan Altima 1996 model (category 11) and 1993 (category 7). The vehicle used in NDD database is Nissan Altima 3.5SE sedans with model year 2003. The default vehicle parameters of CMEM category 11 were used in this study, assuming that vehicle characteristics do not have significant changes from model year 1996 to 2003.

[10] The maximum soak time programmed in CMEM is 1440 minutes. Any soak time longer than that will be automatically changed to 1440 minutes. 1440 minutes soak time was also assigned to the very first trip in the survey period of each driver, assuming that that the instrumented vehicles have been soaked for at least 24 hours before it was given to drivers.

vehicles. Trip characteristics shown in these two datasets are expected to be similar, but not identical. The reasons are that both NDD and NHTS datasets were collected roughly in the same time frame – NDD in the year 2001 and NHTS in the year 2004. Major behavioral changes in travel are less likely to have happened during these years. Meanwhile, travel patterns shown in these two datasets might be different, primarily due to different data collection methods, different samples, and different definition of a trip and trips with different purposes.

As shown in Table 5-3, there are 1,152 persons participated in the NHTS survey. In comparison, the sample size in NDD dataset is much smaller, only 73 drivers. The NHTS was conducted as a telephone survey, using Computer-Assisted Telephone Interviewing (CATI) technology. The survey was mailed to households in the format of trip diaries so that that each household member could record their travel on the assigned single travel day. As for the design of NDD data collection process, each survey respondent drove an instrumented vehicle for a consecutive 25-day travel period, which means that NDD dataset only provides data related to vehicle trips. Compared to NDD, the NHTS dataset contain trips conducted by all travel means, such as buses, bikes, walking as well as vehicles.

The 1,152 persons in the NHTS sample generated 4,884 trips, 4,375 of which are vehicle trips in the one-day survey period. Assuming that the survey respondents in NHTS conducted the same amount of travel each day for 25 days, the 1,152 persons are likely to generate 109,375 vehicle trips. The average number of vehicle trips per person is 95, as shown in Table 5-3, which is smaller than the number in NDD (129.8 for 25 travel days). The numbers overall, are on the same order of magnitude. As shown in Table 5-5, the average vehicle trip distance and trip duration is 8.5 miles and 15.4 minutes respectively in the NDD dataset while the corresponding numbers in NHTS is 8.9 miles and 17.6 minutes.

Table 5-3 Comparison of NDD and NHTS data on person trip characteristics

	2001 NHTS in Detroit-Ann Arbor-Flint MSA*	2004 NDD
Total survey respondents	1152	73
Total trips (including vehicle trips)	122,100	-
Total vehicle trips	109,375	9,476
Average trips per person	106	-
Average vehicle trips per person	95	129.8

Note: * the data for NHTS has been adjusted to 25 days to be comparable with the NDD data.

The following two tables (Table 5-4 and Table 5-5) show that NDD dataset contains slightly higher percent of non-work trips (60.5%) than NHTS dataset (58.8%). Non-work trips in NDD are shorter in distance on average (8.3 miles in NDD, compared to 8.7 miles in NHTS) and faster in time (mean trip duration is 14.7 minutes in NDD, compared to 16.7 minutes in NHTS). Despite the differences, both datasets show that non-work travel is the single dominant type of travel in drivers' daily activities, and work trips, which have been the focus of traditional transportation studies, form the smallest share of the total trips and have the longest average distance.

Table 5-4 Comparison of NDD and NHTS data on vehicle trip generation by trip purposes

	NDD 2004		NHTS 2001	
Trip Purpose	N	% of Total N	N	% of Total N
Non-work	5730	60.5%	2572	58.8%
Home	2767	29.2%	1463	33.4%
Work	979	10.3%	340	7.8%
Total	9476	100.0%	4375	100.0%

Table 5-5 Comparison of NDD and NHTS data on vehicle trip distances and vehicle trip durations by trip purposes

	NDD 2004		NHTS 2001	
Trip Purpose	Mean Distance (miles)	Mean Vehicle Trip Duration (minutes)	Mean Distance (miles)	Mean Vehicle Trip Duration (minutes)
Non-work	8.3	14.7	8.7	16.7
Home	8.3	15.8	8.2	17.6
Work	10.3	18.6	14.0	23.9
Total	8.5	15.4	8.9	17.6

NHTS and NDD datasets demonstrated similar travel patterns for people living in the Detroit metropolitan area. This result confirms the validity of the NDD data collection effort and the reliability of the processing methods. However, differences do exist as respondents from NDD dataset produced more vehicle trips per person with shorter distances and had shorter travel time per trip than NHTS. There are several possible explanations of this discrepancy between these two datasets, as summarized below:

1. Trip definitions are different in the two datasets. NHTS defines a travel day trip as "any time the respondent went from one address to another by private motor vehicle, public transportation, bicycle, walking, or other means." NHTS does not consider a movement as a trip when 1) the movement is to get to another vehicle or mode of transportation in order to continue to the destination; 2) the movement is within a shopping center, mall or shopping areas of 4-5 blocks. However, these two types of trips which are excluded from NHTS are included in NDD dataset. In NDD, a trip is defined as a movement from one location where a vehicle's engine was turned on to another location where the vehicle's engine was turned off. The vehicle trip definition is more inclusive in NDD dataset which includes all types of vehicle movements regardless of its purposes and distances. As a result, the trip generation in NDD dataset could be higher.

2. Sample compositions are different. As shown in Table 5-6 and Table 5-7, the gender composition in these two dataset are roughly the same while the age composition is not. In the NDD dataset, respondents are divided equally into three age groups and each group constitutes about one third of the total sample size. However, in the NHTS dataset, only 9% of the total respondents are from younger groups and 21% are from older groups. Higher percent of younger and older drivers in the NDD dataset may lead to a shorter average travel distance and travel time per trip as these types of drivers may not have the ability or are not willing to travel long distances.

3. Survey methods are not the same. The NHTS implemented a trip diary method where survey respondents use pens or pencils to keep track of their travel activities. The quality of the survey data are heavily relied on the memory and

record-keeping ability of the respondents. Short-distance trips can be easily forgotten and missed out. On the contrary, the GPS data from NDD kept records of all movements made by respondents with a very high precision in both time and location, which could lead to a higher and more accurate trip reporting rate.

Table 5-6 Comparison of NDD and NHTS data on sample composition by gender

	NDD 2004		NHTS 2001	
	Number of Drivers	% of Total N	Number of Respondents	% of Total N
Female	37	51%	593	51%
Male	36	49%	559	49%
Total	73	100%	1152	100%

Table 5-7 Comparison of NDD and NHTS data on sample composition by age groups

	NDD 2004		NHTS 2001	
	Number of Drivers	% of Total N	Number of Respondents	% of Total N
Younger (18-30)	24	33%	98	9%
Middle (31-50)	25	34%	351	30%
Older (51-70)	24	33%	245	21%
Other	0	0%	458	40%
Total	73	100%	1152	100%

In summary, this chapter has demonstrated that it is feasible to derive essential travel attributes based on the passive in-vehicle GPS data. Efforts were devoted to derive trip purposes, identify commuting routes, and estimate energy consumption and emissions from the current GPS traces. In comparison with the 2001 National Household Travel Survey data (NHTS), NDD dataset has shown similar travel patterns in the Detroit metropolitan area, in terms of trip generation rate, trip length, and durations, which confirms the validity and reliability of the processing methods. The trip metrics derived above provided us the essential travel information to be used later in this dissertation.

Chapter 6
Analysis of Travel Behavior and Its Energy and Environmental Outcomes

Introduction

The objective of this chapter is to examine the travel behavior and travel outcomes of the 73 drivers with different demographic features from Southeast Michigan. By analyzing travel attributes tabulated with trip purpose and with drivers' age and gender, the trip-making patterns observed from this exploratory analysis show that travel characteristics vary for drivers with different demographic characteristics. This needs to be controlled for in the regression analysis constructed in later chapter in order to understand the connections between the built environment and travel outcomes.

The spatial aspects of non-work trips and tours are examined spatially and quantitatively. The spatial analysis of the non-work activities shows that urban space near home, work, and commuting routes are three important urban spaces which contain a majority of the non-work activities conducted by drivers. The median distances from non-work activities chained in different types of tours to home, work sites, and commuting routes are calculated to identify the sizes of the urban spaces to be studied quantitatively. Identifying the shape and sizes of the three urban spaces endogenously through the spatial distribution of the non-work activities allows us to identify the urban spaces which have most potential in influencing travel behavior and outcomes.

In the last section of this chapter, energy consumption and emissions are estimated using the instantaneous CMEM model.

Trip-based analysis

Trip characteristics, by drivers' gender and age

In this study, trips are defined as the vehicle movements during which the engine is running. The turn-on and shut-off of an engine correspond to the start and the end of a trip. Each of the 73 drivers participated in the study for four weeks, and collectively generated a total of 9,476 trips that covered 80,529 miles in 2,433 hours driving. The average trip length was 10.1 miles and the average trip duration was 17.8 minutes.

Descriptive statistics on several key trip attributes show that, compared to men, women tend to generate fewer trips (123 trips in four weeks for women and 137 trips for men), shorter trips (the mean trip distance for women is 9.94 miles and 10.27 miles for men), and less total VMT and VHT on average (summarized in Table 6-1). The average trip duration for men and women are roughly the same.

Table 6-1 Trip characteristics by gender

	Number of drivers	Mean number of trips per person in four weeks	Mean VMT per person in four weeks (miles)	Mean trip duration per person in four weeks (minutes)	Average trip length per trip (miles)	Average trip duration per trip (minutes)
Women	37	123	1,006	1,867	9.94	17.81
Men	36	137	1,203	2,135	10.27	17.87
Total	73	130	1,103	1,999	10.10	17.84

Table 6-2 shows the summary of trip generation patterns by age groups. The 73 drivers are divided into three age groups (20–30, 40–50, 60–70) equally. Younger drivers generated the largest number of trips (150 trips on average in four weeks), resulting in the highest total VMT among the three age groups. Trips conducted by middle-age drivers have the longest mean trip distance (10.95 miles) and trip duration (18.65 minutes). Older drivers generate the smallest number of vehicle trips with the lowest mean VMT and the shortest mean trip duration.

Table 6-2 Overall trip characteristics by age groups

	N	Mean number of trips per person in four weeks	Mean VMT per person in four weeks (miles)	Mean trip duration per person in four weeks (minutes)	Average trip length per trip (miles)	Average trip duration per trip (minutes)
Younger	24	150	1,266	2,290	10.22	17.57
Middle	25	126	1,198	2,068	10.95	18.65
Older	24	113	842	1,638	9.10	17.26
Total	73	129	1,103	1,999	10.10	17.84

Table 6-3 shows various trip attributes by trip purposes. Non-work trips constitute the highest percentage (60.5%) of all trips, followed by home trips (29.2%) and work trips (10.3%). The average distance of non-work trips is 8.3 miles which is the shortest among all three types of trips. However, because of the large amount of trips generated for non-work purpose, the total distance traveled and total trip duration for non-work trips is the highest among all three groups of trips. These numbers make it evident that travel to non-work activities is very important and thus its potential economical and environmental outcomes deserve attention from researchers and policy makers.

Table 6-3 also shows that non-work travel is the most flexible type of travel as it has the highest variance in both trip distance and trip duration. Compared to non-work trips, work trips have relatively fixed locations and travel durations. This study primarily focuses on non-work travel which should have a stronger connection with the built environment.

Table 6-3 Trip summary by trip purposes

Trip Purpose	N	% of Total N	Mean Distan ce (miles)	Mean Trip Duration (minutes)	Total Distance (miles)	Total Trip Duration (minutes)	Variance of Trip Distance	Variance of Trip Duration
Non-work	5730	60.5%	8.3	14.7	47,449.2	84,097.4	275.2	342.4
Home	2767	29.2%	8.3	15.8	22,992.5	43,641.2	191.8	309.6
Work	979	10.3%	10.3	18.6	10,087.6	18,217.4	111.3	238.0
Total	9476	100.0%	8.5	15.4	80,529.4	145,955.9	234.3	323.4

Spatial analysis of trips

The following section first analyzes the visit frequency of distinct trip destinations in the four-week survey period. Visit frequency of destinations measures the regularity of trips in terms of its reoccurrence at distinct locations over time. According to the anchor point theory proposed by behavior theorists Golledge and Stimson (1987), destinations which are visited a considerable amount of times by a driver are core destinations (dominant destinations) which structure the rest of this individual's activity patterns.

According to this theory, initially important locations such as home, work, and shopping places anchor the set of spatial information grasped by an individual. Individuals constantly search for paths through which the primary nodes or anchor points are connected. As a result, the urban space around core destinations (such as home and work location) and along major corridors connecting core destinations could influence people's travel behavior. This notion provides an important theoretical base and motivation to identify the core destinations and examine the various urban spaces near them, within which drivers are travelling and interacting with the built environment.

The visit frequency analysis for all trips shows the core destinations whose nearby built environment becomes the focus of this dissertation. In the next step, the geographic locations of all non-work trip destinations for drivers who have one work location are transformed and mapped on a two-dimensional coordinate system. The purpose of this spatial analysis of non-work activities is to visually and quantitatively identify the urban spaces that were frequently visited by drivers and hence have potential important associations with drivers' travel behavior and outcomes. The spatial analysis for drivers with two or more work locations is not included in this section because it requires more advanced techniques to visualize all work locations. This is not further pursued.

Visit frequency analysis and core destinations

All unique destinations (represented by cliques) were sorted and ranked by the number of times they were visited by each driver. The destination with the highest visit frequency is ranked the highest. The average visit frequency for the destination with the same rank across drivers was calculated and plotted against its rank.

Figure 6-1 shows the average visit frequency for destinations from rank one to ten. As shown in the figure, the most-visited destination for an average driver has been visited 36 times in four weeks, which is three times more than the average visit frequency for the second most-visited destination (13 times in four weeks) and five times more than that of the third most-visited destination (7.5 times in four weeks). The average visit frequency decreases dramatically as the rank goes from one to three and levels off when the rank moves beyond three. This pattern indicates the existence of three most important reoccurring destinations for most drivers. Drivers visit these destinations with a considerable frequency.

Figure 6-2 illustrates the same patterns by showing the percentages of trips (of a person's total trips) visiting these reoccurring destinations against the rank of the destinations. It shows that for an average driver, about 46.5 % of his/her total trips visit the top three destinations, whereas the rest of the trips go somewhere else. This finding is consistent with the research results published by Huff and Hanson, who examined the temporal and spatial regularities of people's activity by using 5-week travel diary data in Uppsala, Sweden and concluded that core stops (stops visited four or five times in 35 days) account for about 57% of each person's total stops (Huff and Hanson 1990: 233).

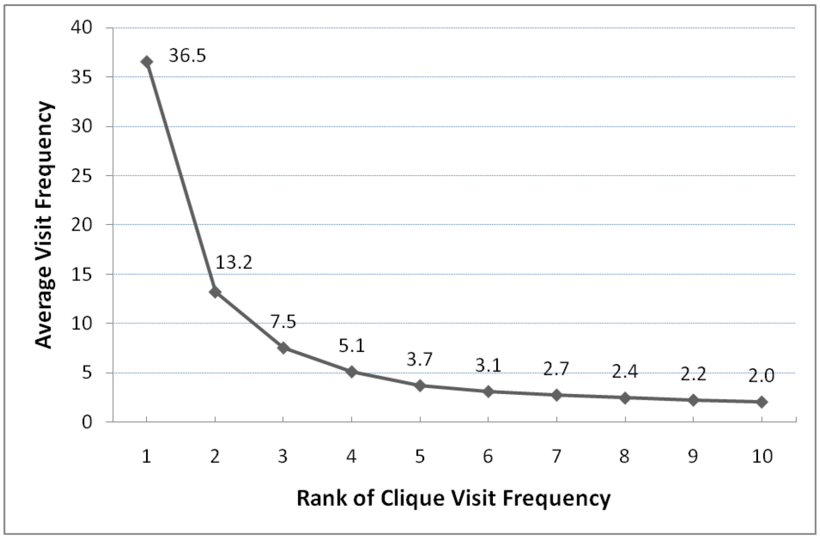

Figure 6-1 Average visit frequency by clique rank (before manual checking)

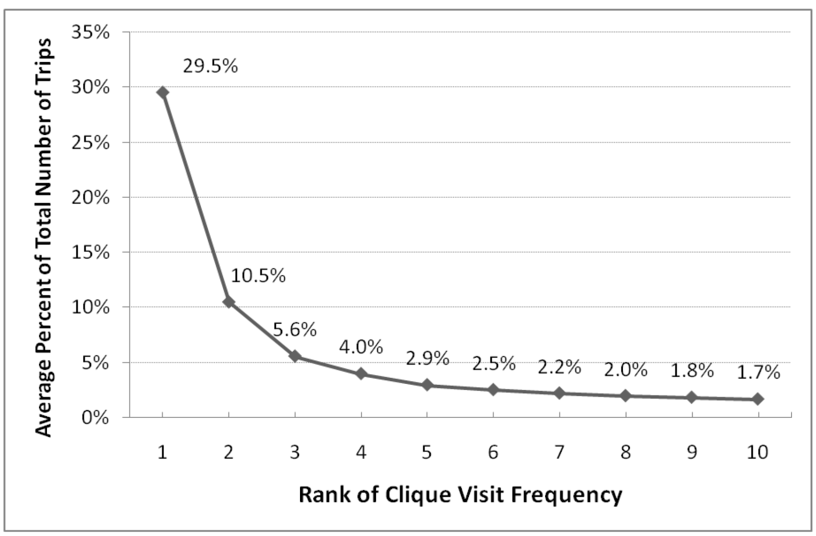

Figure 6-2 Average percent of total number of trips by clique rank (before manual checking)

The above visit frequency analysis provides solid support for the anchor point theory proposed by Golledge and Stimson (1987) by showing the existence of core destinations (core stops). People constantly and repeatedly visit a certain number of key destinations to meet their daily needs; travel associated with these core destinations constitutes a significant amount of the total travel.

Trip purposes (identified in Chapter 6) were overlaid with the core destinations to determine what activities were conducted there. The analysis of trip purposes at the core destinations shows that 1) home is the most-visited core destination for all drivers; 2) work places are often but not always the second most-visited destination; 3) some core destinations (the top three most-visited destinations) are neither home nor work sites.

Because of the methodology limitation on trip purpose identification (as discussed in Chapter 6), trip purposes other than home and work cannot be reliably assigned to all core destinations. A parent's home or a day care center is possible core destinations for some people. In this study, home and work locations were identified as core destinations whose nearby urban spaces presumably influence the rest of individual's daily activity. However, this study does acknowledge that there may be core destinations that are neither home nor work locations which influence people's activity pattern as well.

Spatial analysis of non-work activities for workers with one work location

In order to visually inspect the spatial patterns of non-work activities for multiple drivers on the same scale, regardless of their actual home and work locations, a coordinate transformation was made for each driver to overlay their non-work activities together. The spatial analysis illustrated here is in part motivated by an earlier research effort (Kitamura, Nishii and Goulias 1990) which quantified the spatial distribution of non-work activities in Kyoto-Osaka-Kobe metropolitan area in Japan, by using the same visualization techniques. The purpose of this spatial analysis is to visually identify the important urban spaces within which a majority of the non-work activities occurred. This visualization provides basis for measuring the urban space and its built environment later.

The map transformation, shown in Figure 6-3, is a geometric translation and rotation. By definition (Toll 1999), the geometric translation moves the coordinate origin to a new location and geometric rotation defines a new x-axis and y-axis by rotating the original xy-plane. In this study, the translation moves the original map origins to a driver's home locations and the rotation defines the straight lines connecting home and work locations as the new x-axis. The direction from home towards work locations are defined as the positive directions. Euclidean distances from non-work activities to home and work sites are calculated (represented by D_1 and D_2). Work locations are located along the positive portion of the x-axis. After the map transformation, each non-work activity has a new x and y, x_1 *and* y_1. y_1 represents the straight-line distances between non-work activities and x-axis (note: y_1 is always positive), which is a proxy of the distance between non-work activities and the real commuting routes. If the transformed non-work activity is located in the quadrant on the right-hand side of the y-axis (i.e. away from homes towards work locations), x_1 will have a positive sign, otherwise, it will be negative.

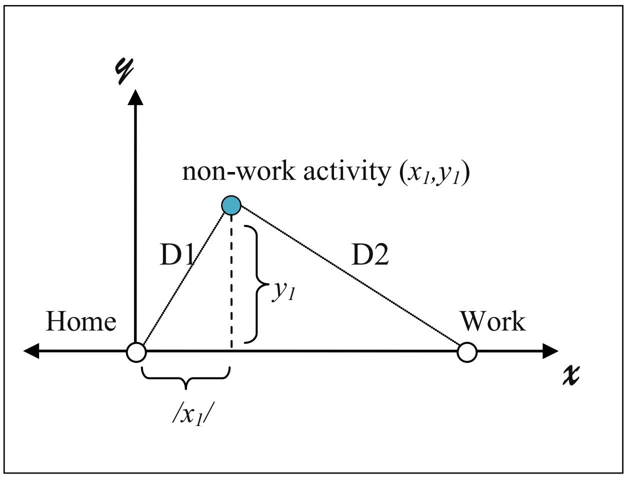

Figure 6-3 Map transformation illustration

Figure 6-4 shows all transformed non-work activity locations (represented by blue dots) and the density of non-work activities (shown in graduated background color) for 34 drivers who have one work location. The darker the graduated color, the higher the non-work activity density. The density was calculated based on a smoothing technique[11].

It is shown in Figure 6-4 that non-work activities tend to concentrate around home locations (represented by the origin). The majority of non-work activities are located within the 5-mile buffer from home locations (shown in the darkest black color). Moreover, the distribution of non-work activities is asymmetric as more activities are

[11] The density of non-work activities for each raster cell is calculated by averaging the values of nearby cells located with a circular neighborhood with 5-mile radius. The purpose of applying the circular neighborhood is to produce a smoother and generalized density map from which a global pattern can be more easily observed.

located in the right quadrate of the coordinate system, indicating that more non-work destinations occur between home and work than in the space away from work.

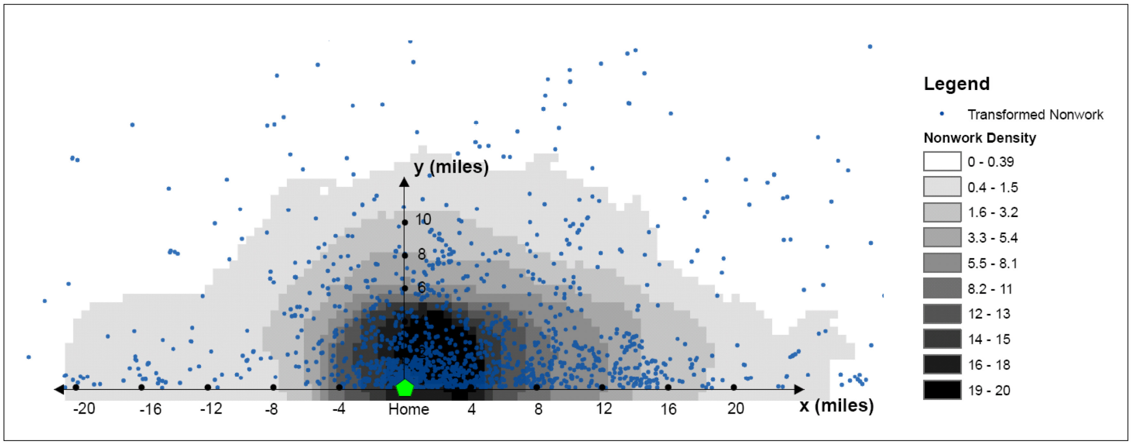

Figure 6-4 Transformed non-work trip destinations and activity density for drivers with one work location

As shown in Table 6-4, for drivers with only one work location, the mean distance between non-work activities and homes is 5.4 miles, suggesting that 50% of non-work activities are located within 5.4 miles from homes, which is consistent with our observations from Figure 1-4. The median distance to home is much smaller than the mean (15 miles), indicating that a number of non-work destinations are located far away from homes. The mean distance between non-work activities and work locations is 16.7 miles and the median is 8.1 miles, both of which are larger than the corresponding values for distances to homes. This shows that non-work activities tend to be located closer to home than to work. The median y_1 is 1.2 miles, which suggests that there are 50% of non-work activities located within 1.2-mile buffer of x-axis (a proxy of commuting routes).

Table 6-4 Euclidean distances from non-work activities to home and work locations for drivers with one work location

	Distance to home	Distance to work	x_1Miles	y_1Miles
Number of non-work activities	2719	2719	2718	2718
Mean	15.0	16.7	6.1	5.1
Median	5.4	8.1	2.2	1.2

Note: N=34

Drivers with only one work location were further divided into four driver groups based on the real travel distances of their commuting routes. As shown in Table 6-5, the 25^{th} percentile (7.74 miles), 50^{th} percentile (13.55 miles) and 75^{th} percentile (19.29 miles) of commuting distances among these drivers were used as the threshold distances to group drivers.

Table 6-5 Four driver groups and average work-to-home distance ranges

Driver Group	Percentiles	Range of Commuting Distance (miles)
1	<25%	0<Distance≤7.7428
2	>25% and <50%	7.7428<Distance≤13.5457
3	>50% and <75%	13.5457<Distance≤19.2881
4	>75%	19.2881<Distance

Activity density maps similar to Figure 6-4 are created for each driver group. The comparison of density maps reveals common characteristics shared by different driver groups in terms of the spatial distribution of their non-work locations. First, all maps show that the spatial distribution of non-work activities tends to be bounded by the locations of drivers' home and work places. Large clusters of non-work activities located far away from home and work places do not exist in the maps. This pattern is consistent for all driver groups, which validates our research assumption that space near home and work as well as along commuting routes are important geographic spaces which influence drivers' travel behavior. Another consistent feature found in every map is the presence of a major cluster near driver's home locations. It confirms that drivers, regardless of their commuting distances, tend to concentrate their non-activities around home and the space near home is the most important space which influences non-work activities.

Comparisons across driver groups also reveal unique spatial patterns for each group. For drivers with the shortest commuting distance (Group 1), a small cluster of non-work activities shows up in the left quadrant (with negative x value) of the density map. This cluster does not appear in any other maps. These non-work locations with negative x value means that they are on the opposite side of work sites in terms of their relative positions to homes. In comparison, when home and work locations are located far away from each other, more non-work activities tend to locate along the home-to-work corridor (indicated by group 2 through 4). These results are consistent with the findings from

Kitamura's study (Kitamura, Nishii and Goulias 1990), which pointed out that non-work activities tend to scatter in every direction when commuting distance is short, but they tend to locate along commuting routes as the home-to-work distance increases.

Another pattern emerged in this series of maps is that when commuting distance is short, a single large activity cluster appears on the map, which covers both home and work locations; as commuting distance increases, two separate clusters emerge with one near homes and the other near work sites; as commuting distance increases further (beyond 19 miles), the cluster near work sites disappears. Such a pattern indicates that most drivers tend to make stops at places near both home and work locations for non-work purposes. The exception is that when work sites are located far away from homes, drivers have the tendency to concentrate their activities solely near homes (rather than work sites). This is likely a consequence of the stricter time constraints posed to drivers with very long commutes, or simply due to their strong desire to go home after work.

In summary, the density maps have shown that distances between home and work locations are important determinants of the location choices of non-work activities. This finding is consistent with Kitamura's conclusions (Kitamura, Nishii and Goulias 1990). The density maps also show that when examining the relationships between location choices of non-work activities and the built environment, the impact of drivers' commuting distances should be controlled for.

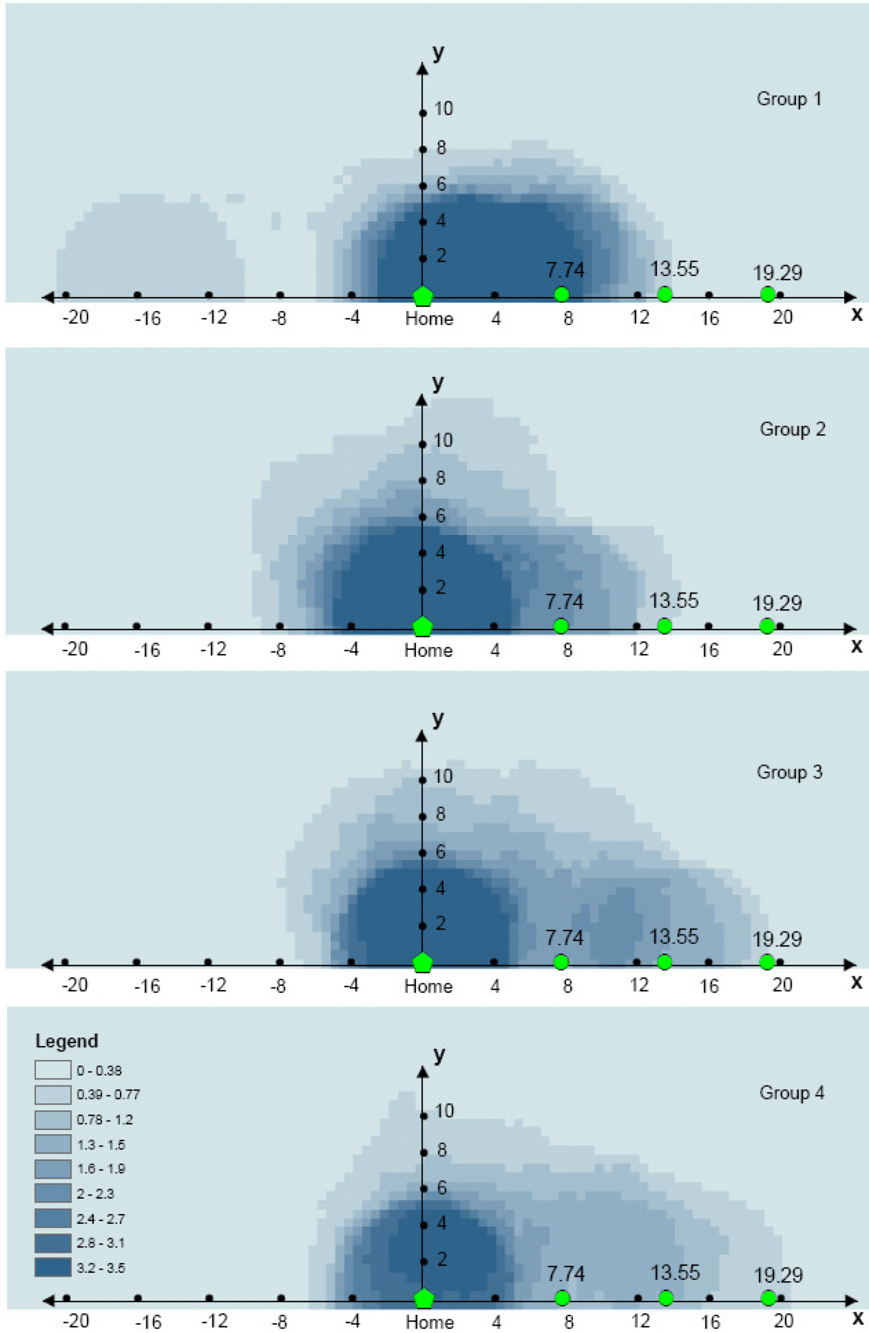

Figure 6-5 Density of non-work activities by driver groups

Tour-based analysis

Summary

Another important dimension of drivers' travel behavior is how drivers chain and sequence their non-work activities. Does travel containing one or more non-work activities always originate and end at homes? How often do drivers conduct non-work activities on their way home or to work? Is this type of travel promoted or limited by the built environment near home, work, or their commuting routes? A tour-based analysis addresses these questions. The following section summarizes the descriptive statistics and the spatial analysis of different types of tours by drivers' ages and genders.

Descriptive statistics of tours

Tours are composed of sequential trips. A tour always starts at home or a work site, and concludes with the next trip that ends at home or a work site. One or more non-work activities are chained in one tour.

Table 6-6 Number of tours by tour types

Types of travel	Sub-types of tours	Number of tours	Percent of total number of tours
Tours	HNH	1729	45.3%
	WNW	212	5.6%
	HNW	206	5.4%
	WNH	286	7.5%
	WNW'	23	0.6%
Other travel	Other	1363	35.6%
	Total	3819	100.0%

Notes: HNH represents home-to-home tour; WNW represents work-to-work tour; tours from home to work, from work to home, and from one work site to another work site are represented by HNW, WNH, and WNW' respectively.

Table 6-6 shows the number of tours by different tour types made by the 73 drivers in the dataset in total, 9476 trips are aggregated into 3819 tours. Tours account for 64.3% of the total travel, and 22.3% of all tours are direct tours which represent the non-stop travel between home and work sites. Other types of travel (about 35% of total travel) include trips directly connecting home and work places and trips which start and end at the same locations (either home or work sites) without containing any non-work stops in between.

It is a special type of travel in which drivers travel in a circle only to stop at where they start. Analyses on these travel were not included in this dissertation.

There are five sub-types of tours: tours originating and ending at homes (HNH), originating at homes and ending at work sites (HNW), originating at work sites and ending at homes (WNH), originating and ending at the same work sites (WNW), originating and ending at different work sites (WNW').

Among these tours, the percentage of home-to-home tours (HNH) in all tours is the highest (45.3%), indicating the important influence of home locations on non-work travel. Work-to-home tour (WNH) has a larger share (7.5%) than home-to-work tour (5.4%), which suggests that drivers are more likely to make non-work stops on their way home than on their way to work.

The following table (Table 6-7) and figures (Figure 6-6 to Figure 6-9) characterize tours by tour types, drivers' age, and gender. Tour-making patterns are characterized in terms of tour generations, tour length, and the number of non-work activities occurred in one tour.

Table 6-7 Total tour generation per person by tour types and gender

Travel Types	Women		Men		Total	
	Tour generation per person	% of total tours	Tour generation per person	% of total tours	Tour generation per person	% of total tours
HNH	24.8	47.7%	22.6	42.8%	23.7	45.3%
WNW	2.6	5.0%	3.2	6.1%	2.9	5.6%
HNW	2.4	4.7%	3.2	6.1%	2.8	5.4%
WNH	3.2	6.2%	4.6	8.8%	3.9	7.5%
WNW'	0.2	0.4%	0.4	0.8%	0.3	0.6%
Other	-	36.1%	-	35.4%	-	35.7%
Total	-	100.0%	-	100.0%	-	100.0%

Table 6-7 shows the descriptive statistics on tour generation by tour types and genders. Women, on average, generated higher percent of HNH tours than men and lower percent of any other types of tours.

As shown in Figure 6-6, the average number of non-work activities (green bars) chained in a home-to-home tour (HNH), work-to-work tour (WNW), home-to-work tour (HNW), or work-to-home tour (WNH) tour is 2.4, 1.6, 1.7, or 2.3 respectively. The average number of non-work activities is above one for all types of tours and for both genders, indicating that drivers are likely to chain more than one non-work activities in a tour on average. The average number of non-work activities chained in a home-to-work (HNW) tour (2.3) is larger than that of a work-to-home (WNH) tour (1.7), indicating drivers tend to make more non-work stops on their way home after work than on their way to work after leaving home. The difference between the before-work travel and after-work travel is likely due to the different time constrains drivers have before and/or after work.

Compared to men, women in general chain fewer non-work activities in most types of tours, with the exception of WNW tours for which women have a similar average number of non-work activities (1.7) to men (1.6).

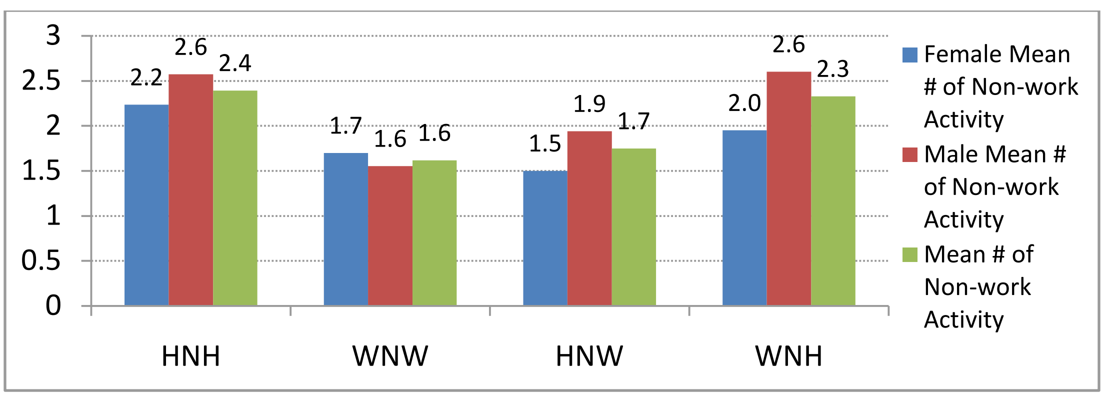

Figure 6-6 Mean number of non-work activity chained in a tour, by gender and tour types

Figure 6-7 shows the average tour distance by tour types by gender. The average distance for a WNH tour is 30 miles for all drivers, the longest among all types of tours. It is likely because of less time constrains after work which allows drivers to travel longer distances and to visit more non-work destinations. Compared to women, men on average travel longer distance per tour for most types of tours. The difference between women and men is the largest when comparing their average tour distances of WNH tours. It indicates that, on the way back to home from work, men are more likely to travel longer distances for non-work activities than women.

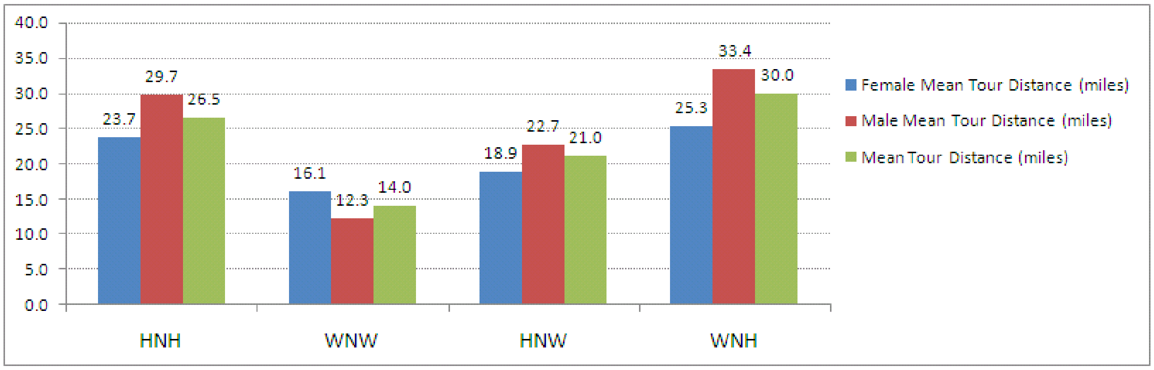

Figure 6-7 Mean tour distance per tour by gender and tour types

Figure 6-8 to Figure 6-9 summarizes the characteristics of different types of tours by age groups. Figure 6-8 shows that HNH tours are predominant types of tours for all drivers. Compared to other drivers, younger drivers generated the highest number of HNH tours (25.3) on average, followed by older drivers. This implies that the built environment features near home likely have stronger influences on younger and older drivers. Compared to other driver groups, middle-age drivers are likely to conduct more WNH tours and hence are more likely to be influenced by the built environment along routes. The total number of HNW tours for all age groups are roughly the same.

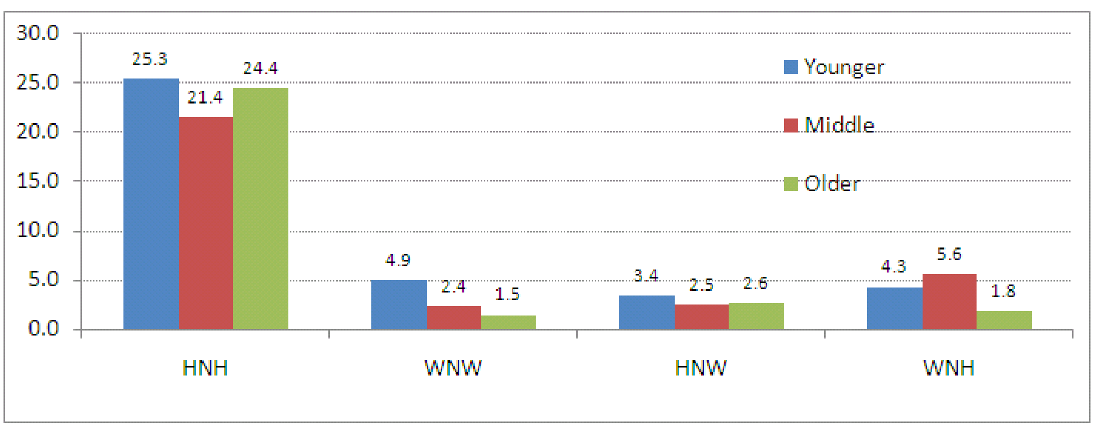

Figure 6-8 Mean number of tours per person by age and tour types.

As shown in Figure 6-9 below, on average, the number of non-work activities chained in HNH and HNW tours are roughly the same for all age groups. Older drivers, who conducted the longest WNW tour on average, have chained more non-work activities in a WNW tour on average. The mean number of non-work activities chained in WNH tours for younger drivers is the highest among all age groups, indicating their tendency to conduct more non-work activities after work before returning home.

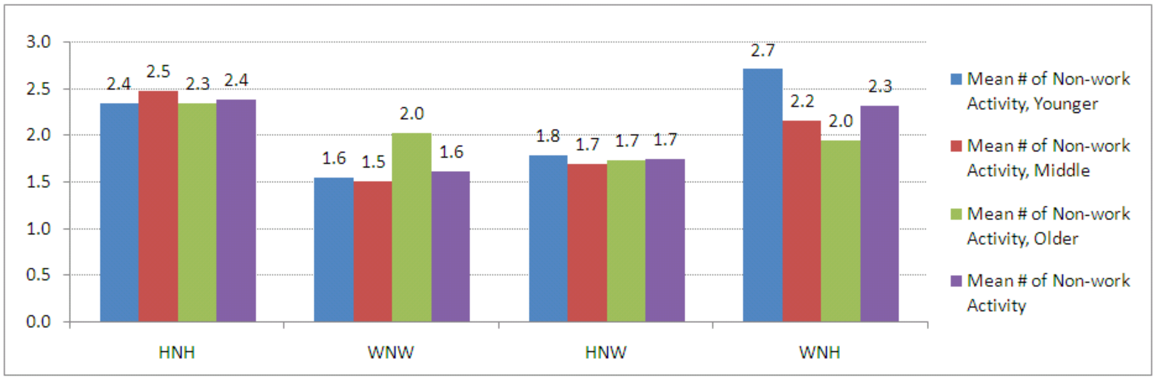

Figure 6-9 Mean number of non-work activity chained in one tour, by age group and tour types

The above analysis has demonstrated that tours which originate and end at different locations have different characteristics in terms of their frequency, tour length, and the number of non-work activities chained in one tour. Each aspect of tour characteristics is specific to drivers' age and gender. When studying the relationships between tours and the built environment, we have to acknowledge these differences among tours as well as the differences in drivers.

The following section focuses on another dimension of the tour-based analysis - the spatial distributions of non-work activities chained in different types of tours.

Spatial analysis of tours

Spatial patterns of non-work activities by tour types for drivers with one work location

Similar to the spatial analysis for trips, spatial analysis on tours examines the spatial distribution of non-work activities chained in different types of tours. Distances between non-work destinations and home/work/commuting routes for drivers with only one work location are calculated using the same method illustrated in Figure 6-3. Different from trip-based spatial analysis where all non-work activities are considered the same, tour-based spatial analysis differentiates these non-work activities by different types of tours into which these non-work activities are chained. Table 6-8 presents the distances of non-work activities to homes, to work sites, and to the hypothetical straight lines connecting home and works. The straight lines between home and work sites are shown in Figure 6-3 as the x-axis, which are proxy of commuting routes.

Table 6-8 Distances between non-work activities and home, work, and straight lines in-between home and work, by tour types, for drivers with only one work location

Types of tours which non-work activities belong	Number of non-work activities	Mean/Median	Distance to home (miles)	Distance to work (miles)	Distance to straight lines between home and work (miles)
H-D...D-H	1772	Mean	14	17	6
		Median	5	10	1
H-D...D-W	238	Mean	6	5	2
		Median	5	3	1
W-D...D-H	470	Mean	12	11	4
		Median	6	5	1
W-D...D-W	152	Mean	11	5	3
		Median	10	2	1
Other	86	Mean	20	18	10
		Median	22	17	6
Total	2718	Mean	13	14	5
		Median	5	8	1

Note: Distance to home, distance to work, and distance to home-to-work straight lines are represented by D_1, D_2, y_1 in Figure 6-3.

Several patterns in the spatial distribution of non-work activities emerge:

1. Non-work activities chained in home-to-home tours (HNH) are located closer to home than to work. More than half of such activities are located within five-mile radius from home (the median distance to home for HNH is 4.6 miles).
2. Non-work activities chained in work-to-work tours (WNW) are much closer to work than to home, more than 50% of which are located within two-mile buffer from work locations (the median distance to work for WNW is 1.9 miles).
3. Non-work activities chained in either home-to-work tours (HNW) or work-to-home (WNH) tours are located in close proximity to x-axis (a proxy of commuting routes). The median Y_1 for HNW is 0.87 mile, and 0.96 mile for WNH. This suggests that

non-work activities chained in either home-to-work tours or work-to-home tours tend to be located in the belt-shaped corridors along commuting routes.

4. Non-work activities chained in home-to-work (HNW) tours and work-to-home (WNH) tours are located slightly closer to work than to home as the median distances from these non-work activities to home are longer than to work.

The above analysis demonstrates that the relative locations of non-work activities to home, to work, and to routes depend on the types of tours in which these activities are chained. The analysis on the spatial distribution of non-work activities also suggests that certain types of urban spaces may have closer relationships with certain types of tours than others. For instance, urban spaces near home and work may have more influences on HNH and WNW tours than on other types of tours; the space between home and work sites may influence the tours travelling between home and work sites more.

Identification of important urban spaces

Based on Table 6-8, this study quantitatively identifies three types of urban spaces which presumably have the most significant impact on travel behaviors: home-related, work-related, and route-related urban space. The home-related and work-related urban spaces consist of a circular area centered at a driver's home and work place, with a radius defined by the median distance of home-to-home tours (HNH) to homes (5 miles) and work-to-work tours (WNW) to work sites (2 miles) respectively, as highlighted in the Table 6-8. Route-related urban space is defined as an elongated buffer zone along his/her commuting routes. The median distance from non-work locations in HNW/WNH tours to the straight hypothetical lines connecting home and work was used to define the width of the buffer along routes. An illustration of the three urban spaces is shown in Figure 6-10.

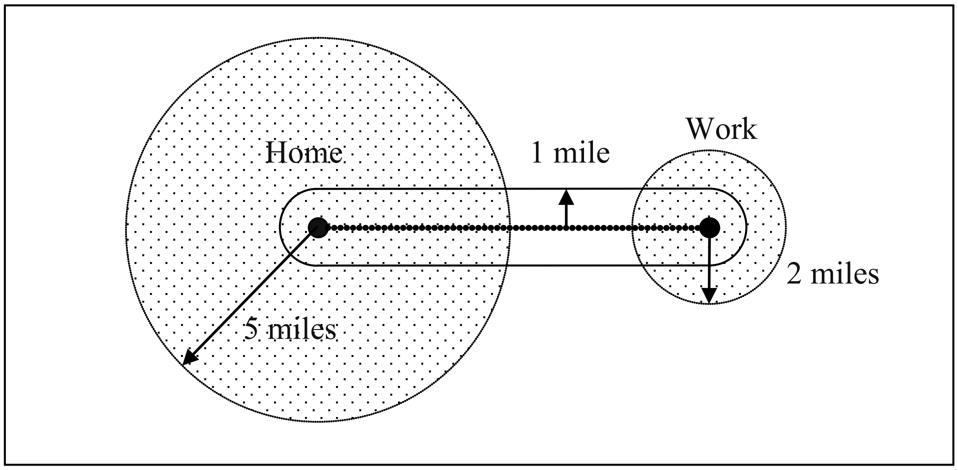

Figure 6-10 Illustration of urban space identification

As shown in Figure 6-10, the three urban spaces are not exclusive of each other; rather, there exists overlapped space shared by them. In these overlapped spaces, different types of tours are likely to happen simultaneously. For instance, the overlapped area between home-based and route-based urban spaces may have associations with both HNH tours and HNW/WNH tours. There may even be space shared by all three buffers zones when home and work are close to each other. In this study, the effort of identifying three different urban spaces is not to make exclusive categories, but rather to sort out the urban spaces within which different non-work activities are likely to happen so that we can measure the built environment within such urban spaces and exam the relationships between the measured built environment and travel behaviors.

Analysis on Energy Consumption and Emissions

The last section of this chapter focuses on summarizing the characteristics of energy consumption and emissions generated by the trips of the 73 study drivers as estimated by CMEM model, in comparison with the more general results obtained from other data sources.

Table 6-9 shows descriptive statistics for total energy consumptions and emissions, total VMT, average emission rates and fuel rate (emissions/fuel consumptions per mile), and fuel efficiency for all trips (miles per gallon). All parameters shown in the NDD column are calculated by using the CMEM model and second-by-second GPS data for 73 drivers in four weeks and expanded to annual rate as needed. The second column of the table shows corresponding national average data compiled and published by the Bureau of Transportation statistics (BTS). Most energy consumption and emission data in the BTS dataset were estimated through MOBILE 6, the U.S. Environmental Protection Agency's (EPA) latest highway vehicle emissions factor model.

Table 6-9 The comparison between NDD and BTS data on total emissions and energy consumptions, total VMT, average fuel and emission rates, and fuel efficiency

	NDD, 2004	BTS, 2004
HC in a year per driver (grams)	2,968	7,551
CO in a year per driver (grams)	121,328	8,354
NOX in a year per driver (grams)	4,043	13,785
CO2 in a year per driver (grams)	6,204,099	4,863,375
Fuel in a year per driver (gallons)	767	553
HC rate (grams per mile)	0.17	0.61
CO rate (grams per mile)	6.77	13.79
NOX rate (grams per mile)	0.23	1.00
CO2 rate (grams per mile)	355.97	390.33
Fuel rate (gallons per mile)	0.04	0.04
Fuel efficiency (miles per gallon)	22.73	22.54
VMT in a year per driver (thousands)	17.25	12.46

Note:
na = data are not available

Total emissions, fuel consumption, and VMT in a year per driver in NDD column are derived by multiplying average numbers in a day per driver with 365 days. The numbers for BTS are derived by calculations as well.

Emissions in BTS are exhaust emissions for passenger cars in the year 2004.

CO_2 emissions in BTS are derived by using fuel consumption with the following calculation: CO_2 emissions from a gallon of gasoline = 2,421 grams x 0.99 x (44/12) = 8,788 grams = 8.8 kg/gallon = 19.4 pounds/gallon

The density of gasoline is assumed to be 2630.8 grams/gallon.

Table 6-9 shows some discrepancy between the estimations from the NDD and the BTS dataset. In general, emission rates (including CO_2 rate) estimated in BTS are higher than the NDD estimations. The total VMT estimated in NDD[12] turns out to be higher than the national average provided in BTS. Total HC and NO_X are higher in BTS than NDD while

[12] Total emissions, fuel consumption, and VMT in NDD are estimated by weighting average emissions and fuel usages in a typical day for each driver by 365 days.

total CO, CO_2, and fuel consumption are lower. Fuel rate and fuel efficiency are roughly the same in both datasets.

The discrepancy between these two datasets is partially due to different samples these estimations were based on and partially due to the different modeling techniques these two datasets employed. Different samples may contribute to the discrepancy in the total VMT to a substantial extent as drivers in the Detroit metropolitan area tend to drive much more than drivers in other areas. Different modeling techniques may be the leading cause of the discrepancy in the estimations of energy and emission rates. In the NDD dataset, we rely on the CMEM model, an instantaneous model, to make estimations on second-by-second energy consumption and emissions, which later are aggregated to trips and tours. MOBILE 6 released from EPA is essentially an "average speed" model which relies on the facility-specific *driving cycles* to estimate energy consumption and emissions. An evaluation study done by ENVIRON corporation concludes that MOBILE 6 has the tendency to over-predict emission rates for HC and CO in recent years despite the mixed results for NO_X. This could explain why emission rates are always higher in the BTS dataset shown in Table 6-9.

In the future, we can account for the first type of discrepancy by applying the EPA MOBILE 6 to the same samples used in the NDD estimation. However, there is no absolute standard by which either set of estimations can be judged without the "real-world" emission and fuel consumption data. "Real-world" emission data can be collected in a more controlled manner by using detectors or remote sensing. Nevertheless, this comparison demonstrates that GPS data combined with instantaneous energy and emission models does provide an alternative to the widely-used and widely-criticized EPA MOBILE models. More rigid comparisons and validations are needed in the future to help us understand the advantages and disadvantages of these models.

Table 6-10 shows statistics for energy consumption and emissions for non-work travel. Each variable will be entered into regression models as a dependent variable in Chapter 8: Correlation and Regression Analysis.

Table 6-11 shows the average speed of different types of tours. Average speed has proved to be a critically important factor which influences fuel rates and emission rates (EPA 2003). Other factors such as acceleration, intermediate stop (or idle), and speed oscillation have impacts too (Ericsson 2001).

Table 6-10 Total emissions and energy consumptions, total VMT and average emission rates and fuel rate for 73 drivers in survey period for non-work trips

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Total HC (grams)	73	39.37	318.12	10,604.36	145.27	66.01
Total CO (grams)	73	440.97	20,993.06	440,268.37	6,031.07	4,526.41
Total NOx (grams)	73	56.33	432.29	14,672.67	201.00	89.05
Total Fuel (grams)	73	22,742.05	206,188.55	7,386,456.44	101,184.33	45,052.56
Total CO2 (grams)	73	69,176.90	639,409.47	22,704,416.46	311,019.40	137,671.84
CMEM Distance (miles)	73	180.02	1,912.78	62,915.01	861.85	409.37
HC per mile	73	0.08	0.37	13.43	0.18	0.07
CO per mile	73	1.25	18.73	500.98	6.86	3.94
NO_X per mile	73	0.16	0.40	17.71	0.24	0.05
Fuel per mile	73	99.98	155.57	8,728.70	119.57	11.32
CO_2 per mile	73	314.95	477.02	26,857.46	367.91	32.85

Table 6-11 Average speed by tour types

	N	Minimum	Maximum	Sum	Mean	Mean (mph)	Std. Deviation
Speed on HNH tours	73	0.29	0.84	39.62	0.54	32.56	0.13
Speed on HNW tours	41	0.30	1.05	22.56	0.55	33.02	0.16
Speed on WNH tours	44	0.32	0.97	24.00	0.55	32.73	0.15
Speed on WNW tours	33	0.06	0.65	13.69	0.41	24.90	0.13

Chapter 7
Characterization of the Built Environment

Introduction

Low-density subdivisions, strip malls, and physical separation of land uses are the norms of the land use development patterns in the Southeast Michigan region. Although with a low regional population growth and a urban center experiencing population loss, agricultural areas and open space at the urban fringes are rapidly transformed to low density residential, commercial, and business development (Norris 2002; Southeast Michigan Council of Governments 2003). The Southeast Michigan region are sprawling and will likely continue to sprawl because of the slow economic growth, a large black population in the Detroit city, fragmented local governments, and a lack of geographic constrains (Fulton, Pendall, Nguyen and Harrison 2001; Loh 2008). Detroit urbanized area ranked the third highest in the degree of sprawl measured by Galster (Galster et al. 2001)[13], following Atlanta (the highest) and Miami (the second highest).

A major concern over choosing Southeast Michigan as the study area is the lack of built environment varieties, especially the scarcity of compact and mixed-use development patterns (as supposed to low-density sprawling development types). Low variations in the built environment could potentially undermine the explanatory power and robustness of the research results. To address this concern and to illustrate the ranges of the built environment, this chapter first explored the built environment patterns in the Southeast Michigan region and presented the ranges of built environment patterns commonly found in the region. This chapter then quantified the built environment experienced by the 73

[13] Galster developed eight indices to measure sprawl, which is defined as " a pattern of land use in a UA (urbanized area) that exhibits low levels of some combination of eight distinct dimensions: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity."

study subjects by using the built environment variables (abbreviated as BE in rest of this dissertation) developed in Chapter 5 Map visualizations were performed to examine whether the built environment experienced by these drivers are different from each other. Limitations of the current measurements are discussed and results from factor analyses which combine individual measurements into composite indices to represent multiple BE dimensions simultaneously are presented.

The built environment pattern in Southeast Michigan

To observe the variations of the built environment in the Detroit metropolitan region, four built environment measurements developed in Chapter 5 were calculated for cells (200 meter by 200 meter) located within the seven counties in the Southeast Michigan region. A simple ranking system was developed. Cells across the region are ranked based on their built environment characteristics on a scale of one to sixteen. Cells with high levels of some combinations of four dimensions: business density, business density, business diversity, network connectivity, and percent of local roads, receive high ranks[14]. The highest rank is sixteen, indicating that the built environments in these cells are the most compact and mixed-use. The ranks are shown in Figure 7-1.

To explore the built environment at the street level, several representative locations with varied ranks were random selected and photos/images of these places were gathered either through field trips or the Street View from Google maps.

As shown in Figure 7-1, the City of Detroit has medium-to-high ranks (in light or dark blue). When moving away from the City to the outskirt of the metropolitan area, the ranks become lower (from yellow to red), indicating a more dispersed and single-use setting. There are a few high rank areas within each county adjacent to the Wayne County (where the City of Detroit resides). Most of the high-rank areas are located close to the

[14] Each built environment variable was classified into four ordered categories by using quantile method: each category contains the same number of cells. Score one to four represents low, median low, median high and high level of one measurement. Overlaying all built environment variables together, the total score for each cell was calculated by summing up the scores for the four individual variables, resulting in the ranks ranging from one to sixteen.

main streets of different cities such as the City of Birmingham, Royal Oak, and Ann Arbor.

Figure 7-1 highlights eight locations: A1 and A2 represent places with low ranks; B1 to B4 are places with medium ranks; C1 and C2 are places with high ranks. The categories are loosely defined as each location covers an area larger than a single cell.

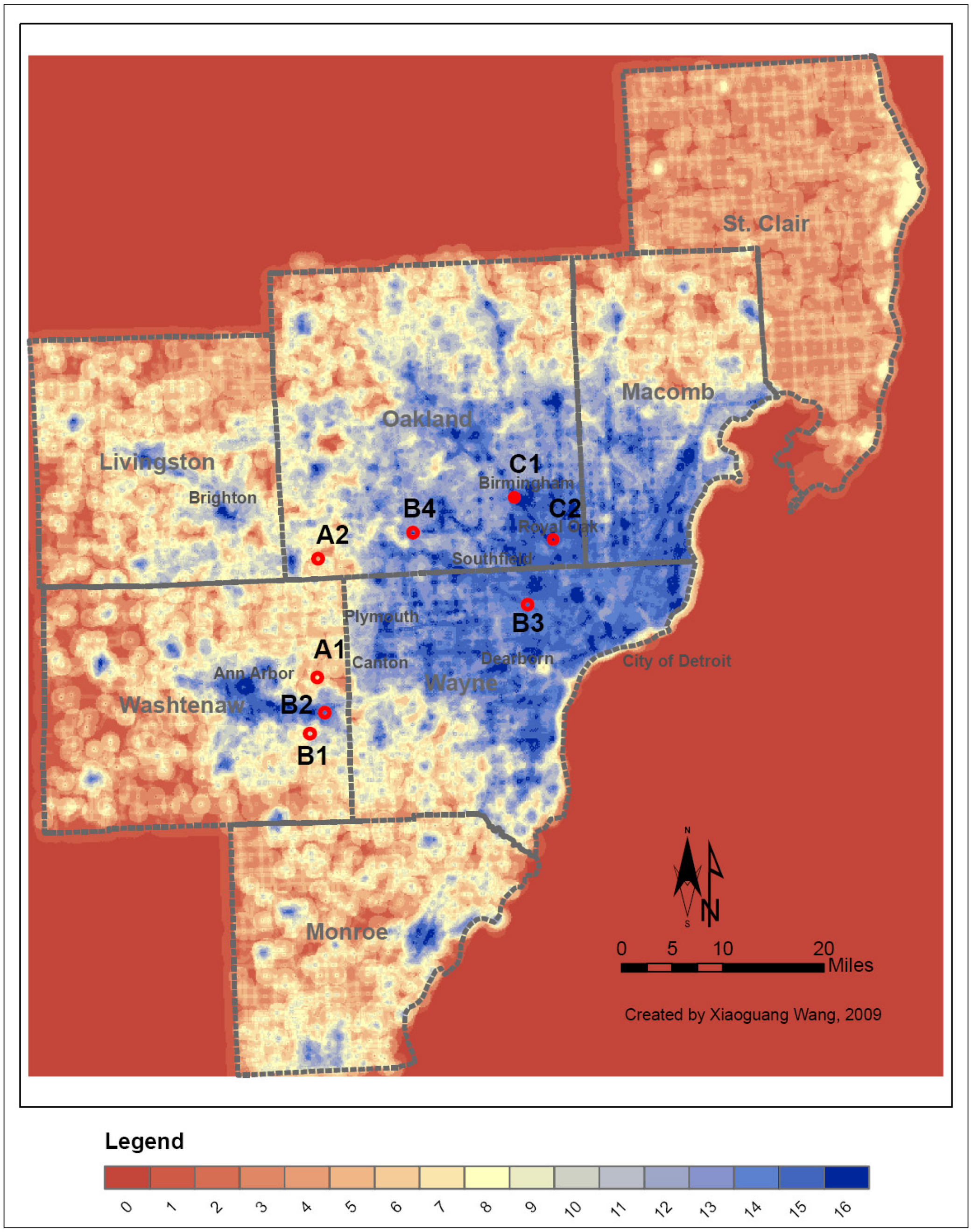

Figure 7-1 The ranks of the built environment in Southeast Michigan

Places with low ranks (i.e. more dispersed and single-use development) are shown in Figure 7-2 and Figure 7-3. In these areas, large patches of farmlands and open spaces can be seen from both figures and they are connected by long and straight streets with few intersections. A Low-density subdivision is visible in Figure 7-3 behind the bushes planted along the roads to separate the development from the road.

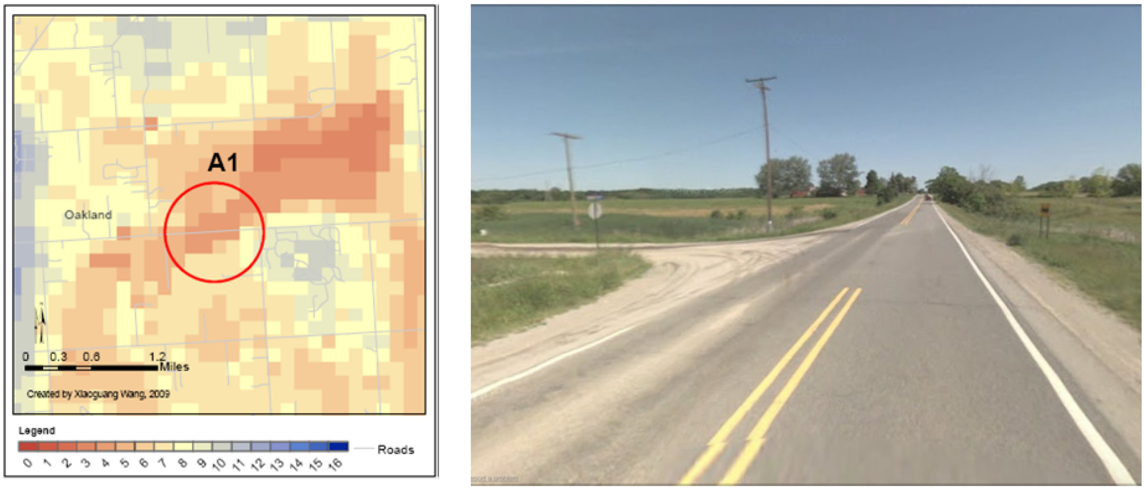

Figure 7-2 Map and photo for place A1 with low rank: N Prospect St, Ypsilanti, MI

Source: Street View from Google map

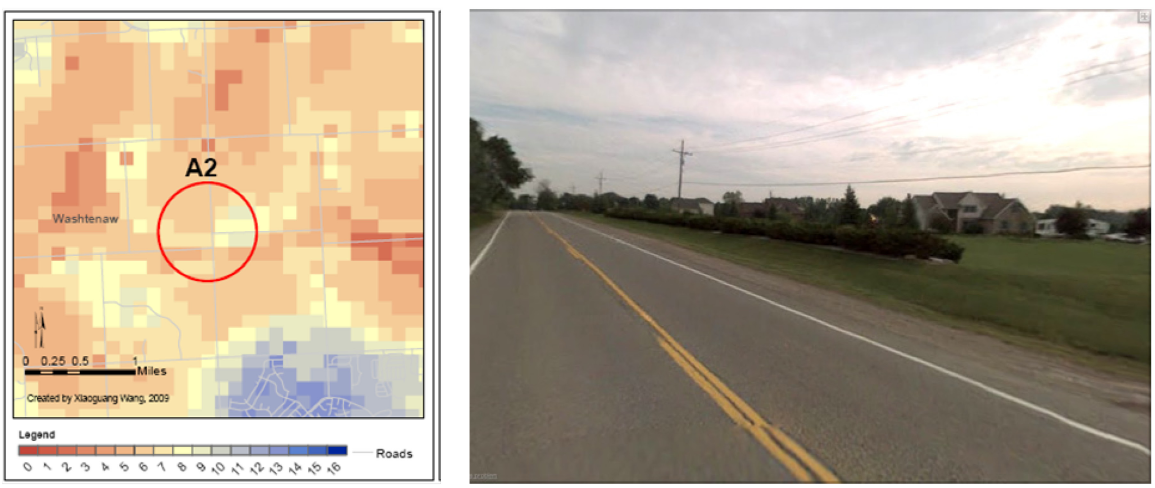

Figure 7-3 Map and photo for place A2 with low rank: Milford Rd, South Lyon, MI

Source: Street View from Google map

Places with medium ranks are shown in the following four figures. Medium-ranked areas (shown in light blue-yellow in Figure 7-1) cover a large portion of the metropolitan region, ranging from inner city of Detroit to outer rings of suburbs. These areas have different appearance at the street level. They may contain strip malls or shopping plazas as shown in Figure 7-4. A large parking lot is usually placed in front of malls or shopping areas. Though people can walk between shops, travel to or from the shopping area can only be done through driving.

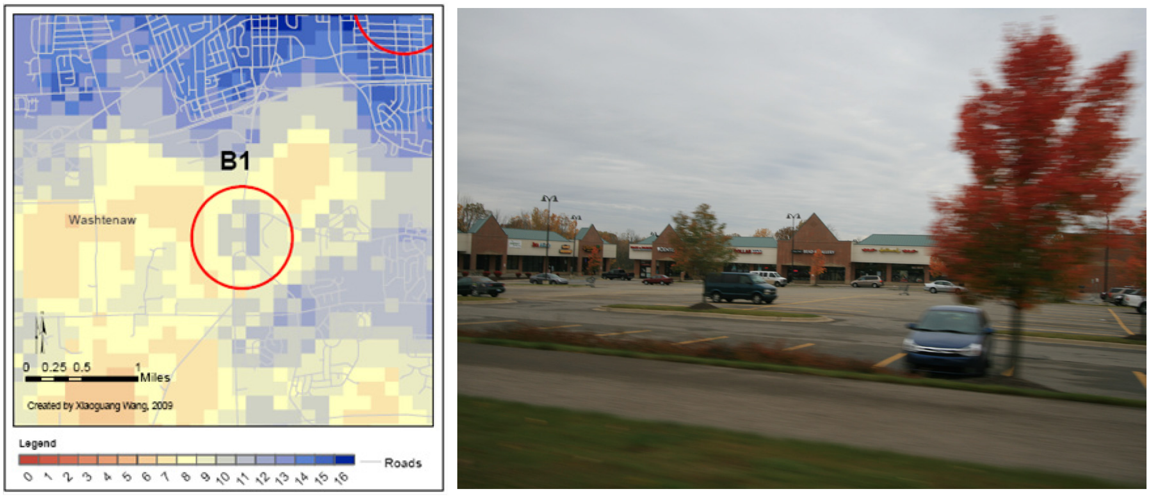

Figure 7-4 Map and photo for place B1 with medium rank: Whittaker Rd, MI

Source: Taken by the author

Medium-ranked place may contain streets as shown in Figure 7-5. A group of single-story shops line up along the street. A curb parking is provided to drivers for their easy access to the shops on the street. Sidewalks are located immediately in front of the buildings and close to the street, providing a more pedestrian-friendly environment. Residential areas are possibly located close by as walkers were observed walking on the street occasionally. Figure 7-6 shows a similar type of built environment, though the buildings are discontinuous and poorly-maintained. It is still possible to walk because of the provision of the sidewalks and buildings located close to streets and also because of the shorter blocks brought by the interconnected grid-like road networks (as shown in the map on Figure 7-6).

Figure 7-5 Map and photo for place B2 with medium rank: E Michigan Ave, MI

Source: Taken by the author

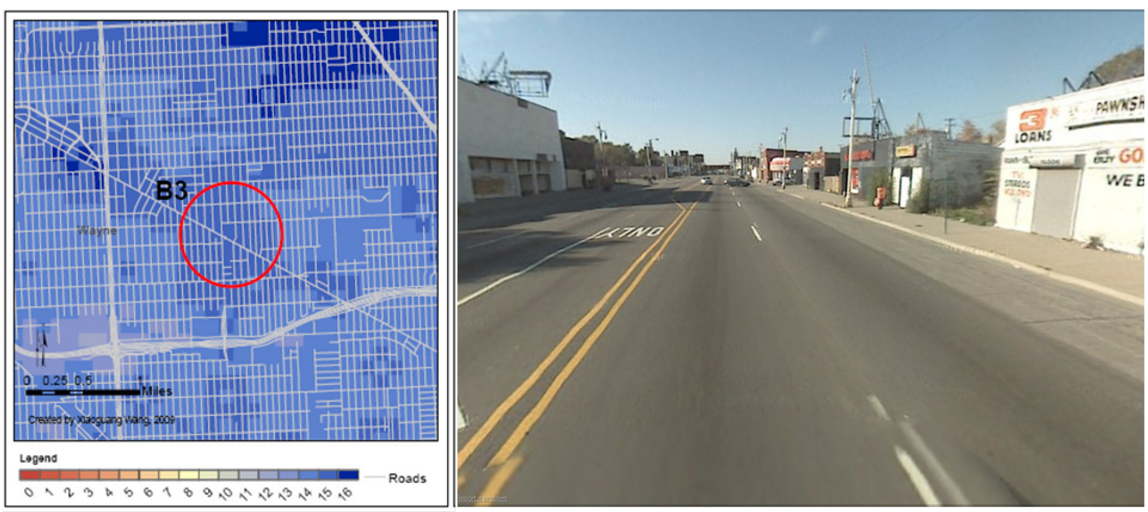

Figure 7-6 Map and photo for place B3 with medium rank: W Grand River Ave, Detroit, MI

Source: Street View from Google map

Figure 7-7 shows a unique example of medium-ranked built environment: a pocket of high-ranked cells surrounded by areas with medium ranks. The high-ranked cells are highly concentrated and they usually contain only one or two buildings which house a mixture of businesses, in this case, a restaurant and several service businesses. Different from the strip mall shown in Figure 7-4, a much smaller parking space is provided and sidewalks leading to this area are provided as well. The size of the parking space is reasonable in that walkers from the street can easily walk through the parking lots and get access to the buildings. The cluster of businesses is located at an intersection of two major arterial roads. It is surrounded by suburban-type of neighbors with curvilinear residential roads and cul-de-sacs.

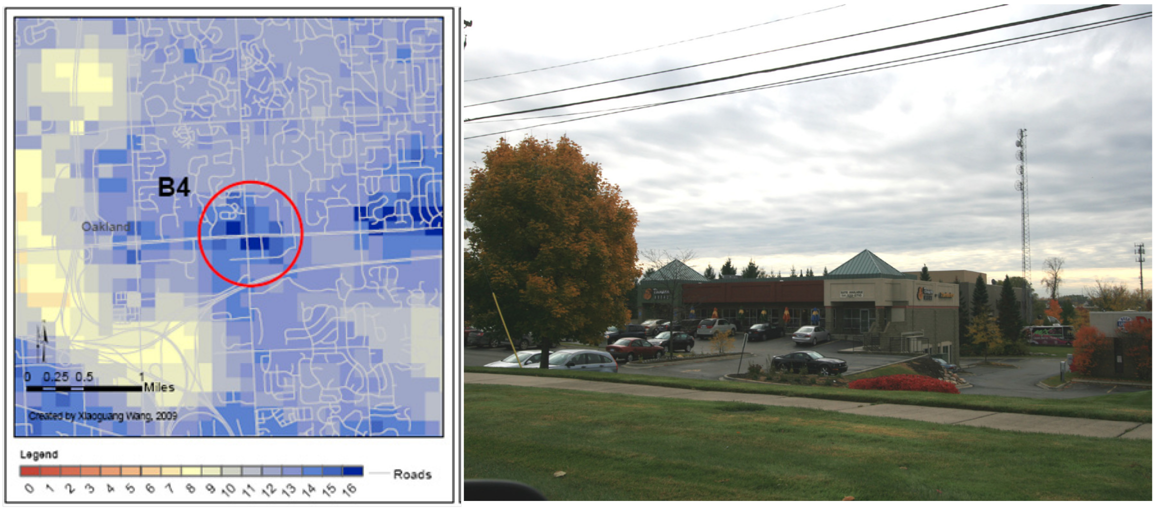

Figure 7-7 Map and photo for place B4 with medium rank: intersection of 12 Mile Rd and Halsted Rd, MI

Source: Taken by the author

As seen from the above four figures, the medium-ranked built environment varies widely in architectural styles, street layouts, and parking provisions. But the common features of these areas are that they all have some combinations of medium levels of density, diversity, connectivity, and local roads. They all have rooms to be improved into a more compact, mixed-use environment just like the places to be shown next.

Figure 7-8 and Figure 7-9 show two examples of urban spaces with the highest ranks: the downtown area of Royal Oak and an area close to downtown Birmingham. In both cases, a large group of continuous cells have the highest rank of sixteen. They have similar looks: tree-lined streets are coupled with pedestrian-friendly sidewalks with lamps and benches; the small shops and buildings have little setback from the streets and they have pleasant facades and architectural details; the buildings often have two-stories, with the second story possibly serving as offices; cars parked along the curbs serving as a barrier between the through traffic and pedestrians.

Figure 7-8 Map and photo for place C1 with high rank: Royal Oak, MI

Source: Taken by the author

Figure 7-9 Map and photo for place C2 with high rank: Birmingham, MI

Source: Taken by the author

In summary, this section has demonstrated a range of built environment patterns across the Southeast Michigan region. It has shown that even in this highly sprawled region the variations of the built environment do exist and they can be quantitatively measured. The four measurements developed in this study reasonably distinguished what were built and seen at the street level.

Drivers live, work, and travel in these different landscapes. They experience them by driving through them. The next section in this chapter evaluated the built environment experienced by each driver. The types of urban space evaluated include a circular area centered at home with 5-mile radius, a circular area centered at work with a 2-mile radius, and a 1-mile buffer zone along commuting routes.

Quantitative evaluation of built environment scores

The four BE dimensions measured at three urban spaces result in 12 BE variables (shown in Table 7-1). Table 7-1 shows descriptive statistics for all BE variables. Several patterns emerge when mean values for the same BE variable at different urban spaces are compared. The built environment near home has the lowest business density and diversity, but the highest intersection density and highest percent of local roads. Such a built environment represents a typical residential landscape in the Southeast Michigan: single-use lands connected primarily by residential roads. In contrast, the built environment near work has the highest business density and diversity, but the lowest intersection density and lowest percent of local roads. It represents a typical industrial/business/commercial land use type. This type of environment contains more businesses, providing services to some drivers or serving as work places for others. This environment also has larger blocks and more high-capacity roads than the environment near homes.

Table 7-1 Descriptive statistics of 12 BE measurements near home locations, work locations, and routes

		N	Minimum	Maximum	Mean	Std. Deviation	Variance
Business density (number of business employees per cell)	Near home	73	0.03	30.86	6.37	5.12	26.18
	Near work	46	0.61	166.36	24.50	31.92	1018.62
	Along routes	46	0.87	59.81	14.91	12.58	158.38

Business variety (number of business types per cell)	Near home	73	0.00	0.64	0.25	0.16	0.03
	Near work	46	0.04	1.03	0.37	0.20	0.04
	Along routes	46	0.05	0.54	0.33	0.13	0.02
Intersection density (number of four-way intersections per cell)	Near home	73	0.01	1.45	0.40	0.41	0.17
	Near work	46	0.01	1.44	0.33	0.33	0.11
	Along routes	46	0.02	1.14	0.39	0.35	0.12
Percent of local roads (percentage of local roads per cell)	Near home	73	0.17	0.75	0.55	0.14	0.02
	Near work	46	0.15	0.68	0.45	0.13	0.02
	Along routes	46	0.20	0.64	0.45	0.11	0.01

Note: the area for each cell is 40,000 sq meters.

Visual evaluation

In addition to the quantitative evaluation, the BE measurements were also visually examined on maps. The main goal of the visual evaluation is to determine whether the current study subjects lived, worked, or commuted in urban spaces with different built environment features and whether the built environment measurements created in this study can capture the built environment variations experienced by these drivers. If the built environments experienced by our sample drivers are relatively homogeneous or the BE variables are unable to capture the variations in the built environment features, it may lead to a low explanatory power of the regression models to be developed later in this dissertation.

For each BE variable, two drivers were selected and the built environments they experienced were mapped and compared. A histogram was created for each BE variable (among twelve BE variables shown in Table 7-1) to display the data distribution of this particular variable among 73 drivers. Two drivers whose built environment values are located at the lower end (25 percentile) or higher end (75 percentile) of the distribution are selected. If the built environment measurements work as intended, the built environment patterns shown on the maps for these two drivers should be dramatically different from one another. If they are not, it indicates that either a relatively similar built environment experienced by the study subjects or that the current measurement is unable to capture the variations presented in the built environment.

An example of the histogram is shown in Figure 7-10. The grey bars represent the distribution of the business density measured at home locations for 73 drivers. The drivers who lived in a built environment with a relatively low business density (represented by the 25 percentile of the distribution) or relatively high business density (represented by the 75 percentile of the distribution) were selected. The built environments near these drivers' home are displayed on Figure 7-11.

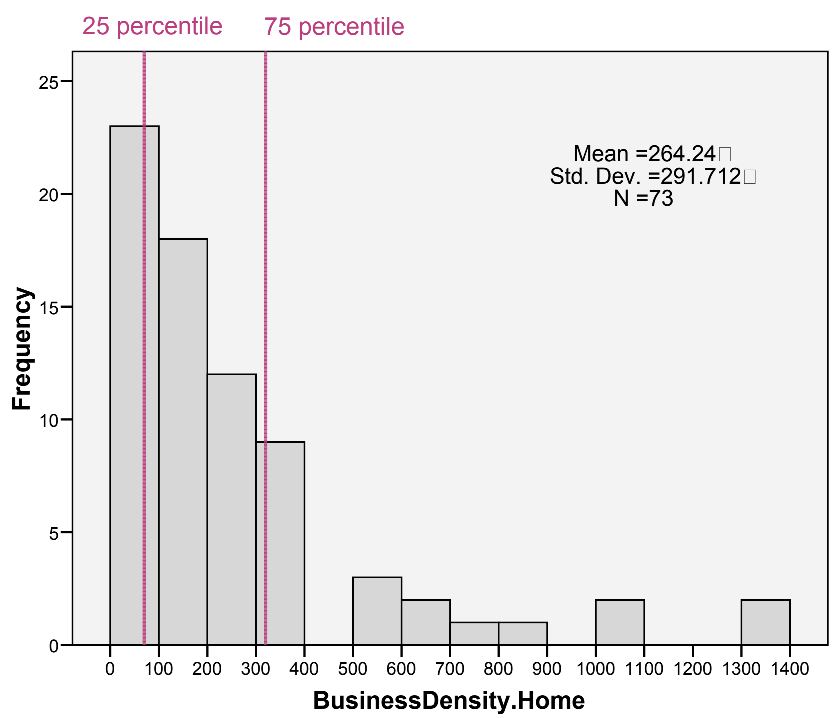

Figure 7-10 Histogram of business density measured near home locations for 73 drivers.

Circles shown in Figure 7-11 represent the five-mile buffer zone around drivers' home and geometric center of the circles represent drivers' home locations [15].The shading gradations shown on the map represent the business density calculated for each cell by

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[15] The geographic centers of all circles were shifted to protect the privacy of survey respondents. The resulting centers do not represent the real home locations; rather, they represent locations close to homes.

applying a smoothing function [16]. The darker the gradient colors, the higher the business density of the cell. It is shown in the map that the business density patterns near these two drivers' homes are different from one another, which indicates that this measurement performs as expected. As shown in the maps on the left panels, several clusters of businesses located in close proximity to drivers' home raise the business density for this driver. In contrast, a single dominant business cluster not in close proximity to homes corresponds to relatively low scores for the driver on the right panel.

Similar observations can be found for comparisons conducted for business diversity, road connectivity and functionality near home locations (as shown in Appendix Figure 1 and Appendix Figure 2); only the differences are even more dramatic.

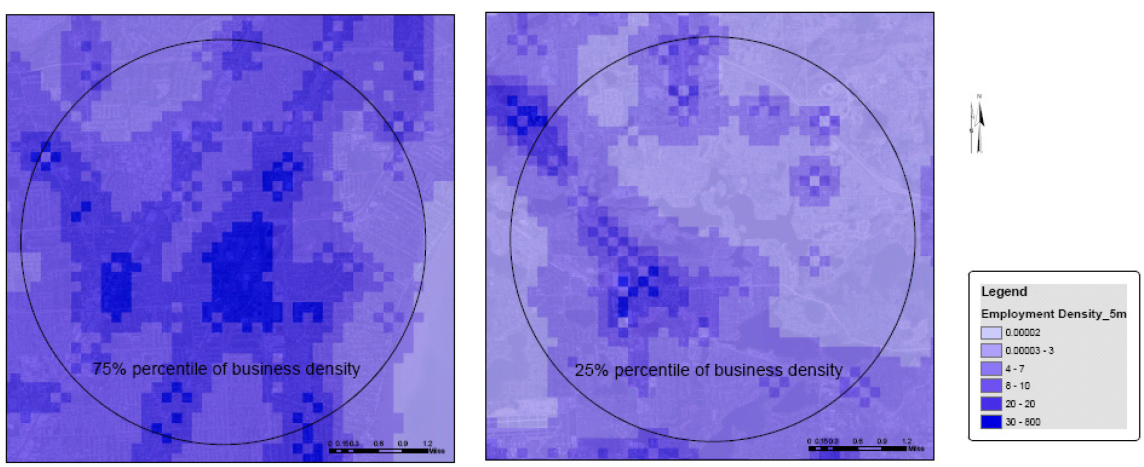

Figure 7-11 Comparisons between drivers who experienced a high-density vs. low-density built environment near home

Figure 7-12 shows an example of the comparisons conducted for BE measurements along routes. It shows the business density along commuting routes for two different drivers. The driver shown on the top panel commuted in a built environment with low business density (25 percentile) whereas the driver at the bottom experienced a high-density built environment along commuting routes (represented by 75 percentile). A one-mile buffer

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[16] The smoothing function contains a five-mile searching radius and inverse distance weights. The value for each cell hence represents the business density for this cell and also reflects the values of nearby cells. The five-mile radius helps to get a smoother surface so that patterns can be easily observed.

was included along the commuting routes for both drivers. Home and work locations are shown as green circles. The background blue colors represent the level of business density in the built environment near routes[17]. The pink-purple colors of the commuting routes represent the business density calculated for each cell located on routes. Scores on route cells are influenced not only by the surrounding built environment features, but also by the frequency of visits and land access of route cells.

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[17] The smoothing function is represented by a one-mile searching radius with inverse distance weights.

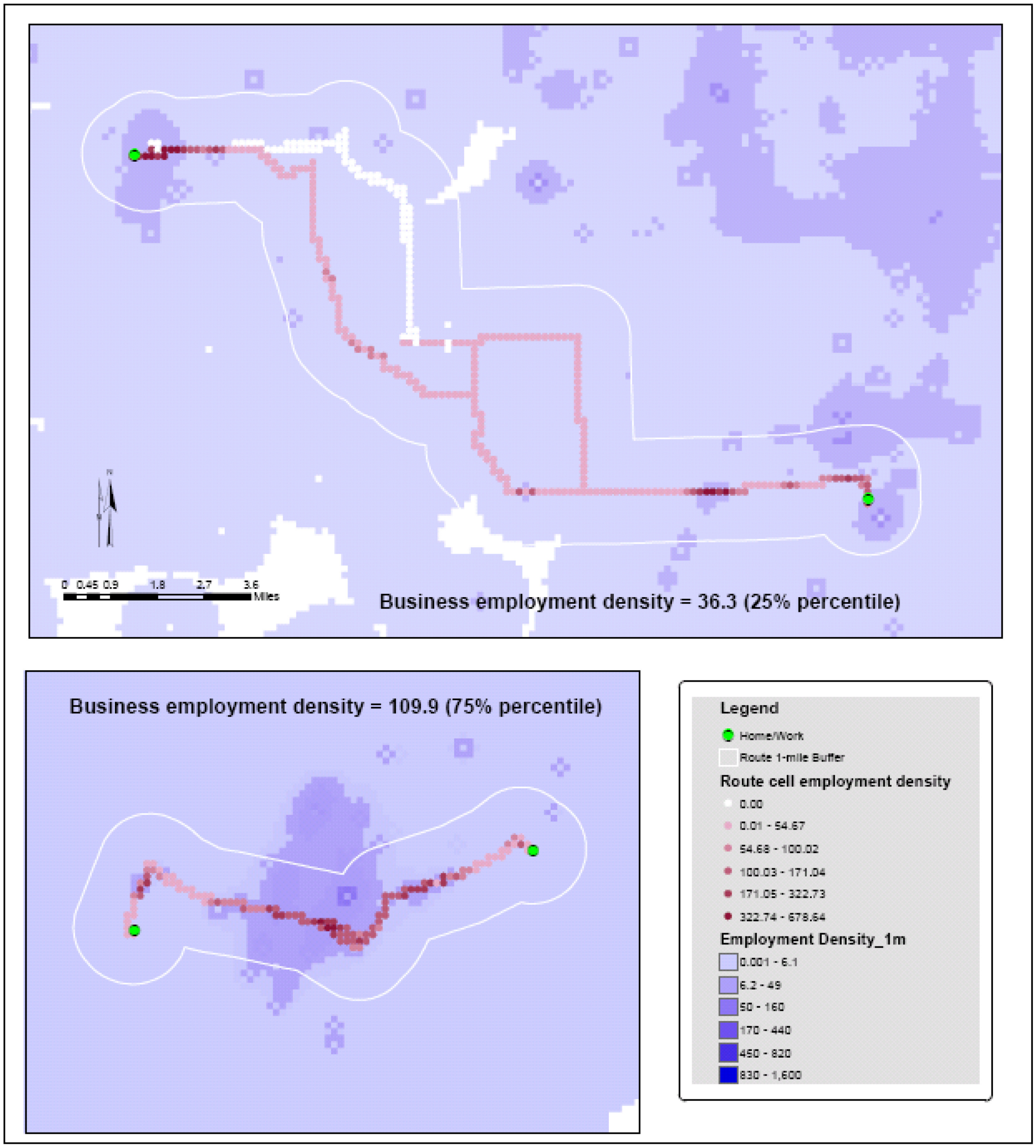


Figure 7-12 Comparisons between 25% and 75% percentile of business density along routes

It is shown in Figure 7-12 that the driver in the upper panel has a low final business density score along route because a large portion of his/her commuting routes run through a low-density built environment. Also, a portion of his/her commuting routes are on limited-access highways (indicated by while colors for routes), which makes the final score for business density even lower. It is assumed that drivers, travelling on limited-access roads, are likely to either get less spatial information en route (limited-access roads usually mean limited views of the surroundings) or have less opportunity to get to the nearby built environment.

The visual inspections of the maps related to the built environment along routes reveal that these route-related BE measurements developed in this study take into account both the characteristics of near-by built environment features and land access of the commuting routes. This is as expected and these measures are thus validated. Other maps can be found in Appendix.

Limitations of the built environment measurements

One of the limitations of the current BE measurements is that comprehensive weighting systems make the measurements harder to interpret than simpler and more straightforward measurements. This complexity brings multiple meanings to a high-value score, which could indicate the appearance of good built environment features (i.e. high density, diversity, connectivity, or more percent of local roads), close proximity of these features to home, work, or routes, frequently-traveled commuting routes, easy access of commuting routes to surrounding land use, or any combination of the four meanings mentioned above. It is often difficult to pinpoint the exact determinant of a high-value score.

Another limitation of the current BE measurements is that the validity of these measurements is dependent on the choices of cell sizes, buffer sizes, and the forms of the impedance function and the sensitivity of these measurements to different choices. In this study, the urban space considered as having the most influence on drivers' travel behavior is that which the drivers frequently visit. The median distance from all non-work activities to home, work, and routes for drivers with only one work location is measured, and defined as the buffer size for home-related, work-related, and route-related BE measurements respectively. However, there are other spaces which might have influences on drivers' driving behavior as well. These may include places which drivers saw, heard of, or have learned about. Questions about what and how much drivers can learn by living, working, or travelling through the built environment, and what are the key factors in determining drivers' spatial knowledge and location choices for non-work activities have yet to be answered. More qualitative studies based behavioral geography are needed to provide theoretical foundations on where and how to measure the built environment.

A different but related concern is about the selection of the impedance function. The current gravity model with a power of two is arbitrary. Compared to other forms of impedance functions, such as inverse distance or negative exponential, the current function places significant weights on the urban space in close proximity to home, work, or routes and the weights decrease dramatically when the distance increases. In the future, different forms of the impedance function can be compared and the rate of distance decay can be estimated by using empirical data. Moreover, the functions can be estimated differently for the built environment near home/work and for the built environment along routes as drivers may have different perceptions of these spaces.

The last limitation worth noting is that the current measurements cannot measure the clustering of different built environment features, such as a cluster of businesses, a cluster of intersections, etc. A cluster of businesses may present a better attraction than the sum of isolated individual business when economies of agglomeration apply. Diseconomies of agglomeration may be at work too when a cluster of businesses with densely-constructed intersections bring crowding or congestion. Despite the importance of clusters, the current measurements cannot locate clusters of any sorts. Studies in the future can incorporate more measurements quantifying the number, the size and locations of clusters.

Factor analysis: reduction of twelve BE variables to three factors

Because multiple built environment features co-exist within the same urban space in our study area, the four built environment dimensions measured in this study are highly correlated with each other. In order to avoid multicollinearity in regression analysis later and make full use of each BE variables, factor analysis is applied in the study. Factor analysis is capable of extracting a small set of factors that explain most of the variance within a large number of observed variables, the individual BE variables in our study. Factor analysis was applied three times to three sets of BE variables related to home, work, and routes, with four variables in each set. This results in three factors: home factor, work factor, and route factor.

Principal component analysis was used as the extraction method without rotation and the regression method was applied to generate the factor score for each factor. Factor scores are used later in the regression analysis as independent variables.

The decision on how many factors to extract is arbitrary. Several methods are available to identify the number of factors to extract. E*igenvalues*, the variances extracted by the factors, were used to determine the number for factor analysis related to home and routes. The criterion for extraction used was that whenever a factor's *eigenvalue* is larger than one, it will be extracted. For home-related and route-related built environment, factor analysis only produces one factor.

Table 7-2 through Table 7-4 show the results for factor analysis on home-related BE variables. Table 7-2 shows that four home-related BE variables are highly correlated with each other (all correlation coefficients are above 0.5) and all correlations are significant at the 0.01 level. The variable, percent of local roads, has slightly lower correlation coefficients with other variables, indicating that the strength of the connections between percent of local roads and other built environment dimensions are smaller. Table 7-3 shows the communalities before and after extraction of the four BE variables near home. *Communality* represents the proportion of variance of a particular variable that is due to common factors (shared with other variables). Principal component analysis works on the initial assumption that all variance is common; so, before extraction the communalities are all 1. The second column labeled *Extraction* indicates the common variance that are shared and explained by the underlying factor. Table 1-3 shows that 0.957 of the variance in business variety can be explained by the factor, which is the highest among the remaining three, whereas percent of local roads has the lowest communality (0.802), which is consistent with our observations based on correlation matrix.

Table 7-4 lists the eigenvalues associated with each component (factor) before extraction. Before extraction, four components (factors) were identified within the data. The eigenvalues associated with each factor represent the variance explained by this particular factor. The second column represents the percentage of the variance explained. Component 1 (Factor 1) explains 85.565 % of the total variance and subsequent factors explain only small amount of variance. Following the eigenvalues-over-1 criteria, only Factor 1 is retained in the analysis.

Table 7-2 Correlation matrix of factor analysis for BE variables near home

	BusinessDensity .Home	BusinessDiversity. Home	Intersection. Home	LocalRoads. Home
BusinessDensity.Home	1	.854(**)	.743(**)	.688(**)
BusinessDiversity.Home	.854(**)	1	.922(**)	.836(**)
Intersection.Home	.743(**)	.922(**)	1	.792(**)
LocalRoads.Home	.688(**)	.836(**)	.792(**)	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 7-3 Communalities before and after extraction in factor analysis for built environment variables near home

	Initial	Extraction
BusinessDensity.Home	1.000	.786
BusinessDiversity.Home	1.000	.957
Intersection.Home	1.000	.878
LocalRoads.Home	1.000	.802

Extraction Method: Principal Component Analysis.

Table 7-4 Total variance explained in factor analysis for BE variables near home

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	3.423	85.565	85.565
2	.320	7.995	93.560
3	.207	5.172	98.732
4	.051	1.268	100.000

It is worth noting that the same criteria of *eigenvalue* larger than one generates two factors for the built environment related to work locations. Table 7-5 and Table 7-6 provide the reasons behind this. The correlation matrix in Table 7-5 shows that percent of local road is not correlated with business density or intersection density. The common variance which is shared with other variables is also very low (0.144) (as shown in Table 7-6), which is the reason why eigenvalues-over-1 criteria produces two factors. The analysis results indicate that higher business density and intersection density do not necessarily mean higher percent of local roads near work locations, which is understandable in that work places tend to have larger blocks which are connected by higher capacity roads.

For this reason road functionality (percent of local roads) was excluded when creating factors for work-related built environment while acknowledging that the uniqueness of the local road network near work may have special connections with drivers' travel behavior. Later in this chapter, both the composite work factor and the work-related percent of local roads are analyzed in linear regressions to determine their connections with travel behavior and outcomes. The final factor analysis on work-related BE variables is shown in Table 7-7 through Table 7-9.

Table 7-5 Correlation matrix of factor analysis for BE variables near work, including percent of local roads

	BusinessDensity.Work	BusinessDiversity.Work	Intersection.Work	LocalRoads.Work
BusinessDensity.Work	1	.637(**)	.725(**)	-.026
BusinessDiversity.Work	.637(**)	1	.640(**)	.527(**)
Intersection.Work	.725(**)	.640(**)	1	.097
LocalRoads.Work	-.026	.527(**)	.097	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 7-6 Communalities of factor analysis for BE variables near work, including percent of local roads

	Initial	Extraction
BusinessDensity.Work	1.000	.707
BusinessDiversity.Work	1.000	.823
Intersection.Work	1.000	.746
LocalRoads.Work	1.000	.144

Extraction Method: Principal Component Analysis.

Table 7-7 Correlation matrix of factor analysis for BE variables near work, excluding percent of local roads

	Business variety	Business density	Intersection density
Business variety	1.000	.801**	.755**
Business density	.801	1.000	.700**
Intersection density	.755**	.700**	1.000

Table 7-8 Communalities of factor analysis for BE variables near work, excluding percent of local roads

	Initial	Extraction
BusinessDensity.Work	1.000	.800
BusinessDiversity.Work	1.000	.733
Intersection.Work	1.000	.802

Extraction Method: Principal Component Analysis.

Table 7-9 Total variance explained in factor analysis for BE variables near work without weighting, excluding percent of local roads

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.335	77.840	77.840	2.335	77.840	77.840
2	.389	12.980	90.821			
3	.275	9.179	100.000			

Extraction Method: Principal Component Analysis.

Chapter 8
Correlation and Regression Analysis

Introduction

The previous chapters analyzed built environment patterns in the Detroit metropolitan area, characterized the travel behavior of a sample of drivers, and estimated the energy consumption and tail pipe emissions from their travel. In this chapter, correlation analysis and multiple linear regressions are conducted to determine the connections between the built environment and travel outcomes.

The analyses use three sets of travel outcomes as dependent variables to test the three research hypothesis sequentially. These consist of: 1) total VMT traveled for non-work purposes; 2) the rates of fuel consumption and emissions for non-work travel (i.e. fuel consumption per distance or emissions per distance); 3) total fuel consumption and emissions for non-work travel. The third set of dependent variables is essentially the product of the previous two. Independent variables include two control variables (age and gender) and built environment measurements represented by twelve individual *elements* (four built environment dimensions measured at three urban spaces), and three composite *factors* (home factor, work factor, and route factor). When constructing the regression models, composite *factors* enter the models as substitutes (rather than supplements) of the twelve built environment *elements.* Therefore, two types of models are created for each dependent variable: one with built environment *elements* and control variables, the other with built environment *factors* and control variables.

The expectations are that, built environment featured by higher business density and diversity, higher road connectivity, and/or more local roads, either near home/work or along commuting routes, are associated with less VMT, higher fuel consumption and emissions per distance traveled, and ultimately, lower total fuel consumption and emissions (as the short travel distance promoted by such build environment is expected to offset the negative energy/emission outcome).

In the first step, simple linear correlation analysis is conducted to test for the existence of significant relationships between the built environment and travel outcomes. Second, multiple regression models are constructed to test the directions and magnitudes of the relationships by controlling for other factors such as age and gender. Independent variables are entered into regression models in a stepwise manner in which, at each step, the variable with the lowest probability (or highest probability) of F statistic are added to (or removed from) models. The stepwise selection[18],requires the probability of F to be 0.05 or less to enter a variable and 0.10 or more to remove a variable.

In addition to the three main dependent variables illustrated above, this chapter also conducts similar correlation and regression analysis to examine several intermediate variables (tour generation or tour length by types of tours) as a function of the built environment features. These analyses on intermediate variables contribute to the understanding about interconnections between the built environment and travel outcomes.

Total distance traveled (VMT)

The correlation analysis results for total distance traveled on non-work trips are presented in Table 8-1. Statistically significant relationships between total VMT and the built environment were identified only for the built environment along commuting routes. The correlation coefficient for the route-related built environment factor is negative (-0.384) and significant at the 0.01 level, meaning that the mixed features of compact, mixed-use business settings combined with well-connected local roads along commuting routes are associated with less VMT for non-work trips. Among the built environment features

[18] The stepwise selection was implemented with SPSS software.

along routes, business density has the highest significant correlations with total VMT, followed by business diversity.

Table 8-1. Correlation coefficients between the built environment elements/factors and total VMT for non-work travel

	Business Density	Business Diversity	Intersection Density	Percent of Local Roads	Factor score
Home-related	0.1	0.09	0.036	0.028	0.069
Work-related	-0.13	0.021	0.111	0.164	0.001
Route-related	-.367(*)	-.343(*)	-0.275	-0.29	-.384(**)

Note: ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

Stepwise models are first constructed for the three composite built environment factors by controlling for drivers' age and gender. The regression results are shown in Table 8-2. The age variable is first added into the model because it has the most significant correlation with total VMT (as shown in Model 1). In the second step (shown in Model 2), the route composite factor is added (in addition to age) as it adds the most significant explanatory power to Model 1. By adding route factor, R Square is increased by 0.086 (i.e., 8.6% more variance can be explained). Consistent with our priori expectation, the coefficient of route factor has a negative sign after controlling for the age variable, which further confirms the negative relationships between route-related built environment features and total VMT. More specifically, a unit increase in built environment factor score along routes will reduce total VMT for non-work travel by 115 miles in a four-week period for an average driver (about 10% of current average level of total VMT per capital).

Table 8-2. Stepwise regression model summary for total VMT (miles) and built environment factors

Model	R Square	Independent variables	Unstandardized Coefficients	Std. Error	Sig.
1	.153	(Constant)	1303.117	151.598	.000
		Age	-9.796	3.479	.007
2	.239	(Constant)	1223.472	149.693	.000
		Age	-7.850	3.449	.028
		Route factor	-115.157	52.042	.032

The stepwise model which uses twelve individual built environment elements as candidate independent variables is constructed as well. This model is useful in identifying the single built environment dimension (i.e. business density, diversity, road connectivity, or functionality) that is most influential in predicting total VMT. Besides the age variable, one and only one built environment element meets the stepwise selection criteria and is entered into the model: route-related business density (results are shown in Appendix Table 1), which suggests its importance, compared to other built environment dimensions in determining total VMT.

The stepwise procedure stops admitting variables into the model after adding the route-related factor or elements, because none of the remaining factor or elements make significant additional contribution to the model. Contrary to expectations, the built environment near home and work places are not strong predictors of total non-work VMT travelled. Statistical tests which examined tour generation rate and average tour distance for tours are employed with the purpose of explaining the loose connections between home-related or work-related built environment and total VMT. Results are summarized in the following tables (Table 8-3 and Table 8-4).

The correlation results shown in Table 8-3 indicate that built environment features near home have significant positive correlations with total number of chained tours and negative correlations with average length of tours. It shows that higher business density, more diverse businesses, higher intersection density and greater percent of local roads are associated with more tours, and shorter distances per tour. This result suggests a possible tradeoff between the shorter-distance tours to the opportunities in such environments and the increased tour generation induced by lower travel cost (i.e. shorter distance) that determines the total distance traveled.

Table 8-3 also shows that both business density along routes and the route factor have significant (at a 0.01 level) negative correlations with the total number of tours, which could be the reason why increased business density or increased route factor score is associated with reduced total VMT (as indicated previously in Table 8-1 and Table 8-2).

Table 8-3. Correlation coefficients between the built environment elements/factors and total number of tours and average tour distance for tours

	Home-related				
	Business Density	Business Diversity	Intersection Density	Percent of Local Roads	Factor score
Number of tours	.509(**)	.579(**)	.508(**)	.739(**)	.630(**)
Average tour distance	-.233(*)	-.266(*)	-.246(*)	-.384(**)	-.304(**)
	Work-related				
	Business Density	Business Diversity	Intersection Density	Percent of Local Roads	Factor score
Number of tours	-0.2	0.222	0.064	.326(*)	0.029
Average tour distance	-0.006	-0.082	0.069	-0.001	-0.006
	Route-related				
	Business Density	Business Diversity	Intersection Density	Percent of Local Roads	Factor score
Number of tours	-.396(**)	-0.264	-0.252	-0.117	-.310(*)
Average tour distance	-0.128	-0.191	-0.109	-0.242	-0.201

The stepwise regression models which regress total number of tours and average tour length on built environment factors confirm the above observations based on correlation analysis: drivers tend to conduct more vehicle tours when the built environment near home is more compact, diverse, and well connected by local roads; however, the same features along commuting routes bring opposite effects (i.e. decrease tour generation).

As shown in Table 8-4, when three built environment factors and control variables are considered as candidates for independent variables, both home factor and route factor are entered into the model as they have significant relationships with total tour generation. Home factor entered the model first, which alone explains 13% of the total variance in tour generation. In the second step, route factor is added into the model, which increases R square by 0. 09. The coefficients for home factor and route factor have opposite signs indicating their diametrically different associations with total tour generation. None of the built environment factors turn out to be strong predictors of average tour length (the regression results are provided in Appendix Table 2), indicating that average tour length is primarily a function of a driver's demographic features.

The positive relationship between home factor and tour generation is generally consistent with what has been found from a previous study which demonstrated that residents living in more compact and mix-use neighborhoods tend to complete more tours and make fewer stops per tour (Krizek 2003). The new finding from this dissertation is that a similar built environment of compact and mix-use land use along commuting routes may result in a different driver behavior, that is fewer tours by drivers. A possible explanation is that drivers experiencing a more densely built environment during commuting trips may stop at multiple places for various non-work activities or finish multiple tasks at fewer locations on their way home or go to work and, as a result, reduce total number of tours and total distance traveled for non-work purposes.

Why do the same built environment features at different urban spaces have different relationships with tour generation? Behavioral theorists told us that it is very likely that drivers perceive the same built environment features differently and hence act (travel) differently at different urban spaces. More behavioral research focusing on activity participation/ scheduling and trip chain generation is needed to shed light on this question.

Table 8-4. Stepwise regression model summary for total number of tours and built environment factors

Model	R Square	Independent Variables	Unstandardized Coefficients	Sig.
1	.130	(Constant)	35.424	.000
		Home factor	5.116	.014
2	.223	(Constant)	35.421	.000
		Home factor	5.043	.011
		Route factor	-3.534	.029

Stepwise regression analysis on tour generation for tours with individual built environment elements (results are shown in Appendix Table 3) suggests that home-related road function, intersection density along routes, and work-related road functionality are the best three predictors of tour generation for non-work travel. Higher percent of local roads near home and work places is associated with higher number of tours whereas higher intersection density along routes is related with lower total number of tours for non-work travel.

Similar analyses are performed on tour generation and tour length cross-tabulated with types of tours (i.e. HNH, HNW, WNH, or WNW tours) to pinpoint which portion of the total travel is influenced by which dimensions of the built environment located at which urban spaces. The analysis (summarized in Appendix 4) has shown that, consistent with the research framework illustrated at the beginning of this dissertation (reproduced below in Figure 8-1), urban space near home locations tend to have more connections with non-work travel originated and ended at home (HNH tours) whereas space near work or along commuting routes travel have closer relationships with non-work travel originated and ended at work places (WNW tours) or travels in-between home and work (WNH or HNW tours).

Significant correlation coefficients (Appendix Table 4) are found between urban spaces and their corresponding types of tours (for instance, home-related urban space with HNH tours). Regression analysis confirms this finding by demonstrating the existence of statistically significant relationships between HNH tour generation and home factor (Appendix Table 5), between HNH tour generation and home-related percent of local roads and business density (Appendix Table 6), between HNW average tour length and route factor (Appendix Table 7), between HNW average tour length and route-related road functionality (Appendix Table 8), and between HNW tour generation and route-related road functionality and business diversity (Appendix Table 9). However, there are a few mismatches. For instance, intersection density near work places turns out to have positive relationships with tour generation for HNW tours (instead of WNW tours) (Appendix Table 9) and home-related factor score is the single best predictor of average tour distance for tours originated and ended at work places (WNW tours) (Appendix Table 10). The mismatches could be caused by the underlying similarity between the built environments across different urban spaces for the same driver. This study will not focus on this phenomenon. However, it is worth further explorations in the future.

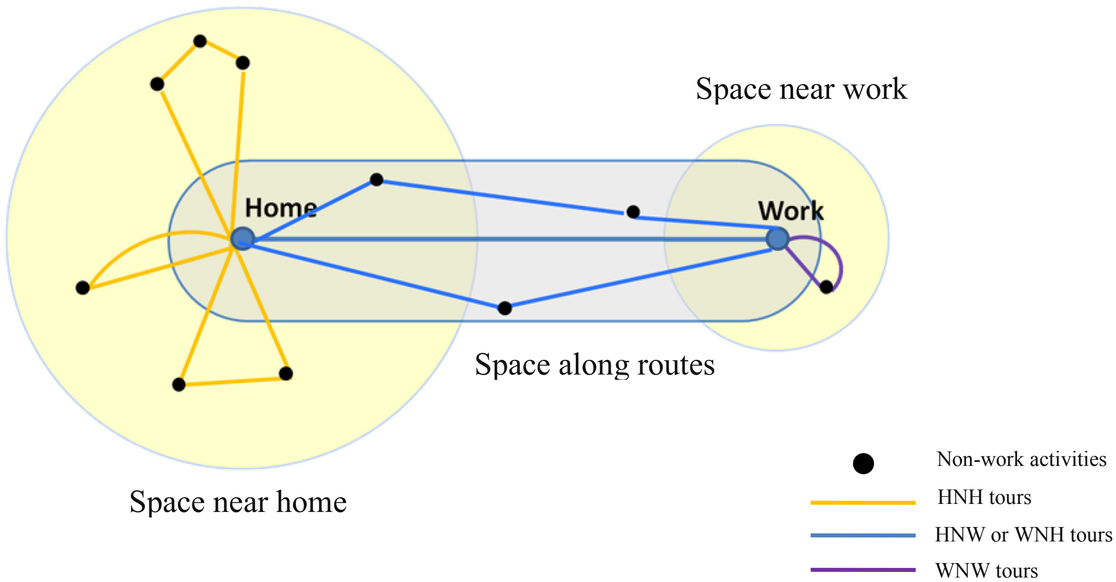


Figure 8-1 Illustration of three types of urban spaces and corresponding non-work travels

Energy consumption and emission per distance

Table 1-5 shows the correlation analysis results for the rates of energy consumption and emissions for non-work travel. Home-related built environment variables have statistically significant relationships with fuel consumption rate and emission rates. Table 8-5 reveals that higher business density, more business variety, higher intersection density, or more percent of local roads near a driver's home are associated with higher fuel consumption per mile as well as emissions of CO_2 per mile. All home-related built environment elements, except for business density, have positive relationships with emissions per mile of the two major tailpipe emitters, HC and NO_X. The signs of the relationships are consistent with our prior expectations. As stated in our second hypothesis, compact, mixed-use land-use developments with well connected local road networks could be associated with higher vehicle energy consumption and emission per distance travelled. In such an environment, drivers tend to make more stop-and-go actions and reduce driving speed, all of which have negative consequences for fuel consumption and emission rates.

Unlike other tailpipe emissions, CO emission is related to only one of the home-related built environment elements (percent of local roads), indicating that CO could be emitted to the atmosphere through a different mechanism. The CO emission rate is negatively associated with intersection density along routes and positively related to road functionality near work places. The underlying reasons of why the relationships between the built environment and CO emission rate are different from other emissions can be further studied by analyzing key factors influencing CO emission rate compared with other tailpipe emissions. These factors may include average speed, acceleration, low-speed driving, and sudden stops.

Unlike the built environment near home, the built environment features along commuting routes and near work places have little connection with the fuel rate and emission rates. The visit frequency of home is much higher than that of routes and work places, which could be the reason why home-related built environment features have a closer connection with fuel rate and emission rate. A driver spends more time in the built environment near his/her home, and consequently his/her travel behavior is likely to be influenced by that build environment. These results make it evident that the effects of the built environment on travel behavior are in fact contingent upon the spatial location of the built environment relative to home, work, or commuting routes. Vehicle travel may be influenced by the built environment at some places (like home), but may not be so at other places (such as work or routes).

Table 8-5 Correlation coefficients of built environment variables on energy and emission rates for non-work travel

		Business Density	Business Diversity	Intersection Density	Local Roads	Factor score
Fuel per mile (grams/mile)	Home-related	.381(**)	.510(**)	.542(**)	.521(**)	.529(**)
	Work-related	0.023	0.07	-0.083	-0.043	0.002
	Route-related	-0.115	0.019	0.081	-0.01	-0.008
CO2 per mile (grams/mile)	Home-related	.393(**)	.526(**)	.552(**)	.519(**)	.539(**)
	Work-related	0.05	0.054	-0.051	-0.118	0.019
	Route-related	-0.069	0.077	0.167	-0.004	0.051
HC per mile (grams/mile)	Home-related	0.196	.257(*)	.279(*)	.356(**)	.294(*)
	Work-related	0.038	0.152	-0.111	0.179	0.028
	Route-related	-0.053	0.016	-0.093	0.185	0.016
CO per mile (grams/mile)	Home-related	0.116	0.158	0.205	.254(*)	0.198
	Work-related	-0.108	0.099	-0.176	.299(*)	-0.073
	Route-related	-0.255	-0.245	-.334(*)	-0.036	-0.262
NOX per mile(grams/mile)	Home-related	.243(*)	.309(**)	.341(**)	.388(**)	.346(**)
	Work-related	0.019	0.158	-0.122	0.173	0.018
	Route-related	-0.076	-0.008	-0.123	0.144	-0.019

*: significant at 0.05 level
**: significant at 0.01 level

Among all regression models conducted for fuel and emission rates, only three stepwise models contain built environment elements that are statistically significant (shown in Table 8-6). They are: 1) fuel rate as a function of home-related local roads (Table 8-6); 2) CO_2 rate as a function of home-related local roads; 3) CO rate as a function of route-related intersection density and age. More specifically, the coefficients show that a unit increase in percent of local roads near home will increase fuel rate and CO_2 emission rate by .342 and .991grams/mile respectively. To put these numbers into context, the average fuel consumption rate for all non-work trips by all 73 drivers is 119.57 grams/mile (22 miles per gallon) and the average CO_2 emission rate is 367.91 grams/mile. The unit increase of fuel consumption and emission rates are about 0.3% of the current average level. Although the magnitudes of the associations look small, the accumulative effect of the built environment near home on every mile a driver travels could be unexpectedly high.

All composite factors turn out to be not significant enough to enter the models. These results suggest that the connections between the built environment and the rates of fuel consumption and emissions are primarily are embedded in the individual built environment elements, particularly those related to road configurations and functions (as supposed to business-related elements or composite built environment factors). Lower road functional class (residential roads) and higher four-way intersection density are associated with increased fuel consumption and emission rates.

Table 8-6 Regression model summary for fuel per mile, CO_2 per mile, and CO per mile and built environment elements

	Dependent variables			
Independent variables	Fuel per mile (grams/mile)	CO_2 per mile (grams/mile)	CO per mile[1] (grams/mile)	CO per mile [2] (grams/mile)
Constant	111.779 (.000)	344.286 (.000)	8.965 (.000)	11.852 (.000)
Home-related local roads	.342 (.005)	.991 (.004)		
Route-related intersection			-.681 (.023)	-.672 (.020)
Age				-.071 (.034)
R Square	.168	.172	.111	.201

Note: numbers shown in parentheses represent the significance level (P).
The stepwise procedure generates two models for CO per mile. Route-related intersection density entered the model first, followed by age variable.

Total energy consumption and emission

The final hypothesis to be tested in this study is about the relationships between the built environment and the total amount of energy consumed and emissions emitted. More compact, mixed-use land-use developments with well connected local road networks are hypothesized to be associated with lower total energy consumption and emissions because it is likely that the short travel distance promoted by such type of build environment will offset the negative energy/emission outcome.

Several relationships can be seen from the correlation results shown in Table 8-7: (1) Built environment features (such as higher business density, more diversity, higher connectivity, and lower road functionality) near home increase the total emissions, specially for HC and NO_X; (2) built environment features along routes always have the opposite effect on total energy and emissions: higher business density, more diversity, higher connectivity, and lower road functionality are associated with lower total energy and emissions; 3) work-related built environment features have little relationship with total energy consumption and emissions.

Table 8-7 Correlation coefficients of built environment variables on various total energy and emissions for non-work travel

		Business Density	Business Diversity	Intersection Density	Local Roads	Factor score
Fuel (grams)	Home-related	0.189	0.211	0.162	0.151	0.193
	Work-related	-0.141	0.023	0.094	0.154	-0.01
	Route-related	-.394(**)	-.357(*)	-0.259	-.308(*)	-.397(**)
CO2 (grams)	Home-related	0.188	0.209	0.158	0.145	0.189
	Work-related	-0.135	0.023	0.102	0.147	-0.004
	Route-related	-.389(**)	-.351(*)	-0.25	-.308(*)	-.391(**)
HC (grams)	Home-related	.271(*)	.336(**)	.306(**)	.382(**)	.350(**)
	Work-related	-0.156	0.107	0.037	0.271	-0.006
	Route-related	-.432(**)	-.380(**)	-.322(*)	-0.21	-.406(**)
CO (grams)	Home-related	0.135	0.178	0.186	0.218	0.194
	Work-related	-0.222	0.015	-0.067	0.232	-0.105
	Route-related	-.383(**)	-.391(**)	-.348(*)	-0.238	-.411(**)
NOx (grams)	Home-related	0.228	.261(*)	0.222	.245(*)	.258(*)
	Work-related	-0.164	0.054	0.062	0.208	-0.019
	Route-related	-.415(**)	-.378(**)	-.305(*)	-0.269	-.413(**)

*: significant at 0.05 level
**: significant at 0.01 level

Regression results for the final travel outcomes (total energy consumption and emissions) are shown in Table 8-8 and Table 8-9. Significant regression results for all travel outcomes which have been tested in this dissertation are summarized in Figure 8-2. Total energy consumption and emissions are highlighted in blue boxes. Blue lines represent negative associations between two variables whereas red lines represent positive associations.

Table 8-8 Significant regression models for total fuel and total CO_2 with built environment elements/factors

	Dependent variables			
Independent variables	Total fuel (grams)	Total fuel (grams)	Total CO2 (grams)	Total CO2 (grams)
Constant	158747.097 (.000)	148771.642 (.000)	482356.989 (.000)	452569.589 (.000)
Age	-1073.817 (.006)	-1037.211 (.009)	-3206.012 (.007)	-3099.289 (.011)
Route employment density	-66.406 (.020)		-199.121 (.022)	
Route factor		-13111.473 (.028)		-39135.396 (.031)
R square	.291	.281	.283	.273

Note: numbers shown in parentheses represent the significance level (P).
This table only shows models created at the final step (no more variables can be added or removed).

Table 8-9 Significant regression models for total HC, CO, and NO_X with built environment elements/factors

	Dependent variables					
Independent variables	Total HC (grams)	Total HC (grams)	Total CO (grams)	Total CO (grams)	Total NO_X (grams)	Total NO_X (grams)
Constant	231.224 (.000)	215.509 (.000)	12523.288 (.000)	11869.038 (.000)	322.955 (.000)	301.550 (.000)
Age	-1.504 (.010)	-1.472 (.014)	-136.778 (.001)	-118.419 (.007)	-2.225 (.005)	-2.154 (.008)
Route employment density	-.113 (.008)				-.145 (.012)	
Route intersection density			-1176.483 (.002)			
Route factor		-20.492 (.022)		-1520.248 (.021)		-28.088 (.020)
Home local roads			130.336 (.034)			
R square	.306	.276	.391	.298	.312	.298

Note: numbers shown in parentheses represent the significance level (P).
This table only shows models created at the final step (no more variables can be added or removed).

The results of the regression analyses show that the route factor is the best predictor of total fuel consumption and all total emissions. Higher route factor (i.e. higher density, more diversity, higher connectivity, and higher percent of local roads along commuting routes) is associated with lower total fuel consumption, CO_2, HC, CO, and NO_X. As indicated in previous analysis, route factor has a negative relationship with total VMT; although its connection with the rates of energy consumption and emissions are not statistically significant. A reduced total travel distance brought by the built environment with higher route factor scores could be the leading cause of the decreased total fuel consumption and emissions.

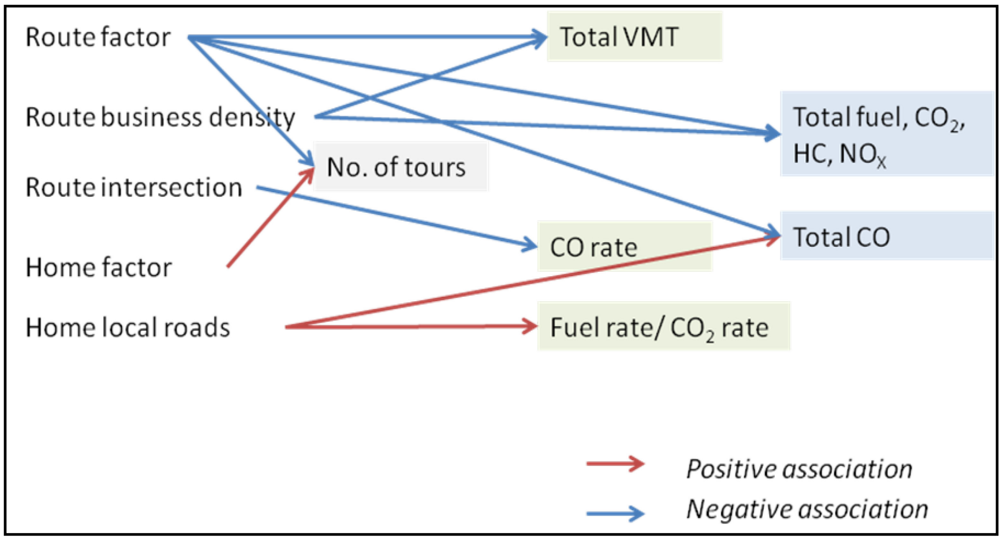


Figure 8-2 Regression results for total fuel consumption and emissions

Among different dimensions of the built environment along routes, business density has the most significant negative relationships with total fuel consumption and emissions (except for total CO emission). Such negative associations can be explained by the negative connections between route-based business density and the total VMT. Why does a higher density environment along commuting routes lead to a reduced total travel distance for non-work activities? Abundant destination choices provided by such an environment along commuting routes may encourage drivers to chain multiple non-work activities together on their way home or to work, as a result of which, total number of tours could be reduced and hence the total travel distance. Previous regression results which regressed total tour generation on built environment elements along routes confirm the above explanation. It was shown previously that higher route-related business density is related with lower total number of tours.

Contrary to our expectations, features near home such as densely-built business settlements, more diverse business mix, and higher road connectivity were actually associated with more emissions. Although these features may provide more non-work destination choices such as stores, banks, or restaurants, with close proximity to home, drivers may generate more vehicle trips which may compromise the total travel distance saved from the shorter travel distance per trip. Meanwhile, such features are associated with higher emissions per mile (as indicted in the previous section), which increases the overall level of emissions.

None of the built environment variables related to work places have relationships with total energy consumption and emissions in a statistically significant way. Certain built environment variables (such as percent of local roads) near work have relationships with tour generations; however, the connections between work-related built environment and total VMT, energy and emission rates, and total fuel consumption and emissions are too weak to be detected.

Chapter 9
Conclusions and Future Research

Research findings and policy implications

This dissertation examines the complex interrelationships between specific attributes of the built environment, VMT, and the associated vehicle fuel consumption and emissions using correlation and regression analyses, and advanced GPS and GIS technology A disaggregated analysis scheme, which related an individual driver's travel outcomes to the built environment he/she experienced, is developed.

Four attributes of the built environment: business density, business diversity, network connectivity, and road functionality are defined and measured near home and work and along a driver's daily commuting routes for 73 drivers in the Detroit metropolitan area. By defining and quantifying the built environment at three urban spaces: space near home, work, and along routes, this study is able to examine the relationships between travel outcomes and the built environment specific to each urban space.

Travel information specific to each trip is derived from an extensive GPS dataset, which was collected over four weeks for each driver on a second-by-second basis. Trip attributes collected include trip purposes (home, work, or non-work), trip frequency, trip length and durations, and speed variations. Trips are furthered combined into tours based on its origin and destinations and the appearance of chained non-work activities. Spatial analysis of tours was conducted to provide in-depth understanding of trip-making patterns in the study area and, furthermore, provide the basis of defining the most important urban spaces which have close relationships with travel behavior. An instantaneous emission model is used to estimate the second-by-second fuel consumption and vehicle tailpipe emissions of carbon dioxide, carbon monoxide, hydrocarbon, and nitrogen oxides. Correlation analysis and multivariate statistical techniques are used to test the direction and magnitude of the associations between the built environment and VMT (a product of tour generation and average tour length, fuel consumption and emissions for non-work travels, controlling for other factors.

To test the six hypotheses of this dissertation, the regression results are summarized in Table 9-1. The research findings from this dissertation are many, but can be synthesized, into three major research findings with far-reaching policy implications. These are: 1) compact mixed-use developments near drivers' home may not associate with beneficial fuel consumption and emission outcomes; 2) different from home-related built environment, compact mixed-use development along major commuting routes is related with reduced total travel distance and reduced total fuel consumptions and emissions; 3) GPS technology combined with GIS tools are powerful tools to study the links between the built environment and energy and environmental outcomes. The first finding is closely related to the first three hypotheses while the second finding is more relevant to the latter three hypotheses. The last finding is regarding the GPS methodology applied in this dissertation in general. The following chapter will elaborate on each finding and its associated policy implications.

Table 9-1 Hypotheses testing results for dimensions of the built environment and travel outcomes

		Total VMT (Hypothesis 1)	Energy/emission rate (Hypothesis 2)	Total energy/emission (Hypothesis 3)
Home/work	Factor score			
	Business density			
	Business diversity			
	Road connectivity			
	Percent of local roads		+ (home only)	+ (home only)
		Total VMT (Hypothesis 4)	Energy/emission rate (Hypothesis 5)	Total energy/emission (Hypothesis 6)
Commuting	Factor score	-		-
	Business density	-		-
	Business diversity			

	Road connectivity		-	
	Percent of local roads			

Note: blank table cells mean that the variables are not significant enough to be entered the stepwise models. The stepwise selection requires the probability of F to be 0.05 or less to enter a variable and 0.10 or more to remove a variable.

"+" means positive relationships; "-" means negative relationships.

The indicated relationships are not specific to emission types. If the built environment variable is significantly related to one type of emission (for example CO), A positive or negative sign will be entered into the table.

Finding # 1: compact mixed-use developments near drivers' home may not associate with beneficial fuel consumption and emission outcomes.

One important finding of this study is that the built environment features identified by new urbanists and others to have beneficial travel outcomes may have negative effects on energy consumption and emissions. Such built environment features located near drivers' home locations do not necessarily mean reduced total VMT or reduced fuel or emissions. More vehicle trips may be generated as a result of more convenient destination choices provided by a more densely built mixed use built environment setting, particularly if non-motorized travel is not available. In our study area (Detroit metropolitan area), the study shows that, mixed features of higher business density, more diversity, higher road connectivity, and more percent of local roads near drivers' home are in fact associated with increased total number of tours.

In such environment, the energy consumption per mile and emissions per mile are higher as well because drivers may travel at relative low speed, stop more at intersections or stop signs, or be stuck in traffic. This study has shown that a unit increase in percent of local roads near home will increase fuel rate and CO_2 emission rate by .342 and .991grams/mile respectively, which are 0.3% of the current emission rate level. The total fuel consumption increase induced by this increase of fuel rate is roughly equal to 2 gallons of gasoline in one year per capita, assuming total distance traveled remains constant. The magnitude of the association seems modest. However, if total distance traveled increases to a large extent, the negative effects of increased fuel consumption rate and emission rate could be magnified.

As planners, we have to keep these potential negative effects in mind and find strategies to restrain these negative outcomes when designing a built environment that is more compact and mixed.

Policy implication: promoting green technologies and providing non-motorized transportation alternatives

As discussed at the beginning of this dissertation, strategies to cope with this problem include technology-oriented strategies and urban planning-strategies.

Green vehicles, (that is, vehicles function fully or partly on alternative energy sources other than fossil fuel), can provide promising solutions. A new generation of hybrid cars improves energy rate and emission rates significantly, especially at the densely-populated urban region. However, as argued at the beginning of this dissertation, the savings of fuel consumption and reduction of emissions brought by this type of new technologies may lead to a higher level of auto-dependency which compromises the benefits. It is essentially the trade-off between the decreased distance traveled by cars and the better fuel efficiency and emission rate that determines the ultimate energy and environmental travel outcomes.

It is also worth noting that all energy sources have their own life-cycle costs. For instance, the electricity to power an electric vehicle may be generated by a plant which is burning coal and contributes significantly to CO_2 emission. More precisely, all electricity needed in US in 2006 was generated from coal (48.95% of electricity), natural gas (20%), nuclear (19.3%), and others. When evaluating the benefits of the green technologies, we have to consider the full life-cycle costs associated with them.

Compact and mixed-use developments which provide non-motorized travel options, as advocated by new urbanists and smart growth supporters, can limit the need of vehicle travel, save energy, and reduce emissions dramatically and fundamentally. If such environment can substitute a portion of the automobile travel with non-motorized travels such as bus, biking, or walking, the negative outcomes brought by the increased rates of fuel and emissions can be easily canceled out. Two gallons gas (the extra cost associated with driving in a compact and mixed use area) is equivalent to about 40 or fewer miles of driving in a year, which means that if a driver can shift only a few auto trips to non-motorized trips in a year period, the negative outcomes will be eased even if the energy and emission rates were not improved by technologies.

The research results presented in this dissertation also suggest that the transportation merit of new urbanism or smart growth lie in the aspect of mode shift which refers to the change of reliance on automobiles to non-motorized means. A compact and mixed use neighborhood will not be associated with reduced VMT, fuel consumption, and emissions if alternative travel means are not provided and most travel needs are met through driving.

Land use strategies which promote alternative transportation options may include: transit-oriented development, pedestrian pocket, bicycle-friendly and pedestrian-friendly design, compact neighborhoods and such. Detailed description and evaluations can be found elsewhere (Ewing 1995; Frank and Pivo 1995; Greenwald 2003; TRB 2005).

As discussed above, technology and land use strategies have their own strength and limitations in saving energy and protecting the environment. The former one improves energy and emission per mile although it might increase total VMT; the latter one might bring the opposite effects: reduce total VMT, but however, worsen energy and emission rates. A combination of the above strategies is likely to bring the most beneficial results.

Finding #2: Built environment along commuting routes matters and compact and mix use developments along routes have statistically significant associations with beneficial energy and environmental outcomes.

Analysis of the spatial distribution of non-work activities in this study has shown that a significant amount of non-work travel happened in urban spaces centered around home, work, and most importantly, along the commuting routes. Previous studies pointed out that a large number of non-work trips are made outside the neighborhoods (TRB 2005). However, these studies do not explain where and why certain non-work trips are located outside the neighborhoods, even when the neighborhoods were relatively compact and of mixed-use. The research conducted in this study adds to our knowledge by demonstrating that a good portion of the non-work trips made outside the neighborhood occur along drivers' daily commuting routes.

It was shown that about 13% of total number of tours are HNW tours or NHW tours, the types of tours which connect home and work locations and chain at least one non-work activity in between. The median distance between these non-work activities and commuting routes is one mile, indicating that these activities happen in the bell-shaped corridor along commuting routes with close proximity to the routes.

The bell-shaped built environment corridor also turns out to have associations with desirable travel outcomes, if they have more compact and mixed use features. It was shown that mixed features along commuting routes, such as higher business density, higher business diversity, higher road connectivity, and more local roads, are associated with lower number of tours, less miles driven, lower rates of fuels and emissions, and lower total amount of fuel consumed and air pollutant emitted for non-work activities. To put these associations into measurable terms, an unit increase in route-related built environment score is associated with a reduction in total number of tours by 3.5 (6.6% of the current average level), a reduction in total VMT by 115.1 miles (13% of the current mean VMT), a reduction in fuel per mile and CO_2 per mile by 0.34 grams/mile and 0.99 grams/mile (0.3% of the current average rates), a reduction in total fuel and CO_2 by 13,111 grams and 39,135 grams respectively (roughly 13% of the current level). Most notably, intersection density along routes has the closest relationships with CO rate and total CO emission. A unit increase in intersection density will result in 9.9% of decrease in CO rate and as high as 25% of decrease in total CO emission. These numbers indicate that the associations and potential influences of route-related built environment on travel outcomes are not negligible.

The reduction of total fuel consumption and emissions is primarily due to the reduction in the number of tours generated (travel that contains at least one non-work activity). A possible explanation of this reduction is that in more densely-built commuting corridors drivers may have more opportunities to meet their daily non-work needs by stopping at multiple places for various non-work activities or finishing multiple tasks at one location on their way to or from work. The non-work activities could be located exactly on the commuting routes, or at locations off but close to the routes (in this case a brief detour from the commuting routes is required).

Consider the following two scenarios: Angelina and Angela both live and work at similar places. They both rely on cars to travel (like people living at the Detroit metropolitan region). With a more compact commuting corridor, Angelina usually runs several errands (e.g. groceries, ice cream stores, etc.) on her way back home from work. Sometimes she prefers the places located en route. Sometimes she gets out of her daily commuting routes to run errands. Because the non-work locations are close to the commuting routes and more accessible, the extra miles she needs to drive are short. Sometimes, she parks the car at one place and goes to other places on foot. Meanwhile without such convenient corridors along her home-work trip, Angela always goes back home first and complete separate single-purpose vehicle trips to ice cream store and to groceries. As a result, Angelina has fewer tours and less VMT for the same amount of activities conducted as Angela.

Policy implication: promote multi-functional corridors

This dissertation is calling for much needed attention and new perspectives on the planning of the built environment along major commuting corridors. Commuting routes have traditionally been regarded by transportation engineers and planners as single-purpose routes, whose main purpose is to deliver commuters to work or back home from work (an obligatory type of travel with fewer choices on the timing of the travel and the routes of the trips). Major commuting corridors were designed and constructed in such way that people can get to work or back home as quickly as possible. To fulfill its purpose, a typical commuting route consists of limited access highways. However, this study argues that people do choose to chain other types of activities on their way to work or after work to make full use of these obligatory trips. The commuting corridors (including the surrounding built environment) should be designed as multi-functional corridors, providing not only direct connections between home and work but also non-work destination choices for commuters to stop by. As indicated in the research findings, a commuting corridor which has compact, diversified businesses and interconnected local streets is likely to reduce total VMT, reduce air pollutions, and decrease fuel consumptions, from drivers' perspective.

It is worth noting that the built environment with "compact, diversified businesses and interconnected local streets" can take different forms. Some form would benefit other users (such as walkers, bus riders, or bikers), while other forms may not. For instance, adequate businesses could be arranged linearly along commuting routes and large parking space could be provided in the front. A strip mall (like the one shown in Figure 7-2 in previous chapters) fits this description. A commuting corridor contains a strip mall may reduce VMT, in comparison with a commuting corridor that contains no business, for reasons illustrated in the Angelina-Angela example. On the other hand, the same amount of businesses could also be arranged in a fashion of one/two-story buildings facing the streets with curb parking and sidewalks (like the ones show in Figure 7-5 and Figure 7-6). This form of built environment is beneficial not only for drivers, but also other street users. One limitation of this dissertation is that it cannot distinguish these different forms of compactness and their influences on different users. Researchers from the field of urban design provide valuable guidance on designing commuting corridors that are multi-functional.

In *the Boulevard Book*, Allan Jacobs criticized the traditional single-purpose roadway design which only facilitates fast auto flow. The author illustrated and advocated the concept of "*multiway boulevards*", streets which provide parallel roadways serving distinctly different traffic functions. The multiway boulevard is "characterized by a central roadway of at least four lanes for general fast and nonlocal traffic; on either side of this roadway are tree-lined medians that separate it from parallel, one- way side access roads for slow-moving traffic…the access roads generally allow for one or two lanes of parking and one moving lane." In another book, *Great Streets*, Jacobs argued that streets should encourage socialization and participation of people in the community.

The merits of multiway boulevards are that they can serve both through traffic and allow continuous access to abutting properties (Jacobs, Macdonald and Rofé 2002) and they can serve both vehicular movement and pedestrians. Jacobs observed numerous multiway boulevards around the world. Several good examples were identified in the book, including the Avenue Montaigne in Paris (shown in Figure 9-1) and the Avinguda Diagonal in Barcelona (shown in Figure 9-2). As noted by Jacobs, the multiway boulevards are rare in the United States. The Eastern Parkway in Brooklyn (Figure 9-3) is a rare example of multiway boulevards in the US. Images from Google Street Views are provided as follows.

Figure 9-1 The multiway boulevard: Avenue Montaigne, Paris, France

Source: Street View from google map

Figure 9-2 The multiway boulevard: Avinguda Diagonal, Barcelona, Spain

Source: Street View from google map

Figure 9-3 The multiway boulevard: Eastern Pkwy, Brooklyn, United States

Source: Street View from google map

Several design elements of the multiway boulevard can be incorporated in multi-functional commuting corridors, as recommended by Jacobs and shown on the above images. These features include adequate buildings facing the streets with little or no setbacks, more access to the streets (by intersecting with other streets), diversity (a combination of restaurants, stores, churches, schools, etc.), more trees, residential density (which supports the usage of the streets), and parking.

Parking is a key element of great streets and has to be provided carefully. Curb parking or parking lanes serve as transition areas between drivers and nearby properties and also a barrier between vehicle traffic and pedestrian. However, too much parking can be a problem. On great streets, according to Jacobs, parking always seems to be not enough; however, they "seem to do well without 'enough'" (Jacobs, Macdonald and Rofé 2002).

In the near future, the biggest opportunities for multi-functional commuting corridors are likely to lie in the improvement of clusters or nodes which are already experiencing density increase, such as places in the inner suburbs, near highway interchanges, or near transit stops.

Finding #3: GPS technology combined with GIS are powerful tools to study the links between the built environment and travel outcomes.

The third finding and contribution of this study is that it proves the feasibility of applying GPS-based data combined with GIS to understand the connections between the built environment and energy consumption and emission outcomes. Extensive data processing procedures have been developed to derive travel information from GPS traces. Methods developed in this dissertation include algorithms to identify valid/invalid trips, identification of intermediate stops (stops made in the midst of a trip), aggregation of trip ends into single destinations, identification of home and work place, map matching which matches GPS points to the underlying road networks, and estimation of energy consumption and emissions by using the Comprehensive Modal Emissions Model (CMEM).

GPS data provide unprecedented opportunities to conduct research related to transportation and land use. This dissertation utilized and capitalized on several of the opportunities. The precise location information collected for each trip destination over four-week period allows this study to visualize the spatial distribution of all destinations and to discern patterns of the most important destinations (designated as home and work places) and their influences on the rest of the destinations. The actual travel route information identified by the map matching procedure helps to uncover the visit frequency and attributes of the real commuting routes, which were not previously available from the conventional trip dairy data. The second-by-second speed and acceleration information provided by GPS data was used as inputs of the instantaneous CMEM model to provide precise estimations of energy consumption and emissions.

GPS data also present unexpected challenges to transportation professions. The massive data set requires tremendous efforts to convert GPS traces into meaningful travel behavior and travel outcomes database. Trip purpose, which can be easily collected through self-reported trip diary, is the single most crucial information which has been missing in the current GPS dataset. This study managed to derive home and work location information endogenously from the GPS dataset without further interviewing the survey respondents; although more detailed categories of trip purposes and activity types at each trip end provided by drivers will be especially valuable for similar research in the future.

Policy implication: GPS technology combined with computer-assisted-self-interview (CSI) will provide promising opportunities for researchers to understand travel outcomes.

To avoid the biggest disadvantages of GPS dataset in terms of its missing trip purpose information, the best travel survey data collection strategy would be to equip survey respondents with both GPS receivers and computer-assisted-self-interview (CSI) devices. There are primarily two types of GPS data collection methods: passive in-vehicle collection (which NDD dataset belongs) and GPS combined with CSI. Different from the passive in-vehicle collection, the CSI device allows respondents to record the trip purpose and vehicle occupancy information directly into a computer (laptop or handheld). CSI will not add too much extra burden to respondents as it only takes about 1 or 2 minutes to input the data. On the other hand, the self-reported information will save tremendous time and efforts later on for the post- processing and deriving of trip purposes.

Large scale GPS data had been and are being collected in several regions, including passive in-vehicle data and CSI equipped GPS data. By understanding the strength and limitations of each data collection effort, researchers can take full advantages of the innovative and valuable GPS dataset to better understand travel behavior and travel outcomes as well as its connections with the built environment.

Limitations and Future researches

Because the present study is cross-sectional, the correlation and regression results from this study show associations but not causality. For instance, we cannot conclude that if we increase business density along routes, it will definitely translate into lower VMT and energy consumption and emissions. The beneficial travel outcomes could be due to the impact of the increased business density, or, it could be the result of people's attitudes and the "self-selection" process (travelers who prefer travel less and consume less fuel tend to travel in a more densely-built environment along routes).

Self-selection has been seen as a bias which needs to be controlled for through other research techniques. However, scholars have also argued that the view that self-selection is a source of bias presupposes that all needs for alternative development patterns have been met under free-market condition (Levine 2005). But the reality is that land development is not a free market. Because of the regulatory impediments which limit the supply of compact and mixed-use development, there is considerable unmet demand in the market for an alternative living to the low density sprawling suburbs. Under such circumstances, providing choices to people to meet the unmet demand would generate real benefits through self-selection (Levine 2005). This study only demonstrated the associations between the built environment and travel outcomes, regardless whether it is the effect of the built environment or of people who choose to live and travel in such built environment. Studies which focus on the portion of the market that has potential interests in compact and mixed use development in the study area are much needed.

Another limitation of this research lies in its small sample size. The GPS data was collected for 78 drivers, of which 73 drivers are included in this study. Only 46 drivers have work places identified while others are assumed to be retirees, part time workers, or working from home. There is a total of 15 built environment variables plus two control variables. Because of a small sample size combined with a relative large number of independent variables, some of the regression models have low power. The stepwise regression technique has its own limitation which is also related to the small sample size. When sample size is small, the capitalization on chance problem is likely to happen. As much as the author likes to include a second set of data to validate the current research results, the reality does not allow. In the future, as more GPS data are collected, the methodologies developed in this dissertation can be applied to a larger sample of drivers, and also in other geographic regions.

The current research focuses only on drivers and vehicle travels. Examinations of travel by other modes (buses, bicycles, or walking) and their relationships with the built environment are missing from this study. The passive in-vehicle data collection method provides the information about the vehicle, not the driver. What are the activities drivers have conducted at certain locations outside the vehicles? Whether multiple activities have combined on foot or buses? The research results show that higher route-related built environment scores are associated with lower number of chained vehicles tours. However, this study is unable to determine the reasons. Is it because more vehicle trips have been chained into tours or vehicle trips have been replaced by non-motorized trips? A fuller set of information collected for all types of travel, either through GPS or other means, can help to answer these questions in the future.

Future research could also emphasize on developing measurements which can characterize built environment from multiple dimensions. The current four aspects of built environment studied in this dissertation are highly correlated with each other. It is possible that there are other dimensions of the built environment that have significant relationships with travel behavior, but have been missed from the current quantification. Centrality is probably one of them. Centrality refers to the clusterness or agglomeration of the development patterns. Centrality presumably should have connections with travel behavior, especially the centrality along commuting routes. Relatively large clusters of businesses are most likely to be noted en route. High density of the centers may encourage drivers to walk or take a bus more. The current density measurement cannot distinguish linearly-located, scattered, or clustered business settings.

More research on quantifying detailed driving behaviors (such as cruising, sudden stops, and sharp turns) and their connections with the surrounding land use and road configurations will also be needed. Energy consumption per mile and emission per mile are largely influenced by these micro-scale driving behaviors. To the authors' knowledge, there have not been many studies dedicated to examine the influences of the built environment on these behaviors. As discussed before, GPS technology combined with GIS tools make this type of research possible.

Appendices

Appendix 1: Business establishment selection

Decisions regarding the selection of business establishment types to be included in the business density and diversity variables are made based on the four-digits Standard Industrial Classification (SIC) code. Business types are included in the final calculation if the business is likely to be visited for non-work purposes at least once in a month for an average driver. Hanson's 1980 study provides valuable references on the types of businesses that meet the above criteria (The study covers one month study period). All businesses included in Hanson's study are included in the measurements. Table 4-4 provides the detailed list of business types defined by two-digit SIC codes.

Certain business types are excluded from the above categories (shown in Table 4-4), including: 1) businesses that are not likely to be visited for non-work purposes once in a month such as mobile home dealers and auto dealers; Colleges, schools, and universities are excluded with the assumption that they are less likely to be visited as locations for non-work activities. For students, going to school is regarded as work-related activity; 2) businesses which do not generate automobile trips (such as direct selling establishments); 3) businesses which only serve business not individuals (such as business service and engineering).

About 83% (56,616 out of 68,617) of the total business establishments were selected to be included in final measurements based on the above selection procedure.

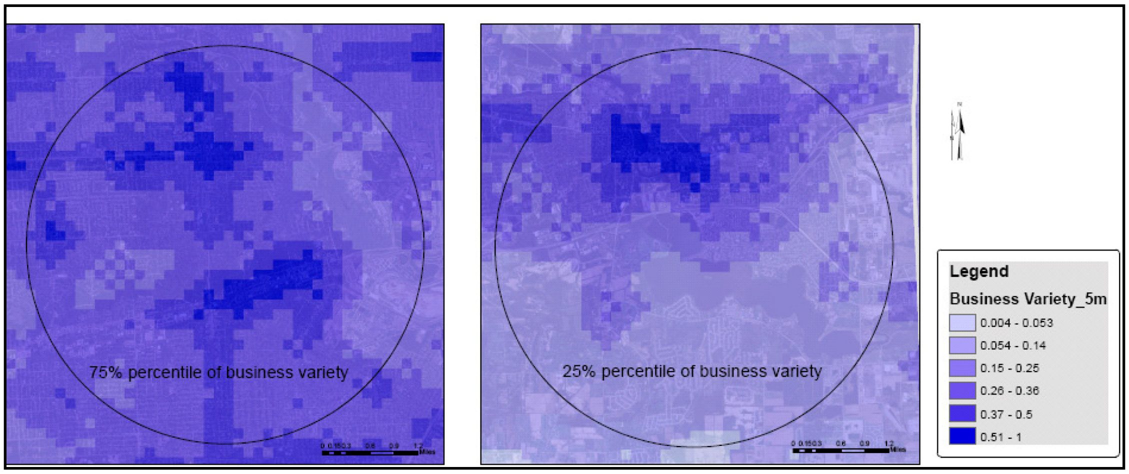
Appendix 2: Manual checking procedure for home and work identification

The procedure involves:

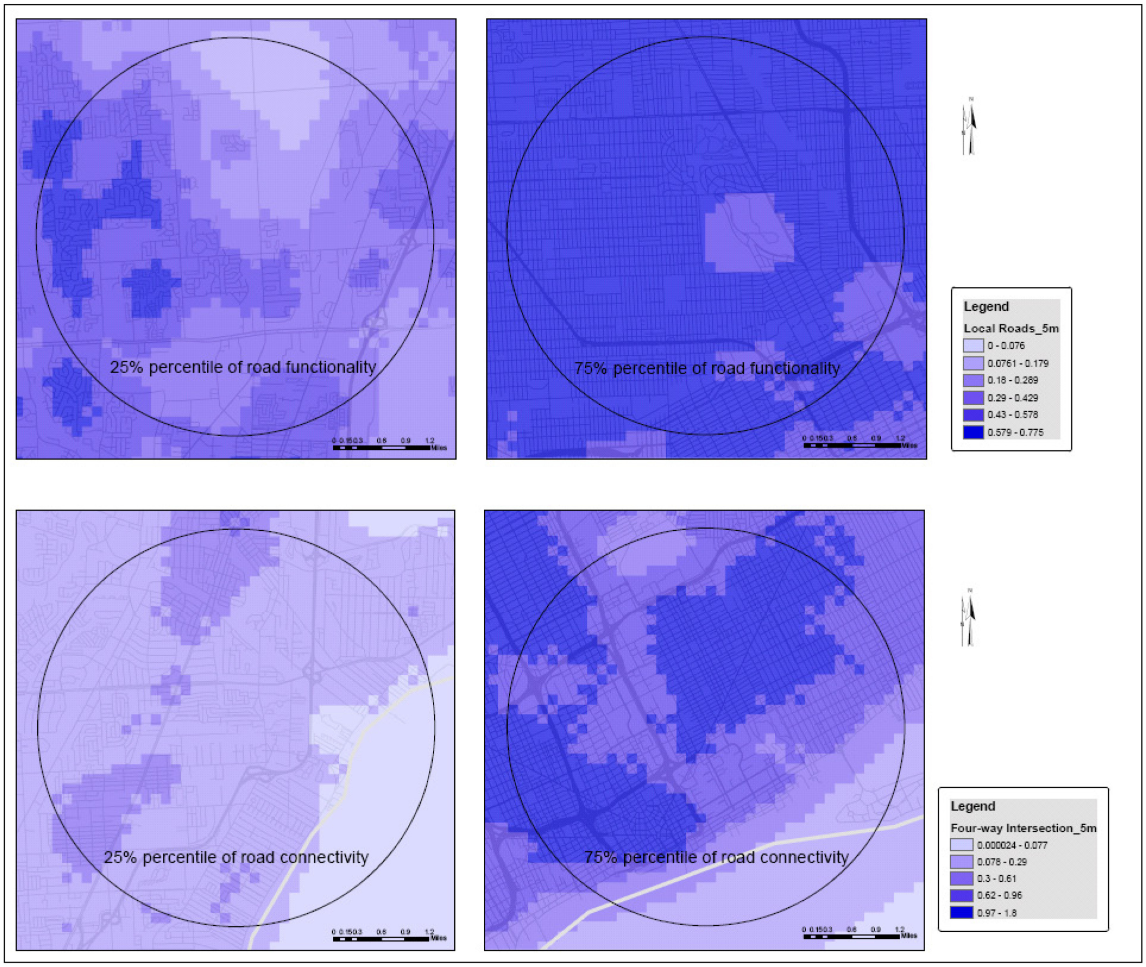
1. Calculate clique 4,620 (cliques with activity duration) distance for each driver
2. Find distances<500 feet cliques and visually exam spatial distribution of these cliques and the satellite images:
    a. Whether potential home or work locations are within 500 feet with each other; whether they are on the same parking area
    b. Whether there are other cliques that are within 500 feet of home location or work location; whether they are on the same parking lot as home or work location
    c. Whether the sum of cliques' visit frequency >=8 times (work location criteria: visit frequency >=8 times in four week and average activity duration >=2 hours)
3. Exam the average activity duration of these marked cliques, how the potential home and work are identified, the ranking of the visit frequency and average activity duration of the updated home and work locations.
4. Note: for a) and b), if by further aggregating marked cliques, home and work criteria are violated. Potential home and work locations might be wrong. Further explanation is needed.

    Refer to the trip purpose clique statistics for updated visit frequency and average activity durations.
5. Finalize home and work locations and trips

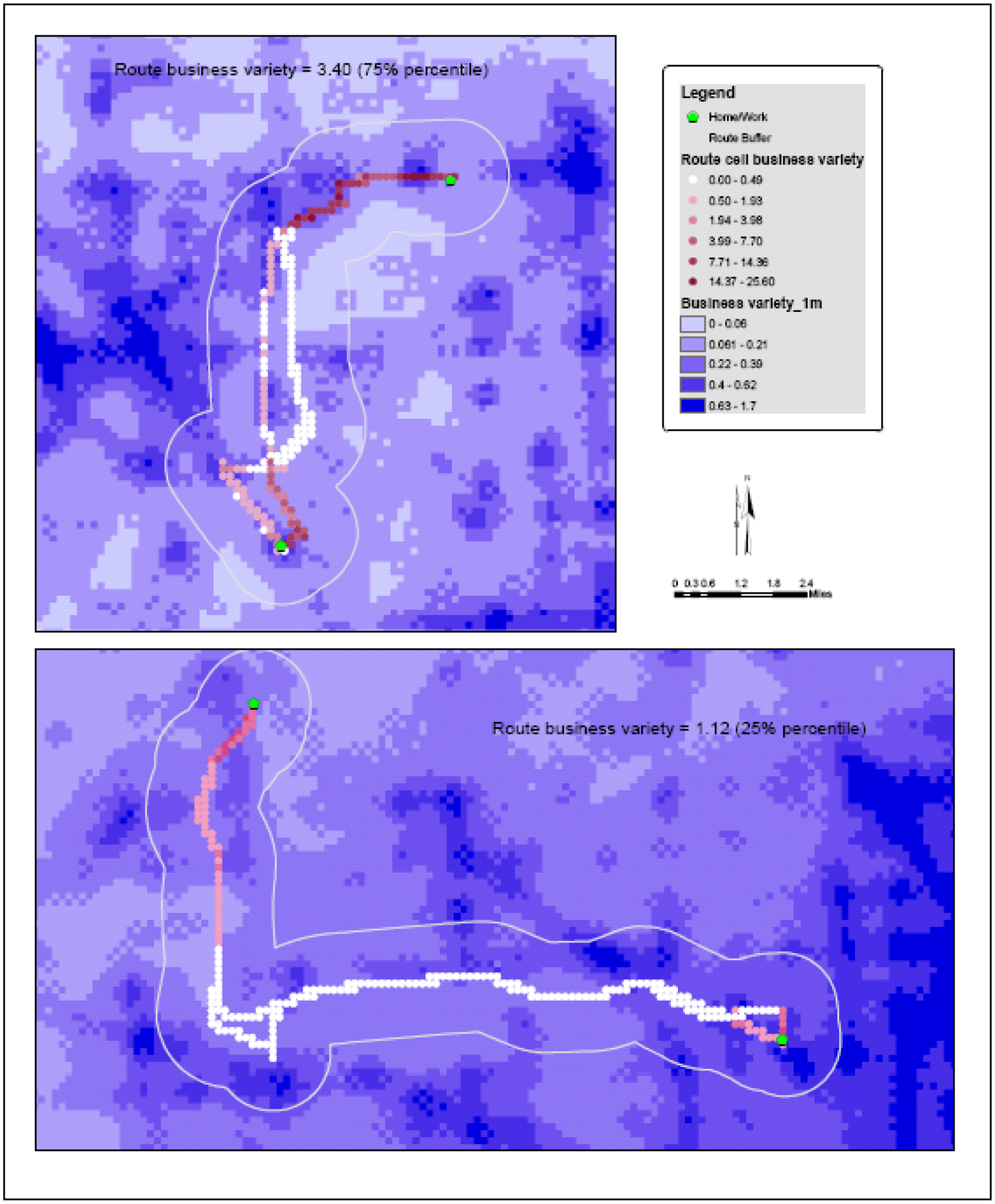
Appendix 3: Visualization of the built environment measurements



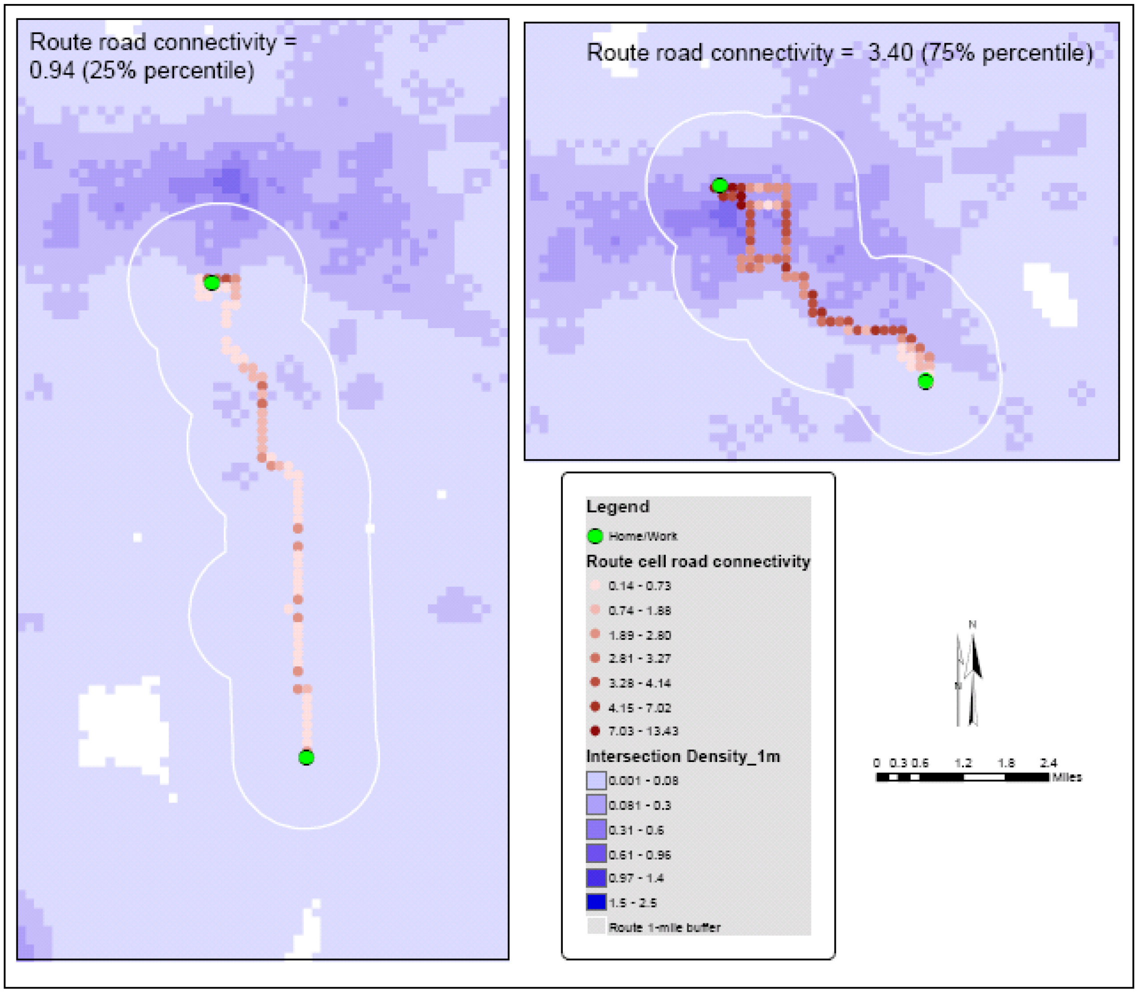
Appendix Figure 1 Comparisons between 25% and 75% percentile of business diversity near home



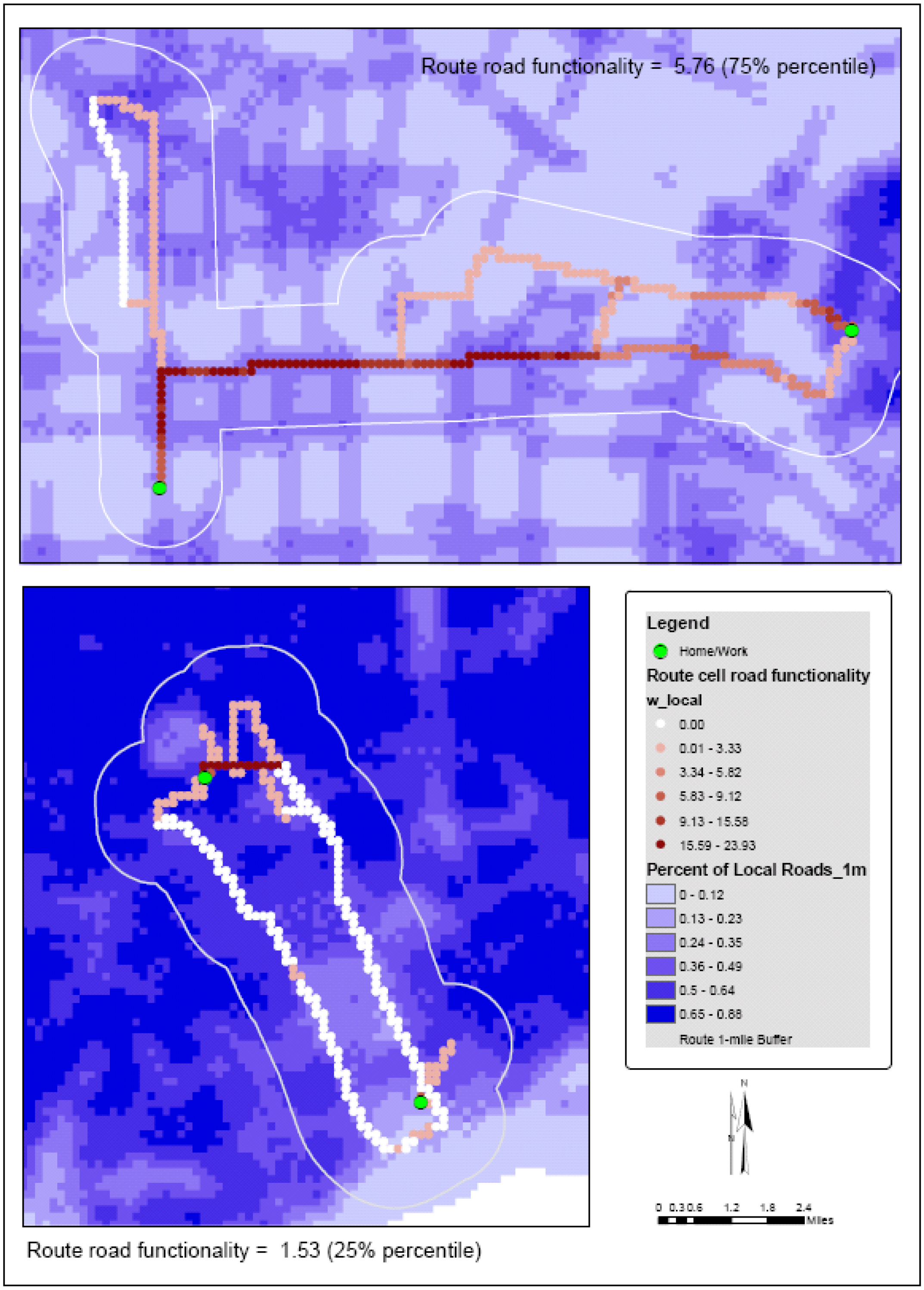
Appendix Figure 2 Comparisons between 25% and 75% percentile of road connectivity and road functionality near home



Appendix Figure 3 Comparisons between 25% and 75% percentile of business variety along routes



Appendix Figure 4 Comparisons between 25% and 75% percentile of road connectivity along routes



Appendix Figure 5 Comparisons between 25% and 75% percentile of road functionality along routes

Appendix 4: correlation and regression analyses

Appendix Table 1 Regression model summary for total non-work VMT and route-related built environment elements

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.391(a)	.153	.133	352.20185
2	.488(b)	.239	.203	337.71960

a Predictors: (Constant), Age

b Predictors: (Constant), Age, route-related employment density

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	1303.117	151.598		8.596	.000
	Age	-9.796	3.479	-.391	-2.815	.007
2	(Constant)	1310.662	145.405		9.014	.000
	Age	-8.258	3.408	-.329	-2.423	.020
	route-related employment density	-.552	.251	-.300	-2.203	.033

a Dependent Variable: total non-work VMT (miles)

Appendix Table 2 Regression model summary for average tour length and built environment factors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.312(a)	.098	.077	8.80339

a Predictors: (Constant), Gender (Female = 1; Male = 0)

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	28.593	1.761		16.240	.000
	Gender (Female = 1; Male = 0)	-5.683	2.606	-.312	-2.181	.035

a Dependent Variable: Average Distance Per Tour

Appendix Table 3 Regression model summary for total number of tours and built environment elements

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.516(a)	.266	.250	10.057
2	.676(b)	.457	.431	8.754
3	.739(c)	.547	.514	8.089

a Predictors: (Constant), LocalRoads.Home

b Predictors: (Constant), LocalRoads.Home, Intersection.Route

c Predictors: (Constant), LocalRoads.Home, Intersection.Route, LocalRoads.Work

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	22.984	3.412		6.737	.000
	LocalRoads.Home	.583	.146	.516	3.996	.000
2	(Constant)	26.372	3.095		8.521	.000
	LocalRoads.Home	.747	.134	.661	5.581	.000
	Intersection.Route	-3.040	.783	-.460	-3.883	.000
3	(Constant)	17.776	4.127		4.307	.000
	LocalRoads.Home	.768	.124	.680	6.197	.000
	Intersection.Route	-2.453	.751	-.371	-3.265	.002
	LocalRoads.Work	.722	.250	.315	2.890	.006

a Dependent Variable: NumOfTours

Appendix Table 4 Correlation coefficients between built environment variables and tour characteristics

	BusinessDensity.Home	BusinessDiversity.Home	Intersection.Home	LocalRoads.Home	Home Factor
Distance per tour.HNH	-.258(*)	-.303(**)	-.252(*)	-.375(**)	-.320(**)
No. of nonwork activities per tour.HNH	-0.138	-0.107	-0.098	-0.156	-0.134
No. of tours.HNH	.643(**)	.695(**)	.637(**)	.791(**)	.746(**)
Speed.HNH	-0.207	-.300(**)	-.261(*)	-.324(**)	-.296(*)
	BusinessDensity.Route	BusinessDiversity.Route	Intersection.Route	LocalRoads.Route	Route factor
Distance per tour.HNW	-.393(*)	-.416(**)	-.359(*)	-.482(**)	-.483(**)
	0.011	0.007	0.021	0.001	0.001
	41	41	41	41	41
No. of nonwork activities per tour.HNW	-0.185	-0.126	0.077	-0.134	-0.108
	0.246	0.434	0.633	0.402	0.501
	41	41	41	41	41
No. of tours.HNW	-0.095	0.002	-0.181	.391(*)	0.052
	0.554	0.989	0.257	0.011	0.747
	41	41	41	41	41
Distance per tour.WNH	-0.116	-0.172	-0.243	-0.051	-0.175
	0.454	0.265	0.112	0.742	0.257
	44	44	44	44	44
No. of nonwork activities per tour.WNH	-0.029	0.101	0.1	0.003	0.055
	0.851	0.513	0.519	0.983	0.721
	44	44	44	44	44
No. of tours.WNH	-0.105	0.015	-0.164	-0.065	-0.09
	0.498	0.923	0.288	0.676	0.561
	44	44	44	44	44
Speed.HNW	-.491(**)	-.512(**)	-.407(**)	-.479(**)	-.552(**)
	0.001	0.001	0.008	0.002	0
	41	41	41	41	41
Speed.WNH	-0.183	-.344(*)	-.358(*)	-0.092	-0.296
	0.235	0.022	0.017	0.552	0.051

	44	44	44	44	44
	BusinessDensity .Work	BusinessDiversit y.Work	Intersection. Work	LocalRoads. Work	Work factor
Distance per tour.WNW	0.001	0.114	0.146	.385(*)	0.1
	0.995	0.527	0.417	0.027	0.579
	33	33	33	33	33
No. of nonwork activities per tour.WNW	0.209	0.245	0.207	0.188	0.255
	0.243	0.169	0.248	0.296	0.152
	33	33	33	33	33
No. of tours.WNW	-0.066	0.314	0.287	.696(**)	0.21
	0.716	0.075	0.106	0	0.24
	33	33	33	33	33
Speed.WNW	0.077	.351(*)	0.224	.551(**)	0.258
	0.669	0.045	0.21	0.001	0.147
	33	33	33	33	33

Appendix Table 5 Regression model summary for total number of HNH tours and built environment factors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.698(a)	.488	.476	7.613

a Predictors: (Constant), Home factor

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	19.742	1.123		17.575	.000
	Home factor	8.979	1.387	.698	6.472	.000

a Dependent Variable: No. of tours.HNH

Appendix Table 6 Regression model summary for total number of HNH tours and built environment elements

Variables Entered/Removed(a)

Model	Variables Entered	Variables Removed	Method
1	LocalRoads.Home	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	BusinessDensity.Home	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a Dependent Variable: No. of tours.HNH

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	3.935	2.504		1.572	.123

	LocalRoads.Home	.737	.107	.720	6.883	.000
2	(Constant)	4.786	2.355		2.032	.048
	LocalRoads.Home	.550	.121	.538	4.557	.000
	BusinessDensity.Home	.012	.004	.325	2.754	.009

a Dependent Variable: No. of tours.HNH

Appendix Table 7 Regression model summary for average distance for HNW tours and built environment factors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.483(a)	.233	.213	12.61630

a Predictors: (Constant), Route factor

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	22.320	1.977		11.290	.000
	Route factor	-7.149	2.076	-.483	-3.443	.001

a Dependent Variable: Distance per tour.HNW

Appendix Table 8 Regression model summary for average distance for HNW tours and built environment elements

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.482(a)	.232	.212	12.62541

a Predictors: (Constant), LocalRoads.Route

Coefficients(a)

Model	Unstandardized	Standardized	t	Sig.

		Coefficients		Coefficients		
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	29.099	2.678		10.866	.000
	LocalRoads.Route	-1.325	.386	-.482	-3.432	.001

a Dependent Variable: Distance per tour.HNW

Appendix Table 9 Regression model summary for number of HNW tours and built environment elements

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.391(a)	.153	.131	3.428
2	.628(b)	.394	.363	2.936
3	.698(c)	.487	.445	2.739

a Predictors: (Constant), LocalRoads.Route

b Predictors: (Constant), LocalRoads.Route, BusinessDiversity.Route

c Predictors: (Constant), LocalRoads.Route, BusinessDiversity.Route, Intersection.Work

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	3.719	.727		5.115	.000
	LocalRoads.Route	.278	.105	.391	2.653	.011
2	(Constant)	4.358	.644		6.767	.000
	LocalRoads.Route	.720	.145	1.013	4.975	.000
	BusinessDiversity.Route	-1.024	.263	-.793	-3.893	.000
3	(Constant)	2.879	.831		3.467	.001
	LocalRoads.Route	.804	.139	1.131	5.787	.000
	BusinessDiversity.Route	-1.091	.247	-.845	-4.422	.000
	Intersection.Work	.214	.083	.315	2.580	.014

a Dependent Variable: No. of tours.HNW

Appendix Table 10 Regression model summary for average tour distance for WNW tours and built environment factors

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.480(a)	.230	.205	6.67331

a Predictors: (Constant), Home factor

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta	B	Std. Error
1	(Constant)	10.578	1.164		9.089	.000
	Home factor	-4.621	1.518	-.480	-3.044	.005

a Dependent Variable: Distance per tour.WNW

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