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The Causal Relationship between the Built Environment and Personal Travel Choice: Evidence from Northern California

Author

Cao, Xinyu

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By

Xinyu Cao
B.S. (Tsinghua University, Beijing China) 1998
M.S. (Tsinghua University, Beijing China) 2001
M.S. (University of California, Davis) 2005

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Committee in Charge

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ABSTRACT

Suburban sprawl has been widely criticized for its contribution to auto dependence. Numerous studies have found that suburban residents drive more and walk less than residents in traditional neighborhoods. Accordingly, smart growth programs have been advocated as a means to reduce auto travel. However, most studies have established only an association between the built environment and travel behavior, but not a causal relationship. Their connection may be more a matter of residential choice than of travel choice. For example, residents preferring walking may selectively live in walkable neighborhoods and thus walk more. If so, the effects of land use policies may be overstated. Using data collected from 1682 respondents living in four traditional and four suburban neighborhoods in Northern California in 2003, this dissertation explored this causal link by employing a quasi-longitudinal research design and controlling for residential self-selection (namely, residential preferences and travel attitudes). Specifically, we investigated the influence of the built environment on various measurements of personal travel choices including uses of different modes (driving, transit, walking, and biking), trip frequencies for different purposes (overall travel, nonwork travel, shopping travel, and strolling), auto ownership, and vehicle type choice. The results showed that residential preferences and travel attitudes have pervasive influences on all measurements of travel choices. The results also provide some encouragement that land-use policies designed to put residents closer to destinations and provide them with alternative transportation options will actually lead to less driving and more walking. Taking the evidence from all our analyses together, however, neighborhood design appears to have a stronger influence on walking than on driving. In other words, the residential environment promoted by smart growth programs may be an effective strategy to encourage walking but have less effect on driving, especially after attitudinal predispositions are accounted for. Given that walking is an inadequate substitute for driving, the smart growth movement seems to be more of a

solution to public health problems than to transportation problems. Even so, it will give residents a choice to drive less and walk more and this choice is highly valued by a large proportion of respondents in our data as well as in other studies.

1. INTRODUCTION

Sprawl is "the process in which the spread of development across the landscape far outpaces population growth" (Ewing et al., 2002, p.3). Sprawl development has been prevailing in the U.S. during the past several decades. For example, the per capita land consumption of Atlanta, one of the most sprawling urban areas, increased 42% from 1970 to 1990 (Kolankiewicz and Beck, 2001); in the Northeast, the urbanized land increased 39.1% from 1982 to 1997, while the population growth was only 6.9% (Fulton et al., 2001). In general, sprawl development has four characteristics: "a population that is widely dispersed in low density development; rigidly separated homes, shops, and workplaces; a network of roads marked by huge blocks and poor access; and a lack of well-defined, thriving activity centers, such as downtowns and town centers" (Ewing et al., 2002, p.3).

Although a subject of some debate (e.g., Bruegman, 2005; Lemmon, 2000), sprawl development has potentially serious consequences for modern society. First, it has been criticized for its contribution to auto dependence. Low density, segregated use, and poor accessibility increase trip lengths and make transit and non-motorized modes unattractive; most people living in sprawling areas have to rely on cars to conduct their daily activities. As a result, they tend to own more vehicles and drive more. Ewing et al. (2002) found that, on average, people in the 10 most sprawling metropolitan areas drove six miles per capita per day more than those in the 10 most compact metropolitan areas. In California, car use increased four times as much as population growth between 1970 and 1990 (ALAC, 2003). Second, suburban sprawl is also being blamed in some planning and public health circles for the obesity trend. According to trends data provided by the Behavior Risk Factor Surveillance System (BRFSS), Centers for Disease Control and Prevention (CDC), the percentage of overweight adults in the U.S. doubled from 1990 to 2002. McCann and Ewing (2003) pointed out that people living in sprawling areas are more likely to be overweight regardless of gender, age, educational background, smoking, and nutritional intake. The underlying mechanism is that low-density and segregated-use suburbs are designed for driving rather than walking, leading people to drive more and walk less, thereby contributing to a decline in physical activity and an increase in weight. Third, sprawl development has a strong association with air quality problems. Ewing et al. (2002) found that degree of sprawl is the best predictor among the variables tested of ozone level in metropolitan areas. In California, more than 60% of smog forming pollutants come from mobile source emissions (ALAC, 2004). Further, sprawl development is said to adversely impact resource consumption, quality of life, and so on (Burchell et al., 2002).

Smart growth has recently been proposed to counter sprawl. The American Planning Association (2002, p.21) defines smart growth as "the planning, design, development and revitalization of cities, towns, suburbs and rural areas in order to create and promote social equity, a sense of place and community, and to preserve natural as well as cultural resources". Specific land use policies used in smart growth programs include mixed-use zoning, infill development, brownfield development, Main Street programs (support for retail establishments in a downtown area), transit-oriented development and pedestrian-oriented development. From a transportation standpoint, the hope is that these strategies will bring residents closer to destinations and provide viable alternatives to driving and thus help to reduce automobile use.

As the popularity of "smart growth" policies increases, a large number of studies have investigated the relationships between the built environment and travel behavior since the 1990s. These studies found that residents living in traditional neighborhoods (characterized as high density, high accessibility, mixed land use, rectangular street network, and so on) own fewer vehicles, drive less, and walk more than those living in suburban neighborhoods (e.g., Cervero and Duncan, 2003; Crane and Crepeau, 1998; Friedman et al., 1994). Recognizing this empirical evidence, the

Environmental Planning Agency (EPA) now accepts land-use policies as an effective tool for improving air quality and allows state and local communities to receive credit for the air quality benefits of smart growth strategies in State Implementation Plans (SIPs) as a part of the Voluntary Mobile Source Emission Reduction Program (EPA, 2001).

However, most previous studies confirm only the associations between the built environment and travel behavior, but have yet to establish the predominant underlying causal link: whether the built environment influences travel behavior or travel attitudes and residential preferences affect residential choice. If the latter direction is the dominant one, the observed relationships between the built environment and travel behavior may be more attributable to residential self-selection. For example, those who prefer walking may consciously choose to live in walkable neighborhoods and thus walk more. If so, the ability to use the built environment to change individuals' travel patterns may be limited by the apparently sizable share of households who favor suburban types of development (Morrow-Jones et al., 2004). In other words, we may overstate the influence of the built environment on travel behavior. The available evidence thus leaves a key question largely unanswered: If cities use land use policies to bring residents closer to destinations and provide viable alternatives to driving, will at least some people drive less and use alternative modes more, thereby reducing emissions? As more smart growth communities are under planning and construction (Steuteville, 2004), it is necessary to address the causality issue so that the relationship between the built environment and travel behavior is properly evaluated.

The purpose of this dissertation is to investigate the causal relationship between the built environment and travel behavior through cross-sectional and quasi-longitudinal designs, using data collected from Northern California in 2003. In particular, it aims to address the following two central questions: (1) Does the built environment itself influence individuals' travel choices, and if so, how? (2) What role does residential self-selection (measured as attitudinal factors) play in the relationship between the built environment and travel behavior?

The organization of this dissertation is as follows. Chapter 2 reviews literature relevant to smart growth programs, efforts to understand the relationship between the built environment and travel behavior, and approaches to addressing residential self-selection. Chapter 3 presents the research design, hypotheses, data and variables used in this dissertation. Chapter 4 examines the unidirectional causal link from the built environment to travel behavior. Chapter 5 explores the influences of the built environment on the auto ownership decision and vehicle type choice. Chapter 6 integrates the multidirectional causal relationships among the built environment, travel behavior, and auto ownership, using a quasi-longitudinal structural equations modelling approach. The final chapter recapitulates the key findings and discusses policy implications of the results.

2. LITERATURE REVIEW

In most studies, travel behavior (such as trip frequency, distance, duration, destination, purpose, and loosely speaking, auto ownership and vehicle type choice) has been tested against characteristics of the built environment. The built environment generally consists of three primary components: land use pattern, urban design, and transportation system. Land use pattern refers to "the distribution of activities across space, including the location and density of different activities, where activities are grouped into relatively coarse categories, such as residential, commercial, office, industrial, and other activities". Urban design means "the design of the city and the physical elements within it, including both their arrangement and their appearance, and is concerned with the function and appeal of public spaces". The transportation system comprises "the physical infrastructure of roads, sidewalks, bike paths, railroad tracks, bridges, and so on, as well as the level of service provided as determined by traffic levels, bus frequencies, and the like" (Handy et al., 2002, p.65).

Handy et al. (2002) summarized one regional characteristic (regional structure) and five dimensions of the built environment at the neighborhood level: density and intensity, land use mix, street connectivity, street scale, and aesthetic quality (Table 1). Another commonly used built environment measure is accessibility, "the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)" (Geurs and van Wee, 2004, p.128). Sometimes, job-housing balance, the ratio of the employment of an area to the number of housing units there, is used as one mixed-use indicator of the built environment (e.g., Cervero, 1996a, Nowlan and Stewart, 1991).

The geographic scale of the built environment may influence its effects on travel behavior. Boarnet and Greenwald (2000) and Boarnet and Sarmiento (1998) found that regional land use characteristics are more important than neighborhood traits in shaping non-work auto travel. By contrast, pedestrian travel is more likely to be affected by characteristics of the built environment at the neighborhood level (Greenwald and Boarnet, 2001; Kockelman, 1997).

Table 1. Dimensions of the Built Environment

Dimension	Definition	Examples of Measures
Density and intensity	Amount of activities in a given area	Persons per acre or jobs per square mile; ratio of commercial floor square to land area
Land use mix	Promixity of different land uses	Share of total land area for different uses; dissimilarity index
Street connectivity	Directness and availability of alternative routes through the network	Intersections per square mile of area; ratio of straight-line distance to network distance
Street scale	Three-dimensional space along a street as bounded by buildings	Ratio of building heights to street width; average distance from street to buildings
Aesthetic qualities	Attractiveness and appeal of a place	Percent of ground in shade at noon; number of locations with graffiti per square mile
Regional structure	Distribution of activities and transportation facilities across the region	Rate of decline in density with distance from downtown; classification based on concentrations of activity and transportation network

Source: Handy et al. (2002)

In this chapter, we first review several land use policies used in smart growth programs. These land use policies, among others, directly affect the alternative types of the built environment from which consumers can choose. If we find that built environment characteristics in turn directly cause travel behavior after controlling for residential predispositions, it may point to supporting some specific land use policies to manage individuals' travel behavior. Second, previous studies focusing on the connection between the built environment and travel behavior are reviewed. Third, we discuss requisites of causality inference in social research within the context of land use and transportation. The final section summarizes a number of studies relevant to understanding the causal relationships between the built environment and travel behavior – that is, studies taking various approaches to addressing the issue of residential self-selection.

2.1 Smart Growth Programs

2.1.1 Principles of smart growth

As a counter to sprawl development, smart growth programs aim to address various issues related to transportation choices, quality of life, community design, economic development, environment preservation, public health, and housing options. Their potential is well reflected in the underlying principles of smart growth, which are documented on Smart Growth Online (http://www.smartgrowth.org/about/principles/default.asp, accessed on February 1, 2006):

1. Create range of housing opportunities and choices;
2. Create walkable neighborhoods;
3. Encourage community and stakeholder collaboration;
4. Foster distinctive, attractive communities with a strong sense of place;
5. Make development decisions predictable, fair, and cost effective;
6. Mix land uses;
7. Preserve open space, farmland, natural beauty and critical environmental areas;
8. Provide a variety of transportation choices;
9. Strengthen and direct development towards existing communities;
10. Take advantage of compact building design.

Most of these principles are relevant to transportation issues. First, the principle of providing various transportation choices (such as expanding the transit network and improving transit service, creating redundancy and resiliency within road networks, and ensuring connectivity between pedestrian, bike, transit, and road facilities) is obviously germane to transportation. The development of walkable neighborhoods expands transportation options by making pedestrian travel a viable alternative. Further, several principles have transportation implications. For example, as various studies suggest, compact design and mixed-use encourage pedestrian travel;

development towards existing communities creates mixed-use and/or high-density neighborhoods; and fostering a strong sense of place provides an inviting social and physical environment for pedestrians.

2.1.2 Land use policies

Specific land use policies used in smart growth programs include transit-oriented development, pedestrian-oriented development, infill development, mixed-use zoning, Main Street programs, brownfield development, and so on. In practice, these land use policies are not separately implemented, and some policy may contain components of other policies. For example, as discussed below, transit-oriented development and mixed-use zoning also aim to provide good walking and biking infrastructures.

Transit-Oriented Development (TOD): According to the City of Portland, Oregon, Office of Transportation (1996, p.119), transit-oriented development means "[a] mix of residential, retail, and office uses and a supporting network of roads, bikeways and walkways focused on a major transit stop and designed to support a high level of transit use. The key features of transit-oriented development include: [1] a mixed-use center at the transit stop, oriented principally to transit riders and pedestrian and bicycle travel from the surrounding area; [2] high-density residential development proximate to the transit stop sufficient to support transit operation and neighborhood commercial uses within the TOD; [3] a network of roads, bikeways and walkways to support high levels of pedestrian access within the TOD and high levels of transit use; [4] a lower demand for parking than auto-oriented land uses." TODs offer diverse benefits to various agents. According to the Transit Cooperative Research Program (2004), the primary benefits for the public sector include (1) increasing ridership and farebox revenues, (2) providing joint development opportunities, (3) revitalizing neighborhoods, and (4) fostering economic development. For the private sector, the primary benefits are the growth of land values and rents and increased affordable housing opportunities. Among these benefits, increasing transit ridership is the most frequently-stated TOD objective by transit-agency respondents. TODs appear to be effective to increase transit ridership in some areas. For example, through an ambitious TOD in the metropolitan areas of Portland (1992-1998), transit ridership increased more than 20% from 1992 to 1996, 20% faster than the growth in vehicle miles traveled (VMT) (Arrington, 1998). However, the proportion of increased ridership substituting for driving is less clear.

Pedestrian-Oriented Development (POD): The Portland Office of Transportation (1996, p.118) defines POD as "[d]evelopment which is designed with an emphasis primarily on the street sidewalk and on pedestrian access to the site and building, rather than on auto access and parking areas. The building is generally placed close to the street and the main entrance is oriented to the street sidewalk." Duany Plater-Zyberk & Company, a leader of the international movement against the proliferation of suburban sprawl, presents the 13 points for PODs (CoolTown Studios, 2005):

1. A pedestrian-oriented neighborhood must have a perceptible center and transit service would be available at this center;
2. The center is located within walking distance (about 2,000 feet) for most dwellers;
3. The neighborhood has various housing types (single-family and multi-family) so that diverse households may find a place to live;
4. The neighborhood contains mixed uses to ensure the supply of weekly household needs;
5. An elementary school is located within walking distance for most children;
6. Residents in every housing unit can access a nearby open space;
7. The neighborhood has a connected street network and provides various transportation options to any destination;
8. The streets are relatively narrow and with ample shade;

9. Buildings at the neighborhood center have shorter setbacks;

10. Parking lots and garage doors are located at the rear of buildings;

11. Civic buildings are located at the neighborhood center;

12. The neighborhood serves itself by self-governing;

13. Small ancillary buildings are allowed in the backyards of single-family houses to promote mixed uses.

PODs create communities where goods and services are within walking distances of residences, which makes walking a competitive alternative to auto for short-distance trips.

Infill Development: “Infill development is the economic use of vacant land, or restoration or rehabilitation of existing structures or infrastructure, in already urbanized areas where water, sewer, and other public services are in place, that maintains the continuity of the original community fabric” (http://www.co.dane.wi.us/plandev/build/about.asp#infill, accessed on February 1, 2006). Infill development can involve any or all of three components: new development on vacant land in urbanized areas, redevelopment of underused buildings, and rehabilitation of historical buildings for new uses. Recently, many infill development projects were implemented or planned in the cities throughout the San Francisco Bay Area. For example, an old Italian market building in downtown Oakland, Swan’s Market, was converted into a block with high-density residential, commercial, office, and institutional uses; San Francisco Mission Bay infill development will provide some 6,000 units of housing and more than five million square feet of space for non-residential uses (Wheeler, 2002). A successful infill development creates mixed-use neighborhoods and makes non-motorized travel attractive (Northeast-Midwest Institute and Congress for the New Urbanism, 2001).

Mixed-Use Zoning: A mixed-use zoning program allows a property owner to have multiple uses on a given parcel of land. It is an effective way to enhance urban and suburban areas and to encourage infill development. A well-known example of mixed-use zoning is the new zoning ordinance adopted by the city of Fort Worth, TX. Its previous version did not allow the combination of residential and commercial uses except for in the central business district (CBD) and site-specific planned development districts. In 2001, the city council approved an ordinance to create two new mixed-use zoning categories: low-intensity mixed use (MU-1) district and high-intensity mixed-use (MU-2) district. The MU-1 district permits neighborhood commercial businesses to be built in a one- and two-family and multi-family zone. The MU-2 district allows a combination of residential, neighborhood commercial, intensive commercial, and selected light industrial uses. In both districts, non-residential uses should constitute at least 10% of the gross floor area. The city of Fort Worth expects that these compact and mixed-use districts can help to discourage car use and reduce vehicular trip distances, promote safe and active pedestrian environments, increase residential and employment density to support transit, and attract new residents and employers looking for urban amenities (http://www.fortworthsouth.org/mixeduse.html, accessed on February 1, 2006).

Main Street Programs: According to the Portland Office of Transportation (1996, p.118), Main Street refers to "[a] street having a mix of multifamily and neighborhood shopping areas along it or at an intersection with good transit service, and sometimes having a unique character that draws people from outside the area. Main streets have an intense mix of pedestrian-scale uses, including residential, good transit service, and pedestrian facilities." Main Street programs aim to revitalize traditional commercial districts; a vibrant main street offers residents local accessibility for goods and services. An example of a Main Street program is the redevelopment plan of the traditional center area of Lithonia, Georgia. There are only two restaurants and two grocery stores in downtown Lithonia. The main street is so underused that it is not only less able to attract regional patrons but also underserves local residents. The Smart Growth Leadership Institute and University of Southern California team proposed using Main Street to create a vibrant traditional center – a mixed-use pedestrian-friendly environment. Specifically, they recommended: (1) a two- to three-story live/work, townhouse development, with retail business on the first floor and office and loft on the second floor, (2) interior surface parking, (3) adding banks and other customer related offices, public parks, pedestrian-friendly uses, children's play area, temporary markets, outdoor cafes, (4) no auto related sales, services and drive-in facilities, (5) increasing maximum lot coverage from 35% to 60%, (6) providing pedestrian infrastructures and amenities, and so on (Banerjee et al., 2004).

Brownfield Development: The EPA defines brownfield as "real property, the expansion, redevelopment, or reuse of which may be complicated by the presence or potential presence of a hazardous substance, pollutant, or contaminant" (http://www.epa.gov/brownfields, accessed on February 1, 2006). Brownfield development enables the reuse of these abandoned properties and revitalizes the areas adjacent to these properties. Brownfield development also reduces the pressure for outlying greenfield development. In California, Redwood City created a mixed-use community by integrating seven different parcels and cleaning up contaminants from an old gas station in downtown (Wheeler, 2002). In Canada, a former rail yard in downtown Kelowna, British Columbia, heavily contaminated with hydrocarbons and heavy metal, was transformed into a pedestrian-friendly mixed-use neighborhood (CMHC, 2005).

Clearly, these land use policies point to offering residents alternative travel choices, as well as to addressing other issues resulting from sprawl development. However, whether these alternative development types directly influence personal travel choices in their own right is still open to debate.

2.2 The Built Environment and Travel Behavior

The idea that land use policies could be used to influence travel behavior was not widely explored until the 1980s. Early interest focused on the connection between density and transit use. The 1977 study by Pushkarev and Zupan suggests that transit use can be increased through polices that increase densities. A heated debate ensued in the 1990s and beyond, over analyses on the correlation between densities and gasoline consumption for a sample of international cities (Newman and Kenworthy, 1999; Mindali et al., 2004). In response to the emergence of the smart growth movement, an increasing amount of effort has gone into examining the relationships between the built environment and travel behavior (as reviewed in Handy, 1996a; Crane, 2000; Ewing and Cervero, 2001).

2.2.1 Analytical methods

Previous research used various analytical approaches to study the relationships between the built environment and travel behavior (these approaches are distinct from those summarized in Section 2.4 in that the latter explicitly or implicitly address the issue of residential self-selection). According to the data used, these approaches can be classified as aggregate or disaggregate analyses (Handy, 1996a). In accordance with the structure of analysis techniques used, these approaches can be divided into three categories: simulation approaches, descriptive approaches, and multivariate statistical approaches (Crane, 2000).

In aggregate analysis, both the built environment and travel behavior are measured at an aggregate level, say, at the level of cities, neighborhoods, or zones (e.g., Cervero and Gorham, 1995; Friedman et al., 1994). In these studies, travel patterns are tested against different measures of the built environment. Techniques used include descriptive analysis and multivariate statistical analysis. Many of these studies provide supportive evidence for the claims that the built environment influences travel behavior. However, the aggregate nature of the data impedes the ability to reflect individuals' diverse responses to the built environment. Therefore, aggregate studies cannot reveal the mechanisms by which the built environment affects travel behavior. Neither do these studies convey much information on the direction of causality between the built environment and travel behavior (Handy, 1996a). In addition, aggregate analysis is notoriously vulnerable to the ecological fallacy (the variations in the disaggregate data may become concealed when analyzed at a larger aggregate level, or relationships observed at the aggregate level do not hold at the disaggregate level).

By contrast, disaggregate analysis is appropriate for overcoming such limitations. It relies on individuals' or households' travel outcomes as well as other micro-level characteristics such as incomes. But, in most studies, characteristics of the built environment are determined at the aggregate level although there are some attempts to incorporate micro-scale measurements of the built environment in the analysis (e.g., Kitamura et al., 1997; Bagley et al., 2000; Handy and Clifton, 2001). Multivariate statistical approaches are commonly used to test the relationships between the built environment and travel behavior at a disaggregate level. Within the derived demand framework, most disaggregate studies apply either econometric models or discrete choice models to match the individual's travel behavior to different built environment characteristics (e.g., Crane and Crepeau, 1998; Cervero, 2003). Most studies provide insightful evidence of the link between the built environment and travel behavior (Handy, 1996a).

Simulation studies such as McNally and Ryan (1994) and Rabiega and Howe (1994) assume that certain relationships exist between the built environment and travel behavior, and then apply this premise to various scenarios to see what happens. Although these studies provide some general insights about the potential effects of different built environment characteristics on travel patterns, their results rely entirely on the assumed behavior. These studies cannot capture individuals' actual responses to changes in the built environment, and thus do not intend to explain travel behavior. Moreover, the oversimplified and hypothetical conditions seriously threaten the accuracy of their results (Crane, 2000; Handy, 1996a). For example, when trip rates are assumed constant, higher density development and mixed land uses make trip lengths shorter on average, and hence reduce VMT. However, this assumption obviously ignores feedback effects of the shorter trip lengths: the benefits of shorter distances may be offset by increased trip rates.

Unlike simulation studies, descriptive studies analyze actual travel behavior (e.g., Friedman et al., 1994). In these studies, observed travel outcomes are measured in different types of neighborhoods and compared. This approach is effective at showing what happens at some particular places. If differences in travel behavior are observed, most studies suggest that some differences in the built environment help explain the differences in travel behavior. However, the descriptive approach seldom tells us much about why observed differences occur, and it cannot identify the degree to which built environment characteristics affect observed travel behavior. Furthermore, other factors (such as incomes), either singly or together with built environment characteristics, may explain the differences in observed behavior. The descriptive approach, however, is unable to examine the combined and incremental contributions of these multiple factors (Crane, 2000).

Multivariate statistical studies constitute a quantum improvement in analytical approach since they attempt to explain rather than only describe observed behavior. Among various techniques, multiple regression analysis makes it possible to examine which aspects of the built environment affect travel in which direction and at what magnitude, controlling for other factors (Crane, 2000). In addition, regression analysis allows a variety of explanatory variables to enter the model, and hence can examine the relative contributions of different groups of variables to travel behavior (as done in Kitamura et al., 1997 and Stead, 2001). However, the multiple regression used in most studies is a single equation model (or separate single equation models). The nature of single equation regression predetermines that travel behavior (when taken as the dependent variable) is viewed as an effect rather than a cause, while the built environment and other characteristics are assumed to be exogenous. Therefore, single equation regression analysis is inadequate for inferring the actual direction of causality.

The structural equations modeling approach is a suitable alternative to address these shortcomings. The structural equations model (SEM) is a comprehensive model, including multiple observed endogenous and exogenous variables, as well as latent variables (not observed but hypothetically existing). It can capture the causal links between endogenous and exogenous variables and the causal relationships among endogenous variables. The structural equations modeling approach has been increasingly widely used in travel behavior research, starting around 1980 (Golob, 2003). A few studies, summarized in Section 2.4, have applied this approach to study the relationships between built environment and travel behavior.

2.2.2 The influence of the built environment on travel behavior

After one of the most thorough reviews of previous studies about the influence of the built environment on travel behavior, Ewing and Cervero (2001) come to several important conclusions: (1) Trip frequencies appear to be primarily a function of the socio-economic characteristics of travelers, and secondarily a function of the built environment; (2) Trip lengths are primarily a function of the built environment and secondarily a function of socio-economic characteristics; (3) Mode choices depend on both socio-economic characteristics and built environment characteristics, though probably more on the former; (4) The built environment characteristics are much more significant predictors of VMT, which is the outcome of the combination of trip lengths, trip frequencies, and mode choice. Based on the results of all available studies and original data analysis for available data sets, they estimated elasticities for VMT and vehicle trips using a meta-analysis. Four measures of the built environment were used: "density," measured as population plus jobs divided by land area; "diversity," a measure of jobs-population balance; "design," a combination of sidewalk completeness, route directness and street network density; and "regional accessibility," an index derived with a gravity model. The results show a statistically significant, but rather limited, link between built environment characteristics and travel behavior (Table 2). A 10% increase in local density, for example, is associated with only a 0.5% decline in vehicle trips and VMT. The highest elasticity is for regional accessibility (a 10% increase in regional accessibility was associated with a 2% decline in VMT), but regional accessibility is also arguably the most difficult characteristic to modify.

Table 2. Typical Elasticities of Travel with Respect to the Built Environment

Measures	Vehicle Trips	VMT
Local density	-0.05	-0.05
Local diversity	-0.03	-0.05
Local design	-0.05	-0.03
Regional accessibility	--	-0.20

Source: Ewing and Cervero (2001)

Most studies summarized in Ewing and Cervero (2001) provide empirical evidence of only the associations between the built environment and travel behavior. However, they have yet to confirm a causal link from the built environment to travel behavior. The literature relevant to this causality issue is presented in Section 2.4.

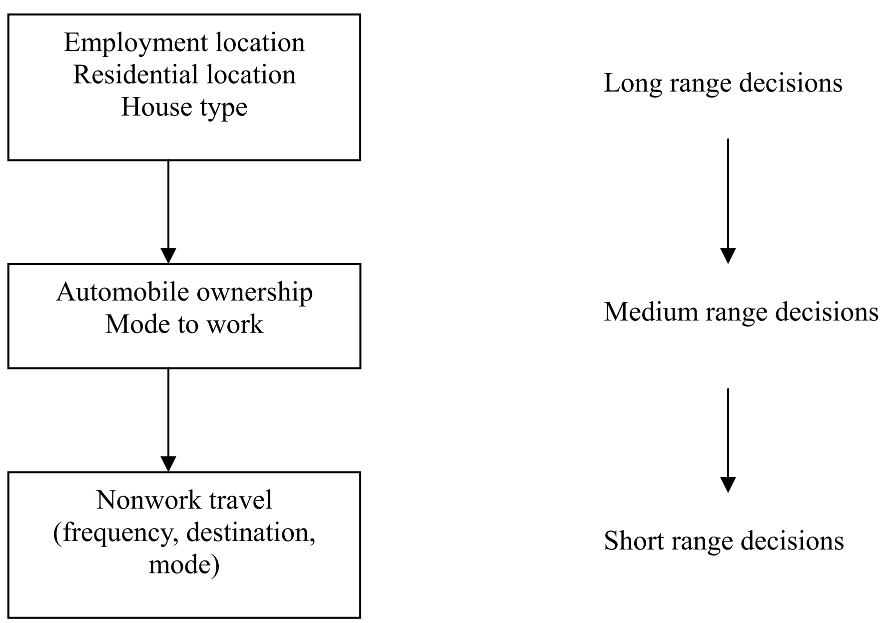
The tenet that travel is a derived demand is embedded in travel behavior theory. It is commonly believed that few trips are made for their own sake, and activities at the destination, such as work and shopping, are the only reason why people travel to that destination. Recently, however, the derived demand idea has been critically challenged by several studies (e.g., Handy et al., 2005; Mokhtarian et al., 2001; Ory and Mokhtarian, 2005). Recreational travel and pedestrian travel are more likely to be pursued for their own sake. Therefore, there should be some distinct differences between determinants of travel for its own sake and those of utilitarian travel. Handy (1996b) is one of the few studies in the travel behavior literature to explore the impacts of the built environment on both types of travel. She concluded that some aspects of urban form – those related to commercial areas and the links between commercial and residential areas – play a greater role in the choice of walking to the store than for strolling trips.

2.2.3 The role of auto ownership

Auto ownership has a strong influence on travel behavior, as countless studies show. Most travel demand forecasting models, widely used in regional transportation planning, incorporate auto ownership as a key variable for predicting trip generation and mode split. Even though households without automobiles often rely on the automobiles of others for their daily travel, the correlation between auto ownership and travel by automobile is strong. According to the 2001 National Household Travel Survey (NHTS), households without a vehicle made 34.1% of their trips by auto, 19.1% by transit, and 43.5% by non-motorized modes; in contrast, households with one vehicle made 81.9% of their trips by automobile and households with 3 or more vehicles made 90.5% of their trips by automobile (Pucher and Renne, 2003). A study of cities in the U.S., Australia, Asia, and Europe found that the significant increase in vehicle travel between 1960 and 1990 was a direct result of increased incomes and greater automobile ownership (Cameron et al., 2004).

Auto ownership is a critical mediating link in the connection between the built environment and travel behavior: the built environment presumably influences auto ownership, which in turn impacts travel behavior. As shown in Figure 1, travel decisions for an individual household are embedded in a choice hierarchy (Ben-Akiva and Atherton, 1977). As a medium-term decision, auto ownership is conditional on long-term decisions such as employment location and residential location. That is, households' auto ownership is likely to be impacted by their long-range decisions through the availability and attractiveness of alternative modes and various elements of the built environment. However, most studies of this connection assume that auto ownership is exogenous to individuals' activity/travel decisions, thereby inadequately evaluating the role auto ownership plays in the land use-transportation interaction (Badoe and Miller, 2000), and hence underestimating the total effects of land use on travel behavior. The argument that auto ownership is endogenous is supported by empirical evidence. For example, Schimek (1996) employed simultaneous equations to model individuals' residential choices and travel decisions, with auto ownership being an intermediating variable; and he found that the total effects of density on household VMT and personal vehicle trips exceed the direct effects of density.

Figure 1. Household Choice Hierarchy



Source: Ben-Akiva and Atherton (1977)

The relationships between the built environment and auto ownership, however, have not been extensively studied. The available evidence suggests that households living in single-family dwellings, homogeneous and/or suburban types of neighborhoods, typically located farther away from employment sites, tend to own more vehicles (and use them more often) than households living in denser neighborhoods and/or closer to the central business district (Bagley and Mokhtarian, 2002; Cervero, 1996b; Chu, 2002; Kitamura et al., 2001; Kockelman, 1997, Lerman, 1979; Sermons and Seredich, 2001). An overview of international cities found that higher urban density is consistently associated with lower auto ownership rate (Kenworthy and Laube, 1999). Similarly, case studies of Chicago, Los Angeles, and San Francisco concluded that automobile ownership was significantly correlated with neighborhood residential density, after accounting for average per capita income, average family size, and availability of public transit (Holtzclaw et al., 2000). However, the way in which individual elements of the built environment affect auto ownership choices is not well understood.

Further, residential self-selection may confound the interaction between the built environment and auto ownership (Boarnet and Crane, 2001a). A study of urban form and auto ownership in Portland, Oregon found that as land use mix changes from homogeneous to diverse, the probability of owning an automobile decreases by 31 percentage points, after accounting for income and other factors (Hess and Ong, 2002). The authors concluded that traditional neighborhoods give households the "opportunity to express their preferences to avoid automobile ownership" (p. 35). In other words, the observed correlations between the built environment and auto ownership may be due in large part to the influence of preferences for auto ownership on residential location choice, rather than entirely to the influence of the built environment on auto ownership decisions. Accordingly, individuals' attitudes, especially travel attitudes and residential preferences, are likely to be antecedent factors of both residential choices and auto ownership decisions. Thus, for example, Wu et al. (1999) found that the performance of auto ownership choice models can be improved by incorporating attitudes towards auto ownership. The implication is that the effectiveness of influencing auto ownership and use through the built environment may be largely limited to the market share of individuals whose attitudes are favorable towards alternative modes and traditional neighborhoods to begin with. However, the absence of attitudinal factors in the literature and in the widely available data constrains our ability to address these complexities.

2.3 Causality Requisites

Before proceeding to the literature relevant to residential self-selection, we first review causality inference in social research. According to the Merriam-Webster online dictionary, causality is defined as "the relation between a cause and its effect or regularly correlated events or phenomena". Causality is inferred from an observed association since what we can observe is the association between events. The association can be categorized into one (or more) of three principles of connection of events: resemblance, contiguity in time or place, and cause or effect (Hume, 1748). Therefore, association itself is insufficient to establish causality. To *robustly* infer causality, scientific research generally requires at least four kinds of evidence: association, non-spuriousness, time precedence (direction of influence), and causal mechanism (Schutt, 2004; Singleton and Straits, 2005).

Association: The presence of a "statistically significant" relationship between two variables (established, for example, through a t-test, chi-square test, analysis of variance, or correlation) is often taken as evidence of association. While useful as a general principle, statistical significance does not guarantee even a meaningful association, let alone true causality. The apparent relationship may be spurious (see below), or may simply constitute a Type I statistical error, in which the null hypotheses of no relationship is erroneously rejected due to random variation making the relationship appear to be stronger than it really is. The latter situation may well arise in a given study in which numerous statistical tests are conducted, but is less likely to explain results that persist across a number of independent studies, as is the case for the observed association between the built environment and travel behavior.

On the other hand, while a statistically significant association is taken to be at least a necessary condition of causality (Singleton and Straits, 2005) if not a sufficient one, this is also not guaranteed to be the case. That is, a weak association does not rule out causality. The causal relationship may be strong for one subgroup of the sample but be diluted when tested across the entire sample; controlling for a third variable may unmask a strong association between the first two (Utts, 1999).

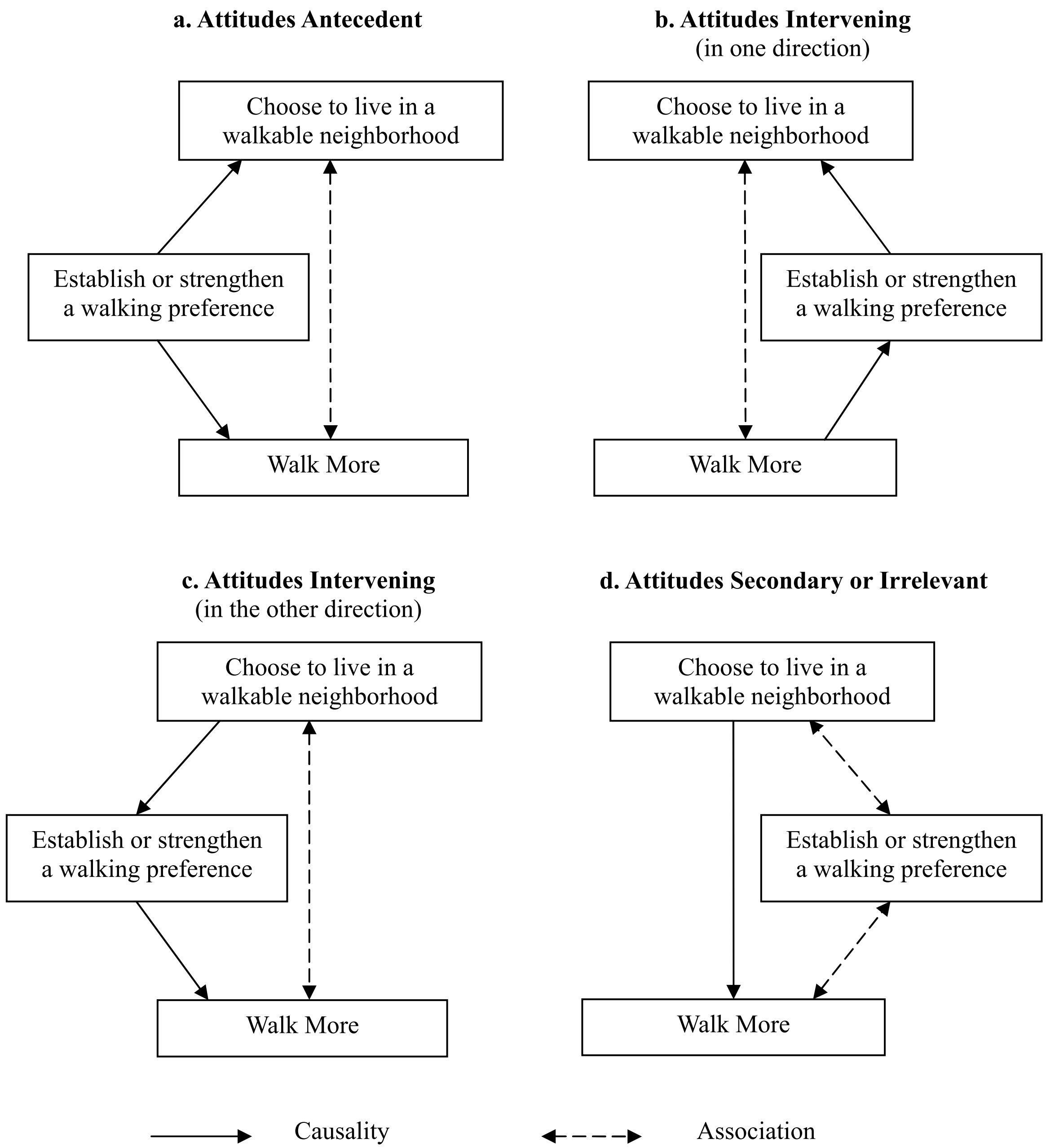
Nonspuriousness: A nonspurious relationship between variables refers to an association that cannot be explained by a third-party (extraneous or antecedent) variable. If a third-party variable happens to cause both a "dependent" variable and an "explanatory variable", a statistically significant association may exist even if the explanatory variable inherently has nothing to do with the dependent variable. Therefore, to infer causality, we should eliminate rival hypotheses that can explain the observed association between variables (Singleton and Straits, 2005). The land use-transportation literature offers evidence of a possible spurious relationship between the built environment and travel behavior. As an example, in the 1995 Nationwide Personal Transportation Survey, it was found that low income households were disproportionately likely to reside in high-density urban areas, and that they were much more likely to walk than their higher-income counterparts (Murakami and Young, 1997). In this case, household income can be a cause of both residential choice and travel behavior, and hence this rival hypothesis weakens the inference of causality between the latter two variables. To establish non-spuriousness in a nonexperimental study, an appropriate method is to show that the relationship still holds when all third-party variables are controlled for (statistical control). In reality, however, we are seldom able to control for all variables. Therefore, we should account for as many variables as possible (Singleton and Straits, 2005).

Time precedence (direction of influence): To infer causality, a cause must precede its effect in time, or at least the direction of influence must be from a cause to an effect (Singleton and Straits, 2005). A causal relationship is "a relationship in which a change in one event forces, produces, or brings about a change in another" (Singleton and Straits, 2005, p.20). Therefore, a panel study showing that changes in built environment characteristics at one point in time are associated with changes in travel behavior at a later time will offer more direct evidence of a causal link from the built environment to travel behavior than cross-sectional analysis can.

For cross-sectional data, it is hard to tell whether the choice of the built environment precedes travel choice or travel choice precedes residential choice. For example, it is evident that highly-walkable neighborhoods are significantly associated with a large amount of pedestrian travel (e.g., Cervero and Duncan, 2003). A common inference from this association is that the influence is from the built environment to travel behavior through an intervening variable – travel costs. This is a strong causal mechanism from the perspective of transportation economics, as discussed later in this section. Alternatively, however, as mentioned in the Introduction, this association may mean that individuals who walk a lot intentionally choose a highly-walkable neighborhood in which to live. In this case, travel attitudes (walking preferences) are likely to confound this direction of influence. As shown in Figure 2, travel attitudes may act as either antecedent or intervening factors in the associations between the built environment and travel behavior. Figure 2a illustrates a potentially spurious relationship between walkable neighborhoods and walking behavior, which can be addressed by controlling for walking preference. In Figure 2b, a large amount of walking (which may or may not have very much to do with the built environment) may stimulate or reinforce an individual's preference for pedestrian travel, which may in turn encourage her choice of highly-walkable neighborhoods. In other words, walking behavior (in that model) is likely to be a proxy for walking preference. If we explicitly account for the influence of walking preference, the influence of the walking behavior on the choice of walkable neighborhood is likely to diminish. Further, an individual's current travel behavior is not a logical indicator of her previous walking preference and residential choice (it may well be correlated with prior attitudes that *are* true antecedents of residential choice, but since the degree of that correlation is unknown, using current behavior as a proxy for past attitudes is in effect assuming what one needs to prove).

Therefore, when only cross-sectional data on the built environment and travel behavior are available, but not attitudes (as is the case in many studies), the influence from the (previously-chosen) built environment to (presently-chosen) travel behavior is generally inferred much more strongly than that from travel behavior to the built environment. In that situation, two roles of walking preference can be distinguished. Travel attitudes may again serve as an intervening variable but in the other direction, as shown in Figure 2c. In particular, if travel attitudes are measured at the current time, these attitudes may be more a function of prior residential choice than the reverse (Chatman, 2005). In this case, we may overstate the influence of travel attitudes. Alternatively, as shown in Figure 2d, the built environment may have a primary and direct influence on travel behavior while travel attitudes may be secondary or irrelevant to this link, as most previous studies have implicitly or explicitly assumed. For example, one may walk to many nearby activities, even if reluctantly (counter to preferences), if the built environment makes it too difficult or expensive to drive; conversely, one may drive to many nearby activities, even if reluctantly, if the built environment is not conducive to walking – heavy, fast, noisy, smelly traffic; no or broken sidewalks; no aesthetic appeal; etc.

Figure 2. Some Potential Relationships among Travel Attitudes, Built Environment, and Travel Behavior



Causal mechanism: The identification of a causal mechanism between the built environment and travel behavior can provide strong support to a causality inference (Singleton and Straits, 2005). Boarnet and Crane (2001a) offer an explicit economic explanation of such a mechanism: the built environment influences the price of travel (an intervening variable), through its impact on travel time and other qualities of travel, which in turn influences the consumption of travel. A similar idea is implicit in discrete choice models of travel behavior: the utility of a particular travel choice – what mode to take or which destination to choose – is influenced by travel time and other characteristics (intervening variables) of the possible choices, characteristics which are influenced by the built environment.

Causal relationships are most validly established through experimental designs, in which individuals are randomized to treatment and control groups (thereby addressing nonspuriousness) and motivations/attitudes and behavior are measured for both groups (also addressing nonspuriousness) before and after the treatment of interest (thereby addressing time precedence) (Singleton and Strait, 2005). However, neither the application of a treatment nor randomization is practical for studying the link between the built environment and travel behavior. First, we are less able to manipulate a treatment regarding the built environment. Some studies adopted residential relocation as a treatment (e.g., Krizek, 2003a). However, the individuals' move is not manipulated by experimenters but is a "voluntary" result of individuals' changes in employment location, lifecycle, and, most importantly, potentially attitudes toward travel modes and residential neighborhood environments. By contrast, an intervention (such as a traffic calming program) is to some extent an experimental manipulation. However, intervention programs are implemented at some specific locations, which themselves are generally not random but rather (often) chosen on the basis of being more deficient on the dimension that the intervention is expected to improve. Further, all residents living at these locations are automatically classified into the treatment group and others are classified into the control group. Accordingly, an individual does not have an equal probability to be assigned to either group, that is, there is a lack of randomization.

Given these limitations, we are unable to completely specify the nature and extent of the causality between the built environment and travel behavior. Nevertheless, we can design studies to satisfy as many requisites of causality inference as possible. Such studies will provide strong evidence for inferring causality.

2.4 Residential Self-Selection

Previous studies assume that the built environment influences travel behavior by influencing the relative attractiveness of each mode – driving, transit, walking, etc. (Boarnet and Crane, 2001a; Krizek, 2003a). However, it is the residential choice that determines what characteristics of the built environment an individual finds in her neighborhood. It is known that individuals with a preference for walking tend to consciously choose a neighborhood conducive to walking (e.g., Handy and Clifton, 2001). In this case, the connections between the built environment and walking behavior can be explained by the influence of a preference for walking on the residential location choice. In other words, walking behavior is explained by prior "self-selection" into a certain kind of neighborhood rather than by the built environment of that neighborhood per se. Thus, simply comparing the differences in travel behavior observed in different neighborhoods, an approach broadly applied in empirical studies, is likely to lead to biased conclusions about the influence of the built environment (Boarnet and Crane, 2001a).

Self-selection in this context refers to "the tendency of people to choose locations based on their travel abilities, needs and preferences" (Litman, 2005, p.6). Residential self-selection generally results from two sources: attitudes and socio-demographic traits. It is known that individuals with a preference for walking tend to selectively live in a neighborhood conducive to walking (e.g., Handy and Clifton, 2001). In this case, the connections between the built environment and walking behavior can be explained by the influence of a preference for walking on the residential location choice (as in Figure 2a). In other words, walking behavior is explained by prior self-selection into a certain kind of neighborhood rather than by the built environment of that neighborhood per se. With respect to socio-demographics, an example of self-selection is that low-income and zero-vehicle households may choose to live in neighborhoods with ample transit service and hence use transit more. In this case, it is not good transit facilities but households' economic constraints that have a true and direct influence on their choice of transit mode. However, since most previous studies have employed multivariate analysis and accounted for the sorting effect of socio-demographic characteristics (e.g., Abreu e Silva et al., 2005; Kitamura et al., 2001), we focus this review on the issue of attitude-induced self-selection. Unless explicitly indicated, residential self-selection in the remainder of the dissertation refers only to that resulting from attitudinal factors.

In simple mathematical terms, the often-observed relationship between the built environment (BE) and travel behavior (TB) is generally modeled as taking the form:

$$TB = f_1(BE, X) + \varepsilon, \quad (2\text{-}1)$$

where X denotes other observed variables such as socio-demographics. The problem is that the standard estimation of such functional forms, whether the dependent variable is continuous and observed (as in linear regression models) or representing a discrete choice (as in logit or probit models), requires that observed explanatory variables (BE, X) be uncorrelated with unobserved explanatory variables (ε). Failure to meet this important condition is broadly refereed to as *endogeneity bias*, and produces coefficients that are biased and inconsistent estimators of the true values (Greene, 2003).

Endogeneity bias can occur in two conceptually distinct ways, either of which could arise in our current context. *Simultaneity bias* is produced when an "explanatory" variable is simultaneously a function of the "dependent" variable it is supposed to explain – that is, when one variable is both a cause and an effect of another. In the present context, this would mean:

$$TB = f_1(BE, X, Y) + \varepsilon_1$$

$$BE = f_2(TB, X, Z) + \varepsilon_2, \qquad (2\text{-}2)$$

where X denotes observed explanatory variables common to both TB and BE, and Y and Z denote observed variables distinctive to TB and BE, respectively. In this formulation, travel behavior is assumed to exert a direct influence on residential choice (and conversely), separate from the influence of attitudes. This could occur if travel behavior were largely determined by constraints such as income (X) – e.g. making it impractical to own a car – and then residential location were influenced by the resulting travel behavior, e.g. a reliance on public transportation (as well as separately by income also). In models such as these, it is easy to see that BE is likely to be correlated with ε_1, because of its correlation with $TB = f_1 + \varepsilon_1$.

The second type of endogeneity bias is *omitted variables bias*. This occurs whenever observed and unobserved explanatory variables are directly correlated, either because one causes the other or because both are functions of the same antecedent variables. The most frequently-discussed form of the residential self-selection problem is

$$TB = f_1(BE(AT), X) + \varepsilon(AT), \qquad (2\text{-}3)$$

in which the attitude (AT) portion of ε partly explains or causes BE. However, as indicated by Figure 2c, the opposite direction of causality between BE and AT is also plausible:

$$TB = f_1(BE, X) + \varepsilon(AT(BE)), \qquad (2\text{-}4)$$

in which travel attitudes are influenced by the built environment.

A number of methodological approaches have been applied to test and control for this endogeneity bias in previous studies; we discuss five such approaches in this section. The general format in each case is that we briefly describe the method, then discuss one or more studies exemplifying the method, and then make some analytical and/or critical observations about the basic approach. Twenty relevant studies and their corresponding methodologies are summarized in Table 3.

2.4.1 Direct questioning

To assess whether people's travel and land use predispositions influenced their choice of residential neighborhood, why not just ask them? Although this approach is primitive in its simplicity, it should not be entirely disdained. Employed together with more sophisticated approaches, it can provide useful insight.

Using 1,368 respondents to a 1995 survey conducted in six neighborhoods in Austin, TX, Handy and Clifton (2001) investigated the potential of providing local shopping as a strategy to reduce auto dependence. Through group discussions with some of the respondents, they found some evidence for residential self-selection and concluded that "having the option to walk to the store [i.e., living in a neighborhood that permits walking] is to some extent an effect of the desire to walk to the store" (p.344).

Table 3. Overview of Residential Self-selection Studies

Studies	Sample	Methodology	Travel Behavior Measurements	Built Environment Measurements	Attitude Measurements	Conclusions
Direct questioning						
Hammond, 2005	90 respondents and 8 interview participants in the Century Wharf, Cardiff, UK, 2004	Descriptive and correlational analyses	Changes in car use to work	Moving to the city center	8 measures for residential preferences	BE and SS [1]. Residents moving to the city center reduced car use to work; residential choice was either conditional on or interacted with current commute mode choice for most respondents.
Handy and Clifton, 2001	1,368 individuals and unspecified interview participants in Austin, TX, 1995	Descriptive analysis and linear regression	Walking to store frequency	Miles to store, perceived store characteristics, and neighborhood dummy	Not available	BE and SS. Local store characteristics influenced walking frequency; but "having the option to walk to the store is to some extent an effect of the desire to walk to the store."
Statistical control						
Cao et al., 2006	1,368 individuals in Austin, TX, 1995	Negative binomial regression	Strolling frequency and walking to store frequency	Objective and perceived neighborhood characteristics, perceived store characteristics	Residential preference for stores within walking distance	BE and SS. Residential preference is the most important single factor explaining walking to store frequency; neighborhood characteristics also had a separate influence on strolling frequency, while characteristics of local commercial areas had a separate influence shopping trips.

1. BE means evidence found for the influence of the built environment on travel behavior and SS means evidence found for the influence of residential self-selection on travel behavior.

(**Table 3 continued**)

Studies	**Sample**	**Methodology**	**Travel Behavior Measurements**	**Built Environment Measurements**	**Attitude Measurements**	**Conclusions**
Kitamura et al., 1997	963 households in the San Francisco Bay Area, CA, 1993	Linear regression	Numbers of trips by non-motorized modes, transit, and all modes; fractions of auto trips, transit trips, and non-motorized trips	Residential density, land use mix, and rail transit accessibility	8 attitude factors	BE < SS. The residential environment had some influence on travel behavior, but attitudes carried more explanatory power in explaining the variation in travel behavior.
Schwanen and Mokhtarian, 2003	1,358 workers in the San Francisco Bay Area, CA, 1998	Oordered probit model	Respective trip frequencies for 6 purposes	Traditional and suburban neighborhoods	Various measures for lifestyle, personality, and travel attitudes, neighborhood type mismatch indictors	BE > SS. Suburban-oriented urban dwellers were able to realize their preference; urban-oriented suburban residents were less able to achieve their preference because of little choice available to suburbanites;
Schwanen and Mokhtarian, 2005a	1,358 workers in the San Francisco Bay Area, CA, 1998	Multinomial logit model	Commute mode choice	Traditional and suburban neighborhoods	Various measures for lifestyle, personality, and travel attitudes; neighborhood type mismatch indictors	BE > SS. Suburban-oriented urban dwellers were able to realize their preference; urban-oriented suburban residents were less able to achieve their preference because of little choice available to suburbanites;

(**Table 3 continued**)

Studies	Sample	Methodology	Travel Behavior Measurements	Built Environment Measurements	Attitude Measurements	Conclusions
Schwanen and Mokhtarian, 2005b	1,358 workers in the San Francisco Bay Area, CA, 1998	Tobit model	Respective distance traveled by auto, rail, bus, walking/ jogging/biking, and all modes	Traditional and suburban neighborhoods	Various measures for lifestyle, personality, and travel attitudes; neighborhood type mismatch indictors	BE > SS. Suburban-oriented urban dwellers were able to realize their preference; urban-oriented suburban residents were less able to achieve their preference because of little choice available to suburbanites;
Instrumental variables and selection models						
Boarnet and Sarmiento, 1998	769 Southern California residents, 1993	Instrumental regression	Nonwork auto trip frequency	Density measures and street grid pattern at the block group/census tract and zip code levels	Not available	BE. The built environment at the neighborhood level had little influence on nonwork auto travel.
Greenwald and Boarnet, 2001	1,091 individuals in the 1994 Household Activity and Travel Behavior Survey in Portland, OR	Instrumental regression	Nonwork walking trip frequency	Density measures, street grid pattern, and pedestrian environment factor at census block group, census tract, and zip code levels	Not available	BE. The residential environment influenced nonwork walking trip generation at the neighborhood level.
Greenwald, 2003	4,235 respondents in the 1994 Household Activity and Travel Behavior Survey in Portland, OR	Multinomial logit model and then linear regression	Eight substitution rates (walking/driving and transit/driving) for consumption, communication, socialization, and all trips	Six groups based on housing tenure and three levels of pedestrian environment factor, and zone-based land use characteristics	Not available	BE. New Urbanist designs increased walking substitution for driving, but had few effects on transit substitution for driving.

(**Table 3 continued**)

Studies	**Sample**	**Methodology**	**Travel Behavior Measurements**	**Built Environment Measurements**	**Attitude Measurements**	**Conclusions**
Khattak and Rodriguez, 2005	453 households in Chapel Hill and Carrboro, NC	Binary choice model and negative binomial/linear regression	Frequencies of auto trips, walking trips and external trips; distances for all trips and nonwork trips; trip duration	Neo-traditional and suburban neighborhoods	8 measures for residential preference	BE. The built environment influenced most measures of travel behavior.
Simultaneous models						
Bagley and Mokhtarian, 2002 [2]	515 individuals in the San Francisco Bay Area, CA, 1993	Structural equations model	Vehicle miles, transit miles, and walk/bike miles	Two factor scores: traditional and suburban, based on various measures such as residential density and land use mix	Various lifestyle and attitude factor scores	BE < SS Residential location type had little impact on travel behavior; attitudes and lifestyles were the most important predictors of travel behavior.
Bhat and Guo, 2005	Alameda County sample in the 2000 San Francisco Bay Area Travel Survey	Joint model	Number of autos	Indicator of 233 TAZs, regional accessibility, density, land use traits, and transportation network characteristics	Not available	BE. The built environment had true effects on auto ownership.
Cervero and Duncan, 2002	11,369 workers in the 2000 San Francisco Bay Area Travel Survey	Nested logit model	Rail commute choice	Residential location within or beyond half a mile of a rail station	Not available	BE and SS. The results showed the dependency between rail commuting and transit-based residency.

2. Of all the papers reviewed, only Bagley and Mokhtarian (2002) investigated multi-directional causality.

(**Table 3 continued**)

Studies	Sample	Methodology	Travel Behavior Measurements	Built Environment Measurements	Attitude Measurements	Conclusions
Longitudinal design						
Boarnet et al., 2005	862 respondents to SR2S program, CA, 2002	T-tests	Walking/biking to school	SR2S projects including sidewalk, crossing, and traffic control improvements	Not available	BE. All improvements increased walking/biking to school for children.
Krizek, 2000	549 households moving over the seven waves of the Puget Sound Transportation Panel, WA	Pairwise t-tests	Respective changes in trip distance, trip time, tour distance, tour time, trips per tour, and percentage of total trips by alternative modes	Changes in the Less Auto Development Urban Form (LADUF) index	Not available	BE. Individuals chose residential neighborhoods partially to match their travel preference; moving to a different residential environment had little influence on travel behavior given that only 9 out of 36 t-tests are significant.
Krizek, 2003a	6,144 individuals over the seven waves of the Puget Sound Transportation Panel, WA	Linear regression	Respective changes in vehicle miles traveled, person miles traveled, number of tours, and number of trips/tour	Respective changes in neighborhood accessibility and regional accessibility at the residence and workplace	Not available	BE. Changes in neighborhood accessibility and regional accessibility at the residence influenced most changes in travel behavior; regional accessibility at the workplace affected some changes in travel behavior.
McBeth, 1999	The central area of Toronto, 1993-1998	Descriptive analysis	Bicycle volume	Bicycle lane installations	Not available	BE. The installation of bicycle lane increased bicycle volume.

(Table 3 continued)

Studies	Sample	Methodology	Travel Behavior Measurements	Built Environment Measurements	Attitude Measurements	Conclusions
Meurs and Haaijer, 2001	189 movers and 524 nonmovers participating in the Dutch Time Use Study in 1990 and in 1999	Linear regression	Respective changes in the number of trips by auto, bicycle, walking, transit, and all modes	Respective changes in home characteristics, street characteristics, and neighborhood characteristics	Not available	BE. Individuals' travel behavior was changed when moving to a different residential environment; nonmovers' travel behavior was also changed but not great when the environment was changed.
Painter, 1996	Three streets and a footpath, London	Descriptive analysis	Pedestrian volume after dark	Street light improvements	Not available	BE. Street light improvements increased pedestrian volume after dark.

Hammond (2005) studied the interdependency between decisions involving residence and mode choice. In a self-administered survey, he first asked respondents living in Century Wharf, Cardiff (an isolated, compact, and mid-size provincial city in the UK), to answer questions regarding residential choice and commute mode choice. He concluded that living in the city center is associated with reduced car use. In fact, living in the city center and workplace proximity are the two most important reasons among others for lower car use. Respondents were also asked to describe their decision sequence with respect to residential choice and commute mode choice. He found that 18% of the 90 respondents pre-selected commute mode and then decided on residential location, and that 39% decided on residence and commute mode at the same time. This result indicates that for more than half of the sample, residential choice is either conditional on or interacts with commute mode choice. Through an eight-person focus group, he found that participants incorporated commute mode choice and access to work into their residential choice, and that all participants were consistently commuting by the mode (including car, bus, and train) that they anticipated they would use (although one participant planned to change mode). Therefore, people selectively locate in a residential neighborhood to realize their travel preferences. However, almost all of these results are not based on statistical tests but on descriptive analysis.

Direct questioning is relatively inexpensive and easy to conduct. It may offer valuable information regarding the process of residential and travel choices, sometimes beyond what multivariate analyses can do. However, direct questioning has several limitations. To begin with, the sample size is generally small and may not be representative of the population of interest. Moreover, direct questioning is likely to suffer from memory, consistency, and social desirability biases: since participants' responses rely on their memory, the accuracy of these responses may be a concern when they relocated to their current residence a long time ago; if we ask about participants' behavior first, they may later (consciously or subconsciously) express attitudes to be consistent with that behavior; and as the conversation goes along, participants may anticipate the objective of the study and hence conform their expressed attitudes and choices either with what they think the researcher wants to hear, or with established social norms. More importantly, direct questioning does not allow us to quantify the respective influences of the built environment and residential self-selection, and determine which is more important. In addition, this approach is vulnerable to most of the limitations discussed in the following sections.

2.4.2 Statistical control

The method of statistical control explicitly accounts for the influences of attitudinal factors in analyzing travel behavior. This approach has been operationalized in two different ways in the literature. The more straightforward one is to incorporate attitudes into the equation for TB. In this case, TB is modeled as a function of AT as well as BE:

$$TB = f_3(BE, AT, X) + \xi, \qquad (2\text{-}5)$$

which removes AT from the ε of equations (2-3) and (2-4), and thereby presumably eliminates any correlation between BE and ξ. If the inclusion of AT drives the influence of BE into insignificance, the natural conclusion is that the influence of BE was entirely due to predispositional attitudes. If BE is still significant, the conclusion is that the BE exerts some influence of its own, separate from the predisposition that led an individual to locate there in the first place.

Using data collected from 1,114 adults in the San Francisco Bay Area and the San Diego metropolitan area in 2003, Chatman (2005) studied the confounding influence of modal (auto, transit, walk/bike) access preferences in the relationship between the built environment and nonwork travel. Through negative binomial regressions, he found that respondents who sought transit and walk/bike access (to shops/services and for all travel purposes) were more likely to conduct nonwork travel by transit and walk/bike, respectively, but auto travel was not significantly influenced by auto access preference. After controlling for these attitudinal factors, he also found that living within half a mile of a heavy rail station and bus frequency had an influence on nonwork travel by transit, and bus frequency and number of four-way intersections influenced walk/bike travel. By further incorporating interaction terms of built environment characteristics and modal access preference indicators in the models, Chatman found that the effects of built environment characteristics showed little difference between those with strong and weak preferences. Chatman also modeled non-work auto mileage as a function of built environment traits and modal access preferences, but he did not find any meaningful influence of the preferences. Chatman concluded that the residential self-selection problem is not a big concern, at least for his dataset.

Kitamura et al. (1997) incorporated attitudinal measures into the specification of linear regression models of travel behavior. This study explored the effects of both the built environment and attitudinal characteristics on disaggregate travel behavior for 1,380 residents in five neighborhoods in the San Francisco Bay Area in 1993. They first regressed socio-demographic and neighborhood characteristics against frequency and share of trips by mode. Measurements of residential density, public transit accessibility, mixed land use, and the presence of sidewalks were found to be significantly related to mode choice and trip generation by mode, controlling for socio-demographic characteristics. After attitudinal measures were incorporated as explanatory variables in the model, they found that attitudes explain travel behavior better than neighborhood characteristics, which lends some support to the self-selection speculation. However, several built environment characteristics (parking spaces available, distance to nearest bus stop, and distance to nearest park) remained significant in the model for fraction of trips by auto, even after including attitudinal variables.

Cao et al. (2006) investigated the determinants of trip frequencies for two types of pedestrian travel: strolling and walking to the store, using the same data as Handy and Clifton (2001). Two separate negative binomial models showed that although residential self-selection (measured as a preference for stores within walking distance when households were looking for a place to live) impacts both types of trips, it is the most important factor explaining walking to a destination (i.e. for shopping) among the variables tested. However, after accounting for the influence of self-selection, neighborhood characteristics, especially perceptions of various characteristics, impact strolling frequency, while characteristics of local commercial areas are important in facilitating shopping trips. Similar to the previous one, this study indicates that residential self-selection at least partially contributes to differences in pedestrian behavior, but that the built environment does exert a separate influence beyond that. However, the single attitude measurement included may not have completely captured the influence of self-selection (e.g., a preference for recreational strolling was not measured). To the extent that unmeasured influences were at work, their models may overstate the influence of the built environment.

The second form of this approach is to compare the travel behavior of residentially matched and mismatched individuals. Here, in addition to incorporating travel-related attitudes into the equation for travel behavior, attitudes toward residential location type are used to classify survey respondents as matched or mismatched with respect to their current residential location. The travel behavior of mismatched residents is then compared to that of matched residents in the type of neighborhood in which they would rather live, and in their current neighborhood. If the travel behavior of mismatched residents is more similar to that of the matched residents in their desired type of neighborhood, it suggests that their predispositions dominate their travel behavior. If their travel behavior is more similar to that of the matched residents in their current neighborhood, it suggests that the built environment exerts a separate influence that outweighs a contrary predisposition. Alternatively, a continuous measure of the degree of mismatch, as well as measures of the built environment, can be incorporated into the travel behavior equation, and tests performed to see whether the built environment remains significant after mismatch is accounted for.

In three studies of a 1998 sample of 1,358 residents of the San Francisco Bay Area, Schwanen and Mokhtarian compared the trip frequency (2003), commute mode choice (2005a), and mode-specific distances traveled (2005b) of mismatched suburban and urban residents (those who preferred a more or less, respectively, dense/diverse neighborhood than the one they currently lived in) to their matched counterparts in both kinds of neighborhoods. In general, they found that while suburban residents' travel behavior was similar whether they were matched or mismatched, mismatched urban residents' behavior fell between that of matched urban and matched suburban residents – more auto-oriented than the former but less so than the latter. These findings suggest that the built environment does in fact play a role, at least in constraining and possibly in shaping, one's underlying preferences. Unfortunately for the goal of reducing auto dependence, the role does not appear to be symmetric: urban-oriented suburban residents are less able to achieve their preference for non-auto travel than suburban-oriented urban dwellers are able to realize their preference for auto travel. However, in these studies too, residential preferences were captured with a single variable, attitude toward residential density/diversity. Although that attitude was a factor score comprising a composite of several different elements (e.g., housing type, having shops and services within walking distance, and yard size), it still leaves room for improved measurement of residential preferences.

Although the statistical control approach can offer insightful evidence of residential self-selection, it is vulnerable to several intrinsic limitations. First, attitudes are not straightforward to measure and analyze, and are often not measured, e.g. not available in standard travel/activity diary data sets, and hence pose significant difficulty in simulation studies. Second, when data are cross-sectional, there can be a temporal mismatch: the attitudes measured in the present may differ from those leading to the prior choice of the built environment. Third, these studies modeled only a single causal direction, from the built environment to travel behavior. As illustrated in Figure 2, this is too simplistic a representation of the interactions among these variables.

2.4.3 Instrumental variables and selection models

Another approach to address residential self-selection is to use instrumental variables (IVs), or a conceptually equivalent two-stage technique, to purge BE of its correlation with ε. A time-honored econometric technique (as applied in this context) is first to model BE as a function of instrumental variables (or "instruments"), z, that are not correlated with ε, and then to replace the observed BE in equation (2-1) with its predicted value $\hat{BE}$ from that model:

$$BE = b(z) + \eta(AT)$$

$$TB = f_4(\hat{BE}, X) + \varepsilon(AT), \tag{2-6}$$

where $\hat{BE} = \hat{b}(z)$. The predicted $\hat{BE}$ will then, by construction, be uncorrelated with ε. The implication is that the entire influence of AT on TB will lie in ε; if $\hat{BE}$ is significant in the equation for TB, it represents an influence of the BE that is purged of the self-selection attitudinal component.

Boarnet and Sarmiento (1998) employed ordered probit models to estimate nonwork auto trip frequency, using 1993 data from 769 Southern California residents. Population density, retail employment density, service employment density, and street grid patterns at the block group/census tract level and at the zip code level were chosen to measure the built environment. They initially found that none of these built environment variables were significant in the models.

Then they chose four non-transportation neighborhood traits as built environment instruments: percentage of population that was African American, percentage of population that was Hispanic, and percentages of housing built before 1940 and before 1960. After performing instrumental variable regressions, they found that the predicted built environment variables remained statistically insignificant in all but one of the model specifications. In particular, predicted service employment density became significant to nonwork auto trip frequency when both employment densities at the zip code level were instrumented.

By contrast, Greenwald and Boarnet (2001) found a different pattern when modeling nonwork walking trip frequency. Using 1,091 individuals from the 1994 Household Activity and Travel Behavior Survey in Portland, OR, they employed ordered probit models to test walking frequency against built environment variables and socio-demographic characteristics. The built environment variables were measured at three geographical levels: census block group, census tract, and zip code. They initially found that population density, retail employment density, street grid patterns, and pedestrian environment factor (PEF) score were significantly associated with nonwork walking frequency. Thereafter, they selected six variables as instruments: per capita income in the area (census block group only), percentage of population living in the geographical area with at least a college education, percentage of population that was African American, percentage of population that was Hispanic, percentage of housing units in the area classified as rural but not farms, and percentage of housing units in the area classified as urban dwelling units. After performing instrumental variable regressions, they showed that most predicted built environment variables at the census block group and census tract levels remained significant while those at the zip code level became insignificant. Therefore, they concluded that the built environment influences nonwork walking trip generation at the neighborhood level.

Using 453 households from a neo-traditional neighborhood in Chapel Hill and a suburban neighborhood in Carrboro, NC, Khattak and Rodriguez (2005) first developed a binary logit model for neighborhood type choice (pseudo R^2 was 0.27), with residential attitudes as instruments. Then they incorporated the predicted probabilities of neo-traditional neighborhood choice (a new explanatory variable) into three negative binomial regression models for auto trip frequency, external trip frequency, and walking trip frequency, and two linear regression models for trip distance and trip duration. They concluded that households with high predicted probabilities of living in the suburban neighborhood conducted more auto trips and external trips, walked less, and traveled longer distances than those with high predicted probabilities of living in the neo-traditional neighborhood. However, some if not all instruments that they selected may not be appropriate. Generally, instrumental variables should satisfy the following criterion: they must be highly correlated with endogenous explanatory variables but not significantly correlated with the error term (Cameron and Trivedi, 2005). Although Khattak and Rodriguez explicitly stated that they excluded attitudes that are expected to be associated with travel behavior and hence correlated with the error term in an equation for travel behavior, they did not provide any empirical evidence of independence from travel behavior for the attitudes they *did* include. To the contrary, other studies suggest that some of their instruments may be correlated with travel behavior. For example, Cao et al. (2006) found that residential preference for stores within walking distance, a dimension similar to "having shops and services close by is important to me" in Khattak and Rodriguez (2005), is significantly associated with walking frequency.

An approach conceptually related to the instrumental variable technique is to use a two-stage model to correct the selectivity bias that results from self-selection into a certain type of built environment (Greenwald, 2003). If there are only two types, this model is called the Heckit model, which includes a binary choice model (participation equation) and an outcome equation (Heckman, 1979). Greenwald (2003) extended the participation equation into a multinomial choice model following Lee (1983). In particular, he classified 4,235 respondents from the 1994 Household Activity and Travel Behavior Survey in Portland, OR, into six types of residential conditions based on residential tenure and three levels of the PEF score. A multinomial logit model was developed to predict individuals' residential choice (pseudo R^2 was 0.33), with socio-demographics and some variables derived from census data being the explanatory variables. Then, he plugged the predicted probability of the *observed* residential choice into eight separate models, with dependent variables being substitution rates of walking versus driving and transit versus driving, for consumption trips, communication trips, socialization trips, and all purposes. He found that the predicted probability significantly influenced the substitution rate of transit versus driving, for communication purposes and for socialization purposes. After accounting for the influence of residential self-selection, he also found that some built environment variables were significant in all models. However, Greenwald's model is not a true selectivity model. First, in a two-stage selectivity model, the new explanatory variable in the outcome equation is not the predicted probability but the inverse Mills ratio (if the participation equation is a binary probit model, the IMR = $\phi(X\beta)/\Phi(X\beta)$, where ϕ and Φ are the PDF and CDF of a standard normal distribution, respectively) derived from the participation equation (Cameron and Trivedi, 2005; Lee, 1983). Second, in a multinomial logit-OLS model, the number of outcome equations is not one but depends on the number of alternatives in the multinomial logit model (Lee, 1983). Therefore, the ability of this model to correct for selectivity bias may be compromised.

In general, however, the IV technique is fundamentally limited. The problem is that BE (in this context) must be *substantially* correlated with ε in order for endogeneity bias to be a problem; small correlations between observed and unobserved variables are tolerated all the time, without remedial measures being taken. Modeling BE as a function of variables *uncorrelated* with ε will necessarily leave a sizable portion of the variance in BE unexplained. Finding suitably uncorrelated variables with which to model BE in the first place can be difficult, and if the model of BE has a low goodness of fit, the predicted BE is not very powerful in the equation for TB. In that case, finding $\hat{BE}$ to be insignificant may not reflect a true lack of influence after controlling for self-selection, but rather the inability of the poor $\hat{BE}$ to capture that influence. Having a poor $\hat{BE}$ can be viewed as an instance of measurement error in the original variable (the true BE), which is known to result in coefficient estimates for that variable that are inconsistent and biased toward zero, and coefficient estimates for the other variables in the equation that are also biased (Greene, 1997). Thus, special account needs to be taken of the sampling variance in the IV, or else incorrect statistical inferences on the significance of its coefficient in the TB model may result. The corrections needed are especially tedious when the TB variable is discrete (Bhat and Guo, 2005).

2.4.4 Simultaneous model

To deal with residential self-selection, some studies have adopted more complex modeling techniques – joint models and structural equations models. Bhat and Guo (2005) developed a joint model structure and parameterized the error terms as follows:

$$RC = b(BE, Z, X) + u \times BE \pm w \times BE + \varsigma$$

$$TB = t(BE, Y, X) + v \times BE + w \times BE + \delta, \qquad (2\text{-}7)$$

where RC stands for residential choice; u and v are unobserved factors impacting households' sensitivity to built environment traits in residential choice alone and travel choice alone, respectively; w stands for unobserved factors impacting both residential and travel choices; and ζ and δ are idiosyncratic terms. By including the common error term $w \times BE$, Bhat and Guo's model simultaneously corrects for the endogeneity of the built environment.

Using data from the 2000 San Francisco Bay Area Travel Survey (Alameda County sample), they calibrated this joint mixed multinomial logit-ordered response model. In their operationalization, RC is measured as a discrete indicator of one of 233 transport analysis zones, BE variables include measures for zonal density, zonal land-use structure, regional accessibility, local transportation network, and commute-related variables, and TB is the ordinal measure of number of vehicles owned by the household. Their results showed that the built environment has a true influence on auto ownership, and the lack of a significant common error term failed to support the speculation that residential self-selection influences auto ownership choice.

Another approach is to jointly estimate the discrete choices of the built environment and travel behavior. Cervero and Duncan (2002) developed a two-level nested logit model, with the upper level indicating the binary choice of residential location (whether or not to live within half a mile of a rail station) and the lower level representing the binary choice of commute modes (rail or auto). The correlation of the error terms for the utility functions of each choice indicates the extent to which the same unmeasured variables (such as attitudes) influence both choices. Using 11,369 workers in the 2000 San Francisco Bay Area Travel Survey, they calibrated the nested logit model. The estimated inclusive value parameter for the choice of rail commuting and living within half a mile of a rail station is 0.269 and significant at the 0.001 level, indicating unobserved similarity between rail commuting and transit-based residency. Therefore, transit-oriented tenancy and rail commuting are interdependent.

Structural equations have also been used to model multiple directions of causality between the built environment and travel behavior. Recognizing that AT influences both BE and TB, and therefore including it in an equation for TB, as in equation (2-5), constitutes a useful improvement in the realism of a model of TB. In fact, however, the influence between attitudes and behavior is probably not entirely unidirectional, as Figure 2 illustrates. It is quite possible that over time, both the BE and TB may affect AT as well, and AT and TB could affect BE (bringing about a residential relocation). There is a sizable literature in transportation (and other fields) on the mutual causality between attitudes and behavior, with ample evidence for impacts in both directions (e.g., Tardiff, 1977; Golob, 2001). Thus, improving the realism of the model even further suggests the need for multiple interrelated equations, reflecting the multiple likely directions of causality. Specifically, one could postulate the following Structural Equations Model (SEM):

$$TB = t(AT, BE, W, X, Y, Z) + \omega_1$$

$$BE = b(AT, TB, W, X, U, V) + \omega_2$$

$$AT = a(TB, BE, W, Y, U, S) + \omega_3, \tag{2-8}$$

where W = observed variables common to all three equations, X = observed variables influencing both TB and BE but not AT; similarly for Y and U; and Z, V, and S are observed variables whose influences are unique to TB, BE, and AT respectively.

Using 1993 data on 515 individuals in the San Francisco Bay Area, Bagley and Mokhtarian (2002) employed SEM to investigate the relationships among the built environment, travel behavior, and attitudes. This study is also the first application of covariance structural analysis in exploration of the relationships between the built environment and travel behavior. In this study, nine endogenous variables were incorporated into the structural model specification: two continuous residential type measures, three measures of travel demand, three measures of attitudes, and one measure of job location. The exogenous variables consisted of socio-demographic characteristics, lifestyle factor scores, and other measurements of attitudes. They found that with respect to direct and total effects, attitudinal and lifestyle variables had the greatest impact on travel demand among all explanatory variables, while residential location type had little influence on travel behavior. These results lend strong support to the speculation that the observed relationships between the built environment and travel behavior are not direct causal links, but are primarily attributed to interactions of these measures with other variables. However, even though allowing multiple directions of causality constitutes an improvement over the single-equation methodology, the use of cross-sectional data is still a drawback to this approach. The same temporal mismatch described in connection with model (2-5) may occur here.

2.4.5 Longitudinal design

A longitudinal design can be used to control for attitudes that do not vary over time: If AT does not change across time, then ΔAT = 0, and in the model

$$\Delta TB = f_4(\Delta BE, \Delta X) + \eta, \qquad (2\text{-}9)$$

ΔBE and η (=Δε) will be uncorrelated (if BE and ε were only correlated through AT). This formulation also controls for any other important variables that are either observed (ΔX) or remain constant (0 change) over the same time period. For these reasons, conventional wisdom holds that modeling the change in a given dependent variable is easier (produces better-fitting models, all else equal) than modeling its absolute level. The situations to which this model has been applied include residential moves, as well as changes "in place" to the built environment, e.g., the "Safe Route to Schools" (SR2S) program.

Some studies have used a pretest-posttest design to investigate the influence of a specific change to the built environment on travel behavior. For example, Painter (1996) found that street light improvements in three urban streets and on a pedestrian footpath (previously prone to crime) in London greatly increased pedestrian street use after dark. McBeth (1999) concluded that installation of bike lanes in downtown Toronto increased bike volume. An advantage of these studies is that they concentrated on the observed changes in travel behavior of people exposed to the study areas, rather than reported changes. However, they did not employ control locations or control for other variables. The lack of controls may confound the intervention effects with other potential effects.

In an evaluation of California SR2S projects, Boarnet et al. (2005) examined the relationship between improvements in walking and biking infrastructures and children's walking and bicycle travel to school, based on retrospective responses of 1,244 parents. Changes in these infrastructures (sidewalks, crossings, and traffic control) serve as a "treatment" for the children who passed the SR2S projects on their way to school (experimental group). The control group consists of those who did not pass the SR2S projects. Through paired-sample t-tests, they found that 15.4% of the 486 children who passed the SR2S projects increased their walking or bicycle travel to school, while only 4.3% of the 376 children who did not pass the projects increased their non-motorized travel. However, the limitations of this study are obvious: changes in the built environment are the only examined determinants of changes in travel behavior.

Krizek (2000) examined the changes in households' travel behavior before and after their residential relocation, using the Puget Sound Transportation Panel data. Households' residential relocation may expose them to different built environments, serving as a "treatment". Households' travel behavior was measured by a variety of variables, including trip distance, trip minutes, tour distance, tour minutes, trips per tour, and percentage of total trips taken by alternative modes. Paired-sample t-tests were conducted to examine the changes in households' travel behavior against the changes in the "Less Auto-Dependent Urban Form (LADUF)" ranking (high, medium, and low), a measurement of built environment based on a normative assessment of density, street pattern, and land use mix. The results showed relatively weak correlations between changes in the built environment and changes in travel behavior. He also found that more than half of sample households chose to relocate in areas either close to their prior neighborhoods or in neighborhoods of similar LADUF dimensions. This result suggests that households may choose residential neighborhoods partly to match their travel preferences, lending additional support to residential self-selection. However, this study is vulnerable to a limitation similar to that of Boarnet et al. (2005).

Using the same dataset, Krizek (2003a) applied linear regression models to test whether changes in travel behavior can be attributed to changes in neighborhood accessibility, controlling for changes in socio-demographic characteristics, workplace accessibility, and regional accessibility. Travel behavior variables used in this study are VMT, person miles traveled, number of tours, and number of trips per tour. The measurements of neighborhood accessibility are dependent on a combination of density, street pattern, and land use mix. Regional accessibility is measured using a simple exponential function of travel impedance with employment as attractiveness. In addition to the changes in socio-demographic characteristics and accessibility, their base values were included in the model specification to capture the effects of starting levels of these variables. The results showed that the base values of neighborhood accessibility and most socio-demographic characteristics are significant in all four models, supporting the premise that starting levels of these variables affect the changes in travel behavior. Also, the changes in neighborhood accessibility are statistically significant in all models, which suggests that when households' neighborhood accessibility changes, their travel behavior also changes, all else being equal. The author pointed out, however, that the results should be interpreted with caution. The changes in both neighborhood accessibility and travel behavior may be attributed to changes in preferences towards travel and/or residential location.

As a part of their work, Meurs and Haaijer (2001) investigated the extent to which changes in residential environment characteristics led to changes in travel patterns, using Dutch data from 1990 and 1999. For the dynamic analysis, the respondents were divided into two segments: movers and non-movers. Regression analyses were conducted on both segments, in which changes in the number of trips by various modes were regressed against changes in residential environment and personal characteristics. For the people who moved, changes in residential environment characteristics have an impact on travel patterns, and changes in personal characteristics, such as employment and auto ownership, have a major impact on changes in the number of auto trips. For the people who did not move, the observed effects of spatial changes (which were relatively minor and incremental, such as an extra garage, the installation of traffic calming measures, and the provision of a bike path) are not great, as they expected.

In a nutshell, longitudinal designs constitute a quantum improvement over cross-sectional designs and can provide a more robust causal inference on the relationship between the built environment and travel behavior. A practical difficulty of true longitudinal studies, however, is that they can be more expensive and are certainly more time-consuming than cross-sectional ones. Perhaps a more important conceptual difficulty (for studies that do not measure attitudes or only measure them at one point in time) is that the assumption that attitudes do not change may not be realistic. In point of fact, it may be precisely a change in attitudes that prompted the relocation in the first place. Also, feedback loops from the built environment to attitudes have not been tested in the longitudinal studies reported to date, although that is not an intrinsic limitation of this approach.

2.4.6 Summary

This section classified previous research that empirically addressed the issue of residential self-selection. In general, research using a direct questioning method qualitatively found some evidence for residential self-selection. Studies using a statistical control approach consistently found a pervasive confounding influence of self-selection in the association between the built environment and travel behavior, and some studies also found the built environment has a separate influence on travel behavior (e.g., Cao et al, 2006; Kitamura et al, 1997). Instrumental regression and conceptually equivalent two-stage models acknowledged residential self-selection and aimed to address the endogeneity of the built environment. The single study adopting a structural equations modelling approach, Bagley and Mokhtarian (2002), found an influence of residential selection, while the single study developing a joint model of discrete residential choice and ordered auto ownership with correlated error terms, Bhat and Guo (2005), found no such influence. Investigations employing a longitudinal design tended to support the argument that the built environment has a causal influence on travel behavior although they acknowledged the influence of attitudinal factors.

Disentangling the influences of the built environment and residential self-selection and determining their relative importance has become one of the most important emerging issues in understanding the relationship between the built environment and travel behavior (Krizek, 2003b). Generally, direct questioning, joint modeling, instrumental regression and selection models do not allow us to quantify the respective influences of the built environment and self-selection. To the contrary, the statistical control approach enables us to determine their relative importance. For example, Kitamura et al. (2001) evaluated the contribution of built environment variables and attitudes by gradually including different groups of variables in their model specifications; Schwanen and Mokhtarian (2003) also discussed the relative importance by comparing the behavior of matched and mismatched residents. By comparing the standardized total effects of a single built environment variable and a single attitudinal variable, a structural equations model allows us to evaluate their relative importance. However, if the model contains multiple built environment and attitudinal variables, we must construct two single latent variables based on the profiles of “observed” built environment and attitude. A longitudinal design also allows us to determine the relative importance if attitudes over time are measured.

2.5 Summary

Previous studies showed strong associations between the built environment and travel behavior, as well as auto ownership. However, few studies answered questions about the causal relationships between the built environment and travel behavior – their connections may be more a matter of residential location choice than of travel choice. For example, residents who prefer to walk may intentionally select to live in neighborhoods more conducive to walking and thus walk more; and residents who prefer not to drive may choose neighborhoods where it is easier to own fewer cars and hence drive less. If so, attitudes towards travel and preferences for residential choice rather than built environment characteristics (a result of residential choice) are the primary factors in explaining the difference in travel behavior observed in different kinds of neighborhoods. These possibilities suggest that studies focused on articulating the relationships between the built environment and travel behavior must also consider longer-term choices about residential location and auto ownership, and the role that attitudes play in these choices. At this point, the issue of causality has become one of the key questions in the debate over the link between the built environment and travel behavior (TRB-IOM, 2005). In the next chapter we describe the methodology used in this dissertation to address that issue.

3. METHODOLOGY

It is quite evident that built environment characteristics are associated with travel behavior. However, association does not mean causality. Although some studies have attempted to test and address the influence of residential self-selection, our understanding of its role in this association is still tentative. Therefore, the causal relationships between the built environment and travel behavior are far from being revealed. The methodology used in this dissertation responds to this causal issue and aims to offer new evidence on the potential for land use policies to influence travel behavior. This chapter outlines the research design, the hypotheses, data, and the variables used in this dissertation.

3.1 Research Design

If local governments use land use policies to bring residents closer to destinations and provide viable alternatives to driving, will people drive less and walk more? To answer this question, the ideal study would measure travel at one point in time, then at a second point in time following a change in the built environment that increases (or decreases) the opportunities for driving less and walking more. The study would use a "treatment group" that experienced the increase in opportunities for driving less and walking more, along with a statistically similar "control group" that did not experience the increase. Participants in the study would be randomly assigned to these two groups. This sort of experimental design would provide the strongest possible evidence of causality between the built environment and travel behavior (Babbie, 1998), but it would also be extremely expensive and generally impractical.

Given financial and practical limitations, most studies rely on cross-sectional designs that compare travel behavior for residents living in neighborhoods with different characteristics. Such studies, as summarized in the previous chapter, show associations between neighborhood characteristics and travel behavior but do not establish causality. One possibility is that the observed associations between neighborhood characteristics and travel behavior are explained by residential and travel preferences, namely that these attitudinal factors influence both the choice of neighborhood and travel behavior. One solution is thus to control for residential and travel preferences in cross-sectional studies. This approach would answer the following question: After controlling for attitudes, do neighborhood characteristics further explain variations in travel behavior?

Another approach is to use a quasi-longitudinal design. If it is not feasible to change the physical characteristics of a neighborhood, it is possible at least to observe changes in travel behavior for people who move from one neighborhood to another and who thus experience a change in neighborhood characteristics. Ideally, the study would observe travel behavior before and after the move and test the degree to which changes in neighborhood characteristics explain changes in travel behavior, controlling for changes in other pertinent characteristics such as attitudes and socio-demographic traits. With limited time and a more restricted budget, researchers can at least identify people who have recently moved and ask about how current travel, residential neighborhood characteristics, and other variables differ from before the move. This approach relies on recall and is unlikely to yield precise measures of some changes in travel behavior, neighborhood characteristics, and other variables; however, it can be used to capture the direction of the change and estimate its order of magnitude. This approach would answer the following question: After accounting for the influence of attitudes on travel behavior, do changes in neighborhood characteristics further explain variations in changes in travel behavior?

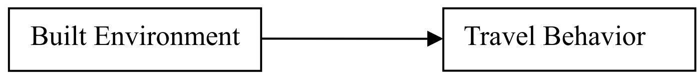
The design used here enables both cross-sectional and quasi-longitudinal analyses, taking into account residential preferences and travel attitudes. As explained in more detail in Sections 3.3 and 3.4, we selected eight neighborhoods in Northern California that differ with respect to neighborhood characteristics. In these neighborhoods, we selected a sample of residents who had moved within the last year and residents who had not. We collected data on travel behavior, perceived neighborhood characteristics, preferences for neighborhood characteristics, travel attitudes, and socio-demographic characteristics using a mail-out/mail-back household survey.

3.2 Hypotheses

In this section, we illustrate four hypotheses on the relationships between the built environment and travel behavior by gradually incorporating residential and travel preferences and auto ownership. The first two hypotheses are applied to cross-sectional data (two additional hypotheses for cross-sectional data are discussed in Appendix A, but not tested in this dissertation) and Hypotheses 3 and 4 are appropriate for longitudinal (quasi-longitudinal) data. In this dissertation, travel behavior mainly refers to trip frequency and/or distance by different modes (auto, transit, walking, and biking). In Chapter 5, auto ownership and vehicle type choice are loosely considered as types of travel behavior, as some previous studies did (e.g., Bhat and Guo, 2005).

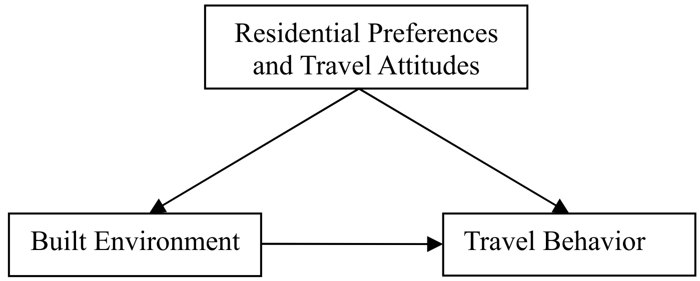
Analogous to most existing studies, the first hypothesis states that there are associations between the built environment and travel behavior and that the direction of influence is from the built environment to travel behavior (Figure 3). Specifically, we attempt to test if neighborhoods that offer greater opportunities for driving less are negatively associated with levels of driving and those providing greater opportunities for walking more are positively associated with levels of pedestrian travel (smart growth programs aim to create or redevelop neighborhoods with greater opportunities for driving less and walking more. Most attributes of smart growth programs can be found in the traditional neighborhoods built before World War II (WWII) rather than conventional suburban neighborhoods). In addition, socio-demographics may be causal factors for both residential choice and travel behavior. Therefore, they must be controlled for in a model to eliminate this rival hypothesis (similar statistical control on socio-demographics is applicable for all hypotheses illustrated below). However, this hypothesis entirely ignores the influence of residential self-selection. Sections 4.3.4 and 5.1.3 test this hypothesis.

Figure 3. Hypothesis 1



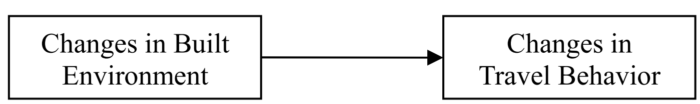
The second hypothesis states that residential preferences and travel attitudes are antecedent factors of both the built environment and travel behavior (Figure 4). Specifically, preferences for driving less and walking more are positively associated with driving less and walking more and with the choices of neighborhoods that offer greater opportunities for driving less and walking more. If the influence of the built environment on travel behavior is independent of residential self-selection, this influence should hold after controlling for residential preferences and travel attitudes. Therefore, this hypothesis starts to test and address residential self-selection. In particular, this hypothesis answers the following questions: (1) To what degree can differences in travel behavior be explained by differences in these attitudinal factors? (2) After controlling for residential preferences and travel attitudes, are neighborhoods that offer greater opportunities for driving less and walking more positively associated with driving less and walking more? A simple way to test this hypothesis is to control for attitudinal factors when exploring the relationship between the built environment and travel behavior. The other way is to treat the built environment as endogenous and apply more sophisticated modelling techniques such as SEM. Sections 4.1.1, 4.2.2, 4.3.4, 5.1.3, and 5.2.4 test this hypothesis using the former simple way.

Figure 4. Hypothesis 2



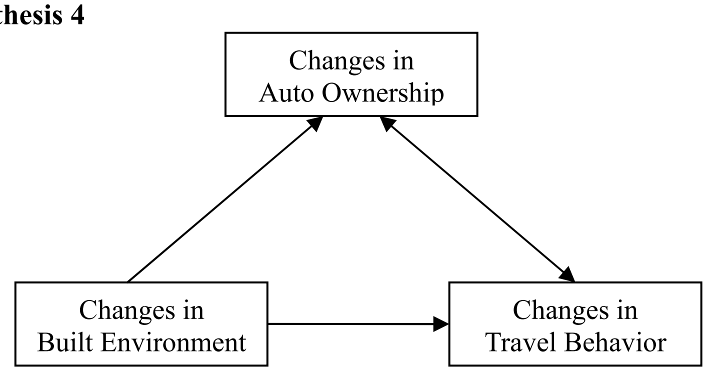
For quasi-longitudinal data, we are able to test Hypothesis 3: changes in the built environment lead to changes in travel behavior (Figure 5). Specifically, we postulate that an increase in opportunities for driving less and walking more is positively associated with driving less and walking more. Since changes in travel behavior occur after the move, this hypothesis testing offers strong evidence on the direction of influence – from the built environment to travel behavior. Further, if individuals' residential preferences and travel attitudes keep constant in the long term, this testing is helpful to control for the permanent effects resulting from these unchanged attitudes. However, it is more likely that attitudes vary over time. Therefore, we must account for the influence of attitudes to establish nonspuriousness. However, because it is not feasible to retrospectively measure attitudes, we can measure only current attitudes and account for their influence. Also, we need to control for changes in socio-demographics to isolate their influence. Sections 4.1.2, 4.2.3, and 5.1.4 test this hypothesis.

Figure 5. Hypothesis 3



As discussed in Section 2.2.3, auto ownership plays an important role in the connection between the built environment and travel behavior. Hypothesis 4 first states that change in auto ownership is an intervening variable in the relationship between change in the built environment and change in travel behavior (Figure 6). Further, although changes in travel behavior occur after residential relocation, they may precede changes in auto ownership. That is, changes in travel behavior lead to changes in auto ownership. For example, individuals substituting for a large amount of driving with alternative modes may be ready to reduce their auto ownership. It is also arguable that individuals may simultaneously coordinate residential choice with travel choice (Hammond, 2005). For example, an individual may anticipate relocating farther from her workplace and hence acquire one more vehicle for the household before the move. However, although changes in auto ownership occur before residential relocation, they are still a result of anticipated changes in the built environment. In other words, the link between changes in the built environment and changes in auto ownership is still from the built environment to auto ownership. For this hypothesis, single equation models are inadequate to test these complex relationships; more sophisticated techniques such as SEM are required. Chapter 6 tests this hypothesis.

Figure 6. Hypothesis 4



3.3 Survey and Data

This section describes the survey sampling, design, pre-testing, and administration methodology, and provides a data summary. Survey content is presented in the next section. Please refer to Handy et al. (2004) for a detailed discussion.

The neighborhoods were selected to vary systematically on three dimensions: neighborhood type, size of the metropolitan area, and region of the state. Neighborhood type was differentiated as "traditional" for areas built mostly in the pre-WWII era, and "suburban" for areas built more recently. Although this design was intended to provide ample variation across neighborhood types, and these discrete indicators of neighborhood type are useful for descriptive comparisons, they are too simplistic for more detailed analyses. For the models, we used a rich set of variables describing the neighborhoods along a variety of dimensions (see Section 3.4).

Using data from the U.S. Census, we screened potential neighborhoods to ensure that average income and other characteristics were near the average for the region. Four neighborhoods in the San Francisco Bay Area, including two in the Silicon Valley area and two in Santa Rosa, had been previously studied (Handy, 1992). Two neighborhoods from Sacramento and two from Modesto were selected to contrast with Bay Area neighborhoods (Figure 7). The four traditional neighborhoods differ in visible ways from the four suburban neighborhoods – the layout of the street network, the age and style of the houses, and the location and design of commercial centers, as shown in Figure 8 for Sacramento as an example.

For each neighborhood, we purchased two databases of residents from a commercial provider, New Neighbors Contact Service (www.nncs.com; this service maintains an overall database of names and addresses for residences throughout the U.S. constructed from a variety of public records. The database is largely used for commercial advertisement mailings): a database of "movers" and a database of "nonmovers." The "movers" included all current residents of the neighborhood who had moved within the previous year. From this database, we drew a random sample of 500 residents for each of the eight neighborhoods. The database of "nonmovers" consisted of a random sample of 500 residents not included in the "movers" list for each neighborhood.

Figure 7. Geography of Neighborhoods

Note: Neighborhoods whose names are shown in dark rectangles are traditional; those in light rectangles are suburban.

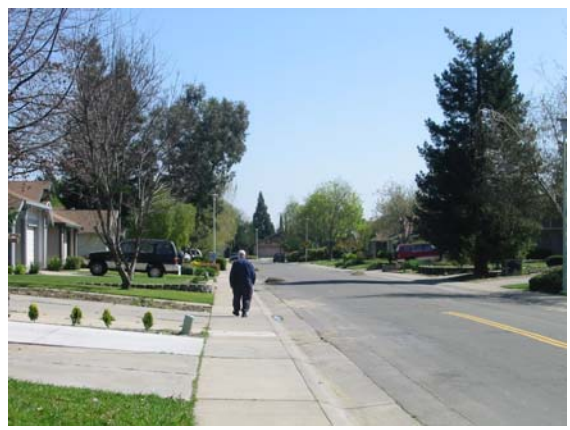
Survey questions were developed from surveys used in previous research projects by Professor Handy, Professor Mokhtarian, and other researchers. The survey was pre-tested on UC Davis students and staff, then on a convenience sample of Davis residents. Participants were asked to first complete the survey, then to discuss the survey questions with the researchers, either in a group meeting or in one-on-one interviews. Based on these pretests, survey questions were modified and refined.

Figure 8. Comparison of Traditional and Suburban Neighborhood (Sacramento)

Traditional | **Suburban**

Street network

Houses



Commercial centers

The survey was administered using a mail-out, mail-back approach. Surveys were mailed to households in the selected neighborhoods, and the cover letter asked for "any adult household member who shares in the decision making for your household and who participated in selecting your current residence" to complete the survey. The initial survey was mailed out at the end of September 2003. Two weeks later, a reminder postcard was mailed to the entire sample using first-class mail. At the beginning of November, a second copy of the survey with a revised cover letter was sent to a shorter list that excluded incorrect addresses and individuals who had already responded to the survey. Two weeks later, a second reminder postcard was mailed to this list of residents. As an incentive to complete the survey, respondents were told they would be entered into a drawing to receive one of five $100 cash prizes; the winners were selected in December.

The original database consisted of 8000 addresses but only 6746 valid addresses. The number of responses totaled 1682 (688 movers), equivalent to a 24.9% response rate based on the valid addresses only. This is considered quite good for a survey of this length, since the response rate for a survey administered to the general population is typically 10-40% (Sommer and Sommer, 1997). A comparison of sample characteristics to population characteristics (based on the 2000 U.S. Census) shows that survey respondents tend to be older on average than residents of their neighborhood as a whole, and that households with children are underrepresented for most neighborhoods while home owners are overrepresented for all neighborhoods (Table 4). In addition, median household income for survey respondents was higher than the census median for all but one neighborhood, a typical result for voluntary self-administered surveys. However, since the focus of this dissertation is on explaining the relationships between the built environment and dependent variables of interest, using multivariate analyses, rather than on describing dependent variables per se, these differences are not expected to materially affect the results (Babbie, 1998). It is worth noting that 10.4% of "movers" had actually changed their residential locations more than a year earlier, and hence had been misclassified by the provider.

Table 4. Sample vs. Population Characteristics

	Traditional				Suburban			
	Mountain View	SR Junior College	MD Central	SC Midtown	Sunnyvale	SR Rincon Valley	MD Suburban	SC Natomas
Sample Characteristics								
Number	228	215	184	271	217	165	220	182
Percent of females	47.3	54.3	56.3	58.2	46.9	50.9	50.9	54.9
Average auto ownership	1.80	1.63	1.59	1.50	1.79	1.66	1.88	1.68
Age	43.3	47.0	51.3	43.4	47.1	54.7	53.2	45.6
Average HH size	2.08	2.03	2.13	1.78	2.58	2.19	2.41	2.35
Percent of HHs w/kids	21.1	18.6	21.7	8.9	42.4	24.8	25.5	31.9
Percent of home owners	51.1	57.8	75.6	47.0	61.1	68.7	81.0	82.4
Median HH income (k$)	98.7	55.5	45.5	64.2	95.0	49.5	55.5	55.3
Population Characteristics								
Population	5,493	9,886	13,295	7,259	14,973	13,617	19,045	13,295
Age	36.1	36.3	36.5	42.7	35.9	38.3	38.1	31.7
Average HH size	2.08	2.21	2.46	1.79	2.66	2.48	2.51	2.57
Percent of HHs w/kids	19.3	20.3	32.9	12.4	35.3	35.4	34.2	41.7
Percent of home owners	34.3	31.2	58.8	34.3	53.2	63.5	61.4	55.2
Median HH income (k$)	74.3	40.2	42.5	43.8	88.4	49.6	40.2	46.2

Notes: SR = Santa Rosa, MD = Modesto, SC = Sacramento, HH = household

3.4 Variables

The key variables measured in the survey are classified into five groups: travel behavior, neighborhood characteristics, neighborhood preferences, travel attitudes, and socio-demographics.

Travel Behavior: Travel behavior was variously measured. A series of questions asked about characteristics of the commute, including frequency of work trip, miles from home to primary place of work, time to get to primary place of work, frequency of stopping on the way home from work, frequency of working at home, and frequency of use of different travel modes. For nonwork travel, respondents were asked to indicate about how frequently they used different modes (driving, public transit, and walking or biking) to get to a selected list of destinations, such as a church, restaurant, or store. For walking, respondents were asked to report how many times in the last 30 days they had walked to a local store and how often they had taken a walk or stroll around the block. Finally, respondents were asked to list vehicles currently available to the household, and to estimate how many miles they drive in a typical week.

Change in travel behavior was measured using a series of general indicators. Because it is difficult for individuals to accurately recall the specifics of their travel behavior from as long as one year ago, respondents were asked to indicate how their travel differs now, from either before they moved (for the sample of respondents who had moved within the last year) or from one year ago (for the sample of respondents who had not recently moved). One question asked about use of different modes compared to previously; on a five-point scale respondents were asked to choose from "a lot less now" to "a lot more now." A second question asked about changes in the commute trip, including frequency of the trip to work, frequency of driving to work, and frequency of stopping on the way home from work; again, on a five-point scale respondents chose from "much less often now" to "much more often now," and on changes in proximity of residence to work, from "much closer now" to "much farther now."

Neighborhood Characteristics and Neighborhood Preferences: Respondents were asked to indicate how true 34 characteristics are for their current and previous (only for movers) neighborhood, on a four-point scale from 1 ("not at all true") to 4 ("entirely true"). The characteristics of these neighborhoods as perceived by survey respondents reflect fundamental differences in the built environment. Also, the importance of these items to respondents when/if they were looking for a new place to live were measured on a four-point scale from 1 ("not at all important") to 4 ("extremely important"). The comparison of individuals' perceived neighborhood characteristics for their current residence and their neighborhood characteristic preferences indicates how well their current neighborhoods meet their preferences. Since some of these characteristics measure similar dimensions of the built environment and are highly correlated, we conducted a factor analysis to identify underlying constructs of perceived (current and previous) and preferred neighborhood characteristics. Finally, these items were reduced to six factors (some items were dropped due to their poor conceptual interpretability): accessibility, physical activity options, safety, socializing, attractiveness, and outdoor spaciousness (Table 5).

Table 5. Pattern Matrix for Perceived and Preferred Neighborhood Characteristic Factors

Factor	Statement	Loading
Accessibility	Easy access to a regional shopping mall	0.854
	Easy access to downtown	0.830
	Other amenities such as a pool or a community center available nearby	0.667
	Shopping areas within walking distance	0.652
	Easy access to the freeway	0.528
	Good public transit service (bus or rail)	0.437
Physical Activity Options	Good bicycle routes beyond the neighborhood	0.882
	Sidewalks throughout the neighborhood	0.707
	Parks and open spaces nearby	0.637
	Good public transit service (bus or rail)	0.353
Safety	Quiet neighborhood	0.780
	Low crime rate within neighborhood	0.759
	Low level of car traffic on neighborhood streets	0.752
	Safe neighborhood for walking	0.741
	Safe neighborhood for kids to play outdoors	0.634
	Good street lighting	0.751
Socializing	Diverse neighbors in terms of ethnicity, race, and age	0.789
	Lots of people out and about within the neighborhood	0.785
	Lots of interaction among neighbors	0.614
	Economic level of neighbors similar to my level	0.476
Attractiveness	Attractive appearance of neighborhood	0.780
	High level of upkeep in neighborhood	0.723
	Variety in housing styles	0.680
	Big street trees	0.451
Outdoor Spaciousness	Large back yards	0.876
	Large front yards	0.858
	Lots of off-street parking (garages or driveways)	0.562
	Big street trees	0.404

a. Extraction method: principal component analysis; Rotation method: oblimin with Kaiser Normalization.
b. The extraction of the accessibility and physical activity options factors is independent of the extraction of the other factors.
c. Loading represents the degree of association between the statement and the factor.
d. Factor loadings lower in magnitude than 0.33 are suppressed.

For the quasi-longitudinal analysis, changes in neighborhood characteristics were measured using the differences between factor scores for the current and previous neighborhoods. It was assumed that changes in neighborhood preferences could not be accurately captured retrospectively, and hence they were not measured. In other words, the data include only current measurement of neighborhood preferences.

Following the survey, objective measures of land use mix and accessibility were estimated for each respondent, based on distance along the street network from home to a variety of destinations classified as institutional (bank, church, library, and post office), maintenance (grocery store and pharmacy), eating-out (bakery, pizza, ice cream, and take-out), and leisure (health club, bookstore, bar, theater, and video rental). Land use mix refers to the relative proximity of different land uses, such as homes, stores, offices, parks, and other uses, within a given area (Handy et al., 2002). In this study, land use mix indicators were measured as the number of different types of businesses within specified distances. Further, according to Hansen (1959), spatial accessibility can be measured as a gravity function of opportunities at the destination and travel costs (such as travel time and travel distance) from origins to destinations. Accessibility indicators used here were simplified to the number of establishments (opportunities) of each business type within specified distances and the distance to the nearest establishment of each type. Commercial establishments were identified using on-line yellow pages, and ArcGIS was used to calculate network distances between addresses for survey respondents and commercial establishments. In the context of the present study, all these measures should be viewed generally as indicators of accessibility and land use mix. It is those general characteristics of a neighborhood that might be expected to influence personal travel choice, rather than the specific land use types themselves.

Travel Attitude: To measure attitudes regarding travel, the survey asked respondents whether they agreed or disagreed with a series of 32 statements on a 5-point scale from 1 (“strongly disagree”) to 5 (“strongly agree”). Factor analysis was then used to extract the fundamental dimensions spanned by these 32 items, for reasons similar to those for neighborhood characteristics. As shown in Table 6, six underlying dimensions were identified: pro-bike/walk, pro-transit, pro-travel, travel minimizing, car dependent, and safety of car. As with residential preferences, changes in travel attitudes were not measured for quasi-longitudinal analysis.

Table 6. Pattern Matrix for Travel Attitude Factors

Factor	Statement	Loading
Pro-Bike/Walk	I like riding a bike	0.880
	I prefer to bike rather than drive whenever possible	0.865
	Biking can sometimes be easier for me than driving	0.818
	I prefer to walk rather than drive whenever possible	0.461
	I like walking	0.400
	Walking can sometimes be easier for me than driving	0.339
Pro-Travel	The trip to/from work is a useful transition between home and work	0.683
	Travel time is generally wasted time	-0.681
	I use my trip to/from work productively	0.616
	The only good thing about traveling is arriving at your destination	-0.563
	I like driving	0.479
Travel Minimizing	Fuel efficiency is an important factor for me in choosing a vehicle	0.679
	I prefer to organize my errands so that I make as few trips as possible	0.617
	I often use the telephone or the Internet to avoid having to travel somewhere	0.514
	The price of gasoline affects the choices I make about my daily travel	0.513
	I try to limit my driving to help improve air quality	0.458
	Vehicles should be taxed on the basis of the amount of pollution they produce	0.426
	When I need to buy something, I usually prefer to get it at the closest store possible	0.332
Pro-Transit	I like taking transit	0.778
	I prefer to take transit rather than drive whenever possible	0.771
	Public transit can sometimes be easier for me than driving	0.757
	I like walking	0.363
	Walking can sometimes be easier for me than driving	0.344
	Traveling by car is safer overall than riding a bicycle	0.338
Safety of Car	Traveling by car is safer overall than riding a bicycle	0.489
	Traveling by car is safer overall than walking	0.753
	Traveling by car is safer overall than taking transit	0.633
	The region needs to build more highways to reduce traffic congestion	0.444
	The price of gasoline affects the choices I make about my daily travel	0.357
Car Dependent	I need a car to do many of the things I like to do	0.612
	Getting to work without a car is a hassle	0.524
	We could manage pretty well with one fewer car than we have (or with no car)	-0.418
	Traveling by car is safer overall than riding a bicycle	0.402
	I like driving	0.356

a. Extraction method: principal component analysis; Rotation method: oblimin with Kaiser Normalization.
b. Loading represents the degree of association between the statement and the factor.
c. Factor loadings lower in magnitude than 0.33 are suppressed.

Socio-demographics: The survey also contained a list of socio-demographic variables. These variables include gender, age, employment status, educational background, household income, household size, the number of children in the household, mobility constraints, residential tenure, and so on. Some changeable socio-demographics such as household structure and income were measured before residential relocation for movers (one year ago for non-movers) and currently.

4. THE BUILT ENVIRONMENT AND TRAVEL BEHAVIOR

From a transportation standpoint, smart growth programs are proposed to create walkable neighborhoods and/or provide a variety of alternative modes to driving. However, it is debatable whether the land use policies used in these programs have a true influence on travel behavior. In this chapter, we assume that auto ownership (as well as bike ownership) is exogenous, and study the unidirectional causal link from the built environment to travel behavior. The travel behaviors of interest include driving, walking (biking), and nonwork travel by various modes.

4.1 Driving Behavior

In this section, we investigate the relationship between the built environment and driving behavior through cross-sectional analyses of vehicle miles driven and quasi-longitudinal analysis of changes in driving. This study tests Hypotheses 2 and 3 (Section 3.2) and thus aims to address the following central questions: (1) Are differences in the built environment associated with differences in travel behavior, after accounting for socio-demographic characteristics and for attitudes and preferences? More specifically, are environments where residents are closer to destinations and have viable alternatives to driving in fact associated with less driving? (2) Are changes in the built environment associated with changes in travel behavior, after accounting for socio-demographic characteristics and for attitudes and preferences? More specifically, are moves to environments where residents are closer to destinations and have viable alternatives to driving associated with a decrease in driving?

4.1.1 Cross-sectional analysis

Total vehicle miles driven (VMD) by the respondent per week is 18% higher for residents of suburban neighborhoods than for residents of traditional neighborhoods (Table 7). This pattern holds true across individual neighborhoods: the highest average level of driving for traditional neighborhoods (161 miles per week in Modesto Central) is still lower than the lowest average level of driving for suburban neighborhoods (166 miles in Sunnyvale). The difference in total VMD appears to come from differences in both work travel and nonwork travel.

Table 7. Vehicle Miles Driven and Explanatory Variables by Neighborhood Type.

	Average for Traditional	Average for Suburban	p-value [c] traditional vs. suburban	p-value [c] traditional only	p-value [c] suburban only
Vehicle miles driven per week [a]	148	175	0.00	0.66	0.64
Neighborhood characteristics [b]					
Accessibility	0.15	-0.18	0.00	0.00	0.00
Physical activity options	0.01	-0.01	0.45	0.00	0.05
Safety	-0.14	0.16	0.00	0.00	0.00
Socializing	0.09	-0.12	0.00	0.00	0.00
Outdoor spaciousness	0.00	-0.01	0.82	0.00	0.00
Attractiveness	0.28	-0.33	0.00	0.00	0.00
Selected objective measures					
# of business types within 400 m	2.6	0.8	0.00	0.00	0.09
# of eat-out places within 400 m	0.7	0.2	0.00	0.00	0.44
Distance to nearest eat-out place	526	789	0.00	0.00	0.00
Neighborhood preferences [b]					
Accessibility	0.03	-0.04	0.14	0.00	0.00
Physical activity options	0.01	-0.02	0.60	0.00	0.00
Safety	-0.18	0.21	0.00	0.00	0.48
Socializing	0.05	-0.05	0.05	0.00	0.00
Outdoor spaciousness	-0.05	0.06	0.02	0.00	0.03
Attractiveness	0.04	-0.05	0.04	0.00	0.00
Travel attitudes [b]					
Pro-bike/walk	0.20	-0.23	0.00	0.00	0.00
Pro-travel	-0.03	0.03	0.27	0.03	0.01
Travel-minimizing	0.01	-0.01	0.69	0.23	0.02
Pro-transit	0.15	-0.17	0.00	0.00	0.00
Safety of car	-0.27	0.31	0.00	0.00	0.00
Car dependent	-0.06	0.07	0.01	0.03	0.00

a. Six respondents reported over 1000 miles per week; these values were treated as outliers and recoded to 1000.

b. Scores normalized to a mean value of 0 and variance of 1.

c. p-values for F-statistics from analyses of variance (ANOVAs).

What explains these differences? According to analyses of variance (ANOVAs), traditional neighborhoods score significantly higher than suburban neighborhoods on factors for perceived accessibility, socializing, and attractiveness, but lower on safety; residents in these neighborhoods are also closer to more businesses. Traditional neighborhoods also score higher on factors for pro-bike/walk and pro-transit attitudes and lower on the safety of car attitude. To complicate matters, differences are often significant between neighborhoods of each type on both neighborhood characteristics and attitudinal factors; traditional neighborhoods are not all alike, nor are all suburban neighborhoods alike. To sort out the relative importance of neighborhood characteristics, attitudes, and preferences in explaining levels of driving, a multivariate model is estimated.

Most previous studies have used cross-sectional models of driving behavior to test the significance of built environment characteristics as explanatory variables. For comparison purposes, we also estimated a cross-sectional model, but unlike most previous studies we incorporated preferences for neighborhood characteristics and travel attitudes into the model to account for the possibility of self-selection. This model tests the hypothesis that environments where residents are closer to destinations and have viable alternatives to driving are in fact associated with less driving, after accounting for attitudes and preferences as well as socio-demographic characteristics; lower levels of driving might result from shorter and/or fewer driving trips. Because of the skewed distribution of VMD, the natural log of VMD was used as the dependent variable and the model was estimated using ordinary least squares regression. Potential explanatory variables were entered into the model in groups, starting with socio-demographic factors, followed by travel attitudes and preferences for neighborhood characteristics, then perceived neighborhood characteristics and objective measures. At each step, insignificant variables were dropped and the model re-estimated before the next set of variables was entered.

Perhaps not surprisingly, the variable with the highest standardized coefficient was the factor for car dependent attitude (Table 8). This factor reflects a perceived need for a car, which may or may not reflect the actual availability of alternatives to driving. Other attitudes were also significant: pro-bike/walk and pro-transit attitudes were negatively associated with driving, and the safety of car attitude and a preference for outdoor spaciousness were positively associated with driving. With these attitudes accounted for, no measures of the actual built environment – neither objective measures nor perceived characteristics – were significant. As a result, it appears that observed correlations between neighborhood characteristics and levels of driving are better explained by attitudes towards transportation than by the built environment itself. The model does not support the hypothesis that the built environment has a causal relationship with travel behavior and suggests that self-selection plays a significant role in explaining the observed correlations between the built environment and travel behavior. This finding differs from previous studies that found a significant relationship between the built environment and driving and demonstrates the importance of accounting for attitudes and preferences.

Table 8. Regression Model for Ln(VMD+1)

Variables	Coefficient	Standardized Coefficient	t-statistic	p-value
Constant	3.646		11.317	0.000
Socio-demographics				
Female	-0.282	-0.140	-5.650	0.000
Worker	0.298	0.112	4.034	0.000
Age	-0.006	-0.094	-3.296	0.001
Driver's license	1.050	0.086	3.519	0.000
Cars per adult	0.170	0.069	2.852	0.004
Travel attitudes				
Pro-bike/walk	-0.055	-0.054	-1.973	0.049
Pro-transit	-0.048	-0.046	-1.784	0.075
Safety of car	0.060	0.058	2.255	0.024
Car dependent	0.271	0.260	10.566	0.000
Neighborhood preferences				
Outdoor spaciousness	0.054	0.052	2.110	0.035
N	1466			
R-square	0.160			
Adjusted R-square	0.154			

4.1.2 Quasi-longitudinal analysis

A stronger test of a causal relationship between the built environment and travel behavior involves an examination of the association between a change in the built environment and a change in driving. Such an approach addresses the time-order criterion for establishing causal validity: if the change in the built environment precedes the change in driving, then a causal relationship is more certain (Singleton and Straits, 2005). In the quasi-longitudinal approach used here, changes are measured for residents who have recently moved from before to after their move, and for non-movers from one year earlier to the present time. The quasi-longitudinal model estimated from these data tests the hypothesis that moves to environments where residents are closer to destinations and have viable alternatives to driving are associated with numerically more negative or less positive changes in driving after accounting for neighborhood preferences and travel attitudes; decreases in driving might result from a decrease in driving distances and/or a decrease in driving frequencies.

As noted in Section 3.4, we measured change in driving and the use of other modes using a 5-point scale, from "a lot less now" to "a lot more now." For the sample of movers only, changes in the built environment could be measured by taking the difference between perceived characteristics of the current and previous neighborhoods; the built environment was assumed unchanged for the sample of non-movers. A simple bivariate analysis of these variables for movers (Table 9) shows several significant associations. In general, changes in neighborhood characteristics have the strongest association with changes in walking: for increases in all but one of the factors for neighborhood characteristics, a significantly higher share of respondents said that their walking levels had increased than said they had decreased. In contrast, only changes in the accessibility factor had a significant association with changes in driving: among respondents who reported that accessibility increased, a significantly higher share said that driving had decreased rather than increased. This finding is interesting given that accessibility may have two opposite effects on driving: (1) higher accessibility reduces the cost of driving and may increase levels of driving as a result; (2) higher accessibility reduces the cost of walking and may lead to a substitution of walking for driving. These results suggest that the latter effect outweighs the former (they also suggest that changes in the built environment at the neighborhood level are more important in explaining changes in walking than changes in driving, a point we confirm in Section 4.2).

Table 9. Change in Driving or Walking vs. Change in Neighborhood Characteristics [a] (%)

	Decrease in Characteristic		**Increase in Characteristic**		
	Incr in Driving or Walking	Decr in Driving or Walking	Incr in Driving or Walking	Decr in Driving or Walking	p-value [b]
For driving					
Accessibility	31.0	28.3	23.9	47.6	0.00
PA options	28.3	38.3	24.7	44.2	0.34
Safety	30.3	41.0	23.2	42.6	0.11
Socializing	28.7	38.6	24.2	44.1	0.31
Spaciousness	24.4	44.6	27.4	39.6	0.42
Attractiveness	26.3	40.3	25.8	43.0	0.77
For walking					
Accessibility	37.4	27.8	55.9	16.7	0.00
PA options	35.4	28.8	58.9	15.1	0.00
Safety	44.8	28.0	54.2	14.9	0.00
Socializing	38.9	27.8	58.0	14.9	0.00
Spaciousness	50.6	22.4	50.4	17.7	0.21
Attractiveness	35.7	31.9	59.0	13.1	0.00

a. Movers only (N = 688).
b. Based on chi-square tests of whether proportions in the first two columns differed significantly from those in the second two.

The relationship between changes in the built environment and changes in driving while controlling for attitudes (and changes in socio-demographics) was estimated using an ordered probit model. This technique is appropriate for an ordinal dependent variable, and its model structure is parsimonious. In developing this model, the following sets of variables were tested: current socio-demographic characteristics, changes in socio-demographic characteristics, travel attitudes (assumed constant over this period), preferences for neighborhood characteristics (also assumed constant), objective measures for the current neighborhood, perceived neighborhood characteristics for the current neighborhood, and changes in perceived neighborhood characteristics. Non-movers were also included in the model, with changes in driving and socio-demographic characteristics measured from one year ago and changes in perceived neighborhood characteristics assumed to be zero. The resulting equation can be interpreted as representing the propensity of an individual to have a numerically larger change – either less of a decrease or more of an increase – in driving following the move. A statistically significant association between a change in the built environment and a change in travel behavior provides evidence of a causal relationship.

Change in the accessibility factor was the most important factor in explaining changes in driving, as indicated by the standardized coefficients, with an increase in accessibility associated with either a smaller increase or a larger decrease in driving (Table10). Change in the safety factor was also significant, with an increase in safety associated with either a smaller increase or a larger decrease in driving. Three accessibility measures were also significant: number of grocery stores and number of pharmacies within 1600m and number of theaters within 400m. Note that objective accessibility was measured for the current neighborhood only, rather than as the change in accessibility; however, a high current level of accessibility is more likely to be associated with an increase in accessibility than a decrease as a result of a move. In all of these cases, an increase in accessibility is associated with a higher propensity to drive less. Two travel attitudes were also significant: car dependent, with a positive effect on the propensity to drive more, and pro-bike/walk, with a negative effect on the propensity to drive more. These results support the hypothesis that changes in the built environment are associated with changes in driving and point to increases in accessibility as the factor having the greatest negative effect on driving.

It is worth noting that changes in auto ownership do not appear in the final model. However, if we manually remove changes in household income from the model, changes in auto ownership have a significantly positive association with changes in driving. This finding suggests that changes in income carry more explanatory power for the variations of changes in driving than do changes in auto ownership. Changes in income are positively associated with changes in auto ownership, as shown in Section 5.1; the change in income is a determinant of changes in auto ownership. Therefore, changes in income accommodate some impacts of changes in auto ownership. On the other hand, a growth in income also separately increases an individual's ability to drive more (i.e., to afford more vehicular travel), as well as often increasing the demand for more vehicular travel (e.g., through a greater demand for discretionary or work-related travel, or through a higher value of time motivating a shift from slower non-motorized or transit modes).

Table 10. Ordered Probit Model for Change in Driving

Variables	Coefficient	Standardized Coefficient [a]	p-value
Constant	1.508	1.147	0.000
Socio-demographics			
Current age	-0.006	-0.084	0.014
Currently working	0.155	0.059	0.065
Current # of kids (<18)	0.070	0.057	0.051
Limitations on driving	-0.678	-0.074	0.000
Change in income (k$)	0.008	0.155	0.000
Neighborhood characteristics			
# of groceries within 1600 m	-0.014	-0.066	0.048
# of pharmacies within 1600 m	-0.028	-0.069	0.041
# of theaters within 400 m	-0.703	-0.057	0.055
Change in accessibility	-0.269	-0.226	0.000
Change in safety	-0.088	-0.086	0.000
Travel attitudes			
Car dependent	0.115	0.111	0.000
Pro-bike/walk	-0.070	-0.070	0.020
Threshold parameter 1	0.543	0.543	0.000
Threshold parameter 2	2.142	2.142	0.000
Threshold parameter 3	2.589	2.589	0.000
N	1490		
Log-likelihood at 0	-2378.038		
Log-likelihood at constant	-1954.785		
Log-likelihood at convergence	-1869.302		
Pseudo R-square	0.214		
Adjusted pseudo R-square	0.209		

a. All independent variables except constant term were standardized and model was reestimated; dependent variable was not standardized.

4.1.3 Summary

One lesson that emerges from this study is that different types of analyses yield different answers to the question: does the built environment have a causal relationship with travel behavior? A simple comparison of neighborhoods of different types shows significant differences in levels of driving. However, a multivariate analysis of cross-sectional data shows that these differences are largely explained by attitudes and that the effect of the built environment mostly disappears when attitudes and socio-demographic factors have been accounted for. But a quasi-longitudinal analysis of changes in driving and changes in the built environment shows significant associations, even when attitudes have been accounted for, providing support for a causal relationship. These results highlight the limitations of previous studies, which mostly rely on cross-sectional analyses and rarely account for attitudes and preferences – but also suggest that despite these limitations their conclusions are not entirely off the mark.

Of course, these analyses are still not definitive, nor do they clarify the nature of the causal relationship. More sophisticated analyses of these data, such as structural equations modeling, will help to establish the strength and direction of the relationships between attitudes, changes in the built environment, changes in driving behavior, and other factors. Nevertheless, the results presented here provide some encouragement that land-use policies designed to put residents closer to destinations and provide them with viable alternatives to driving will actually lead to less driving. In particular, it appears that an increase in accessibility and/or safety may lead to a decrease in driving, all else equal.

4.2 Walking Behavior

In this section, we explore the causal link between the built environment and walking (and biking in a quasi-longitudinal multivariate analysis) in three ways: correlational analysis of walking behavior for traditional and suburban neighborhoods, cross-sectional multivariate analysis, and quasi-longitudinal multivariate analysis. This study tests Hypotheses 2 and 3 and thus aims to address the following central questions: (1) Are differences in the built environment associated with differences in walking, after accounting for socio-demographic characteristics and for attitudes and preferences? More specifically, are environments that offer better opportunities for walking associated with more walking? (2) Are changes in the built environment associated with changes in walking, after accounting for socio-demographic characteristics and for attitudes and preferences? More specifically, are moves to environments that offer better opportunities for walking associated with an increase in walking?

4.2.1 Cross-sectional correlational analysis

Residents of traditional neighborhoods walk substantially more than residents of suburban neighborhoods (Table 11). A significantly higher share of residents in these neighborhoods reported walking to a store at least once in the last 30 days, and the average frequency of walking to the store was 4.9 for traditional neighborhoods versus only 1.8 for suburban neighborhoods. The differences for strolling around the neighborhood were also significant, though not as dramatic: over 86% of residents of traditional neighborhoods strolled at least once in the last 30 days, versus 79% of residents of suburban neighborhoods, with an average frequency of 10.1 strolls versus 7.7 strolls. Walking behavior varies across the traditional neighborhoods, however, with residents of Modesto Central walking to the store at frequencies comparable to those found in suburban neighborhoods rather than the other traditional neighborhoods.

Table 11. Walking Behavior by Neighborhood Type and Neighborhood

	Traditional	Silicon Valley - Mountain View	Santa Rosa - Junior College	Modesto -Central	Sacramento - Midtown	**Suburban**	Silicon Valley - Sunnyvale	Santa Rosa - Rincon Valley	Modesto - Suburban	Sacramento - Natomas	**p-value nbhd type**[a]
% Walking to store at least once in last 30 days	**74.9**	81.9	73.2	50.5	86.9	**42.5**	47.9	37.0	39.4	45.0	**0.00**
Walks to store in last 30 days	**4.9**	5.3	5.0	2.2	6.3	**1.8**	2.0	1.4	1.8	2.1	**0.00**
% Strolling at least once in last 30 days	**86.5**	88.5	87.2	75.7	91.4	**79.2**	83.7	76.1	77.7	78.2	**0.00**
Strolls around the neighborhood in last 30 days	**10.1**	9.7	10.6	8.2	11.2	**7.7**	8.0	8.3	7.9	6.7	**0.00**
Percent walking more than once per month to…											
Church/Civic	**29.0**	37.7	23.9	12.6	36.9	**7.2**	5.8	11.0	3.3	10.1	**0.00**
Service	**43.1**	59.0	39.2	18.7	49.2	**13.3**	15.6	9.8	11.8	15.7	**0.00**
Restaurant	**57.7**	71.1	49.8	25.3	74.9	**14.9**	15.9	16.0	15.4	12.0	**0.00**
Shop	**57.4**	58.8	56.0	32.0	74.6	**26.0**	27.3	24.1	22.3	30.7	**0.00**
Exercise place	**44.2**	52.4	37.5	27.3	54.4	**30.0**	33.5	29.4	24.8	32.6	**0.00**
No particular destination	**57.4**	58.9	54.8	43.1	68.4	**37.7**	35.8	36.6	40.1	38.2	**0.00**
N	**887**	219	205	171	253	**777**	205	158	205	173	

a. Based on t-test for difference of means or Pearson chi-square statistic from cross-tab analysis for traditional neighborhoods versus suburban neighborhoods.

Residents of traditional neighborhoods report walking to all destinations significantly more frequently, on average, than residents of suburban neighborhoods. The differences are smallest for walking to places to exercise (which could include parks as well as gyms and other destinations) and for walking with no particular destination in mind. Across all destination types, residents of traditional neighborhoods walk more frequently to shops and restaurants than to other destinations; in suburban neighborhoods, places to exercise are the most frequent destination, followed by shops. In both types of neighborhoods, residents are at least as likely to walk once per month or more “with no particular destination in mind” as they are to walk to any one type of destination. Interestingly, the shares of respondents saying they walk at least once a month during a *typical* month are considerably lower than the shares who reported walking to the store or strolling at least once in the *previous* month. These differences, which are consistent across neighborhoods, may stem from differences in the two questions or may reflect reluctance on the part of respondents to report no walks in the last month if they sometimes do walk.

To what degree are these differences explained by differences in the built environment? Neighborhood characteristics were measured both objectively and as perceived by survey respondents. A selection of the accessibility (including land use mix) measures, presented in Table 12, reveals distinct differences between traditional and suburban neighborhoods. Residents of traditional neighborhoods on average have considerably more businesses and more types of businesses within 400m (about ¼ mile) from home. In addition, the average distance to the nearest establishment of any type for residents of traditional neighborhoods (247m) is less than half the distance for suburban residents (557m), and residents of traditional neighborhoods are closer to every type of establishment on average than suburban residents. These differences suggest greater potential for walking more in traditional neighborhoods. However, these patterns are not entirely consistent across individual neighborhoods: Modesto Central offers accessibility levels more comparable to the suburban neighborhoods than to the other traditional neighborhoods, perhaps explaining the lower frequency of walking to the store in this neighborhood than in other traditional neighborhoods.

Table 12. Objective Neighborhood Characteristics: Traditional vs. Suburban Neighborhoods

	Traditional	Silicon Valley - Mountain View	Santa Rosa - Junior College	Modesto -Central	Sacramento - Midtown	**Suburban**	Silicon Valley - Sunnyvale	Santa Rosa - Rincon Valley	Modesto - Suburban	Sacramento - Natomas	**p-value nbhd type**[a]
Number within 400 meters…											
Business types	**2.6**	2.5	2.1	1.2	4.1	**0.8**	1.1	0.8	0.8	0.6	**0.00**
Institutional	**1.5**	1.5	1.2	0.7	2.3	**0.4**	0.4	0.2	0.5	0.3	**0.00**
Maintenance	**0.9**	0.6	0.8	0.4	1.4	**0.2**	0.3	0.3	0.1	0.1	**0.00**
Eat-out	**0.7**	0.6	0.8	0.2	1.5	**0.2**	0.3	0.2	0.2	0.3	**0.00**
Leisure	**0.9**	1.0	0.5	0.2	1.5	**0.3**	0.4	0.3	0.2	0.2	**0.00**
Minimum distance in meters to…											
Any business	**247**	284	235	298	192	**557**	462	581	502	704	**0.00**
Institutional	**377**	417	381	427	305	**760**	574	727	683	1087	**0.00**
Maintenance	**380**	351	408	478	317	**819**	873	851	663	898	**0.00**
Eat-out	**526**	587	438	816	349	**789**	794	955	696	740	**0.00**
Leisure	**508**	547	618	654	293	**814**	692	932	799	869	**0.00**
N	**882**	220	208	183	271	**741**	209	155	197	180	

a. Based on t-test for difference of means for traditional neighborhoods versus suburban neighborhoods.

The characteristics of the eight neighborhoods as perceived by survey respondents also reflect fundamental differences in neighborhood types, as reflected in the average factor scores for perceived neighborhood characteristics (Table 13). Residents of traditional neighborhoods gave higher scores on average to accessibility, socializing, and attractiveness. Residents of suburban neighborhoods gave higher scores on average to safety. The differences between the groups for the physical activity options and spaciousness factors were not significant. The difference on accessibility suggests that residents of traditional neighborhoods perceive greater opportunities for walking than residents of suburban neighborhoods, and higher scores on the socializing and attractiveness factors might imply a better walking environment. However, the higher score for suburban neighborhoods for safety and the lack of difference on the physical activity options and spaciousness factors suggest that the differences in walking environment between suburban and traditional neighborhoods are not simply defined. The differences by neighborhood also warn against a simple classification: only for perceived attractiveness do the average scores by neighborhood follow the overall pattern for suburban and traditional neighborhoods.

Table 13. Perceptions, Attitudes, and Preferences: Traditional vs. Suburban Neighborhoods

	Traditional	Silicon Valley - Mountain View	Santa Rosa - Junior College	Modesto -Central	Sacramento - Midtown	**Suburban**	Silicon Valley - Sunnyvale	Santa Rosa - Rincon Valley	Modesto - Suburban	Sacramento - Natomas	**p-value nbhd type[a]**
Perceived neighborhood characteristics											
Accessibility	**0.15**	0.30	0.25	-0.41	0.32	**-0.18**	-0.07	-0.52	-0.36	0.23	**0.00**
PA options	**0.01**	0.35	-0.29	-0.40	0.25	**-0.01**	-0.02	-0.14	-0.02	0.10	**0.45**
Safety	**-0.14**	0.12	-0.20	0.07	-0.46	**0.16**	0.46	0.27	0.14	-0.25	**0.00**
Socializing	**0.09**	0.21	0.03	-0.15	0.21	**-0.12**	-0.05	-0.37	-0.14	0.06	**0.00**
Spaciousness	**0.00**	-0.21	0.06	0.74	-0.37	**-0.01**	-0.19	-0.16	0.25	0.03	**0.82**
Attractiveness	**0.28**	0.01	0.17	0.32	0.57	**-0.33**	-0.39	-0.33	-0.07	-0.56	**0.00**
Travel attitudes											
Pro-bike/walk	**0.20**	0.21	0.19	-0.14	0.42	**-0.23**	-0.17	-0.22	-0.41	-0.10	**0.00**
Pro-travel	**-0.03**	-0.19	0.02	0.08	0.00	**0.03**	-0.13	0.00	0.10	0.17	**0.27**
Travel minimizing	**0.01**	0.06	0.08	-0.11	-0.01	**-0.01**	-0.08	0.00	-0.12	0.19	**0.69**
Pro-transit	**0.15**	0.42	-0.07	-0.28	0.38	**-0.17**	0.07	-0.31	-0.38	-0.09	**0.00**
Safety of car	**-0.27**	-0.40	-0.25	0.01	-0.36	**0.31**	0.04	0.24	0.48	0.50	**0.00**
Car dependent	**-0.06**	0.08	-0.02	-0.10	-0.19	**0.07**	0.28	0.09	0.07	-0.19	**0.01**
Neighborhood preferences											
Accessibility	**0.03**	0.22	-0.01	-0.33	0.16	**-0.04**	-0.13	-0.25	-0.08	0.32	**0.14**
PA options	**0.01**	0.03	-0.09	-0.25	0.25	**-0.02**	-0.13	-0.23	0.00	0.28	**0.60**
Safety	**-0.18**	-0.18	-0.14	0.07	-0.39	**0.21**	0.26	0.16	0.23	0.17	**0.00**
Socializing	**0.05**	-0.05	0.04	-0.08	0.24	**-0.05**	0.66	-0.28	0.07	0.16	**0.05**
Spaciousness	**-0.05**	-0.15	-0.01	0.33	-0.26	**0.06**	-0.08	-0.02	0.16	0.17	**0.02**
Attractiveness	**0.04**	-0.16	-0.12	0.26	0.19	**-0.05**	-0.29	-0.06	0.12	0.05	**0.04**
N	**888**	227	214	182	265	**762**	211	161	212	178	

Note: Scores normalized to a mean value of 0 and variance of 1.
a. Based on t-test for difference of means for traditional neighborhoods versus suburban neighborhoods.

If self-selection occurs, then these differences are not independent of the attitudes and preferences of the residents who choose these neighborhoods. Travel attitudes show distinct, and potentially important, differences by neighborhood type (Table 13). The differences in average scores between suburban and traditional neighborhoods were significant for four of the six factors. Residents of traditional neighborhoods had higher scores on average for the pro-bike/walk and pro-transit factors and lower scores on average for the safety of car and car dependent factors. The differences on the pro-travel and travel-minimizing factors were not significant, however. These differences suggest a strong connection of neighborhood choice to attitudes about travel modes but not to attitudes about travel itself. The differences by neighborhood are not always consistent with this pattern; for example, residents of Modesto Central have lower scores than average on the pro-bike/walk factor, while residents of Mountain View are higher than average on the car dependent factor.

Preferences for neighborhood characteristics are also different significantly by neighborhood type (Table 13). Suburban residents have higher scores on average for safety and for outdoor spaciousness, while residents of traditional neighborhoods have higher scores on average for socializing and attractiveness. The scores for accessibility and physical activity options were not significantly different, however. Again, it is important to note that the scores across neighborhoods do not perfectly follow the patterns for neighborhood type; only for preferences for safety are the average scores for all traditional neighborhoods lower than the average scores for all suburban neighborhoods.

By comparing scores on preferences to scores on perceived neighborhood characteristics it is possible to get some sense of the degree to which residents get what they want. Residents of traditional neighborhoods have higher preferences for and perceptions of attractiveness and socializing, but while their preferences for accessibility are not significantly higher, their perceived accessibility is. Suburban residents have higher preferences for and perceptions of safety, but while they have higher preferences for spaciousness, the perceived differences for this characteristic are not statistically significant. These results thus provide mixed evidence on the possibility of self-selection: residents of traditional neighborhoods want and get two factors that might lead to more walking (attractiveness and socializing) and get one factor that they did not necessarily want that might also lead to more walking (accessibility). At the same time, residents of suburban neighborhoods also get one factor that might lead to more walking (safety).

4.2.2 Cross-sectional multivariate analysis

Multivariate analyses help to sort out the relative importance of these different effects on walking behavior: Once attitudes and preferences (as well as socio-demographic characteristics) are controlled for, is the built environment further related to walking?

Because the frequency of walking to the store constituted count data with overdispersion, a negative binomial regression model was estimated for this variable (using the Limdep 8.0 statistical package). The final model had a deviance R^2 of 0.32 (analogous to the "McFadden R2" measure in discrete choice models, the deviance R^2 recommended by Cameron and Windmeijer (1996) represents the proportionate reduction, due to the explanatory variables in the model, in the deviance of the log-likelihood of the constant-only model from the maximum possible log-likelihood), a strong result for a cross-sectional model of disaggregate travel behavior, and yields interesting insights into walking behavior (Table 14). Among socio-demographic characteristics, age and being a worker have the largest standardized coefficients, negative in both cases. Among attitudes, a pro-bike/walk attitude has the largest standardized coefficient, with a pro-transit attitude also positively associated with walking frequency and a safety of car attitude negatively associated. The significance of preferences for neighborhood characteristics is also notable. Respondents expressing a preference for physical activity options and for having stores within walking distance walk to the store more frequently, all else equal, suggesting a self-selection effect. Respondents with preferences for safety and for cul-de-sacs walk less frequently, all else equal; these variables are likely associated with a preference for suburban neighborhoods, again pointing to self-selection. Neighborhood characteristics, however, are significant even after accounting for these attitudes and preferences, suggesting the possibility that the built environment has a direct causal effect on walking behavior. Not surprisingly, the distance to potential destinations, both objective and perceived, plays an important role; more subjective factors such as perceived safety and attractiveness are also significant but less important than distance.

Table 14. Negative Binomial Regression for Walking to the Store Frequency

Variables	Coefficient	Standardized Coefficient [a]	p-value	Marginal Effect
Constant	0.408	0.845	0.080	1.517
Socio-demographics				
Limitations on walking	-0.398	-0.078	0.026	-1.481
Age	-0.010	-0.145	0.000	-0.036
Number of autos	-0.082	-0.069	0.048	-0.305
Worker	-0.328	-0.126	0.001	-1.219
Neighborhood preferences				
Physical activity options	0.115	0.118	0.004	0.426
Safety	-0.124	-0.102	0.008	-0.459
Stores w/in walking distance	0.172	0.168	0.000	0.639
Living in cul-de-sac	-0.063	-0.065	0.084	-0.236
Travel attitudes				
Pro-bike/walk	0.314	0.313	0.000	1.168
Pro-transit	0.228	0.227	0.000	0.848
Safety of car	-0.121	-0.121	0.002	-0.451
Neighborhood characteristics				
Safety	-0.076	-0.071	0.029	-0.281
Attractiveness	0.083	0.078	0.038	0.308
Stores within walking distance	0.286	0.268	0.000	1.065
Distance to nearest grocery store (km)	-0.200	-0.144	0.000	-0.745
Number of business types within 800 m	0.050	0.191	0.000	0.186
Dispersion parameter α	1.208	0.067	0.000	
N	1480			
Deviance R-square	0.32			

a. All independent variables except constant term were standardized and model was reestimated; dependent variable was not standardized.

The model for frequency of strolling, also a negative binomial regression, has a deviance R^2 of only 0.11, with fewer significant variables (Table15), suggesting that strolling is less well explained by the variables examined here than walking to the store. Among socio-demographic variables, being a worker has the largest standardized coefficient (negative), followed by income (positive), and having limits on walking (negative). The pro-bike/walk and pro-transit attitudes are again significant, with positive effects on the frequency of strolling; in this model, the travel minimizing attitude is also positively associated with strolling, although the standardized coefficient is not large. Once these variables have been accounted for, two measures of the built environment have a statistically significant effect on strolling: socializing perception and attractiveness perception. This result is consistent with expectations: accessibility to stores and other destinations should not matter for strolling trips, but the quality of the environment, both physical and social qualities, should. These models thus support both sides of the debate: residents who prefer walking, either walking to the store or strolling around the neighborhood, do self-select into traditional neighborhoods, but certain qualities of the built environment seem to have an effect even when the self-selection effect has been accounted for.

Table 15. Negative Binomial Regression for Strolling Frequency

Variables	**Coefficient**	**Standardized Coefficient** [a]	**p-value**	**Marginal Effect**
Constant	1.722	2.073	0.000	15.141
Socio-demographics				
Limitations on walking	-0.630	-0.126	0.000	-5.540
Age	0.008	0.115	0.002	0.067
Worker	-0.480	-0.186	0.000	-4.219
Female	0.188	0.094	0.002	1.653
Income ($k)	0.004	0.131	0.000	0.032
Travel attitudes				
Pro-bike/walk	0.233	0.233	0.000	2.051
Pro-transit	0.091	0.091	0.002	0.803
Travel minimizing	0.062	0.062	0.048	0.548
Neighborhood characteristics				
Socializing	0.146	0.123	0.000	1.281
Attractiveness	0.110	0.103	0.000	0.963
Dispersion parameter α	1.241	0.052	0.000	
N	1534			
Deviance R-square	0.11			

a. All independent variables except constant term were standardized and model was reestimated; dependent variable was not standardized.

4.2.3 Quasi-longitudinal multivariate analysis

Our quasi-longitudinal analysis provides a more direct test of a causal relationship between the built environment and walking by examining the association between a change in the built environment and a change in walking. This study measured change in walking either from before the move (for movers) or from one year ago (for the non-movers) through an ordered categorical variable, defined using a 5-point scale ranging from “a lot less” to “a lot more” walking now; change in biking was similarly measured. Changes in the built environment were measured for the sample of movers by taking the difference between perceived characteristics of the current and previous neighborhoods; the built environment was assumed constant for non-movers. Changes in selected socio-demographic variables (age, household size, presence of children, income) were measured for both movers and non-movers. Travel attitudes and preferences for neighborhood characteristics were assumed to be constant.

The relationships between changes in the built environment and changes in walking, while controlling for attitudes, were estimated using an ordered probit model. The resulting equation can be interpreted as representing an underlying latent variable, in this case a continuous propensity to change one’s amount of travel, from a substantial decrease in walking or biking at one end to a substantial increase at the other. A statistically significant association between a change in the built environment and change in walking or biking provides evidence of a causal relationship.

In the model for change in walking (Table 16), change in the attractiveness factor had the highest standardized coefficient: an increase in the attractiveness factor is associated with either a smaller decrease in walking or a larger increase. Several socio-demographic variables were significant, with older age, a current limitation on walking, and an increase in income contributing to a larger decrease or smaller increase in walking, and with the addition of children under the age of five to the household contributing to a larger increase or smaller decrease in walking. Only one attitudinal variable was significant: the pro-bike/walk factor, with a higher level of this factor associated with either a smaller decrease or a larger increase in walking. After accounting for these effects, changes in several perceived built environment characteristics had positive impacts on walking change (smaller decrease or larger increase): accessibility, physical activity options, safety, and socializing. One objective measure was also positively significant: number of types of businesses within 1600m. Although this variable is measured for the current neighborhood, a high current level of this variable is more likely to be associated with an increase rather than a decrease in its level as a result of a move. The spaciousness factor for the current neighborhood was also significant, with a higher score on the factor associated with either a larger decrease or a smaller increase in walking. These results also support the hypothesis that changes in the built environment are associated with changes in walking and point to increases in accessibility, alternatives to driving, safety, socializing interactions, and attractiveness as having positive effects on walking in the neighborhood.

Table 16. Ordered Probit Model for Change in Walking

Variables	Coefficient	Standardized Coefficient [a]	p-value
Constant	1.402	1.677	0.000
Socio-demographics			
Current age	-0.005	-0.081	0.004
Current income ($k)	0.002	0.067	0.033
Limitations on walking	-0.511	-0.102	0.000
Change in income ($k)	-0.003	-0.061	0.021
Change in # of kids (<=5)	0.260	0.074	0.005
Travel attitudes			
Pro-bike/walk	0.154	0.154	0.000
Neighborhood characteristics			
# of business types within 1600 m	0.024	0.062	0.028
Current outdoor spaciousness	-0.064	-0.059	0.039
Change in accessibility	0.126	0.106	0.000
Change in physical activity options	0.123	0.102	0.000
Change in safety	0.148	0.145	0.000
Change in socializing	0.176	0.142	0.000
Change in attractiveness	0.193	0.199	0.000
Threshold parameter 1	0.644	0.644	0.000
Threshold parameter 2	2.154	2.154	0.000
Threshold parameter 3	2.868	2.868	0.000
N	1505		
Log-likelihood at 0	-2735.015		
Log-likelihood at constant	-2059.568		
Log-likelihood at convergence	-1887.869		
Pseudo R-square	0.310		
Adjusted pseudo R-square	0.304		

a. All independent variables except constant term were standardized and model was reestimated; dependent variable was not standardized.

The implications of the model can also be depicted graphically. Figure 9 shows the predicted probabilities for each category of change in walking (from “a lot less” to “a lot more” now) given different changes in accessibility, for an individual who has average values of the other explanatory variables in the model. The upward slope of the lines for “a little more” and “a lot more” walking shows that the probability of an average individual being in these categories increases as accessibility improves, while the downward slope of the lines for “a little less” and “a lot less” walking shows that the probability of an average individual being in these categories decreases as accessibility improves. For an increase in the accessibility factor of 2 points, the combined probability of an average individual walking either a little more or a lot more following an improvement in accessibility is substantially greater than the combined probability of walking a little less or a lot less but still lower than the probability of walking about the same as before. Only when the increase in the accessibility factor reaches 4 points (equal to 4 standard deviations – an extreme increase) does the combined probability of the walking-more categories exceed the probability of walking about the same. This analysis suggests that while the impacts of changes in accessibility are significant, large improvements in accessibility are needed to produce a substantial increase in walking. On the other hand, when accessibility does not change, there is a 54% chance of staying at the same level of walking and a 30% chance of increasing walking level; when accessibility increases 2 points, there is a 50% chance of staying at the same level of walking and a 39% chance of increasing walking level. These results mean that out of 100 average people, about 9 more will increase walking and 4 fewer will stay the same at a 2-point increase in accessibility than at no change in accessibility. These changes in walking are potentially non-trivial. The effects of change in attractiveness on change in walking are even larger (Figure 10).

Figure 9. Predicted Probabilities of Categories of Change in Walking as a Function of Changes in Accessibility

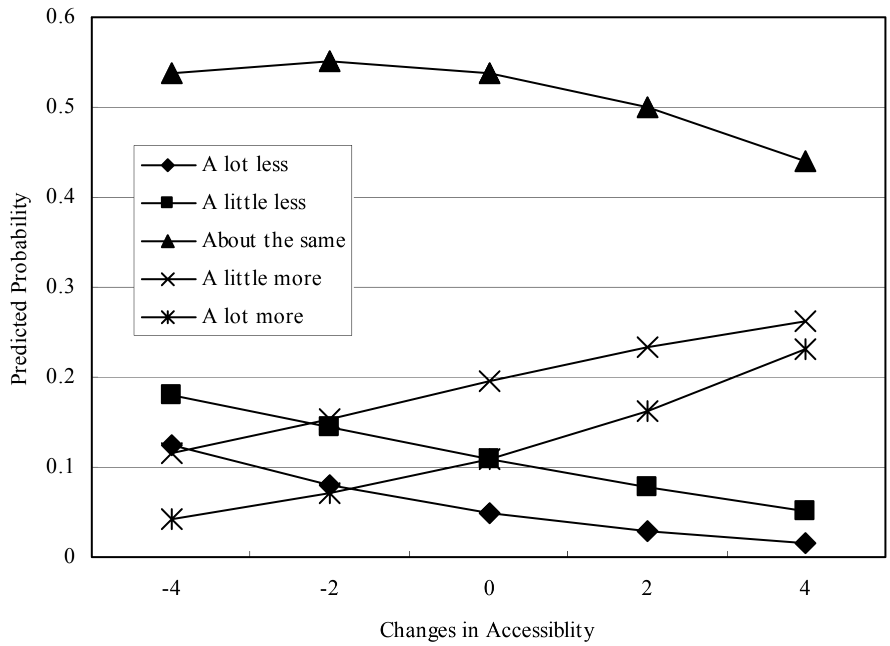
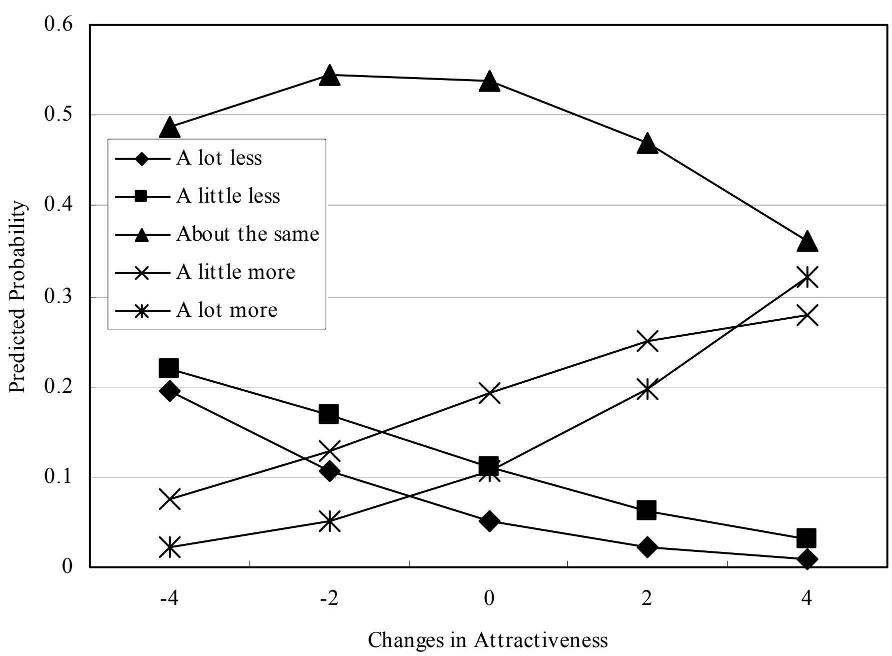


Figure 10. Predicted Probabilities of Categories of Change in Walking as a Function of Changes in Attractiveness



Attitudes play a much more significant role in the model for change in biking (Table 17). Residents who own more bikes, are younger, and have higher levels of education are more likely to report an increase in biking. But a pro-bike/walk attitude has a standardized coefficient more than twice as high as any other variable. Other attitudes are also significant: travel minimizing attitude, pro-transit attitude, and spaciousness preference are all negatively associated with changes in biking (greater decrease or smaller increase in biking), while an attractiveness preference is positively associated. Once these attitudes and preferences have been accounted for, several measures of the built environment are significant. An increase in the attractiveness factor or the socializing factor is associated with a greater increase or smaller decrease in biking. The current number of maintenance businesses within 1600 meters has a positive effect on change in biking, as does the minimum distance to a health club, although the standardized coefficients are small. This model suggests that a pro-bike/walk attitude is most important in explaining changes in biking, but that changes in the built environment also contribute.

Because bicycling and walking are both forms of utilitarian travel and physical activity, it is possible that they serve as substitutes for each other to some degree. In other words, an individual who now bicycles more might be walking less as a result. If so, the errors in the models for change in walking and change in bicycling could be correlated, leading to consistent but inefficient coefficient estimates, and biased standard errors. A seemingly unrelated regression analysis is appropriate for this problem. However, it can be performed for linear models, but is not readily available for non-linear ordered probit models.

Table 17. Ordered Probit Model for Change in Biking

Variables	Coefficient	Standardized Coefficient [a]	p-value
Constant	0.915	1.181	0.000
Socio-demographics			
Current # of bikes	0.064	0.097	0.004
Current age	-0.011	-0.155	0.000
Education	0.067	0.087	0.005
Neighborhood preferences			
Outdoor spaciousness	-0.114	-0.111	0.002
Attractiveness	0.085	0.074	0.019
Travel attitudes			
Pro-bike/walk	0.365	0.359	0.000
Travel minimizing	-0.078	-0.077	0.014
Pro-transit	-0.124	-0.121	0.000
Neighborhood characteristics			
Change in attractiveness	0.169	0.144	0.000
Change in socializing	0.150	0.121	0.000
# of maintenance within 1600 m	0.015	0.090	0.012
Distance to nearest health (km)	0.143	0.071	0.045
Threshold parameter 1	0.351	0.351	0.000
Threshold parameter 2	2.261	2.261	0.000
Threshold parameter 3	2.908	2.908	0.000
N	1328		
Log-likelihood at 0	-1986.718		
Log-likelihood at constant	-1616.707		
Log-likelihood at convergence	-1474.989		
Pseudo R-square	0.258		
Adjusted pseudo R- square	0.252		

a. All independent variables except constant term were standardized and model was reestimated; dependent variable was not standardized.

4.2.4 Summary

Similar to the analyses of driving behavior in Section 4.1, these analyses are still not definitive, nor do they completely clarify the nature of the causal relationship between the built environment and walking/biking. More sophisticated analyses of these data, such as structural equations modeling, will help to establish the strength and direction of the relationships between attitudes, changes in the built environment, changes in walking behavior, and other factors. Nevertheless, the results presented here are helpful to answer the question – what aspects of the built environment are most important for encouraging an increase in walking? Our models point to accessibility, particularly close proximity to potential destinations such as shops and services, as an important factor. Enhancements to other qualities of the built environment might also increase walking: physical activity options (bike routes, sidewalks, parks, public transit), safety (quiet, low crime, low traffic, safe for walking, safe for kids to play, street lighting), attractiveness (appearance, level of upkeep, variety in housing styles, big street trees), and socializing (diverse neighbors, people out and about, interaction among neighbors, similar economic levels).

4.3 Home-based Nonwork Travel

Individuals may generate daily trips by at least three primary modes: auto, transit, and non-motorized modes. Measures of individuals' travel behavior by each mode (e.g. trip length and trip frequency) are likely to be correlated with each other. For example, given a fixed number of activities, a large amount of travel by one mode may discourage the use of other modes (Cervero and Radisch, 1996). On the other hand, travel time savings, due to faster speed and/or reduced distance among other causes, may induce travel demand by other modes (Crane, 1996; Matt et al., 2005). Also, some unobserved factors such as travel affinity may simultaneously influence trip generation by different modes. However, when modeling the effects of the built environment on travel behavior, previous studies (e.g., Cervero, 1996b; Kitamura et al., 1997; Krizek, 2003a) generally assume independent errors across different modes, i.e. that there are no correlations among the unobserved variables contributing to trip generation by different modes. However, if trip generation by different modes is correlated, this assumption yields statistically consistent but inefficient parameter estimates.

In this section, we investigate the causal relationship between the built environment and home-based nonwork travel by different modes, relaxing the assumption that the error terms of the equations by different modes are independent. We chose nonwork travel as our primary interest here because most smart growth strategies have more potential to influence nonwork travel than work travel (Boarnet and Crane, 2001a). This study tests Hypothesis 2 and thus aims to address the following central questions: (1) What aspects of neighborhood characteristics influence individuals' decisions on nonwork travel? (2) Does residential self-selection impact individuals' nonwork travel choices? (3) If there is an apparent influence of the built environment on nonwork travel choice, does residential self-selection account for all of it? (4) Is the assumption of independent error terms valid?

4.3.1 Behavioral framework

Crane (1996) proposed a rational choice framework underlying individuals' travel decisions for different modes. He formalized this decision process as a constrained utility maximization problem: given a limited budget of time, individuals choose the number of trips by each mode to maximize their travel benefits. Specifically, individuals decide their desired frequency of trips by each mode to maximize U (x, $\mathbf{a}$, $\mathbf{w}$, $\mathbf{t}$) subject to r = $\mathbf{a'p_a} + \mathbf{w'p_w} + \mathbf{t'p_t}$ + x, where U is an index of the benefits of using resources (time and income) for all activities; r is the total available resources; $\mathbf{a}$, $\mathbf{w}$, and $\mathbf{t}$ are the respective vectors of the number of trips by auto, walking, and transit for each purpose; $\mathbf{p_a}$, $\mathbf{p_w}$, and $\mathbf{p_t}$ are the respective vectors of "prices" for each trip purpose by auto, walking, and transit; and x is a composite of resources spent on all other activities. The solution to this problem yields trip demand functions for each purpose by the three different modes:

$$a = f(p_a, p_w, p_t, r)$$

$$w = f(p_a, p_w, p_t, r) \tag{4-1}$$

$$t = f(p_a, p_w, p_t, r).$$

Unlike Crane (1996), Boarnet and Crane (2001b) considered all purposes together. That is, **a, w, t,** $\mathbf{p_a}$, $\mathbf{p_w}$, and $\mathbf{p_t}$ were simplified to scalars. Travel cost is a generalized cost including time, out-of-pocket monetary expenditures, and psychological effects such as aesthetics and comfort. Travel costs can be influenced by the characteristics of the built environment that connects trip origins and destinations. They specified three alternative ways the built environment could affect travel costs: (1) the built environment captures all variation in travel costs, and hence travel costs are not included in the model specification; (2) variation in travel costs is only partially explained by the built environment, and hence both built environment characteristics and travel costs (such as trip distance and trip speed) are allowed to enter the model; (3) the built environment influences travel costs, which in turn determine individuals' decisions on trip generation, a two-step procedure. Given that travel costs were not measured in our data, we must, by default, adopt the first alternative for our specification: travel costs are fully determined by the built environment. Specifically we assume that,

$$
\begin{aligned}
p_a &= f(BE) \\
p_w &= f(BE) \qquad (4\text{-}2) \\
p_t &= f(BE),
\end{aligned}
$$

where BE is a vector of built environment characteristics. Accordingly, Equation (4-1) is reduced to:

$$
\begin{aligned}
a &= f(BE, r) \\
w &= f(BE, r) \qquad (4\text{-}3) \\
t &= f(BE, r).
\end{aligned}
$$

The extent to which travel costs are affected by the built environment is debatable. Built environment characteristics may be good predictors of non-motorized travel costs, moderate predictors for auto travel costs, but inferior predictors for transit travel costs (Table 18). Although this simplification may not fully capture travel costs, it avoids the need to explicitly treat the potential endogeneity of travel costs in trip generation (Boarnet and Crane, 2001b). Empirically, Boarnet and Crane's application of the first two alternatives to Los Angeles and San Diego data yielded similar results in terms of the significance and magnitude of built environment parameters.

Table 18. The Influence of the Built Environment on Elements of Generalized Travel Costs

Mode	Time	Monetary Expenditures	Psychological Effect
Auto	Moderate	Moderate	Minor
Walk/Bike	Strong	NA	Strong
Transit	Minor	No (flat fare); Minor (non-flat fare)	Moderate

4.3.2 Variables

The dependent variables in this study are the frequencies of home-based nonwork trips by auto, walking/biking, and transit, respectively, to selected destinations. In the survey, respondents were asked to report how often they use auto, walking/biking, and public transit from their home to particular nonwork destinations in a typical month with good weather. The prespecified nonwork destinations include six types: church and civic building, service provider, restaurant and coffee, store, a place to exercise, and out of the house without a particular destination. The frequency was reported on a six-point ordinal scale from "Never" to "Two or more times per week". An approximate indicator of overall trip frequency for each mode was calculated by summing the individual frequency measure (0 to 5) across the six types of destinations. Therefore, the overall frequency indicator ranges from 0 to 30. Table 19 presents the means of this indicator for home-based nonwork trips, by neighborhood type and mode. The mean walking/biking trip frequency indicator is significantly different between traditional neighborhoods (10.99) and suburban neighborhoods (4.63), while auto trip and transit trip frequencies are not different. This finding suggests that residential neighborhood type may be a better predictor for non-motorized trips than for auto trips, consistent with results found previously. The explanatory variables comprise neighborhood characteristics, neighborhood preferences, travel attitudes, and socio-demographics.

Table 19. Mean Home-based Nonwork Trip Frequency Indicator by Neighborhood Type

	Auto	Transit	Walk/bike
N	1,554	1,623	1,581
Total	15.64	0.73	8.05
Traditional neighborhood	15.56	0.85	10.99
Suburban neighborhood	15.72	0.60	4.63
p-value (traditional vs. suburban)	0.636	0.131	0.000

Note: The measure of interest is an index of trip frequency ranging from 0 to 30.

4.3.3 Analytical method

The explanatory variables in Equation (4-3) include neighborhood characteristics and socio-demographics. In the data, non-motorized trip frequency is significantly correlated with auto trip frequency and transit trip frequency at the 0.05 level. Although this does not guarantee that the unobserved determinants of those variables will be correlated, it is suggestive that they may be. Therefore, when estimating Equation (4-3), we relaxed the independence assumption and assumed that the error terms follow a multivariate normal distribution. Specifically, we applied the seemingly unrelated regression equations (SURE) model. The estimation approach is generalized least squares (GLS). The GLS used here is based on the following stacked system (Greene, 2002):

$$\begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \end{pmatrix} = \begin{pmatrix} X_1 & 0 & 0 \\ 0 & X_2 & 0 \\ 0 & 0 & X_3 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix}$$

or

$$Y = X\beta + \varepsilon \,, \tag{4-4}$$

where Y_i and ε_i are n × 1 vectors (i =1, 2, 3); β_i is a p_i × 1 vector; X_i is an n × p_i matrix; Y and ε are 3n × 1 vectors; β is a ($p_1 + p_2 + p_3$) × 1 vector; X is a 3n × ($p_1 + p_2 + p_3$) matrix; E(ε) = 0 and E(εε') = Σ. So the GLS estimator is $\hat{\beta} = \left[X'\Sigma^{-1}X\right]^{-1}\left[X'\Sigma^{-1}Y\right]$.

According to discussions in Section 2.4, a model with neighborhood characteristics and socio-demographics is able to provide evidence to establish association and non-spuriousness. A further incorporation of travel attitudes and residential preferences in the model will shed light on the directions of influence, and hence offer strong evidence to infer causality. Accordingly, to test the causal link from the built environment to travel behavior, we developed two separate models: Model 1 (without attitudes) and Model 2 (with attitudes). The models were estimated using Limdep 7.0 software.

4.3.4 Seemingly unrelated regression

Trip frequencies were first regressed against socio-demographic variables and neighborhood characteristics. As shown by Model 1 in Table 20, socio-demographics are significantly associated with travel behavior, illustrating individuals' taste differences and distributional effects. First, individuals' travel behavior is determined by the choice set of travel modes available to them. Household auto ownership appears in all three equations, having a positive correlation with auto trip frequency and negative associations with transit or walking/biking trip frequencies. These results are not surprising since individuals' travel decisions strongly depend on the level of household auto ownership (Pucher and Renne, 2003). Similarly, it is plausible that bike ownership is a positive predictor of walking/biking trip frequency. Mobility constraints also affect individuals' travel decisions. Those who do not hold a driver's license are more likely to take transit; individuals with walking limitations are less likely to walk; and physical or psychological limitations on driving on the freeway tend to encourage the use of transit and non-motorized modes. Second, household structure influences individuals' trip generation. The number of children under five years old in the household tends to reduce auto trip frequencies, presumably because of time constraints or the inconvenience of taking a child out. The number of driving-age household members has a positive association with transit choice. Given a fixed number of autos in the household, the more driving-age people there are, the less the car is available to an individual, and hence the more likely she is to take transit. In addition, household incomes have a positive influence on the number of auto trips, a natural result. Workers conducted fewer nonwork trips either by auto or by walking/biking, presumably due to time constraints. The negative association of age with both auto and walking/biking trip frequencies may reflect mobility limitations or possibly safety concerns, consistent with Cao et al. (2006). Education is found to be positively associated with walking/biking trip frequency, consistent with other studies showing that recreational physical activity is positively correlated with education (Brownson and Boehmer, 2004).

After accounting for the influence of socio-demographics, we found that neighborhood characteristics affect trip frequency by each mode. Similar to the finding presented in Table 19, neighborhood type is an important predictor of non-motorized trip frequency, with traditional neighborhoods associated with more walking/biking trips. With respect to specific neighborhood characteristics, the number of business types within 400 meters of the residence is negatively associated with auto trip frequency and positively associated with non-motorized trip frequency, and the number of business types within 800 meters positively impacts transit trip frequency. These results suggest that mixing land uses tends to discourage the generation of auto trips and facilitate the use of transit and non-motorized modes. Those who perceived themselves to be living close to their family made more auto trips, presumably a result of greater social interaction.

Table 20. Seemingly Unrelated Regression for Nonwork Travel: without attitudes

Variables	Model 1: Without Attitudes		
	Auto	**Transit**	**Walk/bike**
Constant	17.061 (0.000)	4.549 (0.000)	13.087 (0.000)
Socio-demographics			
# of autos	0.967 (0.000)	-0.369 (0.000)	-0.541 (0.016)
# of bikes			0.839 (0.000)
Age	-0.053 (0.000)		-0.071 (0.000)
Worker	-3.286 (0.000)		-2.045 (0.000)
Education			0.564 (0.000)
Income ($k)	0.018 (0.001)		
# of kids (≤ 5)	-1.142 (0.006)		
# of diving-age household members		0.415 (0.000)	
Driver’s license		-4.482 (0.000)	
Limitation on driving on the freeway		2.044 (0.002)	3.363 (0.008)
Limitation on walking			-4.748 (0.000)
Neighborhood characteristics			
Neighborhood type (1: traditional; 0: suburban)			2.112 (0.011)
# of business types within 400 m	-0.224 (0.000)		0.310 (0.000)
# of business types within 800 m		0.051 (0.009)	
Distance to nearest library (km)			-0.448 (0.044)
Distance to nearest theater (km)			-0.607 (0.000)
Distance to nearest post office (km)			-0.738 (0.001)
Perceived physical activity options	-0.411 (0.066)		0.591 (0.011)
Perceived socializing			0.435 (0.051)
Perceived attractiveness			0.557 (0.007)
Perceived closeness to family	0.574 (0.001)		
N	1319	1319	1319
R-square	0.066	0.114	0.311

Note: The numbers in parentheses are p-values.

In contrast to the relatively small set of neighborhood variables affecting auto (3) and transit (1) frequencies, individuals’ decisions to use non-motorized modes are greatly influenced by a variety (8) of neighborhood characteristics. Also, the R^2 for the walk/bike model is 0.311, much larger than those for the auto and transit models. This suggests that neighborhood characteristics carry significant explanatory power for the variations in walking/biking behavior.

As expected, the distances to the nearest destinations such as library, theater, and post office have negative associations with non-motorized travel. These distance variables are taken to be indicators of overall neighborhood accessibility, since the presence of these specific businesses in residential areas would probably not substantially increase walking/biking trips by themselves.

Further, the perception of physical activity options offered by the neighborhood positively affects individuals' walking/biking travel. By contrast, it has a negative influence on auto trip frequency. The implication is that providing walking and biking infrastructures around a residential neighborhood tends to discourage residents' auto travel and facilitate non-motorized travel. Perceived socializing and attractiveness of residential neighborhoods are positively associated with walking/biking trip frequency. This result suggests that pedestrian-friendly design, including social environment and aesthetic quality, tends to change the psychic costs of non-motorized travel by making it more comfortable and pleasant (Boarnet and Crane, 2001a).

Except for the relaxation of the independent errors assumption, Model 1 replicates the modeling approaches used in most previous studies: individuals' travel decisions are a function of built environment traits and socio-demographic characteristics. Generally, the findings suggest that individuals' nonwork travel decisions are largely dependent on their socio-demographic characteristics and the choice set of travel modes available and feasible to them. Neighborhood characteristics tend to encourage or discourage their choices of travel frequency, and non-motorized travel appears to be most affected by residential neighborhood design. However, these findings are based on the assumption that residential choice is exogenous to travel choice.

The results presented in Model 2 in Table 21 suggest that travel attitudes and residential preferences play an important role in individuals' travel decisions. First, incorporating attitudinal factors greatly increases the goodness of fit of our models. The R^2 measures for auto, transit, and walk/bike models increase 43.9%, 35.1%, and 53.15%, respectively. Further, a variety of attitudes are significantly present in the models. In particular, those who prefer living in a quiet and safe place (typical of suburban neighborhoods) tend to make more auto trips. As expected, the preference for good public transit service is positively associated with transit trip frequency. Further, the preferences for accessibility, physical activity options, and outdoor spaciousness significantly influence walking/biking travel choice. It is worth noting that, for walking/biking trip frequency, the incorporation of the preference for physical activity options drove out its corresponding perceived measure and so did accessibility preference with respect to some objective accessibility measures. This lends credible support to the speculation that residential self-selection influences non-motorized travel behavior. As for travel attitudes, the car dependent factor is positively associated with auto trip frequency and negatively related to transit trip frequency. Those who like travel conducted more auto trips. Individuals valuing automobiles as a safe mode are less likely to choose non-motorized modes. Pro-transit and pro-bike/walk factors are positively associated with transit and non-motorized travel, respectively. Interestingly, we also found that a pro-transit attitude tends to reinforce the choice of walking/biking while a pro-walk/bike attitude tends to reduce transit trip frequency. These results are natural since walking or biking trips are necessary to reach transit stations and hence individuals favoring transit are more likely than others to also choose walking/biking as a travel mode; but a preference for walking/biking may not necessarily be associated with transit trips. It is in fact possible that biking is an alternative to transit for people who don't want to drive, i.e. for those faced with choosing either biking or transit instead of driving, but the same is probably not true for walking since walking trips tend to be short and transit is usually not worth it for short trips (Kwong et al., 2005).

After controlling for attitudinal factors, two objective accessibility measures and the perception of physical activity options drop out of the walking/biking model; the perception of people out and about within the neighborhood (an observed dimension of the latent perceived socializing factor) substitutes for socializing; and the four other neighborhood characteristic measures are maintained. Therefore, although residential self-selection impacts individuals' non-motorized travel, the differences in neighborhood characteristics do also contribute to the differences in their non-motorized travel decisions. Except for the replacement of the number of business types within 800 meters by the number of institutional businesses, all neighborhood characteristics (as well as most socio-demographics) still appear in the auto and transit model. Therefore, with respect to built environment characteristics at the neighborhood level, the presence of attitudinal factors seems to offer an additional contribution in explaining the variation in auto and transit travel.

Table 21. Seemingly Unrelated Regression for Nonwork Travel: with attitude

Variables	**Model 2: With Attitudes**		
	Auto	**Transit**	**Walk/bike**
Constant	17.823 (0.000)	4.803 (0.000)	9.671 (0.000)
Socio-demographics			
# of autos	0.940 (0.000)	-0.293 (0.003)	
# of bikes			0.243 (0.034)
Age	-0.060 (0.000)		-0.050 (0.000)
Worker	-3.720 (0.000)		-1.877 (0.000)
Income ($k)	0.016 (0.004)		
# of kids (≤ 5)	-1.357 (0.000)		
# of driving-age household members		0.352 (0.001)	
Driver’s license		-5.142 (0.000)	
Limitation on walking			-2.114 (0.013)
Neighborhood characteristics			
Neighborhood type (1: traditional; 0: suburban)			3.539 (0.000)
# of business types within 400 m	-0.166 (0.026)		0.308 (0.000)
# of institutional businesses within 800 m		0.053 (0.001)	
Distance to nearest theater (km)			-0.438 (0.000)
Perceived physical activity options	-0.501 (0.025)		
Perceived attractiveness			0.371 (0.043)
Perceived closeness to family	0.525 (0.004)		
Perceived people out and about within the neighborhood			0.413 (0.036)
Residential preferences			
safety	0.523 (0.022)		
accessibility			0.613 (0.004)
Physical activity options			0.530 (0.010)
Outdoor spaciousness			-0.481 (0.009)
Good public transit service		0.207 (0.005)	
Travel attitudes			
Car dependent	0.766 (0.000)	-0.180 (0.018)	
Safety of car			-1.283 (0.000)
Pro-transit		0.380 (0.000)	1.482 (0.000)
Pro-bike/walk		-0.174 (0.024)	1.902 (0.000)
Travel liking	0.582 (0.001)		
N	1277	1277	1277
R-square	0.095	0.154	0.476

Note: The numbers in parentheses are p-values.

4.3.5 Independence of error terms

The estimated correlations of error terms for Model 2 are presented in Table 22. The correlation between unobserved variables for auto and walking/biking frequencies and the correlation between those for transit and walking/biking frequencies are somewhat larger than that between unobserved variables affecting auto and transit frequencies. Generally, however, the magnitude of estimated correlations is not large (0.124 at most), reflecting weak associations among the error terms for these three modes. With respect to the statistical significance of estimated correlations, we are not aware of any test in Limdep. Instead, we verified this SURE model using maximum likelihood estimation in Amos 5.0 (for this data set, a GLS estimation could not be accomplished in Amos, even though it could be in Limdep). We found that all parameter estimates and correlation coefficients were similar to the previous ones, and all correlation coefficients were statistically significant at the 0.01 level. Therefore, the SURE model seems to produce more statistically efficient parameter estimates than do separate regression models. However, since the correlations between the error terms are relatively small, the efficiency gain is generally not great (Greene, 2003).

Table 22. Estimated Correlations of Error Terms

	Auto	**Walk/bike**	**Transit**
Auto	1.000		
Walk/bike	0.124	1.000	
Transit	0.080	0.116	1.000

4.3.6 Summary

This study investigated the causal link from the built environment to home-based nonwork travel behavior at the neighborhood level by controlling for residential self-selection. This study has several limitations. First, residential neighborhood characteristics may be a good predictor for non-motorized travel, but the absence of characteristics of specific destinations visited by the respondents may constrain our understanding of the relationship between the built environment and auto travel. Second, the nonwork travel analyzed here is not comprehensive, and the retrospective trip frequencies obtained are not exact numbers but approximates. Nevertheless, it offers some insights into the relationship between the built environment and nonwork travel behavior.

This study shows that neighborhood characteristics are associated with individuals' travel decisions, especially non-motorized travel frequency. We found that having mixed land uses tends to dampen auto travel and facilitate the use of transit and non-motorized modes; the availability of transit service and walking/biking infrastructures are important predictors for transit and non-motorized travel; and walking/biking behavior is also affected by the aesthetic quality and social context of the built environment. All these associations are present even after accounting for the influences of residential preferences and travel attitudes. Therefore, although this study does not definitely confirm causality between the built environment and travel behavior, it strongly suggests that the built environment itself influences individuals' travel behavior. On the other hand, residential self-selection does play an important role in influencing individuals' travel decisions, given the pervasive presence of travel attitudes and residential preferences in the model. In addition, the displacement of objective or perceived neighborhood characteristics by the similar/same aspects of neighborhood preferences provides strong evidence for the argument that residential choice is endogenous to a model of travel behavior.

In addition, this study relaxes the assumption adopted in most studies, of independence for unobserved characteristics affecting the frequency of using different travel modes. We found significant but weak correlations among the error terms for different modes. Therefore, although the seemingly unrelated regression model is more efficient than the separate regression models, the efficiency gain achieved here is not likely to be substantial.

5. THE BUILT ENVIRONMENT AND AUTOMOBILE CHOICE

In this chapter, we study the relationship between the built environment and automobile choice. As discussed in Section 2.2.3, understanding the influence of the built environment on auto ownership is essential to explore the causal link between the built environment and travel behavior, especially driving.

Land use policies have recently been used as a strategy to improve air quality (Liu, 2003). One cause of worsening air quality is the increasing share of light-duty trucks (LDTs, including minivans and pickup trucks as well as sport utility vehicles (SUVs)) in the passenger vehicle fleet due to the differential fuel efficiency and emissions standards between passenger cars and LDTs. According to the 2004 Fuel Economy Guide (www.fueleconomy.gov), for example, on average a 2WD Ford F150 (a pickup truck) consumes 35% more gasoline per mile than a Ford Taurus (a passenger car), and produces 30% more greenhouse gases and 200% more air pollutants. To improve air quality, therefore, it is also important to understand whether and how the built environment influences vehicle type choice.

5.1 Auto Ownership

Auto ownership is a critical mediating link in the connection between the built environment and travel behavior: the built environment presumably influences auto ownership, which in turn impacts travel behavior. However, the way in which individual elements of the built environment affect auto ownership choices is far from understood. Also, residential self-selection may confound the interaction between the built environment and auto ownership. The scarcity of longitudinal data further impedes our understanding of the causal relationship between the built environment and auto ownership. Cross-sectional analysis is sufficient to provide robust tests of the existence of a correlation between variables. However, both individuals' location choices and auto ownership choice are conditioned on their lifestyle choices with respect to family, employment, and leisure (Salomon and Ben-Akiva, 1983). Accordingly, this relationship could be largely spurious if some third variable – such as preferences – were a causal factor for both the built environment and auto ownership. A longitudinal study showing that changes in built environment characteristics are associated with changes in auto ownership (while controlling for socio-demographic changes that might also be a factor) will offer more direct evidence of a causal link from the built environment to auto ownership than cross-sectional analysis can (Finkel, 1995).

In this section, we investigate the causal relationship between the built environment and auto ownership using cross-sectional and quasi-longitudinal analyses. Specifically, this study tests Hypotheses 1, 2, and 3 and thus aims to address the following central questions: (1) What aspects of the built environment influence individuals' decisions on auto ownership? (2) Do changes in built environment characteristics lead to changes in auto ownership? (3) Does residential self-selection impact individuals' auto ownership choices? (4) If there is an apparent influence of the built environment on auto ownership, does residential self-selection account for all of it?

5.1.1 Variables

The dependent variables are household auto ownership level and changes in auto ownership measured as number of vehicles. In the survey, respondents were asked to report their household vehicles available for daily use and (only for movers) to recall the number of vehicles they had just before their residential relocation. Table 23 presents an overview of auto ownership and changes in auto ownership. On average, households living in suburban neighborhoods own 0.14 (9%) more vehicles, but also have 21% more people in the household. In the cross-sectional analysis, four vehicles and five or more vehicles are recoded as three or more vehicles due to the limited number of observations in these two categories.

Table 23. An Overview of Auto Ownership and Changes in Auto Ownership

	Category	Traditional	Suburban
Observations		898	784
	0	4.8%	3.6%
	1	42.8%	36.7%
Auto ownership [a]	2	40.8%	44.8%
	3	9.0%	10.8%
	4	2.0%	3.2%
	5+	0.6%	0.9%
	Average [b]	1.62	1.76
Observations		292	386
	Decrease	19.4%	18.8%
Changes in auto ownership	Constant	67.6%	68.8%
(Movers only)	Increase	13.0%	12.4%
	Total	386	292

a. Differences between neighborhood types significant at the 0.05 level (χ^2 test).
b. Differences between neighborhood types significant at the 0.01 level (t test).

More than two-thirds of movers in both types of neighborhoods kept their auto ownership unchanged after residential relocation. Many who changed auto ownership, of course, did so for reasons unrelated to their new neighborhoods. Only 49 (7.4% of) movers explicitly responded that they changed auto ownership owing to the characteristics of their current residential neighborhood, and 49 movers considered getting another vehicle or getting rid of a vehicle for the same reason. For 59 (60%) of those 98 cases, the actual or considered changes were in the expected direction (e.g. they increased vehicle ownership after a move to a suburban area), but the remaining 40% were counter to the expected direction. Overall, there was no significant difference in the distribution of responses between those moving to traditional neighborhoods and those moving to suburbs (neither for the 98 alone, nor for the entire sample of movers), and so the descriptive statistics suggest that the apparent overt impact of a change in built environment on a change in auto ownership is relatively minor. However, the multivariate static score model may modify this conclusion after confounding factors are controlled for.

The explanatory variables are those regarding neighborhood characteristics, neighborhood preferences, travel attitudes, and socio-demographics. Although variables related to travel behavior were measured in the survey, they are not used in this study. In the near term, travel behavior is conditional on auto ownership (Ben-Akiva and Atherton, 1977), and an apparent influence of travel behavior on auto ownership is likely to be a proxy for the influence of travel-related attitudes, which is directly taken into account in this study.

5.1.2 Analytical method

The multinomial logit (MNL) model is commonly used in auto ownership modeling at the disaggregate level (e.g., Purvis, 1994). The MNL model is a random utility model of individual choice among a set of alternatives, and requires an assumption of independence of irrelevant alternatives (IIA) (Ben-Akiva and Lerman, 1985). Accordingly, the MNL model treats auto ownership as an unordered categorical response.

Recently, several studies have employed ordered-response techniques to model auto ownership (Bhat and Pulugurta, 1998; Chu, 2002; Hess and Ong, 2002; Kitamura et al., 2001). In contrast to the MNL model, ordered-response models consider auto ownership level as an ordinal scale (Y = 0, 1, 2, …j, …, J). It assumes an underlying latent continuous variable, Y*, representing a household's propensity to own cars (Daykin and Moffatt, 2002). Y* is expressed in the following form:

$$Y^* = \beta' X + e, \tag{5-1}$$

where X is a vector of explanatory variables, β is a vector of parameters, and e is the unobserved error term. The relationship between the latent Y* and the observed Y is:

$$Y = j \text{ if } \mu_{j-1} < Y^* \leq \mu_j, \text{ j} = 0, 1, 2, ..., \text{J}, \tag{5-2}$$

where the μ_js are cut points or threshold parameters, defined as $\mu_{-1} = -\infty$, $\mu_J = +\infty$, and $\mu_{j-1} < \mu_j$ for all j. In the context of the ordered probit model, we assume $e \sim N[0, \sigma_e^2]$, and thereby obtain the following probabilities:

$$P(Y = j) = P(\mu_{j-1} < Y^* \le \mu_j) = \Phi(\frac{\mu_j - \beta' X}{\sigma_e}) - \Phi(\frac{\mu_{j-1} - \beta' X}{\sigma_e}) . \qquad (5\text{-}3)$$

where Φ denotes the standard normal CDF.

It is worth noting that Bhat and Pulugurta (1998) found MNL models to be superior to ordered models in terms of predictive adjusted likelihood ratio index, average probability of correct prediction, and non-nested hypothesis test. However, the IIA assumption cannot reflect the ordered nature of household auto ownership. The ordered probit model is adopted in this study due to its parsimonious model structure, although oversimplification may also be a concern.

We use a different approach for modeling changes in auto ownership for movers. As discussed previously, our data contain measurements of variables for each mover at time t and t-1. Thus, a causal model can be constructed and estimated based on quasi-longitudinal data. A variety of alternative specifications of the causal effect are available, modeling Y or ΔY as a function of X_{t-1}, X_t, ΔX, or some combination of these variables (Finkel, 1995). Specifically, the changes in auto ownership are expressed as a function of prior and current values of explanatory variables as well as the changes between them:

$$\Delta Y = Y_t - Y_{t-1} = \alpha_1' X_t + \alpha_2' X_{t-1} + \alpha_3'(X_t - X_{t-1}) + e . \qquad (5\text{-}4)$$

In reality, however, the inclusion of all three X terms on the right-hand side is over-specified and hence will result in collinearity. Therefore, on a variable-by-variable basis, at most two of the three measurements for each explanatory variable were included simultaneously when we calibrated the model using ordinary least squares (since ΔY could take on the nine integer values from –4 to 4, with several of those values containing few observations, we chose to treat the dependent variable for this model as quasi-continuous, and use the robust OLS approach).

5.1.3 Cross-sectional multivariate analysis

Using the software package Limdep 8.0, we developed two ordered probit models for auto ownership: Model 1, without attitudinal factors in the model specification, and Model 2, including attitudes. As shown in Table 24, ρ^2 for Model 2 is larger than that for Model 1. Since neither model is a nested or constrained version of the other, the non-nested hypothesis test was used to evaluate the performance of the two models (Ben-Akiva and Lerman, 1985). Specifically, if Model 1 (containing K_1 parameters) is the true model, the probability of finding a Model 2 (with K_2 parameters) having an adjusted ρ^2 z units greater is not larger than $\Phi\left\{-\left[-2z\, LL(C)+(K_2-K_1)\right]^{1/2}\right\}$ asymptotically, where Φ is the standard normal cumulative distribution function and LL(C) is the log-likelihood evaluated for a model with only a constant term and the threshold parameters (Bhat and Pulugurta, 1998). Thus, if that probability is small for Model 2, we reject the null hypothesis that Model 1 is correct. The test result indicates that Model 2 is significantly better than Model 1. Therefore, incorporating attitudes in the model significantly improves the model.

As shown in Model 1, household size, the number of household members within driving age (16-85), and the number of workers in the household each increase the propensity to own more vehicles. This indicates, not surprisingly, that household mobility needs are important in the auto ownership decision-making process, but it is interesting that three different measures of household size are simultaneously (highly) significant. The relative magnitudes of the three coefficients show that among them, the largest marginal impact on latent ownership propensity arises from simply being of driving age, with smaller additional incremental impacts for each worker and non-driver in the household.

Table 24. The Ordered Probit Models for Auto Ownership

Variables	**Model 1: Excluding Attitudes**			**Model 2: Including Attitudes**		
	β	**Std. β [a]**	**p-value**	**β**	**Std. β [a]**	**p-value**
Constant	0.685	2.492	0.000	0.653	2.538	0.000
Socio-demographics						
Female	-0.207	-0.103	0.000	-0.195	-0.100	0.002
HH income ($k)	0.00844	0.305	0.000	0.00817	0.295	0.000
HH size	0.0828	0.0982	0.014	0.0786	0.0932	0.023
# of driving-age HH members	0.588	0.450	0.000	0.617	0.472	0.000
# of workers in the HH	0.147	0.125	0.000	0.136	0.115	0.001
Limitations on driving	-1.360	-0.167	0.000	-1.192	-0.147	0.000
Limitations on taking transit	0.473	0.0705	0.010	0.323	0.0482	0.085
Home renter	-0.254	-0.122	0.000	-0.269	-0.129	0.000
Neighborhood characteristics						
Outdoor spaciousness	0.0699	0.0649	0.044			
# of business types w/in 400 m	-0.0246	-0.0572	0.081			
Neighborhood preferences						
Accessibility	-		-	-0.102	-0.0954	0.004
Outdoor spaciousness	-		-	0.0871	0.0800	0.015
Travel attitudes						
Car dependent	-		-	0.0977	0.0967	0.002
Safety of car	-		-	0.0980	0.0974	0.004
Threshold parameter 1	2.240	2.240	0.000	2.290	2.290	0.000
Threshold parameter 2	3.940	3.940	0.000	4.000	4.000	0.000
Number of observations		1495			1495	
Degrees of freedom (K)		10			12	
Log-likelihood at constant (LL(C))		-1639.7			-1639.7	
Log-likelihood at convergence (LL(β))		-1305.6			-1292.1	
ρ^2 (1-LL(β)/LL(C))		0.204			0.212	
Adjusted ρ^2 (1-[LL(β)-K]/LL(C))		0.198			0.205	
Non-nested test result [b]			Φ (-5.002) = 0.000000284			

a. Dependent variable and constant term were not standardized.

b. The statistic is $\Phi\left\{-\left[-2z\,LL(C)+(K_2-K_1)\right]^{1/2}\right\}$, where z = [adjusted ρ^2 (Model 2) - adjusted ρ^2 (Model 1)].

The model also shows that individuals who are lower-income have a lower latent propensity for vehicle ownership, as expected. Those having constraints on driving have a lower propensity for vehicle ownership, while individuals who are limited or prevented from using transit have a higher one. Home renters have a lower propensity for vehicle ownership. This is plausible since in this dataset home renters are more likely than owners to be lower income, and to live with fewer household members, but it is interesting that the variable appears in addition to those others. This suggests that there is something beyond the raw socio-demographic traits for which being a renter is a marker – perhaps indicating a lifestyle in transition, or a philosophy of accumulating fewer material possessions (cars as well as homes). Female respondents tend to have lower vehicle ownership propensities. In this dataset, being female is associated with households having lower income, a smaller number of workers, and a smaller number of driving-age members. Therefore, gender is likely to be a proxy for these and related household characteristics and offers additional explanatory power to the model.

Individuals' neighborhood characteristics have associations with their auto ownership decisions. The perception of outdoor spaciousness, in the form of large yards and off-street parking, typical characteristics of suburban neighborhoods, is related to higher propensities. Conversely, the objective number of business types within 400 meters of the residence negatively affects auto ownership, which suggests that mixed land uses make it easier for residents to own fewer vehicles.

However, the effects of the spaciousness factor and land use mix indicator on auto ownership are marginal. Among the variables significant in the model, they are the least important according to the standardized coefficients. In contrast, socio-demographics show a strong influence on auto ownership. This pattern suggests that auto ownership is heavily determined by socio-demographic characteristics, especially household structure and income.

When residential preferences and travel attitudes are taken into account, as shown in Model 2, the perceived spaciousness and land use mix indicator become insignificant (specifically, the p-values for these two variables, if retained, would be 0.215 and 0.351, respectively); instead, preferences for spaciousness and accessibility enter the model, with the expected signs. Therefore, the effects of actual (perceived or objective) neighborhood characteristics on auto ownership seen in Model 1 are likely to be proxies for the preferences for those neighborhood characteristics. This result lends credible support to the speculation that residential self-selection explains correlations between the built environment and auto ownership. Travel attitudes also influence auto ownership. Those who think their daily activities are dependent on vehicles and who consider the car to be a superior mode in terms of safety have a higher ownership propensity.

A comparison of standardized parameter estimates shows that socio-demographic characteristics are the most important determinants of auto ownership propensity even after incorporating attitudinal factors in the model. Each attitudinal factor alone has only a marginal effect on the decisions of auto ownership. However, the extensive presence of residential preferences and travel attitudes in the model implies that attitudes may collectively play an important role in individuals' auto ownership behavior.

5.1.4 Quasi-longitudinal multivariate analysis

Because we wanted to isolate the effects (if any) of changes in the built environment on changes in auto ownership, we estimated the quasi-panel model for movers only. In contrast to the previous case, here the addition of attitudinal variables did not affect the inclusion of any of the other variables in the model, so we present only the single final model, including attitudes, in Table 25.

Among various categories of determinants of auto ownership, socio-demographic characteristics are the most important because of their extensive presence in the model and their large standardized coefficients. In particular, changes in vehicle ownership are positively associated with changes in income, changes in the number of driving-age members, and changes in the number of children under 5 years old. Older people tend to reduce their number of vehicles. Ultimately, these findings reinforce the argument that socio-demographics are the fundamental determinants of auto ownership, and that the built environment works at best as a facilitator or a constraint.

Table 25. The Static-Score Model for Changes in Auto Ownership (movers only)

Variables	β	Std. β	p-value
Constant	0.00654		0.953
Socio-demographics			
Changes in household income ($k)	0.00147	0.161	0.000
Changes in # of driving-age HH members	0.244	0.272	0.000
Changes in # of kids (<=5)	0.167	0.0705	0.069
Current age	-0.00606	-0.106	0.007
Neighborhood characteristics			
Changes in outdoor spaciousness	0.0807	0.0217	0.000
Current Dist. to nearest fast food (km)	0.114	0.0838	0.033
Neighborhood preferences			
Outdoor spaciousness	-0.105	-0.120	0.003
Number of observations	551		
R-square	0.197		
Adjusted R-square	0.187		

Residential preference affects changes in auto ownership. Those preferring large yards and off-street parking tend to reduce their auto ownership, probably because they have owned a larger-than-average number of vehicles before moving. Compared to Model 2 of Table 24, the relative absence of attitudinal factors indicates that this panel model is effective at controlling for some individual permanent effects resulting from unchanging explanatory variables. Of course, those unchanging variables can include not just attitudes, but other characteristics both measured, such as gender (note that gender is significant to the level of auto ownership in Table 24, but not to the change in number of autos in Table 25), and unmeasured, such as lifestyle indicators.

Changes in perceived spaciousness are positively related to changes in auto ownership. In addition, individuals living in high-accessible areas (i.e., having shorter distances to activity opportunities) tend to reduce their auto ownership, presumably because they are more likely to be able to conduct their daily activities with one fewer vehicle. Since the changes in auto ownership were measured after residential relocation and attitudes are controlled for, we can more confidently conclude that there is a causal effect from built environment characteristics to auto ownership. However, these effects are marginal in terms of the size of standardized coefficients.

5.1.5 Summary

Communities throughout the US are turning to compact development, neotraditional design, and smart growth in the hope of reducing auto dependence. As an intermediating bridge, auto ownership plays an important role in the interactions between the built environment and travel behavior: auto ownership influences travel behavior and the built environment may influence auto ownership. Simply treating auto ownership as an exogenous socio-demographic trait in practice may result in endogeneity bias and hence threaten the validity of parameter estimates of models that link the built environment and travel behavior. However, the connection between the built environment and auto ownership has not received much attention from researchers and planners. This study describes an effort to investigate their causal link by applying cross-sectional and quasi-longitudinal analyses.

The assumption that attitudes remained stable before and after the move should be tested with a true panel, providing data on their attitudes in real time, across multiple waves including residential relocations. In the present study, it is possible that changes in the built environment are confounded with unmeasured changes in attitude. That is, perhaps it is in fact changes in tastes that prompted a change in the built environment, and it is those preference changes rather than the built environment changes per se that are influencing auto ownership in the static-score model.

Our results, however, contribute to answering the four questions posed at the beginning of this section. With respect to question 1, we first find dominant influences of socio-demographics on auto ownership, suggesting that households' auto ownership decisions are primarily dependent on their mobility needs and purchasing power. The persistence of ownership may be a further factor, since a vehicle, once acquired, is not readily discarded. Given the relatively low operating costs of vehicles, we cannot expect that changes in the built environment will greatly change individuals' auto ownership.

Built environment elements do affect household auto ownership levels, but the effects are marginal. First, a cross-sectional model confirms that neighborhood characteristics have some association with auto ownership, controlling for socio-demographics. Specifically, perceived spaciousness is positively associated with auto ownership propensity, while the number of business types within 400 meters of the residence is negatively related to that propensity. Therefore, it appears that more space and homogeneous land uses tend to increase auto ownership. However, the inclusion of preference factors pushes those neighborhood characteristics out of the model, suggesting that attitudes are more strongly associated with auto ownership than are built environment elements per se. Further, the displacement of neighborhood perception by preferences for the same aspect provides evidence for the argument that the observed correlation between the built environment and auto ownership is a consequence of residential self-selection (question 3).

In contrast, the results of the panel model indicate the existence of a causal relationship between changes in the built environment and changes in auto ownership (question 2), even after accounting for attitudes: increases in perceived spaciousness (such as large yards and off-street parking) are associated with increases in auto ownership, and current access to local businesses is related to decreases in auto ownership. According to the former association, this study demonstrates that changes in the outdoor spaciousness of one's neighborhood will lead to changes in auto ownership. This effect is moderate in terms of its standardized coefficient, but the significance of these two variables suggests that residential self-selection does not account for all influences of the built environment on auto ownership (question 4). Therefore, this study provides encouraging evidence that land use policies designed to reduce auto ownership and auto use (especially, limited space and high accessibility) will lead to a marginal reduction in auto ownership.

While individuals' attitudes and the built environment both influence auto ownership decisions, it is possible that the built environment also plays an additional indirect role by influencing these attitudes over time. Living in a suburban-style development, for example, may foster the formation of an auto-oriented lifestyle along with attitudes that favor the car. Conversely, it is possible that attitudes that favor the car can be altered over time through the implementation of neighborhood design strategies that increase the attractiveness of alternatives to driving. Without changes to suburban-style development, attitudes towards auto dependence and auto-oriented development are unlikely to change, for this generation or the next. Although we cannot test these possibilities with the data used in this study, our results point to the importance of additional research that will help us to better understand the complex interactions between attitudes, the built environment, and auto ownership.

5.2 Vehicle Type Choice

A few recent studies have found that suburban development is associated with the unbalanced choice of LDTs. For example, an analysis of the 1995 Nationwide Personal Transportation Survey (NPTS) showed that suburban residents own a disproportionate share of LDTs (Niemeier et al., 1999). After examining data from the San Francisco Bay Area, Bhat and Sen (2006) found that households living in denser areas are less inclined to drive SUVs and pickup trucks. However, these studies seldom reveal which specific characteristics of the built environment matter to vehicle type choice. Further, they have not shed much light on the underlying direction of causality: in particular, whether neighborhood designs themselves, as opposed to preferences for neighborhood characteristics or attitudes towards travel, more strongly influence individuals' decisions regarding vehicle type. The available evidence thus leaves unanswered questions: if policies encourage more compact development, will more people choose to drive passenger cars over LDTs, with a corresponding benefit to air quality?

In this section, we investigate the role of the built environment in vehicle type choice. In particular, it tests Hypothesis 2 and thus aims to address the following questions: (1) What aspects of the built environment influence vehicle type choice? (2) Controlling for socio-demographic traits, what is the role of residential preferences and travel attitudes in vehicle type choice? Answering these questions helps us answer the ultimate question of interest: Can land use policies contribute to air quality improvement by influencing vehicle type choice?

5.2.1 Background

A number of studies have investigated households' or individuals' vehicle type choices (e.g., Beggs and Cardell, 1980; Berkovec and Rust, 1985). Their main interests focused on vehicle attributes (such as purchasing and operating costs, horsepower, and scrappage) and household characteristics (such as household structure and income), in order to identify the factors that impact consumers' vehicle-purchasing or holding behavior. These studies highlighted that households' socio-demographics are primary determinants of their vehicle type choices. Further, it was found that vehicle type choice strongly depends on drivers' travel attitudes, personality, and lifestyle (Choo and Mokhtarian, 2004). However, whether the built environment provides an incremental contribution to vehicle choice has seldom been explored.

A few recent studies have pointed to this question. A correlational analysis found that the percentage of households with LDTs decreases as residential density increases in the 2001 National Household Transportation Survey (NHTS) data (Golob and Brownstone, 2005). However, this relationship may be confounded by socio-demographics. For example, more affluent households may choose to live in large-lot houses in suburban neighborhoods and drive SUVs at the same time. Using the 1995 NPTS data, Kockelman and Zhao (2000) found that LDTs were more often driven by households living in lower density areas, after accounting for the influences of socio-demographics. On the surface, these findings seem to suggest that the built environment influences vehicle type choice, with traditional neighborhood residents favoring passenger cars and suburban residents favoring LDTs. Therefore, suburban development might be further blamed for its contribution to the disproportionate growth of low-efficiency and high-emission LDTs.

However, researchers recognize that density is a coarse measure of the built environment due to its high correlation with other neighborhood characteristics such as parking and transit service, and hence its theoretical connection with travel choice is not clear (Handy, 2005). Thus, what is it about suburban development that results in choices of LDTs? Low accessibility? Segregated use? Availability of space for parking? All of these, none of these, or some combination? Without an understanding of what the influential characteristics are, policy makers and city planners have little guidance on how to potentially affect vehicle choice through the built environment. Therefore, it is important to address how individual elements of the built environment and their integration might influence vehicle choice, rather than simply comparing the impacts of traditional and suburban developments. Kitamura et al. (2001) found that accessibility (as well as various density measures) influences vehicle type choice in the Los Angeles metropolitan area, controlling for socio-demographics. Specifically, auto accessibility has a negative association with choosing sport cars, transit accessibility is negatively associated with the choice of SUVs, and sedans are less likely to be chosen in areas where public transit is not available. However, what are the underlying mechanisms by which accessibility and other neighborhood characteristics affect vehicle type choice? The limited number of studies conducted to date have not fully enlightened our understanding of the relationships between the built environment and vehicle type choice.

Further, it is not clear whether the observed associations can be attributed to the influence of living in an urban area on the decision to buy a passenger car, or to a correlation between preferences for passenger cars and preferences for urban environments, or the combined effects of these two factors. Previous studies have found associations between the built environment and vehicle type choice. However, an association does not mean a causal relationship. To infer causality, scientific research generally requires at least three kinds of evidence: association, time precedence, and nonspuriousness (Singleton and Straits, 2005). Given cross-sectional data, however, it is hard to determine time precedence. A nonspurious relationship between variables refers to an association that cannot be explained by an antecedent variable. In this context, some variables such as attitudes and socio-demographics are probably causal factors for the choices of both the built environment and vehicle type (Figure 11). Therefore, the observed correlations between the built environment and vehicle type choice may be partially spurious, caused by the antecedent variables. Empirically, Choo and Mokhtarian (2004) found that those preferring denser neighborhoods were more likely to drive passenger cars (but also SUVs), lending at least some support to the self-selection speculation. To establish nonspuriousness, an appropriate strategy is to examine the effects of the built environment, controlling for antecedent variables. Therefore, incorporating attitudinal factors in addition to socio-demographics in the model will help clarify the relationships between the built environment and vehicle type choice.

5.2.2 Variables and hypotheses for neighborhood characteristics

The dependent variables are the possible categories for the vehicle that a respondent drove most frequently. These vehicles were classified into four categories: passenger car, minivan, SUV, and pickup truck, based on reported make, model, and year combinations. In this study, we will for convenience refer to the latter three categories collectively as LDTs, to reflect their (generally) larger size, lower fuel economy, and higher emissions relative to passenger cars. As shown in Table 26, there are some distinctions in vehicle type choice between traditional and suburban neighborhoods – residents living in suburban neighborhoods more frequently drive minivans and pickup trucks. On the other hand, contrary to Kitamura et al. (2001), there is no difference in the share of SUVs between traditional and suburban neighborhoods. The explanatory variables are those regarding neighborhood characteristics, neighborhood preferences, travel attitudes, and socio-demographics.

Figure 11. Potential Relationships between the Built Environment and Vehicle Type Choice

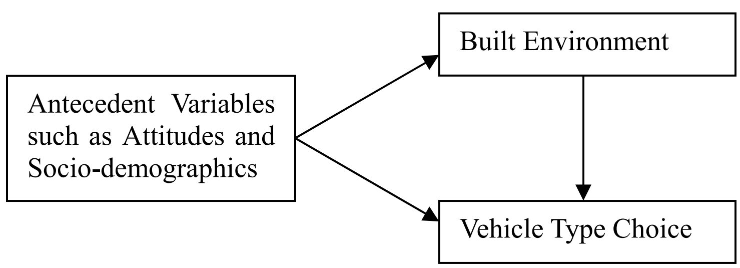


Table 26. Vehicle Type Choice in Traditional and Suburban Neighborhoods

Neighborhood Type	**Vehicle Type**				**p-value**
	Car	Minivan	SUV	Pickup	(χ^2 test)
Suburban	472 (66.1%)	56 (7.8%)	94 (13.2%)	92 (12.9%)	
Traditional	576 (70.8%)	37 (4.6%)	108 (13.3%)	92 (11.3%)	0.032

Socio-demographic variables (e.g., income and household size) are widely understood to affect vehicle type choices, and attitudes, although less often measured, are also expected to affect them. In addition to socio-demographics and attitudes, we hypothesize that the built environment further contributes to explaining variations in vehicle type choice. However, since the survey was originally developed to explore the relationship between the built environment and travel behavior, not all neighborhood characteristics presented above have meaningful connections with vehicle type choice. For example, neighborhood attractiveness is a good predictor for pedestrian travel (see Section 4.2), but it may have nothing to do with vehicle choice. For this study, we speculate that vehicle type choice is influenced by outdoor spaciousness and commute distance, and that the various measures of accessibility (including land use mix and number of opportunities) are proxies for other factors.

Compared to passenger cars, a larger space is generally required to accommodate LDTs. Therefore, we assume that outdoor spaciousness has a positive association with LDT choices. Specifically, off-street parking is more able to accommodate large vehicles; the driveway associated with large front yards and large back yards (if rear parking) offers a common alternative to park LDTs. Commute distance is hypothesized to have the potential to influence vehicle type choice. In contrast to most non-work activities, the commute is a necessary and spatially constrained trip for workers. A long commute may encourage individuals to use a more fuel-efficient vehicle (passenger car), or conversely it may encourage individuals to buy a larger vehicle which they perceive to be safer and/or more comfortable.

Lower accessibility and segregated uses are assumed to be associated with the choice of LDTs. In particular, living in a lower-accessibility area can be a surrogate for larger lot and housing sizes, and people living in such an area may have more of a need for LDTs owing to larger gardens and greater home improvement demands. This association between lower accessibility and choice of LDT may also be due in part to the higher proportion of home ownership in such neighborhoods (given that home owners are more likely to conduct improvement projects than renters are), although home owners in higher-accessibility as well as lower-accessibility neighborhoods may require a larger-capacity vehicle. Further, towing is one of the fundamental functions of pickup trucks and SUVs, and they are advertised as powerful vehicles operating in rugged environments. Therefore, residents in lower-accessibility (although more especially rural) areas may be more likely to choose those vehicles, with residential location serving partly as a proxy for attitudes, and partly as an indicator of greater need for such a vehicle.

5.2.3 Correlational analyses

One-way ANOVA was used to identify significant differences among the four vehicle categories at the 0.05 level. Once we found the existence of significant differences, Bonferroni pairwise comparison tests were used to further identify which categories are significantly different from other categories.

As shown in Table 27, drivers of different categories of vehicles live in areas with different neighborhood characteristics. First, as expected, accessibility (measured in several different ways) is related to vehicle type choices. Vehicle type choices are significantly associated with the number of business types, maintenance, leisure, and eat-out businesses within 800 meters of the residence. The Bonferroni test suggests that compared to minivan and pickup drivers, passenger car drivers are more likely to live in high-accessible areas. On average, passenger car drivers live closer to various types of businesses than do the drivers of one or more LDT categories. Also, passenger car drivers tend to perceive a higher accessibility than pickup drivers. Second, also as hypothesized, SUV and pickup drivers are more likely to live in areas with large yards and off-street parking than are passenger car drivers. In addition, SUV and pickup drivers tend to live farther from their employment locations than do passenger car drivers. This finding is opposite to our expectation with respect to the choice of more fuel-efficient vehicles, but consistent with other evidence associating minivan and pickup drivers with suburban locations, which in turn are associated with longer commutes. Generally, most differences observed in the built environment are between passenger cars and LDTs, especially minivans and pickup trucks. These results suggest that minivans and pickup trucks tend to be associated with a suburban culture while SUVs fit both urban and suburban cultures.

However, the causality between the built environment and vehicle type choice is not straightforward. It is possible that self-selection is at work. A further examination of attitudinal factors somewhat supports this argument. To begin with, when looking for a place to live, LDT drivers think that large yards and off-street parking are more important than do passenger car drivers. That is, these drivers may have preferred more space to accommodate their large LDTs and may have consciously chosen such a residence. Further, travel attitudes influence vehicle type choice. SUV drivers are more likely to prefer walking and biking than are passenger car drivers, while pickup drivers have less favorable views of public transit as a mode of transport. SUV and pickup drivers are more likely than others to believe that a car is safer than other modes of transportation. In addition, passenger car drivers have a greater tendency to minimize their travel than do pickup drivers. These results suggest that attitudes may play a more direct role in the choice of LDTs than does the built environment.

Table 27. One-way ANOVAs for Vehicle Type Choice

Variables	Car	Minivan	SUV	Pickup	p-value
Objective characteristics					
# business types w/in 800 m	6.00 [Van, Pickup] [a]	4.44 [Car]	5.57	5.02 [Car]	0.000
# maintenance businesses w/in 800 m	2.48 [Van]	1.66 [Car]	2.22	2.23	0.009
# leisure businesses w/in 800 m	3.01 [Pickup]	2.40	2.55	2.14 [Car]	0.016
# eat-out businesses w/in 800 m	2.97 [Van, Pickup]	1.91 [Car]	2.67	2.34 [Car]	0.000
Distance to nearest post office (km)	2.73 [Van, Pickup]	3.26 [Car]	2.88	3.13 [Car]	0.002
Distance to nearest bank (km)	0.93 [Pickup]	1.00	0.93	1.06 [Car]	0.005
Distance to nearest fast food (km)	1.03 [Van]	1.21 [Car]	1.09	1.10	0.018
Distance to nearest pizza (km)	0.82 [Pickup]	0.89	0.85	0.92 [Car]	0.037
Distance to nearest ice cream (km)	1.35 [Van]	1.63 [All types]	1.29 [Van]	1.31 [Van]	0.012
Distance to nearest pharmacy (km)	0.97 [Van] [b]	1.12 [Car] [b]	0.99	1.07	0.017
Distance to nearest bakery (km)	0.91 [SUV] [b]	1.04	1.02 [Car] [b]	1.01	0.007
Commute distance (miles)	9.23 [SUV, Pickup [b]]	10.23	13.12 [Car]	13.22 [Car] [b]	0.007
Neighborhood perceptions					
Accessibility	0.516 [Pickup] [b]	0.338	0.461	0.354 [Car] [b]	0.030
Outdoor spaciousness	0.029 [SUV, Pickup]	0.249	0.244 [Car]	0.290 [Car]	0.000
Residential preferences					
Outdoor spaciousness	-0.182 [All types]	0.328 [Car]	0.187 [Car]	0.238 [Car]	0.000
Travel attitudes					
Pro-walk/bike	-0.034 [SUV]	-0.103	0.175 [Car]	0.089	0.019
Pro-transit	0.008 [Pickup]	-0.108	-0.027	-0.280 [Car]	0.002
Safety of car	-0.042 [SUV, Pickup]	-0.030	0.182 [Car]	0.173 [Car]	0.003
Socio-demographics					
Household income ($k)	67.5 [SUV]	74.5	84.5 [Car, Pickup]	69.2 [SUV]	0.000
Household size	2.05 [Van, SUV]	3.38 [All types]	2.48 [Car, Van]	2.24 [Van]	0.000
Education	4.23 [Pickup]	4.25 [Pickup]	4.36 [Pickup]	3.75 [All types]	0.000

a. The vehicle types in brackets indicate categories whose means are significantly different from the mean of this category, at the 0.05 level if not otherwise indicated.
b. Significant at the 0.1 level.

Further, several socio-demographic characteristics are associated with vehicle type choice. Less-educated people have a higher probability of driving pickups than do their more highly-educated counterparts. Individuals with higher household incomes have a greater tendency to drive SUVs than passenger cars and pickups. Compared to the other three categories, minivans are more likely to be driven by larger households, and those in larger households are more likely to drive SUVs than passenger cars. In addition, chi-squared tests show that housing tenure and gender are significantly associated with vehicle type choices, with home renters favoring passenger cars and men favoring pickups. Since larger households are more prevalent in the suburbs and renters are more prevalent in traditional neighborhoods (as shown for these data by Table 4), it may be that the greater popularity of minivans in the suburbs and greater prevalence of passenger vehicles in traditional neighborhoods (shown in Table 26) are entirely due to socio-demographic factors rather than to the built environment per se.

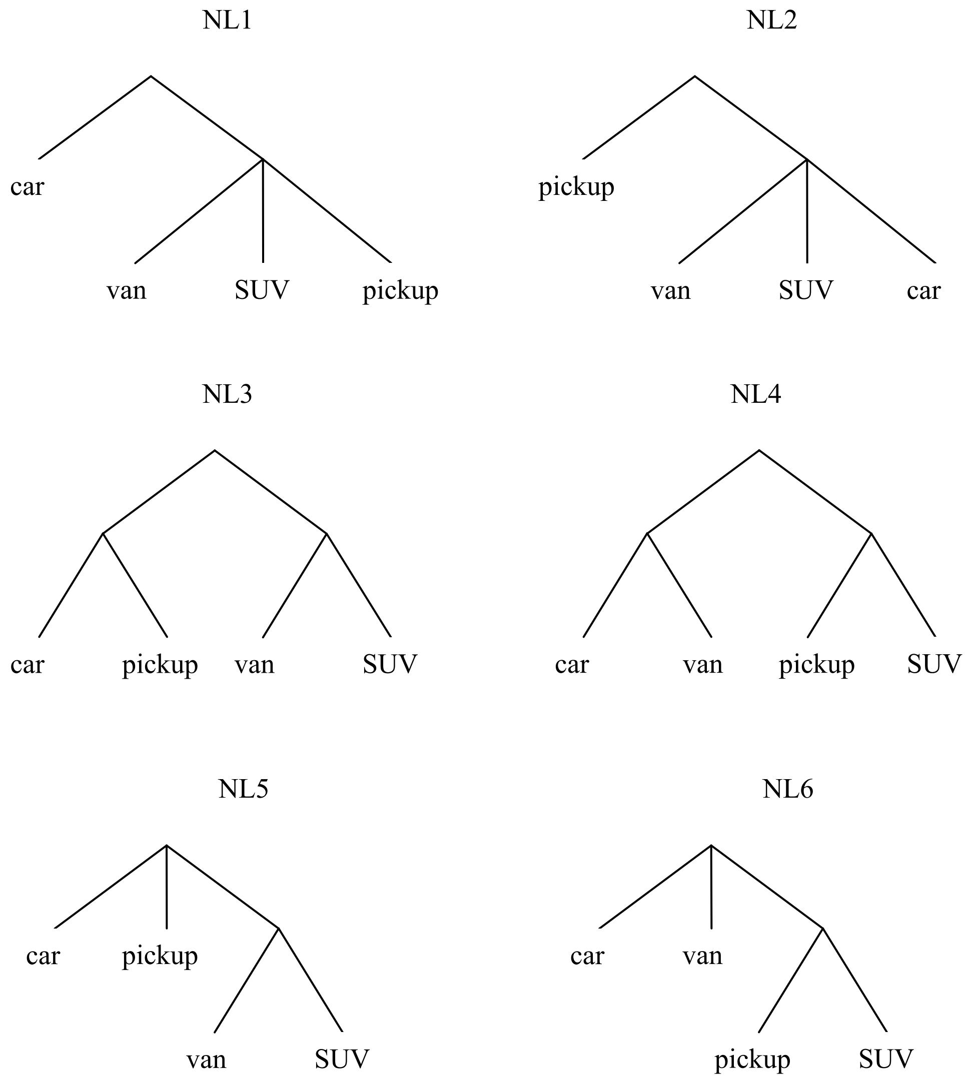
Given the existence of multiple confounded effects, it is hard to tell which effect is dominant through pairwise relationships alone. Accordingly, it is necessary to employ multivariate analysis to investigate the effects of the built environment on vehicle type choices, controlling for attitudes and socio-demographics.

5.2.4 Nested logit model

Since the dependent variable consists of four nominal categories and some categories share common characteristics, we attempted to estimate various nested logit (NL) models for vehicle type choice using Limdep 8.0 (Figure 12). The inclusive value (IV) parameters for most of these models were either outside the permitted range (i.e., greater than 1) or not significantly different from 1 (i.e., not different from the multinomial logit model). Initial structure NL4 performed the best, but its IV parameter for the pickup-SUV nest was not significantly different from 1 and hence that nest collapsed. The parameter for the car-van nest, however, was estimated at 0.299 and significantly different from 1, so it is that final structure whose model we present in Table 28. Since the fundamental function of both passenger cars and minivans is more to carry passengers than to carry goods, it is reasonable that these two vehicle types share the same nest. In fact, the correlation of unobserved variables for these two alternatives is very high at $1 - 0.299^2 = 0.91$. As shown in Table 28, the ρ^2 of the final model is 0.472, which is quite good for a disaggregate model involving four discrete choices. The χ^2 statistic, for the comparison of the full model to the market share model, is 266.4 and significant at less than the 0.001 level, indicating that the true variables significantly improve the model over one containing the constant terms alone.

Socio-demographic characteristics significantly affect vehicle type choice. Those who are more affluent and have more children under 18 years old in the household tend to drive SUVs. Men and people with less education are more likely to choose pickup trucks, consistent with Mohammadian and Miller (2003). Those owning more vehicles are also more likely to drive pickup trucks, suggesting that a pickup is often the second, third, or later vehicle acquired in order to diversify the household's transportation options. This result is consistent with Kockelman and Zhao (2000) and Golob and Brownstone (2005). As expected, individuals who are home owners and have more children under 18 years old are more likely to drive minivans. Perhaps surprisingly, age is positively associated with the choice of minivans; the mean age of minivan drivers (48.6) is highest among the four vehicle types. However, this result is consistent with other studies. In the Canadian Automobile Association's 2000 Auto Ownership Survey, the older age group had three minivans among the top 10 vehicles of their dreams, but no minivans were chosen in the top 10 by the younger respondents (Hunt, 2001). Anecdotal explanations for this pattern include the relative ease of getting in and out of a minivan for older people and images of minivans as boring among younger people.

Figure 12. Nested Logit Model Structures Tested



Attitudinal factors play an important role in influencing vehicle type choice. Individuals who prefer living in less accessible areas are more likely to drive minivans and pickup trucks, and those preferring large yards and off-street parking have an inclination for all three types of LDTs. Interestingly, a preference for walking and biking is positively associated with the choice of SUVs and pickup trucks. It is possible that this association results from a preference for outdoor activities of various kinds, which is linked to both a preference for SUVs and pickups and a preference for walking and biking. Further, those vehicle types may be consciously chosen for their capacities to carry cycling, hiking, and camping gear. In any case, this result offers an intriguing paradox in view of the stereotype that walking and biking are good for the environment, while SUVs and pickup trucks are the most fuel-inefficient and polluting of personal vehicles.

Table 28. Nested Logit Model for Vehicle Type Choice (base alternative: passenger car)

Variables	**Coefficients**		
	Minivan	SUV	Pickup
Constant	-1.383 [0.000]	-2.884 [0.000]	-0.664 [0.081]
Socio-demographics			
Home owner	0.202 [0.077]		
Number of kids (<18)	0.296 [0.000]	0.296 [0.000]	
Age	0.009 [0.016]		
Household income ($k)		0.012 [0.000]	
Female			-1.313 [0.000]
Education			-0.303 [0.000]
Number of vehicles			0.233 [0.038]
Neighborhood preferences			
Accessibility	-0.106 [0.013]		-0.106 [0.013]
Outdoor spaciousness	0.176 [0.001]	0.176 [0.001]	0.176 [0.001]
Travel attitudes			
Pro-bike/walk		0.287 [0.000]	0.287 [0.000]
Pro-transit			-0.423 [0.001]
Safety of car		0.331 [0.000]	
Neighborhood characteristics			
Outdoor spaciousness			0.199 [0.060]
Commute distance (miles)		0.008 [0.018]	
IV parameter		0.299 [0.000]	
Number of observations		1387	
Log-likelihood at 0: LL(0)		-2238.4	
Log-likelihood at constants: LL(C)		-1331.5	
Log-likelihood at convergence: LL		-1198.3	
Model improvement χ^2 = -2[LL-LL(C)]		266.4	
ρ^2 = 1-LL/LL(0)		0.472	
Adjusted ρ^2 = 1-(LL-18)/LL(0)		0.457	

Note: The number in brackets indicates the p-value for that coefficient.

By contrast, those who have positive attitudes toward public transit are less likely to choose pickup trucks. It is possible that this association is also spurious and results from a concern for the environment that is positively linked to a preference for transit and negatively linked to driving pickups, which get relatively poor gas mileage. Underlying differences in lifestyle between transit users and pickup drivers might also help to explain this association. In addition, people who think the car is a safer mode are more likely to drive SUVs. One selling point of the SUV is its safety: some studies have found that SUV drivers have a lower percentage of injuries in accidents with passenger cars (Ulfarsson and Mannering, 2004). However, SUVs may not be as safe even for their drivers as those drivers perceive them to be (Kweon and Kockelman, 2003), and they are more dangerous for occupants of other vehicles in an accident (Gayer, 2001).

After accounting for the influences of socio-demographic traits and attitudes, two neighborhood characteristics appear significant in the model. Individuals who live in areas with more space are more likely to drive pickup trucks (significant at the 0.1 level). This finding is consistent with our hypothesis, but the fact that a *preference* for more space has already been accounted for is important. The implication is that availability of parking space *itself* exerts some influence toward choosing a pickup truck. Further, workers living farther from their employment locations are more likely to drive SUVs. It is worth noting that none of the accessibility measures appear in the model when housing tenure, spaciousness, and attitudes are controlled for. This result supports our speculation that their relationships with vehicle type choice are primarily spurious. Given the extensive influence of socio-demographics and attitudinal factors, however, we cannot expect that the built environment will heavily determine vehicle type choice; suburban development at most facilitates LDT choices.

5.2.5 Summary

This section explores the influences of the built environment on vehicle type choice. Correlational analyses showed that the built environment has a strong association with vehicle type choice. Specifically, traditional neighborhood designs (exhibiting high accessibility and mixed use) are correlated with the choice of passenger cars, while suburban designs (including large yards and off-street parking) are associated with the choice of LDTs, especially minivans and pickup trucks.

However, the relationships between the built environment and vehicle type choice are confounded by the significant influences of attitudinal and socio-demographic factors: the disproportionate representation of LDTs in suburban neighborhoods is to some extent a result of preferences for suburban environments and the disproportionate representation in the suburbs of the demographic characteristics associated with the choice of LDTs.

The NL model controls for these other influences, and shows that both attitudinal and socio-demographic factors play important roles in vehicle type choice. Number of children, age, income, and gender are significant in the generally-expected ways, as are home ownership, education, and number of vehicles in the household. With respect to attitudes, those who value parking space or devalue accessibility in their residential choice are more likely to drive LDTs; safety of car and pro-walk/bike factors are positively associated with the choice of one or more LDT categories; but individuals favoring public transit have a disinclination for pickup trucks.

Nevertheless, after controlling for attitudinal factors and socio-demographic variables, we found that outdoor spaciousness (a factor based on yard sizes and off-street parking availability) and commute distances were significant. Thus, the built environment appears to play a separate, though modest, role in vehicle type choice: suburban development itself has an incremental impact on encouraging the acquisition of LDTs and hence contributes to the deterioration of air quality. Given the fact that LDT owners drive more miles, on average, than do passenger car drivers (as shown in our data as well as by Kockelman and Zhao, 2000), this contribution is compounded.

Further research, however, should explore in more detail the process by which the built environment exerts an influence of its own on vehicle type choice. One promising approach is to study vehicle transactions after a residential relocation. Changes in vehicle holdings may not happen instantaneously, but they may well happen at natural decision points within a few years of a move. For example, the move from renting an apartment in an urban neighborhood to buying a home in the suburbs may eventually, if not immediately, precipitate the acquisition of a pickup truck for hauling home improvement materials. Conversely, the move from a spacious suburban home to an apartment in a high-density neighborhood may make that pickup seem out of scale and lead one to trade it in for a smaller, more maneuverable automobile. Of course, such scenarios probably involve a number of confounding factors such as changes in income and stage in life cycle together with the residential move, and these must also be controlled for.

6. STRUCTURAL EQUATIONS MODELS

In Chapter 4, we examined the unidirectional causal link from the built environment to travel behavior. The quasi-longitudinal analyses provide supportive evidence for the argument that the built environment has a true direct influence on driving and walking behavior. However, these analyses are still not definitive, nor do they clarify the nature of the causal relationship. First, the built environment is, at least partially, endogenous to travel behavior. Although we took into account individuals' self-selection of the built environment by employing a quasi-longitudinal design and by controlling for residential preferences and travel attitudes, we did not model the influence of attitudinal factors on the choice of the built environment. Second, although auto ownership was treated as exogenous in Chapter 4, it is actually endogenous in the relationship between the built environment and driving behavior. The quasi-longitudinal analyses (Sections 5.1 and 4.1.2) show that changes in the built environment influence changes in auto ownership, which in turn affect changes in driving. Therefore, more sophisticated analyses of these data, namely structural equations modeling, will help to establish the strength and direction of the relationships among changes in the built environment, changes in travel behavior, changes in auto ownership, and other factors.

This chapter tests Hypothesis 4 and thus aims to address the following question: Are changes in the built environment associated with changes in travel behavior, after taking multiple interactions into account and controlling for socio-demographics, attitudes, and preferences? More specifically, are moves to environments where residents are closer to destinations and have viable alternatives to driving associated with a decrease in driving and/or an increase in walking? Although this chapter answers central questions similar to those in Chapter 4, the application of the structural equations modelling approach will establish the strongest inference of causality possible with the data. This approach overcomes the limitations mentioned above, which are intrinsic to previous approaches. First, the built environment is treated as endogenous by allowing potential factors to influence the choice of the built environment. Second, we treat auto ownership as a mediating variable connecting residential and travel choices. In this way, we are able to address multiple interactions among individuals' residential choice, auto ownership decision, and travel behavior.

It is worth noting that we are able to test Hypotheses 5 and 6 presented in Appendix A, using our cross-sectional data. However, we conducted only quasi-longitudinal SEMs in this chapter since a static SEM is inferior to a dynamic SEM in terms of causality inference. First, with cross-sectional data, it is hard to tell whether a residential choice precedes a travel choice or a travel choice precedes a residential choice. That is, we are less able to establish time precedence of a causal relationship between two choices. By contrast, if changes in the built environment and changes in travel behavior are present in longitudinal data, the former must precede the latter. Second, temporal mismatch in cross-sectional data is still a big concern. For example, attitudes measured in the present may differ from those leading to a residential choice made some time earlier. Accordingly, relationships among variables found in a cross-sectional analysis may not represent their true relationships. Although we did not measure changes in attitudes in our quasi-longitudinal data, we are still able to control for current attitudes as a cross-sectional SEM can do. More importantly, a longitudinal analysis controls for any observed and unobserved attitudinal variables that remain constant (0 change) over the same time period. Therefore, modeling the change in a given dependent variable is easier (produces better-fitting models, all else equal) than modeling its absolute level. Third, to accommodate all possible influences over time, we have to hypothesize complex simultaneous relationships among endogenous variables in a static SEM. A direct consequence of this complexity is that the SEM may be under-identified. In this case, we also have to constrain some coefficients to be zero to achieve model identifiability. These path manipulations may distort true relationships among variables, especially when the manipulations are short of theoretical support. On the other hand, the directions of influences among endogenous variables in a longitudinal SEM are much simpler. Therefore, a longitudinal SEM can produce more robust results than a cross-sectional SEM.

6.1 Model Framework, Specification, and Procedure

6.1.1 Model framework

Although SEMs can include latent endogenous variables (captured through the measurement of several related observed variables), the present application is restricted to the case where all endogenous variables are observed. Using the matrix notation in Mueller (1996), an SEM for observed variables can be defined as having the following form (where the case subscript is suppressed for simplicity):

$$Y = BY + \Gamma X + \zeta , \qquad (6\text{-}1)$$

where

$\mathbf{Y}$ = ($N_Y \times 1$) column vector of endogenous variables (N_Y = number of endogenous variables),

$\mathbf{X}$ = ($N_X \times 1$) column vector of exogenous variables (N_X = number of exogenous variables),

$\mathbf{B}$ = ($N_Y \times N_Y$) matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables,

$\mathbf{\Gamma}$ = ($N_Y \times N_X$) matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and,

$\boldsymbol{\zeta}$ = ($N_Y \times 1$) column vector of errors.

The two coefficient matrices $\mathbf{B}$ and $\mathbf{\Gamma}$ determine the structure of an SEM. In addition, a covariance matrix $\mathbf{\Phi}$ ($N_X \times N_X$) for exogenous variables X and a covariance matrix $\mathbf{\Psi}$ ($N_Y \times N_Y$) for error terms $\boldsymbol{\zeta}$ can be specified. The $\mathbf{B}$, $\mathbf{\Gamma}$, $\mathbf{\Phi}$, and $\mathbf{\Psi}$ matrices together establish an SEM for observed variables.

To estimate an SEM, **Σ**, the model-implied covariance matrix of observed variables **X** and **Y**, will be reproduced in terms of specific functions of unknown model parameters (namely, the **B**, **Γ**, **Φ**, and **Ψ** matrices). If specific values for the unknown parameters are inserted in these functions, a model-implied (reproduced) covariance matrix is obtained, and then the difference between this matrix and the observed (sample) covariance matrix **S** is calculated based on some criterion. A structural equations modeling program fits the specified model to the data by repeatedly inserting better and better estimates of these parameters until the difference between the reproduced and observed covariance matrices is optimally minimized in terms of some criterion. In view of the nature of the estimation process, the SEM is commonly referred to as covariance structure analysis. The goodness-of-fit of an SEM relies on how well its model-implied covariance matrix **Σ** conforms to its observed covariance matrix **S** (Raykov and Marcoulides, 2000).

6.1.2 Model specification

Model specification means that research hypotheses are expressed in the form of an SEM. In our study, we addressed two fundamental issues in this step. First, changes in travel behavior, changes in the built environment, and changes in auto ownership were selected as endogenous variables, based on the findings of Chapters 4 and 5 as well as previous studies. As discussed in Section 3.4, changes in auto ownership were measured by taking the difference between the reported number of vehicles after and before residential relocation (since the survey did not measure changes in auto ownership for nonmovers, only the movers subset of the data was analyzed); similarly, we measured changes in the built environment by taking the difference between perceived characteristics of the current and previous neighborhoods; changes in individuals' driving and walking behavior were measured on a 5-point scale from "a lot less now" to "a lot more now", compared to their behavior before the move.

Second, we set the presumed directions of influences. The directionalities of the presumed causal effects are important in a longitudinal study. As an example, changes in travel behavior after residential relocation are likely to be a result of changes in built environment characteristics, but the reverse direction seems to be implausible according to the temporal nature of influences. For endogenous variables, our assumed directions of influences are shown in Hypothesis 4: changes in the built environment affect both changes in auto ownership and changes in travel behavior, and the latter two changes influence each other. Further, we assumed that changes in all endogenous variables are additionally influenced by changes in socio-demographics (which were measured by taking the differences between individuals' characteristics after and before the move) and by attitudinal factors (which were assumed to be constant over the retrospective measurement period). Since the base values of (as well as the changes in) changeable explanatory variables influence dependent variables (Krizek, 2003a), we allow current or previous measures of these variables (as well as change measures) to enter the model.

6.1.3 Modelling procedure

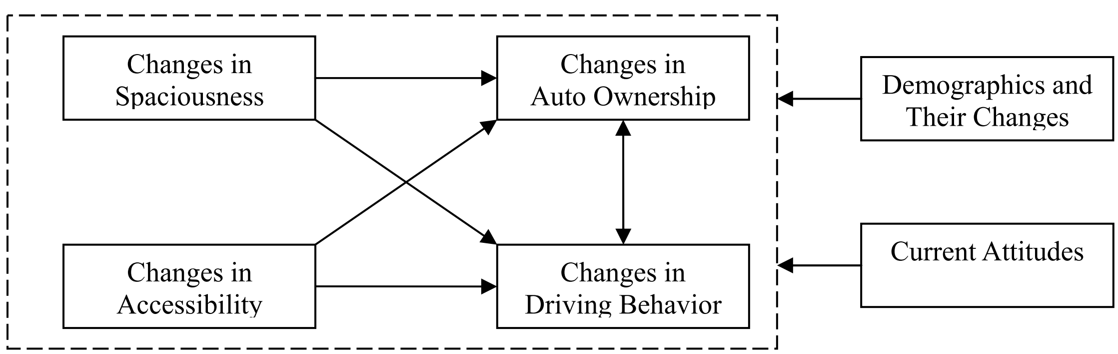
The maximum likelihood estimation (MLE) approach, commonly used in practice, was chosen to develop the SEMs. We adopted the following estimation procedure. First, single equation models for each endogenous variable were estimated by SPSS 12.0, with both exogenous and other endogenous variables as explanatory variables. Then these equations were integrated by Amos 5.0, with insignificant explanatory variables being removed. Finally, to capture any variables omitted in the initial specification, variables which were significantly associated with each endogenous variable in bivariate tests such as a one-way ANOVA were allowed to enter the model.

We first developed an SEM studying the relationships among changes in driving, changes in the built environment, and changes in auto ownership, which is presented in Section 6.2. Since changes in auto ownership did not have a direct influence on changes in walking in our model, we did not develop a separate model integrating walking behavior. Instead, we present a model incorporating both walking and driving behavior in Section 6.3. Since the number of exogenous variables far exceeds the number of endogenous variables in these two SEMs, model identification is not a problem.

6.2 Driving Behavior

Exploratory single equation models showed that changes in driving behavior are influenced by changes in accessibility, and that changes in auto ownership are affected by changes in outdoor spaciousness. Therefore, changes in accessibility and outdoor spaciousness were chosen as endogenous variables regarding changes in the built environment. Accordingly, we specified Hypothesis 4 in the context of our data, as shown in Figure 13. We assumed that the error terms of all equations for endogenous variables are correlated.

Figure 13. Conceptual Structural Model: driving



6.2.1 Multivariate normality examination and goodness-of-fit

We first estimated an SEM with the endogenous variables in their original form. The parameter estimates of the structural equations were consistent with our prior expectations. However, the validity of MLE theoretically depends on whether the SEM meets the assumption of multivariate normality of its variables. When this assumption holds, estimates of the variances of parameters are consistent. By contrast, when the data seriously deviate from multivariate normality, the standard errors of parameter estimates can be substantially underestimated, leading to false conclusions of significance (West et al., 1995).

A review of the literature reveals that meeting this condition is a problem in many studies. Bentler and Dudgeon (1996, p.566) stated that "in practice [for structural equation models], the normality assumption will often be incorrect." Micceri (1989) reviewed numerous data sets that were used in journal articles and found that a majority of the conclusions were based on data that were nonnormally distributed. Other researchers (e.g., Breckler, 1989) have noted that it is very common for practitioners to ignore the assumption of normality and to make conclusions as if the assumption were met.

We considered it important at least to test for departures from normality, and to attempt to achieve normality or come as close as practicable. Thus, we reviewed the Mardia statistic (a measure of multivariate kurtosis) associated with our original SEM. That statistic was equal to 66.53, with a critical ratio of 28.99 (a critical ratio above 1.96 signifies departure from multivariate normality with 95% confidence). Given this significant failure of the multivariate normality assumption, modifications were in order.

We transformed (taking the natural log of) the five variables (changes in auto ownership, changes in income, changes in the number of driving-age members, changes in the number of children under 5 years old, and number of children under 18 years old) that had high kurtosis values, as such transformations have been found to be potentially effective in making the distribution of a variable more normal (West et al., 1995). After re-estimating the previous model with the newly transformed variables, the Mardia statistic was reduced to 33.70. Since the transformed changes in the number of children under 5 years old had an extremely high kurtosis value (12.94, whereas the mean kurtosis of the normal distribution is zero), this variable substantially contributed to the large Mardia statistic. Given that this variable was significant only at the 0.08 level, it was removed from the model specification and the model was re-estimated. The resulting Mardia statistic was reduced to 15.88, with a critical ratio of 7.31.

It is worth noting that, to make even the log-transformed data conform to the multivariate normality assumption, Bagley and Mokhtarian (2002) had to remove 100 extreme data points (16.3% of the sample) according to their Mahalanobis distances (the greater the distance, the greater the contribution to the departure from multivariate normality). We tried the same approach in this application. However, the data points with high Mahalanobis distances are those that we expected to observe. In other words, these data points contain presumably reasonable outcomes for endogenous variables of interest. Therefore, removing a large number of informative observations is not appealing. On the other hand, the removal of only a small number of extreme data points did not improve the critical ratio of the Mardia statistics to the optimal level (1.96). Bagley and Mokhtarian (2002) pointed out that (at least in their case) the model that met the multivariate normality assumption was very similar in terms of parameter estimates and goodness-of-fit measures to the model that violated this assumption. In view of this encouraging evidence of the robustness of the results to departures from normality, we abandoned further attempts to achieve normality by discarding observations.

Although our SEM with four transformed variables may still deviate somewhat from the multivariate normality assumption, the influences of non-normal data are reduced when using MLE with a larger sample size (Anderson and Amemiya, 1988; Lei and Lomax, 2005). What constitutes a large sample size? First, Stevens (1996) suggested that the ratio between the sample size and the number of observed variables should not be less than 15. In our model, the sample size is considered to be quite large since this ratio is 547/17 > 32, more than twice the recommended threshold. Second, when the sample size is larger than 500 and the degrees of freedom of an SEM are over 30, we can achieve a relatively high power (over 0.95) for hypothesis testing, even in the presence of non-normality (MacCallum et al., 1996). Therefore, the possible non-normality of the data after the transformations does not seem to be a serious problem.

Given the substantial improvement of the Mardia statistic after transformation over that of the original model, the large sample size, and generally good measures of fit (Table 29), the SEM with four transformed variables is chosen as the final model.

Table 29. Measures of Fit for the Structural Equations Model: driving (N = 547)

Degrees of freedom	35
χ^2: measures discrepancy between the sample and model-implied covariance matrices; the smaller the better.	78.80
χ^2/d.f.: a "relative chi-square value" corrected for degrees of freedom; values of 3 or less indicate a good fit, and values as high as 5 represent an adequate fit.	2.25
Goodness-of-Fit Index (GFI): the relative proportion of variance and covariance in the sample covariance matrix explained by the model-implied covariance matrix, with values closer to 1 being better.	0.98
Normed Fit Index (NFI): proportion of worst (independence) model χ^2 explained by the model of interest; varies between 0 and 1, with values larger than 0.90 indicating a well-fitting model.	0.91
Comparative Fit Index (CFI): assumes a noncentral χ^2 distribution for the worst (independence) model discrepancy; varies between 0 and 1, with values closer to 1 indicating a good fit.	0.94
Incremental Fit Index (IFI): the incremental improvement of the model of interest over the worst (independence model); values closer to 1 indicate a good fit.	0.95
Root Mean Square Error of Approximation (RMSEA): measures the estimated discrepancy between the model-implied and true population covariance matrix, corrected for degrees of freedom; values less than 0.05 indicate a good fit, and values as high as 0.08 represent a reasonable fit.	0.048

Sources of definitions: Byrne (2001), Kline (1998), and Marsh and Hocevar (1985)

6.2.2 Model results

The final model consists of four endogenous variables: changes in outdoor spaciousness, changes in accessibility, changes in auto ownership, and changes in driving. The error terms for changes in outdoor spaciousness and changes in accessibility are negatively correlated at the 0.05 level, indicating that unobserved factors influence these two variables in opposite ways (as would be expected, since the variables themselves are negatively correlated). However, other error terms are not significantly correlated, suggesting that the unobserved factors do not jointly influence the choices of the built environment and travel decisions.

Table 30 presents the matrix of (non-standardized) direct effects (standardized coefficients are shown in Appendix B, and the same applies to Tables 31, 35, and 36), which largely follow expectations. Changes in outdoor spaciousness are positively associated with a preference for spaciousness and with changes in the number of driving-age members in the household, but negatively related to a preference for accessibility and to the current measure for age. Changes in accessibility are exclusively determined by attitudinal factors: individuals preferring high-accessibility neighborhoods are more likely to move to neighborhoods with higher accessibility; so are those having a tendency to minimize their daily travel; but people who value the safety nature of cars are more likely to move to lower-accessibility neighborhoods.

Changes in incomes and changes in the number of driving-age members in the household have positive associations with changes in auto ownership, while older people are more likely to reduce their auto holdings after a move. Preference for outdoor spaciousness has a negative association on changes in auto ownership. Since those who prefer outdoor spaciousness have a slight tendency to have already owned a larger number of autos before they moved (the correlation is 0.09, significant at the 0.05 level), they are less likely to increase their auto ownership levels. So this association is plausible. In addition, changes in auto ownership are positively associated with two built environment measurements: changes in outdoor spaciousness and a current objective accessibility measure (distance to the nearest fast food). These associations hold even after residential preference is controlled for, suggesting that the built environment has a direct causal influence on auto ownership.

Table 30. Direct Effects: driving

Variables	**Changes in spaciousness**	**Changes in accessibility**	**Changes in automobiles [a]**	**Changes in driving**
Constant	0.678 (0.000)	0.760 (0.000)	0.036 (0.061)	3.685 (0.000)
Endogenous variables				
Changes in spaciousness	0	0	0.049 (0.000)	
Changes in accessibility	0	0		-0.223 (0.000)
Changes in automobiles [a]	0	0	0	0.283 (0.017)
Changes in driving	0	0	0	0
Exogenous variables				
Socio-demographics				
Changes in income [a]			0.008 (0.002)	0.016 (0.035)
Changes in # of driving-age members [a]	0.339 (0.006)		0.278 (0.000)	
Current education				-0.079 (0.052)
Ln (1+current # of kids < 18)				0.291 (0.020)
Current age	-0.014 (0.002)		-0.004 (0.002)	-0.010 (0.012)
Neighborhood characteristics				
Current socializing	0	0		-0.132 (0.034)
Current dist. to nearest fast food (km)	0	0	0.060 (0.052)	
Current # of leisure businesses w/in 1600 m	0	0		-0.011 (0.058)
Travel attitudes				
Travel minimizing		0.163 (0.001)		
Safety of car		-0.129 (0.013)		
Car dependent				0.142 (0.008)
Residential preferences				
Accessibility	-0.237 (0.000)	0.183 (0.002)		
Outdoor spaciousness	0.360 (0.000)		-0.051 (0.008)	
Squared multiple correlations	0.093	0.056	0.189	0.131

Note: The numbers in parentheses are p-values. 0s are imposed constraints according to the hypothesized model (i.e., structural zeros). A blank cell indicates that this variable was found to be insignificant in the model and hence constrained to have a zero coefficient (i.e., empirical zeros).
a. Because these variables are centered around zero, the logarithm transformation is problematic (since the natural logarithm function is undefined for zero and negative numbers). To address this problem, these variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}(-X + 1)$. This transformation retains the symmetry and sign properties of the original X; for example, the values -2, -1, 0, 1, 2 are transformed to –ln 3, –ln 2, ln1 = 0, ln 2, ln 3.

Changes in driving are negatively affected by current measures for age and education, and positively impacted by current number of children under 18 years old in the household. In addition to changes in household income, a larger increase in auto ownership leads to a larger increase in driving. It is worth noting that in the model representing the initially assumed bi-directional associations between changes in auto ownership and changes in driving behavior (Figure 13), both coefficients are empirically insignificant. Since auto ownership is a mid-term choice while travel behavior is a near-term choice (Ben-Akiva and Atherton, 1977), we constrained the link from changes in driving behavior to changes in auto ownership to be structurally zero, yielding the model of Table 30 in which the influence of changes in auto ownership on changes in driving is significant. Only one travel attitude factor (car dependent) directly influences changes in driving although others have an indirect influence as seen below. Further, three built environment measurements are negatively associated with changes in driving: changes in accessibility, the level of socializing factor and number of leisure businesses within 1600 meters in the current neighborhoods. This finding suggests that there is a causal link from the built environment to driving behavior.

There are some interesting results when we examine the (non-standardized) total effects of each explanatory variable (Table 31). First, although changes in outdoor spaciousness do not have a direct influence on driving behavior, moving to a more spacious environment does encourage driving through its influence on auto ownership. So does a current objective accessibility measure, distance to the nearest fast food establishment. Second, some attitudinal factors and socio-demographics have additional influences on driving behavior through their effects on changes in the built environment and changes in auto ownership.

Table 32 presents the *standardized* direct and total effects of explanatory variables on changes in driving. The total influence of built environment variables appears similar to that of socio-demographics. Among variables tested, changes in accessibility have the largest standardized total effects. Further, if we increase the three built environment variables having negative coefficients by one standard deviation and decrease the two built environment variables having positive signs by one standard deviation simultaneously (as might be the case with a move from a suburban to a traditional neighborhood, since the former three variables and the latter two variables might tend to vary together but in opposite ways), on average driving behavior will be reduced by 0.397 standard deviations (= 0.206 + 0.087 + 0.080 +0.016 + 0.008). In other words, roughly speaking, the overall marginal effects of built environment variables on driving behavior are 0.397.

Table 31. Total Effects: driving

Variables	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving
Endogenous variables				
Changes in spaciousness	0	0	0.049	0.014
Changes in accessibility	0	0		-0.223
Changes in automobiles [a]	0	0	0	0.283
Changes in driving	0	0	0	0
Exogenous variables				
Socio-demographics				
Changes in income [a]			0.008	0.018
Changes in # of driving-age members [a]	0.339		0.295	0.083
Current measure for education				-0.079
Ln (1+current # of kids <18)				0.291
Current age	-0.014		-0.005	-0.011
Neighborhood characteristics				
Current socializing	0	0		-0.132
Current dist. to nearest fast food (km)	0	0	0.060	0.017
Current # of leisure businesses w/in 1600 m	0	0		-0.011
Travel attitudes				
Travel minimizing		0.163		-0.036
Safety of car		-0.129		0.029
Car dependent				0.142
Residential preferences				
Accessibility	-0.237	0.183	-0.012	-0.044
Outdoor spaciousness	0.360		-0.032	-0.009

Note: 0s are structural zeros and the blank cells are empirical zeros (see the note of Table 30).
a. These variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}(-X + 1)$.

Table 32. Comparison of Standardized Parameter Estimates for Changes in Driving by Different Modelling Approaches

Variables	SEM Direct Effects	SEM Total Effects	Model 1 OLS "Direct Effects"	Model 2 OLS "Total Effects"	Model 3 OLS BE Exogenous
Socio-demographics					
Changes in automobiles [a]	0.099 (0.017)	0.099	0.098 (0.019)	0.099 (0.026)	0.104 (0.019)
Changes in income [a]	0.087 (0.035)	0.100	0.087 (0.037)	0.095 (0.032)	0.087 (0.049)
Changes in # of driving-age members [a]		0.031		-0.023 (0.613)	-0.022 (0.634)
Current education	-0.079 (0.052)	-0.079	-0.078 (0.055)	-0.066 (0.126)	-0.068 (0.101)
Ln (1+current # of kids <18)	0.096 (0.020)	0.096	0.095 (0.021)	0.106 (0.013)	0.095 (0.025)
Current age	-0.104 (0.012)	-0.118	-0.103 (0.013)	-0.105 (0.014)	-0.109 (0.010)
Neighborhood characteristics					
Changes in spaciousness		0.016		0.011 (0.806)	-0.004 (0.927)
Changes in accessibility	-0.206 (0.000)	-0.206	-0.204 (0.000)	-0.204 (0.000)	-0.209 (0.000)
Current socializing	-0.087 (0.034)	-0.087	-0.086 (0.041)	-0.086 (0.045)	-0.073 (0.082)
Current dist. to nearest fast food (km)		0.008		0.027 (0.535)	0.030 (0.490)
Current # of leisure businesses w/in 1600 m	-0.080 (0.058)	-0.080	-0.079 (0.068)	-0.078 (0.091)	-0.082 (0.070)
Travel attitudes					
Travel minimizing		-0.028		-0.0002 (0.997)	
Safety of car		0.021		0.056 (0.199)	
Car dependent	0.108 (0.008)	0.108	0.107 (0.009)	0.110 (0.008)	
Residential preferences					
Accessibility		-0.029		0.066 (0.125)	
Outdoor spaciousness		-0.006		-0.043 (0.322)	
R-square [b]	0.131	-	0.146	0.153	0.136

Notes: The values in parentheses are p-values. Models 1, 2, and 3 are linear regressions for changes in driving behavior estimated on the same sample as the SEM. Model 1 considered all variables having direct effects on changes in driving behavior. Model 2 incorporated all variables having direct and indirect effects on changes in driving behavior. Model 3 removed the attitudinal factors from the set of explanatory variables used in Model 2; that is, the built environment is considered entirely exogenous to driving behavior.

a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

b. The squared multiple correlation of the SEM is not bounded by [0, 1], and hence is not comparable to R^2 of the OLS (Bentler and Raykov, 2000).

It is of interest to compare the SEM results to those that can be obtained from single-equation regression. The remaining columns of Table 32 present the standardized regression coefficients of variables in the driving behavior change equation using different methodologies and different model specifications. Model 1 contains the same set of explanatory variables as the SEM direct effects on changes in driving behavior. Although we employed a different modeling technique (a single-equation regression rather than an SEM) to estimate the coefficients of Model 1, parameter estimates as well as their p-values for SEM direct effects and Model 1 are quite similar. This is not surprising, since only the error terms of the two built environment variables among the four endogenous variables in the SEM were significantly correlated. However, a comparison between the SEM total effects and the coefficients for Model 1 indicates that the SEM explicitly captured indirect effects of built environment variables as well as other variables. Therefore, a single equation for changes in driving behavior apparently tends to neglect the effects of these variables.

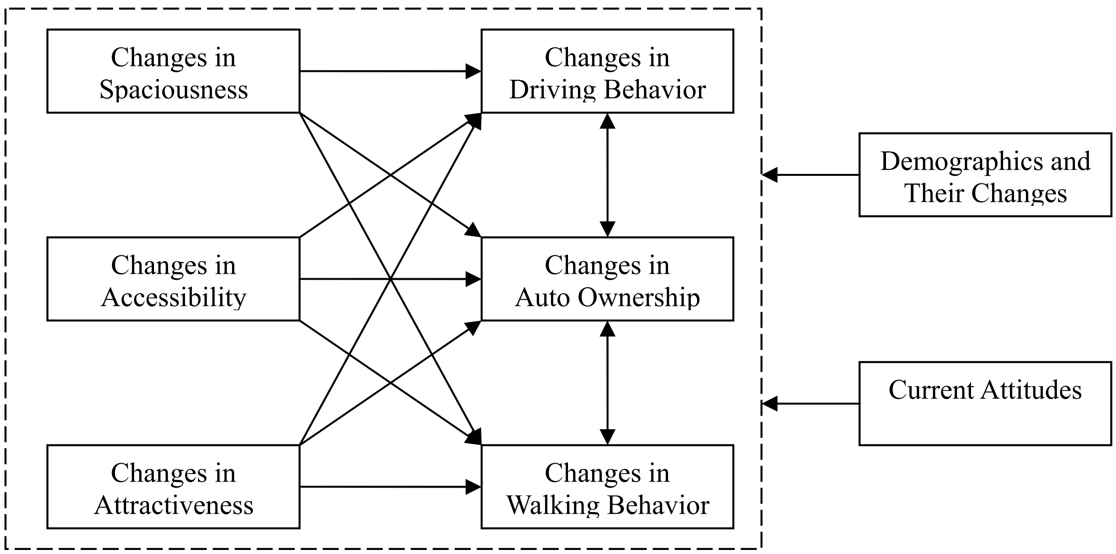
However, this comparison may be unfair since Model 1 contained only a subset of the explanatory variables included in the SEM. Alternatively, we regressed *all* explanatory variables against changes in driving behavior in Model 2. The influence of variables *significant* in Model 2 is similar to their SEM total effects. The age variable has the largest relative difference (underestimated by 11% in Model 2). For built environment variables, the overestimation and underestimation is negligible. With respect to variables insignificant in Model 2, their SEM total effects are not very large. Therefore, although the SEM is a more advanced modelling technique, the OLS parameter estimates for changes in driving behavior can still be meaningful. Two cautions are in order, however. One is that it is easy to overlook indirect effects when estimating a single equation, so that statistically and practically significant relationships might be excluded if their path of influence were not fully understood. The second is that the similarities between SEM and OLS seen here may be specific to the relatively simple, “recursive” structure of our conceptual model, and do not necessarily generalize to more complex, and especially "non-recursive" structures.

In Model 3, to replicate a typical scenario in the extreme, the built environment is considered entirely exogenous to driving behavior. In other words, we neither consider multiple interactions (i.e. have multiple equations) nor control for attitudinal factors. Comparing the parameter estimates in Model 3 and the SEM total effects regarding significant built environment variables, we find that the biases resulting from residential self-selection are not substantial. In particular, the effect of the current measure for socializing is underestimated by 16.1% if we assume that the built environment is exogenous to driving behavior, while the effects of changes in accessibility and the current measure for number of leisure businesses within 1600 meters are overestimated by 1.5% and 2.5%, respectively. If we increase these three variables by one standard deviation at the same time, Model 3 underestimates the overall effect of built environment variables only slightly ($2.4\% = [(-0.206 - 0.087 - 0.080) - (-0.209 - 0.073 - 0.082)]/(-0.206 - 0.087 - 0.080) \times 100\%$). Therefore, we acknowledge the influence of residential self-selection on driving behavior, but that influence appears not to be large enough to call for extra attention.

6.3 Driving and Walking Behavior

In this application, we further incorporated changes in walking behavior into our conceptual model shown in Figure 13. The exploratory single equation for changes in walking behavior showed that this variable is influenced by four change variables of the built environment: attractiveness, physical activity options, safety, and socializing. Since the inclusion of more equations tends to result in inferior goodness-of-fit, we chose only changes in attractiveness (having the largest standardized coefficient among the four change variables) as an endogenous variable, in addition to the two built environment variables already included in Figure 13. Figure 14 illustrates the new conceptual model tested in this section. The association between changes in driving and changes in walking is constrained to be zero since their relationship is expected to be spurious, due to the simultaneous influence of the built environment and auto ownership on each separately. As before, we assumed that the error terms of all equations for endogenous variables are correlated.

Figure 14. Conceptual Structural Model: driving & walking



6.3.1 Multivariate normality examination and goodness-of-fit

We first estimated an SEM with the endogenous variables in their original form. As before, the parameter estimates of the structural equations were consistent with our prior expectations. The Mardia statistic was equal to 83.89, with a critical ratio of 25.71. Again, we transformed (taking the natural log of) the same five variables as before (changes in auto ownership, changes in income, changes in the number of driving-age members, changes in the number of children under 5 years old, and number of children under 18 years old). After re-estimating the previous model with the newly transformed variables, the Mardia statistic was reduced to 51.41. The transformed changes in the number of children under 5 years old still had an extremely high kurtosis value. Although this variable substantially contributes to the large Mardia statistic, it also significantly influences changes in attractiveness and changes in walking, as expected. More importantly, the removal of this variable did not yield a quantum improvement in the Mardia statistic (the statistic is reduced to 33.30). Therefore, we decided to keep it in the model. For the reasons discussed in Section 6.2.1, we did not adopt the approach of removing observations with large Mahalanobis distances.

Table 33 presents goodness-of-fit measures for the model with the newly transformed variables. Generally, these measures are inferior to those for the model discussed in Section 6.2. We tried several approaches (such as removing some observations and removing an equation) to improve measures of fit. However, none of them produced satisfactory results. Given that this model offers insightful practical interpretations, we accepted it as our final model.

Table 33. Measures of Fit for the Structural Equations Model: walking & driving (N = 547)

Degrees of freedom	98
χ^2: measures discrepancy between the sample and model-implied covariance matrices; the smaller the better.	345.0
χ^2/d.f.: a “relative chi-square value” corrected for degrees of freedom; values of 3 or less indicate a good fit, and values as high as 5 represent an adequate fit.	3.52
Goodness-of-Fit Index (GFI): the relative proportion of variance and covariance in the sample covariance matrix explained by the model-implied covariance matrix, with values closer to 1 being better.	0.96
Normed Fit Index (NFI): proportion of worst (independence) model χ^2 explained by the model of interest; varies between 0 and 1, with values larger than 0.90 indicating a well-fitting model.	0.84
Comparative Fit Index (CFI): assumes a noncentral χ^2 distribution for the worst (independence) model discrepancy; varies between 0 and 1, with values closer to 1 indicating a good fit.	0.87
Incremental Fit Index (IFI): the incremental improvement of the model of interest over the worst (independence model); values closer to 1 indicate a good fit.	0.88
Root Mean Square Error of Approximation (RMSEA): measures the estimated discrepancy between the model-implied and true population covariance matrix, corrected for degrees of freedom; values less than 0.05 indicate a good fit, and values as high as 0.08 represent a reasonable fit.	0.068

Sources of definitions: Byrne (2001), Kline (1998), and Marsh and Hocevar (1985)

6.3.2 Model results

The final model consists of structural equations for six endogenous variables: changes in attractiveness, changes in outdoor spaciousness, changes in accessibility, changes in auto ownership, changes in driving, and changes in walking. Table 34 presents the statistically significant correlations among the error terms in these equations. A positive correlation between error terms for two variables indicates that unobserved variables affect the two variables in the same direction; a negative sign suggests that unobserved variables affect the two variables in opposite ways.

Table 34. Correlations of the Error Terms

	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles	Changes in driving	Changes in walking
Changes in attractiveness	1					
Changes in spaciousness	0.637 (0.000)	1				
Changes in accessibility	0.265 (0.000)	-0.173 (0.012)	1			
Changes in automobiles				1		
Changes in driving					1	
Changes in walking					-0.236 (0.000)	1

Note: The numbers in parentheses are p-values.

It may seem that the high and positive correlation between unobserved influences on changes in spaciousness and changes in attractiveness is counterintuitive. Generally, attractiveness is a trait more strongly associated with traditional neighborhoods, while suburban neighborhoods have more space. Therefore, unobserved variables could be expected to affect joint choices of attractiveness and spaciousness in an opposite way. In this dataset, however, there is no significant difference in perceived outdoor spaciousness between traditional and suburban neighborhoods (see Table 13). And although individuals living in traditional neighborhoods on average perceive attractiveness to be higher than do suburban residents, about a fifth (21.5%) of residents in traditional neighborhoods perceive attractiveness to be lower than the median level of attractiveness perceived by suburban residents, while a similar proportion (19.5%) of suburban residents perceive attractiveness to be higher than the median level perceived by those in traditional neighborhoods. So, for example, a move from an urban area perceived to be somewhat blighted to a lower-density area may generate increases in both perceived attractiveness and spaciousness.

The matrix of (non-standardized) direct effects is shown in Table 35. Compared to the SEM presented in Section 6.2.2, the explanatory variables in the equations for changes in outdoor spaciousness, changes in accessibility, and changes in auto ownership remain significant in this SEM, but the number of leisure businesses within 1600 meters became insignificant and hence was dropped out of the equation for changes in driving. It is worth noting that the influence of changes in walking on changes in auto ownership was found to be insignificant in the model and hence was constrained to be empirically zero, while the influence of changes in driving on changes in auto ownership was constrained to be structurally zero for the same reason as that discussed in Section 6.2.

Changes in attractiveness are influenced by three variables. Attractiveness preference positively influences changes in attractiveness, a clear (and expected) sign of self-selection. The moves of older people tend to result in larger decreases or smaller increases in attractiveness. And increases in the number of children under 5 years old are negatively associated with changes in attractiveness, consistent with the stereotypical move from the traditional to suburban neighborhood with the expansion of the household.

Individuals experiencing an increase in the number of children under 5 years old tend to have a larger increase or smaller decrease in walking trips, while the converse is true for those currently working. A pro-walk/bike attitude is positively associated with changes in walking, but the safety of car factor has a negative association with changes in walking. After controlling for socio-demographics and attitudes, various measurements for changes in the built environment – attractiveness, safety, physical activity options, and socializing – have positive influences on changes in walking. Further, the current number of business types within 400 meters is positively associated with changes in walking. These results suggest that the built environment has a causal influence on walking behavior. The total effects of built environment variables on walking behavior are the same as their direct effects since these variables affect only changes in walking (Table 36).

For changes in driving behavior, this SEM dropped current number of leisure businesses, which was significant in the SEM in Section 6.2. However, the influence of this variable was relatively weak and significant only at the margin. With respect to parameter estimates, changes in the number of children under 18 years old have the largest difference (0.347 versus 0.291). For other variables, this SEM yields parameter estimates quite similar to the SEM considering only driving behavior.

Table 35. Direct Effects: walking & driving

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving	Changes in walking
Constant	1.225 (0.000)	0.702 (0.000)	0.774 (0.000)	0.036 (0.062)	3.539 (0.000)	3.328 (0.000)
Endogenous Variables						
Changes in attractiveness	0	0	0			0.165 (0.000)
Changes in spaciousness	0	0	0	0.049 (0.000)		
Changes in accessibility	0	0	0		-0.230 (0.000)	
Changes in automobiles [a]	0	0	0	0	0.282 (0.016)	0
Changes in driving	0	0	0	0	0	0
Changes in walking	0	0	0	0	0	0
Exogenous Variables						
Socio-demographics						
Changes in # of kids (≤ 5) [a]	-0.629 (0.026)					0.522 (0.016)
Changes in # of driving-age members [a]		0.355 (0.002)		0.278 (0.000)		
Changes in income [a]				0.008 (0.002)	0.014 (0.051)	
Ln (1 + current # of kids < 18)					0.347 (0.004)	
Current age	-0.014 (0.002)	-0.014 (0.002)		-0.004 (0.002)	-0.010 (0.012)	
Currently working						-0.270 (0.047)
Current education					-0.081 (0.044)	
Neighborhood characteristics						
Changes in physical activity options	0	0	0			0.133 (0.000)
Changes in safety	0	0	0			0.104 (0.001)
Changes in socializing	0	0	0			0.158 (0.000)
Current socializing	0	0	0		-0.144 (0.019)	
Current # of business types w/in 400 m	0	0	0			0.044 (0.014)
Current dist. to nearest fast food	0	0	0	0.060 (0.052)		
Residential preferences						
Accessibility		-0.200 (0.003)	0.201 (0.000)			
Outdoor spaciousness		0.345 (0.000)		-0.051 (0.013)		
Attractiveness	0.343 (0.000)					

Notes: The numbers in parentheses are p-values. 0s are structural zeros and the blank cells are empirical zeros (see notes of Table 30).
a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

(**Table 35 continued**)

Variables	**Changes in attractiveness**	**Changes in spaciousness**	**Changes in accessibility**	**Changes in automobiles** [a]	**Changes in driving**	**Changes in walking**
Travel attitudes						
Safety of car			-0.122 (0.017)			-0.158 (0.001)
Travel minimizing			0.150 (0.002)			
Car dependent					0.149 (0.005)	
Pro-bike/walk						0.124 (0.009)
Squared multiple correlations	0.064	0.087	0.055	0.189	0.125	0.200

a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}(-X + 1)$.

Table 36. Total Effects: walking & driving

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving	Changes in walking
Endogenous Variables						
Changes in attractiveness	0	0	0			0.165
Changes in spaciousness	0	0	0	0.049	0.014	
Changes in accessibility	0	0	0		-0.230	
Changes in automobiles [a]	0	0	0	0	0.282	0
Exogenous Variables						
Socio-demographics						
Changes in # of kids (≤ 5) [a]	-0.629					0.419
Changes in # of driving-age members [a]		0.355		0.295	0.083	
Changes in income [a]				0.008	0.017	
Ln (1 + current # of kids < 18)					0.347	
Current age	-0.014	-0.014		-0.005	-0.011	-0.002
Currently working						-0.270
Current education					-0.081	
Neighborhood characteristics						
Changes in physical activity options	0	0	0			0.133
Changes in safety	0	0	0			0.104
Changes in socializing	0	0	0			0.158
Current socializing	0	0	0		-0.144	
Current # of business types w/in 400 m	0	0	0			0.044
Current dist. to nearest fast food	0	0	0	0.060	0.017	
Residential preferences						
Accessibility		-0.200	0.201	-0.010	-0.049	
Outdoor spaciousness		0.345		-0.034	-0.009	
Attractiveness	0.343					0.057
Travel attitudes						
Safety of car			-0.122		0.028	-0.158
Travel minimizing			0.150		-0.034	
Car dependent					0.149	
Pro-bike/walk						0.124

Notes: 0s are structural zeros and the blank cells are empirical zeros (see notes of table 30). a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}(-X + 1)$.

Table 37 presents the *standardized* direct and total effects of explanatory variables on changes in walking. As before, the total influence of built environment variables is equivalent to or even larger than that of socio-demographics. Changes in attractiveness have the largest standardized effects among variables tested. Further, if we decrease changes in safety by one standard deviation and increase the other four built environment variables by one standard deviation at the same time (as might be the case with a move from a suburban to a traditional neighborhood), on average walking behavior will be increased by 0.482 standard deviations (= 0.137 + 0.164 + 0.213 +0.096 – 0.128). In other words, roughly speaking, the overall marginal effects of built environment variables on walking behavior are 0.482.

Similarly to the approach in Section 6.2, for changes in walking behavior we compared the SEM results to standardized single-equation regression coefficients using different methodologies and model specifications (Table 37). Comparing Model 1 and SEM direct effects, we found that there are some changes in parameter estimates. However, these changes are not substantial; changes in safety have the largest difference between the models, with effects overestimated by 11% in the single-equation regression model. Comparing Model 1 and SEM total effects, we found similar results for most variables. However, the effects of changes in the number of kids under 5 years old were overestimated by 30% since we could not capture the indirect effect of this variable through changes in attractiveness. A comparison of Model 2 and SEM total effects showed a similar pattern, with the effect of currently being a worker additionally overestimated by about 35%.

Table 37. Comparison of Standardized Parameter Estimates for Changes in Walking by Different Modelling Approaches

Variables	SEM Direct Effects	SEM Total Effects	Model 1 OLS "Direct Effects"	Model 2 OLS "Total Effects"	Model 3 OLS BE Exogenous
Socio-demographics					
Changes in # of kids (≤ 5) [a]	0.092 (0.015)	0.073	0.095 (0.012)	0.091 (0.017)	0.092 (0.018)
Currently working	-0.075 (0.047)	-0.075	-0.079 (0.037)	-0.101 (0.012)	-0.099 (0.016)
Current age		-0.026		-0.064 (0.125)	-0.078 (0.062)
Neighborhood characteristics					
Changes in PA options	0.137 (0.000)	0.137	0.121 (0.003)	0.123 (0.003)	0.139 (0.001)
Changes in socializing	0.164 (0.000)	0.164	0.157 (0.000)	0.154 (0.000)	0.163 (0.000)
Changes in safety	0.128 (0.001)	0.128	0.142 (0.001)	0.146 (0.001)	0.120 (0.005)
Changes in attractiveness	0.213 (0.000)	0.213	0.207 (0.000)	0.197 (0.000)	0.212 (0.000)
Current # of business types w/in 400 m	0.096 (0.014)	0.096	0.098 (0.014)	0.090 (0.025)	0.121 (0.003)
Travel attitudes					
Pro-bike/walk	0.103 (0.009)	0.103	0.110 (0.006)	0.105 (0.008)	
Safety of car	-0.127 (0.001)	-0.127	-0.133 (0.001)	-0.130 (0.001)	
Residential preferences					
Attractiveness		0.045		0.019 (0.623)	
R-square [b]	0.200	-	0.241	0.244	0.211

Notes: The values in parentheses are p-values. Models 1, 2, and 3 are linear regressions for changes in walking behavior estimated on the same sample as the SEM. Model 1 considered all variables having direct effects on changes in walking behavior. Model 2 incorporated all variables having direct and indirect effects on changes in walking behavior. Model 3 removed the attitudinal factors from the set of explanatory variables used in Model 2; that is, the built environment is considered entirely exogenous to walking behavior.

a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

b. The squared multiple correlation of the SEM is not bounded by [0, 1], and hence is not comparable to R^2 of the OLS (Bentler and Raykov, 2000).

In Model 3, the built environment is entirely exogenous to walking behavior. Comparing Model 3 and SEM total effects, we did not find any substantial differences in the effects of the change variables regarding the built environment. The largest difference is for changes in safety, and its effect is underestimated by only 6.3% if we assume that the built environment is exogenous to walking behavior. In other words, the inclusion of change variables in a model appears to greatly reduce the influence of residential self-selection. However, the effect of current number of business types within 400 meters is overestimated by 26.0%. This result suggests that the effect of current number of business types (i.e., of accessibility to diverse activity opportunities) is largely determined by travel attitudes, and hence ignoring residential self-selection tends to greatly overstate the influence of current measures of the built environment on walking behavior.

6.4 Summary

This study explored the causal relationships among the built environment, auto ownership, and travel behavior using the structural equations modelling approach. The results showed that there is a causal connection from the built environment to driving and walking behavior. Residential self-selection also has some impacts on travel behavior. In particular, if we do not account for the influence of attitudes and do not allow for multiple interactions through the inclusion of multiple equations, the effects of *changes* in built environment characteristics are only slightly different, but we tend to greatly overstate the influence of *current* measures of the built environment on changes in walking behavior. Therefore, for walking behavior, cross-sectional analyses appear to be more vulnerable to the influence of residential self-selection. On the other hand, ignoring residential self-selection does not appear to substantially influence the effects of built environment variables on changes in driving behavior. However, this minor influence may result from the fact that we measured built environment characteristics and residential preferences at the neighborhood level alone (as opposed to a regional scale or a dwelling-unit scale), which constitute only some of the factors affecting driving behavior.

Although the dynamic structural equations modelling approach is a quantum improvement over prior work in terms of methodology, there are still limitations in our application of it, given the limitations of our data. For example, because it is not feasible to retrospectively measure attitudes, we have data on current attitudes only, and our interpretation of the results of the model is predicated on the assumption that attitudes (those unmeasured as well as measured) remained constant over time and hence are controlled for. But we cannot rule out the competing hypothesis that an attitude change preceded and (partly) prompted the residential location change. To the extent that is true, the attitude change is confounded with the change in built environment and may account for some of the apparent effect of the built environment seen here. Further, since our data do not have attitudes over time, we cannot examine feedback loops from the built environment to attitudes toward travel and residence. That is, we are less able to understand how the built environment affects the formulation and change of these attitudes. This understanding is critical for planners and policy makers to manage individuals' travel behavior through land use policies over the long term. Therefore, future work should choose a true panel design so that we can capture changes in attitudes.

7. CONCLUSIONS

7.1 Summary and Policy Implications

A large number of previous studies have found that the built environment apparently influences travel behavior. However, most of these studies confirm only the associations between the built environment and travel behavior, but do not establish the predominant underlying causal link: whether the built environment influences travel behavior, or whether travel attitudes and residential preferences affect residential choice as well as travel behavior. Therefore, the available evidence leaves a key question largely unanswered: If cities use land use policies to bring residents closer to destinations and provide viable alternatives to driving, will at least some people drive less and use alternative modes more, thereby reducing congestion, fuel consumption, and emissions?

This dissertation addresses the causal relationships between the built environment and personal travel choice, using 1682 respondents from eight neighborhoods in Northern California. These respondents were grouped into movers (who changed their residential location within the last year) and nonmovers. The built environment was measured both subjectively, through factor analysis of respondents' perceptions of their residential neighborhood, and objectively, through GIS applications. Changes in built environment characteristics for movers were measured using the differences between factor scores for respondents' current and previous neighborhoods. Built environment characteristics for nonmovers are assumed to be constant over the last year. Personal travel choices include measurements of driving behavior, transit taking behavior, walking and biking behavior, auto ownership decision, and vehicle type choice. Change in travel behavior was measured using a series of general indicators of the use of different modes compared to previously, measured on a five-point scale ranging from "a lot less now" to "a lot more now." The survey also measured respondents' residential preferences, travel attitudes, and socio-demographics.

Attitudinal factors are assumed to remain constant during this period. Changeable socio-demographics were measured in terms of their differences before and after the move (or between now and a year ago for nonmovers).

Various modelling techniques were employed to investigate the connections between the built environment and travel choice in both static and dynamic ways (Table 38). An overview of the results indicates that residential preferences and travel attitudes have pervasive influences on all measurements of travel choices, strengthening the role of attitudinal factors in understanding as well as predicting individuals' travel choices. After accounting for the influences of attitudes and socio-demographics, quasi-longitudinal multivariate analyses consistently showed that the built environment also has causal influence on all measurements of travel choices. On the other hand, the results from cross-sectional multivariate analyses were mixed: some built environment variables remain significant in the model for *walking behavior* after controlling for attitudinal and socio-demographic factors, while the variations in *vehicle miles driven* and *auto ownership* are not explained by the built environment but by attitudes and socio-demographics. The occurrence of this pattern suggests that although the residential environment at the neighborhood level is a good predictor for walking behavior, it may not be sufficient to understand driving behavior and auto ownership decisions. This pattern also suggests that cross-sectional multivariate analysis may not be adequate to reveal the causal relationship between the built environment and auto-related travel choice once attitudes are controlled for.

Table 38. Overview of Findings

Section	Travel Choice Variables	Modeling Approach	Influence of Attitudes	Influence of the Built Environment
Cross-sectional data				
4.1.1	Vehicle miles driven	ANOVA	Yes	Yes
4.1.1	Vehicle miles driven	Linear regression	Yes	No
4.2.1	Strolling frequency and walking to the store frequency	T-test	Did not test	Yes
4.2.2	Strolling frequency and walking to the store frequency	Negative binomial regression	Yes	Yes
4.3.4	Home-based nonwork trip frequencies by mode	Seemingly unrelated regression	Yes	Yes
5.1	Auto ownership	T-test	Did not test	Yes
5.1.3	Auto ownership	Ordered probit model	Yes	No
5.2.3	Vehicle type choice	ANOVA	Yes	Yes
5.2.4	Vehicle type choice	Nested logit model	Yes	Yes
Quasi-longitudinal data				
4.1.1	Changes in driving	Ordered probit model	Yes	Yes
4.2.3	Changes in walking	Ordered probit model	Yes	Yes
4.2.3	Changes in biking	Ordered probit model	Yes	Yes
5.1.4	Changes in auto ownership	Linear regression	Yes	Yes
6.2.2	Changes in driving and changes in auto ownership	Structural equations model	Yes	Yes
6.3.2	Changes in driving, changes in walking, and changes in auto ownership	Structural equations model	Yes	Yes

The results presented here provide some encouragement that land-use policies designed to put residents closer to destinations and provide them with viable alternatives to driving will actually lead to less driving and more alternative-mode use (Table 39). Specifically, it appears that an increase in accessibility may lead to a decrease in driving, all else equal. In quasi-longitudinal analyses, we found that changes in accessibility have the largest standardized coefficient, pointing to the important influence of the built environment on driving behavior. Policies that could increase accessibility in new areas include mixed-use zoning that allows for retail and other commercial establishments within close proximity to residential areas, and street connectivity ordinances that ensure more direct routes between residential and commercial areas. Policies that could increase accessibility in existing areas include Main Street programs designed to enhance and revitalize traditional neighborhood shopping areas, incentives for infill development and redevelopment of underutilized shopping centers, and the like. Taking into account the influences of accessibility on auto ownership decision, which in turn affects vehicle miles driven, the effects of such policies are compounded. In addition, physical activity options and safety are associated with less driving, presumably because walking becomes a viable substitute for driving.

The results also show that an increase in accessibility, physical activity options, aesthetic quality, and a social and safe environment may lead to an increase in walking, which is a desirable goal from the standpoint of public health, among others. In fact, changes in attractiveness are the most important among variables tested to explain changes in walking, in terms of the standardized coefficients. Then, what policies can most effectively and efficiently bring these changes about? Creating environments conducive to walking is undoubtedly easier in new developments than in existing environments. Cities can modify zoning and subdivision ordinances to ensure closer proximity to shops, services, parks, and other potential destinations for walking trips and to require more from developers in the way of infrastructure for pedestrians and bicyclists. The nascent movement toward form-based codes might facilitate such efforts. Changing the environment in existing neighborhoods is much more challenging. Policies to promote infill development and investments in pedestrian infrastructure such as sidewalks and specially designed street crossings can help. Traffic calming programs, popular throughout the U.S., are an important strategy; the more recent "road diets" and "complete the streets" movements may also play a role. Improvements in street lighting and neighborhood watch programs could help to increase the sense of safety in a neighborhood, and neighborhood events such as block parties or walking groups might increase levels of socializing. Clearly, a comprehensive package of policies and programs will be needed.

Table 39. Summary of Influences of Built Environment Variables on Travel Choices

Built environment variables	**Influences of the built environment variable found in multivariate analyses**	**Policies that can create such a built environment**
Accessibility	Driving: - Auto ownership: - Transit and walking/biking: + Vehicle type choice: 0	Mixed-use zoning Infill or brownfield development Main street program Pedestrian-oriented development Transit-oriented development
Outdoor spaciousness	Auto ownership: + Driving: + (an indirect effect through auto ownership) Choosing pickup truck: + Walking: - Biking and transit: 0	(Off-street parking restrictions) (Caps on lot size)
Physical activity options	Driving: - Walking: + Biking, transit, auto ownership, and vehicle type choice: 0	Pedestrian-oriented development Transit-oriented development
Safety	Driving: - Walking: + and - Biking, transit, auto ownership, and vehicle type choice: 0	Traffic calming programs Street lighting Neighborhood watch
Attractiveness	Walking/biking: + Driving, transit, auto ownership, and vehicle type choice: 0	Infill (brownfield) development Main street program Pedestrian-oriented development
Socializing	Walking/biking: + Driving, transit, auto ownership, and vehicle type choice: 0	Block parties Walking groups
Commute distance	Choosing SUV: + Driving, walking/biking, transit, and auto ownership: 0	Job-housing balance

Notes: "0" means that our results did not show any influence of the built environment variable; the policies in parentheses have reverse effects on creating such a built environment.

To minimize the acquisition of LDTs and hence improve air quality, two approaches might be taken: creating more neighborhoods that offer traditional characteristics associated with lower LDT use, or modifying the characteristics of suburban neighborhoods that are associated with higher LDT use. The success of the former approach depends on the ability of such areas to attract residents who would otherwise live in neighborhoods with suburban characteristics and choose to own LDTs. Recent studies have found that traditional neighborhoods are undersupplied relative to the demand (Levine, 1998; Levine and Inam, 2004), suggesting that such an approach has promise. Our results show that outdoor spaciousness (a factor score based on off-street parking availability and yard size) and commute distance influence individuals' vehicle type choice. Therefore, the latter approach could include restrictions on the provision of off-street parking in new suburban developments, caps on lot size to reduce home improvement demand and parking space, and efforts to bring more matching jobs to suburban areas to reduce commute distances. Such strategies might prompt suburban residents to forego LDTs for passenger cars. Also, the parking restrictions will limit the acquisition of more automobiles, and hence contribute to less driving.

Taking the evidence from all our analyses together, neighborhood design appears to have a stronger influence on walking than on driving although influences on both are present. In other words, the residential environment promoted by smart growth programs may be an effective strategy to encourage walking but have less effect on driving, especially after attitudinal predispositions are accounted for. Given that walking is an inadequate substitute for driving (e.g., Handy and Clifton, 2001) and that transit has a limited ability to attract middle- and upper-income, car-owning travelers except for those living in city centers (Giuliano, 2005), the smart growth movement seems to be more of a solution to public health problems than to transportation problems. Even so, it will give residents a choice to drive less and walk more and this choice is highly valued by a large proportion of respondents in our data as well as in other studies. More importantly, providing alternatives to conventional suburban neighborhoods may gradually foster the formation of a pedestrian- and/or transit-oriented lifestyle among more people, a long-term benefit, although there is little evidence on that issue available to date.

7.2 Limitations and Contributions

This dissertation has several limitations. First, changes in the built environment and socio-demographics were measured based on respondents' recall. The accuracy of those changes largely depends on whether respondents can remember these attributes precisely. Second, changes in travel behavior were measured on an ordinal scale. Although we are more confident on the direction of the influence of changes in the built environment on changes in travel behavior, the specific magnitude of the influence cannot be determined. Third, since it is not feasible to retrospectively measure attitudes, we had to assume the attitudes remained constant over the measurement period. Although we have accounted for the influence of current measures of attitudes, changes in the built environment may also be confounded with unmeasured changes in attitudes. In other words, changes in travel behavior may be a result of changes in attitudes rather than changes in the built environment. Fourth, the data include objective and perceived built environment characteristics at the trip origin (residential neighborhood), but we have little information on built environment characteristics at the workplace and potential nonwork destinations (especially those related to distant trips). Therefore, the influence of the built environment on driving behavior as well as transit behavior may not be fully captured.

Nevertheless, this dissertation contributes to the state of the art of understanding the connection between the built environment and personal travel choice in the following several aspects. First, the hypotheses presented in Section 3.2 and Appendix A systematically conceptualize the complex relationships among the built environment, travel behavior, auto ownership, and attitudes regarding these choices. These hypotheses provide fundamental frameworks for future research. Second, I thoroughly discussed the requisites of causality inference in the context of the built environment and travel behavior and summarized/analyzed previous research to test and address the issue of residential self-selection in Sections 2.3 and 2.4, respectively. To my knowledge, this is the most comprehensive review and critique on this topic to date. This effort offers general methodological guidelines for investigating the causal relationship between the built environment and travel behavior. Third, this dissertation explored the causal influence of the built environment on various measurements of personal travel choices including uses of different modes (driving, transit, walking, and biking), trip frequencies for different purposes (overall travel, nonwork travel, shopping travel, and strolling for its own sake), auto ownership decision, and vehicle type choice. Therefore, this dissertation yields ample evidence for understanding this causal influence. Fourth, although the structural equations modelling approach has been widely used in travel behavior research, Chapter 6 represents the first application of structural equations modeling (as far as I know) to investigate the relationships among the built environment, travel behavior, and auto ownership in a dynamic (*quasi-longitudinal*) way, representing a quantum improvement. Therefore, the causal evidence presented here is much more robust than that of previous studies.

Although we accounted for the influences of attitudes, adopted a quasi-longitudinal design, and employed the structural equations modelling approach, our analyses are still not definitive. Future studies adopting research designs that more closely resemble a true experimental design will lead to more definitive inferences regarding causality. Two types of studies are possible: true panel studies of residents who move from one type of neighborhood to another (with measurements of attitudes as well as socio-demographic traits and travel behavior before and after, and further exploration of the reasons behind the move), and natural experiments that examine the impact on travel behavior in response to a change in the built environment, such as the implementation of a traffic calming program. Only with causal findings based on such evidence can we determine whether by increasing opportunities for driving less and walking more through land use policies, cities will indeed help to reduce driving and increase walking, and thus reduce congestion, fuel consumption, and emissions as well as increase physical activity.

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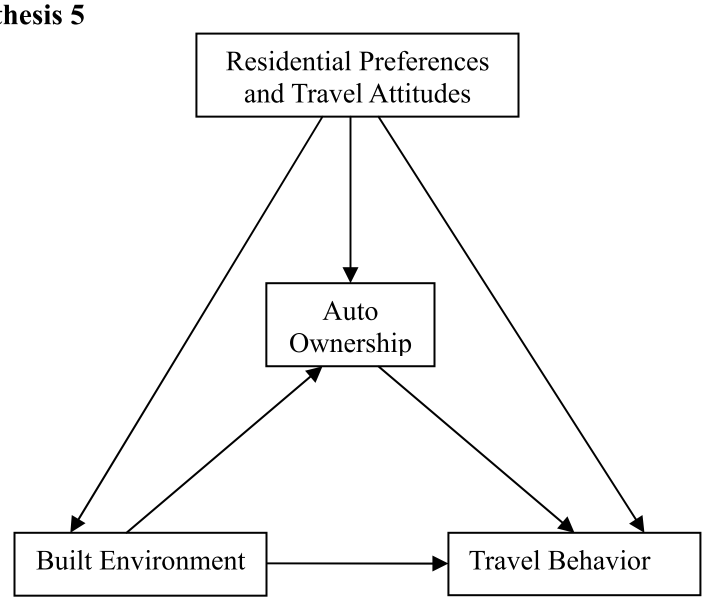
APPENDIX A: HYPOTHESES ADDITIONAL TO SECTION 3.2

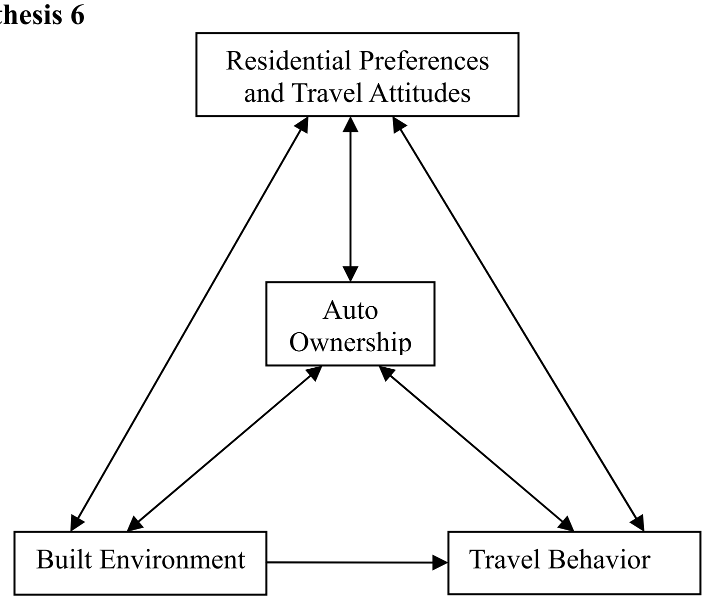
We discussed two hypotheses for cross-sectional data in Section 3.2. Here we further present two hypotheses by incorporating auto ownership. As discussed in Section 2.2.3, auto ownership plays an important role in the connection between the built environment and travel behavior. The fifth hypothesis states that auto ownership is an intervening variable bridging the built environment and travel behavior (Figure 15). In addition, households' preferences for driving less and walking more may influence their decisions to own fewer cars. In this case, single equation models are inadequate to test these complex relationships; more sophisticated techniques such as SEM are required.

Figure 15. Hypothesis 5



Furthermore, most relationships among these variables may be bi-directional, at least over time (Figure 16). For example, living in an environment that offers ample opportunities for driving less might over time increase the preference for driving less or lead to a decline in auto ownership; or, high levels of walking might lead to higher preferences for walking, and so on. It is worth noting that travel behavior is assumed not to directly influence the choices of residential neighborhoods. Both travel behavior and residential choices may be consequences of attitudinal predispositions, but since those relationships are explicitly accounted for, there does not seem to be a need to allow travel behavior to serve as a proxy cause for neighborhood choice. Similar to Hypothesis 5, we must apply more sophisticated techniques to address these complex relationships.

Figure 16. Hypothesis 6



APPENDIX B: STANDARDIZED COEFFICIENTS OF STRUCTURAL EQUATIONS MODELS

Table 40. Standardized Direct Effects: driving

Variables	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving
Endogenous variables				
Changes in spaciousness	0	0	0.158 (0.000)	
Changes in accessibility	0	0		-0.206 (0.000)
Changes in automobiles [a]	0	0	0	0.099 (0.017)
Changes in driving	0	0	0	0
Exogenous variables				
Socio-demographics				
Changes in income [a]			0.130 (0.002)	0.087 (0.035)
Changes in # of driving-age members [a]	0.112 (0.006)		0.294 (0.000)	
Current education				-0.079 (0.052)
Ln (1+current # of kids < 18)				0.096 (0.020)
Current age	-0.128 (0.002)		-0.123 (0.002)	-0.104 (0.012)
Neighborhood characteristics				
Current socializing	0	0		-0.087 (0.034)
Current dist. to nearest fast food (km)	0	0	0.076 (0.052)	
Current # of leisure businesses w/in 1600 m	0	0		-0.080 (0.058)
Travel attitudes				
Travel minimizing		0.138 (0.001)		
Safety of car		-0.103 (0.013)		
Car dependent				0.108 (0.008)
Residential preferences				
Accessibility	-0.140 (0.000)	0.130 (0.002)		
Outdoor spaciousness	0.221 (0.000)		-0.099 (0.008)	

Notes: The numbers in parentheses are p-values. 0s are structural zeros and the blank cells are empirical zeros (see notes of Table 30).
a. These variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

Table 41. Standardized Total Effects: driving

Variables	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving
Endogenous variables				
Changes in spaciousness	0	0	0.158	0.016
Changes in accessibility	0	0		-0.206
Changes in automobiles [a]	0	0	0	0.099
Changes in driving	0	0	0	0
Exogenous variables				
Socio-demographics				
Changes in income [a]			0.130	0.100
Changes in # of driving-age members [a]	0.112		0.312	0.031
Current measure for education				-0.079
Ln (1+current # of kids <18)				0.096
Current age	-0.128		-0.143	-0.118
Neighborhood characteristics				
Current socializing	0	0		-0.087
Current dist. to nearest fast food (km)	0	0	0.076	0.008
Current # of leisure businesses w/in 1600 m	0	0		-0.080
Travel attitudes				
Travel minimizing		0.138		-0.028
Safety of car		-0.103		0.021
Car dependent				0.108
Residential preferences				
Accessibility	-0.140	0.130	-0.022	-0.029
Outdoor spaciousness	0.221		-0.064	-0.006

Notes: 0s are structural zeros and the blank cells are empirical zeros (see notes of Table 30).
a. These variables (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \text{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\text{Ln}(-X + 1)$.

Table 42. Standardized Direct Effects: walking & driving

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving	Changes in walking
Endogenous Variables						
Changes in attractiveness	0	0	0			0.212 (0.000)
Changes in spaciousness	0	0	0	0.157 (0.000)		
Changes in accessibility	0	0	0		-0.213 (0.000)	
Changes in automobiles [a]	0	0	0	0	0.099 (0.016)	0
Changes in driving	0	0	0	0	0	0
Changes in walking	0	0	0	0	0	0
Exogenous Variables						
Socio-demographics						
Changes in # of kids (≤ 5) [a]	-0.086 (0.026)					0.092 (0.016)
Changes in # of driving-age members [a]		0.118 (0.002)		0.294 (0.000)		
Changes in income [a]				0.130 (0.002)	0.080 (0.051)	
Ln (1 + current # of kids < 18)					0.114 (0.004)	
Current age	-0.125 (0.002)	-0.129 (0.002)		-0.123 (0.002)	-0.101 (0.012)	
Currently working						-0.075 (0.047)
Current education					-0.081 (0.044)	
Neighborhood characteristics						
Changes in physical activity options	0	0	0			0.137 (0.000)
Changes in safety	0	0	0			0.128 (0.001)
Changes in socializing	0	0	0			0.164 (0.000)
Current socializing	0	0	0		-0.094 (0.019)	
Current # of business types w/in 400 m	0	0	0			0.096 (0.014)
Current dist. to nearest fast food	0	0	0	0.076 (0.052)		
Residential preferences						
Accessibility		-0.118 (0.003)	0.143 (0.000)			
Outdoor spaciousness		0.212 (0.000)		-0.099 (0.013)		
Attractiveness	0.210 (0.000)					

Notes: The numbers in parentheses are p-values. 0s are structural zeros and the blank cells are empirical zeros (see notes of Table 30).
a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

(**Table 42 continued**)

Variables	**Changes in attractiveness**	**Changes in spaciousness**	**Changes in accessibility**	**Changes in automobiles** [a]	**Changes in driving**	**Changes in walking**
Travel attitudes						
Safety of car			-0.098 (0.017)			-0.127 (0.001)
Travel minimizing			0.127 (0.002)			
Car dependent					0.113 (0.005)	
Pro-bike/walk						0.103 (0.009)

a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = Ln(X + 1)$; if $X < 0$, $X_{new} = -Ln(-X + 1)$.

Table 43. Standardized Total Effects: walking & driving

Variables	Changes in attractiveness	Changes in spaciousness	Changes in accessibility	Changes in automobiles [a]	Changes in driving	Changes in walking
Endogenous Variables						
Changes in attractiveness	0	0	0			0.213
Changes in spaciousness	0	0	0	0.157	0.016	
Changes in accessibility	0	0	0		-0.213	
Changes in automobiles [a]	0	0	0	0	0.099	0
Exogenous Variables						
Socio-demographics						
Changes in # of kids (≤ 5) [a]	-0.086					0.073
Changes in # of driving-age members [a]		0.118		0.312	0.031	
Changes in income [a]				0.130	0.093	
Ln (1 + current # of kids < 18)					0.114	
Current age	-0.125	-0.129		-0.143	-0.115	-0.026
Currently working						-0.076
Current education					-0.081	
Neighborhood characteristics						
Changes in physical activity options	0	0	0			0.137
Changes in safety	0	0	0			0.128
Changes in socializing	0	0	0			0.164
Current socializing	0	0	0		-0.094	
Current # of business types w/in 400 m	0	0	0			0.096
Current dist. to nearest fast food	0	0	0	0.076	0.008	
Residential preferences						
Accessibility		-0.118	0.143	-0.019	-0.032	
Outdoor spaciousness		0.212		-0.066	-0.006	
Attractiveness	0.210					0.045
Travel attitudes						
Safety of car			-0.098		0.028	-0.127
Travel minimizing			0.127		-0.027	
Car dependent					0.113	
Pro-bike/walk						0.103

Notes: 0s are structural zeros and the blank cells are empirical zeros (see notes of Table 30). a. These variables and changes in driving behavior (called X) are transformed in the following way: if $X \geq 0$, $X_{new} = \mathrm{Ln}(X + 1)$; if $X < 0$, $X_{new} = -\mathrm{Ln}(-X + 1)$.