Exploring Travel and Activity Behavior in Transit-Oriented Developments: Insights Into Transportation Benefits and Travel Demand Modelling

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EXPLORING TRAVEL AND ACTIVITY BEHAVIOR IN TRANSIT-ORIENTED DEVELOPMENTS: INSIGHTS INTO TRANSPORTATION BENEFITS AND TRAVEL DEMAND MODELLING

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ABSTRACT

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As a sustainable urban development and transportation planning strategy, researchers and planners are increasingly interested in transit-oriented development (TOD). By integrating transit system and neighborhood design, TOD aims to provide a livable environment that is alternative mode friendly, higher density, and mixed-use to residents and workers in the vicinity of transit stations. Despite the recent growing interest in TOD, however, transportation benefits of TOD are not well quantified and characteristics of TOD are not adequately reflected in travel demand models.

This dissertation contributes to understanding of the travel and activity behavior by comprehensively exploring them in the context of TOD. Key dimensions of the behavior identified and analyzed in this study are activity location, travel mode use, activity time allocation, location choice and sequence, and commute time and schedule delay. With a strong research design of comparing TOD (0.5 mile buffer areas around transit stations) with auto-oriented development (AOD) that features relatively low density and mainly residential use, behavioral differences in each dimension were hypothesized and tested. Focusing on the Washington, D.C. metropolitan area, this study used the state of the art address-based household travel survey (N=11,436). The validity of the data was systematically checked for 1) non-coverage errors due to recently increasing mobile phone-only households and 2) trip underreporting as measurement errors. The data appropriateness was confirmed.

Rigorous statistical models were estimated at the household, person, trip, and activity levels, ranging from a local neighborhood to regional space. Results suggest that the travel and activity behavior between TOD and AOD contexts is significantly different. Key findings are that TOD residents tends to 1) make fewer and shorter automobile trips, but use transit more and walk more for their daily travel, 2) participate

in out-of-home activities and sequence the activity locations centered on transit stations, and 3) commute more reliably (less variant travel time and more on-time arrival by using a subway or walking), compared to AOD residents. These are largely attributed to the characteristics of the integrated built and transportation environments (e.g., mixed-use, high density, walkable design, accessibility, and/or connectivity). Implications of the findings for sustainable urban development, travel demand modeling, and geographical travel time reliability are discussed.

This thesis is dedicated to my family.

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CHAPTER 1

INTRODUCTION

1.1 Background

Modern metropolitan cities have suffered from a number of urban transportation problems including traffic congestion during peak hours, parking space shortages in downtown areas, and air pollution from exhaust emission. For example, because of the congestion, the additional travel time spent by urban residents in the United States was 4.8 billion hours, and 3.9 billion gallons of extra fuel was purchased in 2009 (Tim Lomax et al. 2011). To a certain extent, these contemporary problems have occurred and/or worsened due to urban sprawl, which features low-density and automobile-dependent development in suburban and exurban areas, coupled with segregated land use between residential and commercial uses (Reid Ewing, Rolf Pendall, and Don Chen 2002). In the urban sprawl, therefore, car ownership and trips by driving are inevitable for the residents to conduct their daily activities such as working, schooling, and shopping.

In response to the social and environmental costs resulting from such development, over the past decades the urban planning paradigm has been shifting to more sustainable approaches, e.g., New Urbanism and smart growth. With key principles of compact development, mixed land use, and walk/bicycle-friendly street design, smart growth strategies have been widely adopted, providing viable, livable, and sustainable communities. To date, many smart growth programs have been implemented across the United States (Environmental Protection Agency), intending that the provision of close proximity to activity locations and alternative travel modes to driving can change travel demand effectively and reduce the negative externalities consequently. Recent empirical studies have demonstrated that residents in such development (high density and/or diverse use) use fewer automobiles but more alternative transportation modes, e.g., walking and bicycling (Cervero and Kockelman 1997; Ewing and Cervero 2001; Cervero and Duncan 2003; Khattak and Rodriguez 2005; Cao, Mokhtarian, and Handy 2007; Ewing and Cervero 2010).

Another sustainable urban planning strategy to address urban problems is transit-oriented development (TOD). Compared to other smart growth strategies, TOD can

create very unique urban and suburban space by integrating land use and public transit system (ranging from heavy and light rails to bus rapid transit). TOD aims to provide not only higher density, diverse use, and pedestrian/bicycle friendly environments around transit stations, but also greater transit accessibility and regional connectivity to the residents in the vicinity of transit stations (approximately within 0.5-mile radius) (Calthorpe 1993; Bernick and Cervero 1997). In this way, the area around the stations can be attractive and sustainable communities in which residents desire to live and work, using alternative modes (e.g., transit and walking) more conveniently and frequently than automobiles. Thus, the negative externalities resulting from the transportation sector can be mitigated.

As of 2011, a total of 1,583 transit stations were recently proposed over 54 metropolitan areas in the United States (Center for Transit-Oriented Development); they are now in various stages of planning and construction. This mushrooming increase is mainly due to TOD's various potential benefits. For one thing, TOD is believed to reduce the residents' automobile trips while increasing transit and walking/bicycle trips. Also, trips are expected to shorter at various levels (e.g., individual trip, person, and household) due to its design. Clearly, the reduction in automobile use can directly alleviate traffic congestion and air quality deterioration while saving enormous costs for roadway investment and maintenance[1] (Calthorpe 1993; Bernick and Cervero 1997; Cervero, Ferrell, and Murphy 2002; Cervero 2004; Dittmar and Ohland 2004; Evans et al. 2007). For these reasons, TOD has gained popularity by transportation and planning agencies in metropolitan areas as a sustainable urban development strategy.

Despite the unique built and transportation environments of TOD[2], which is integrated urban space, and recent increasing demand for TOD in the public sector as an urban design strategy, TOD is not well understood in terms of travel and, particularly, activity behavior, excepting for transit ridership and mode choice aspects. As a result, the quantitative benefits of TOD are still not clear and the characteristics of TOD are not

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[1] TOD can bring about many other types of benefits such as housing, economy, health, and so forth. The other benefits are discussed later in the dissertation.

[2] The built environment generally means places and spaces made by human, as opposed to natural landscape, including land use patterns, transportation system, and design features (Committee on Physical Activity 2005). As opposed to the conventional notion (Handy et al. 2002), this study used the term of transportation environment to encompass the presence of transit systems and its service served for TOD.

adequately reflected in travel demand models. Thus, a more comprehensive empirical understanding of travel and activity behavior in the context of TOD is needed. Better knowledge of interactions between travel and activity behavior and urban space of TOD, which is unique and increasingly important, is required. In this regard, this dissertation can 1) fill the gaps in the literature on urban and transportation planning, 2) reflect sustainable policy urgencies, and 3) support travel demand modeling efforts.

1.2 Purpose

The purpose of this dissertation is to comprehensively explore travel and activity behavior of TOD residents, in comparison with their auto-oriented development (AOD) counterparts. As noted, AOD refers to a conventional neighborhood in urban and suburban areas. The neighborhood generally features with low-density, relatively single-use, and automobile-dependent. This study identifies and focuses on several dimensions of travel and activity behavior at the household, person, trip, and activity levels. These include 1) out-of-home activity location and trip length, 2) mode use in terms of trip frequency and travel distance, 3) activity participation and time allocation, 4) activity location choice and sequence, 5) variation of commute time, and 6) schedule delay (lateness) at work. Based on the better understanding, this dissertation aims to answer the following research questions: is travel and activity behavior of TOD residents different from AOD counterparts? And if they are different, how are they different?

1.3 Contributions

This dissertation is unique in several ways. First, this study fills a gap in a large body of urban and transportation planning literature on travel and activity behavior by systematically analyzing the behavior in underpinning conceptual structure. This is a significant contribution of this study. To date, the travel and activity behavior has been intensively researched in many contexts; however, understanding of travel and activity behavior and its connection with socio-demographics and spatial/temporal characteristics is limited in the TOD context. The reason for this is partly because TOD is relatively new and unique urban space in a sense that the built environment and transit system are

integrated. In this study, several dimensions of travel and activity behavior (e.g., activity participation, time allocation, location choice, etc.) are comprehensively investigated at various levels (e.g., activity, trip, person, and household) and from different spatial perspectives (e.g., local neighborhood, metropolitan region, etc.). Taken all together, this dissertation adds new and rich understanding of travel and activity behavior to the literature and the fundamental framework of the behavior for future research.

Second, a methodological contribution of this dissertation stems from assessing validity or reliability of the behavioral data. This study discusses and examines potential errors that might occur during household travel survey implementation: non-coverage and measurement errors. These errors can limit the understanding of actual travel undertaken and participate in activities as well as potentially lead to incorrect conclusions about transportation decision making. Recently, there is a growing concern of non-coverage of mobile phone-only households in household travel surveys. Also, the measurement error, e.g., trip underreporting, commonly takes place due to the nature of self-reporting in the travel surveys. The findings provide insights into behavioral survey methodology to transportation agencies, industry professionals, and academic researchers who heavily collect and utilize data on travel and activity behavior.

Third, this study sheds light on transportation benefits of TOD, based on the empirical understanding of activity and travel behavior. With a strong study design comparing TOD and AOD, which is somewhat unique in transportation, this study captures behavioral differences more appropriately and attempts to translate them into transportation benefits. Although the impacts of TOD on transit ridership or property values are relatively well researched, other aspects of benefits such as travel demand are not comprehensively quantified in the literature. Also, because associations between travel patterns and built environment, coupled with transit system, are normally found with regard to several aspects (e.g., density, diversity, design, distance, etc.), synergetic effects that can exist among these aspects are overlooked. While considering TOD as a whole, this study demonstrates how the transportation benefits of TOD can be achieved, as guidance for planning agencies and decision makers.

Fourth, new aspects of activity behavior investigated in detail can considerably assist in improving travel demand modeling, given the recent movement toward the

activity-based modeling approach. The activity behavior includes activity participation of TOD residents and their time use. Also, activity location choice and sequence behavior is significantly useful. In general, transportation planning agencies widely use travel demand models to make informed decisions on infrastructure investment or policy implementation. Behavioral understanding of activity and travel supports this effort. Moreover, an activity-based approach gradually becomes a new paradigm of travel demand analysis, taking into account travel as a derived demand of out-of-home activities. This study timely provides a sounder basis that can be incorporated in travel demand analysis

Fifth, to the author's knowledge, this study is the first attempt to intersect the concept of travel time reliability with built environment and transportation systems. The travel time reliability is of interest in transportation agencies to offer more consistent and expected travel time to travelers. Existing studies have solely focused on a single mode (e.g., automobile or transit) and/or over time (e.g., from day to day or time to time). Broadening those perspectives, this study analyzes the reliability of travel time across travel modes and over the entire metropolitan region, focusing on commuting time and schedule delay. This innovative approach provides better understanding travel-related behavior in TOD in multi-modal settings. Also, travel mode choice and residential location are insightfully discussed, highlighting travel time reliability as a new benefit of TOD policy.

1.4 Organization

Note that some chapters in this dissertation are published in a scientific peer–reviewed journal. Also, partial contents of some chapters are presented in a conference and/or conference proceeding. In the beginning of each chapter, this is explained in detail. The remainder of the dissertation is organized as follows:

- Chapter 2 provides a synthetic literature review on TOD, including definitions, historical background, and potential benefits. Earlier studies on travel and activity behavior are summarized in the various contexts, including the built environment and TOD. After that, gaps in the literature are discussed.

- Chapter 3 presents the conceptual framework for travel and activity behavior, with hierarchical transportation decision making and consequences. With the framework, how TOD, as an integrated built and transportation environment, comes into play in the context of travel and activity behavior is elaborated upon, together with other influencing factors. Also, a study area (with the respective behavioral data) is introduced.
- Chapter 4 examines the validity of the travel survey data, focusing on non-coverage and measurement errors. The definition of the errors and the impacts on research results are discussed. The behavioral data are analyzed in terms of socio-demographics and travel behavioral representativeness and trip-underreporting by travel mode.
- Chapter 5 explores activity location choice and travel mode use behavior of residents in a TOD neighborhood, by comparing residents in a matched pair of AOD neighborhood. The distributions of activity locations are spatially analyzed while the travel mode use in trip frequency and travel distance are modeled.
- Chapter 6 investigates time use by activity type and activity location as well as location choice and sequence behavior from a regional perspective. Several statistical models are estimated to compare these aspects among three groups (e.g., TOD, AOD close to TOD, and AOD far from TOD).
- Chapter 7 compares commuting behavior between TOD and AOD residents, focusing on variations of travel time and schedule delay. Characteristics of travel mode (e.g., automobile, transit, subway, and walking) and the built environment in terms of travel time reliability are discussed.
- Finally, Chapter 8 summarizes key research findings and concludes this dissertation by providing limitations, implications, and further study. Implications of the findings for sustainable urban development, travel demand modeling, and geographical travel time reliability are discussed.

CHAPTER 2

LITERATURE REVIEW

This chapter comprehensively reviews studies on TOD and travel and activity behavior to date. After that, major gaps in the literature are identified and stated, reflecting recent research trends and policy urgencies. Some of the contents in this chapter are presented in a conference paper (Son, Khattak, and Choi 2014).

2.1 Transit-oriented Development

2.1.1 Definition and Classification

Over the decades, TOD has been conceptually and physically defined by several studies. Calthorpe (1993) stated that TOD is "a mixed-use community within average 2,000-foot walking distance of a transit stop and core commercial area." Bernick and Cervero (1997) defined TOD as "a compact, mixed-use community, centered around a transit station that, by design, invites residents, workers, and shoppers to drive their cars less and ride mass transit more." Other similar definitions were offered elsewhere (Parker et al. 2002; Dittmar and Ohland 2004; Evans et al. 2007). Among the literature, notably, Dittmar and Ohland (2004) discussed a performance-based definition, pointing out five main goals to achieve[3]. Based on these definitions, key elements of TOD can be summarized: mixed land use, proximity to transit, compactness, pedestrian/bicycle-friendly environments, public spaces near stations, and stations as community hubs (Cervero, Ferrell, and Murphy 2002).

With regard to the physical boundary of TOD, a radius of 0.25- to 0.5-mile from transit stations or approximate 5-10 minutes walking distance has been consistently mentioned, though the actual size of TOD can vary depending on station-specific features (Calthorpe 1993; Dittmar and Ohland 2004). However, TOD is not limited to neighborhood design; rather, it can also play an important role in regional planning. In other words, a pair of a residential area and an employment center can be also TOD, when they are connected each other by transit system. In this sense, the boundary of TOD

[3] Five main goals are location efficiency, rich mix of choices, value capture, place making, and regional role (Dittmar and Ohland 2004).

can be broadened to a regional transportation network (Dittmar and Ohland 2004). By mixing residential, commercial, public spaces in walking distance, the TOD can provide more convenient and diverse transportation options to the residents and employees at the community level. Also, developing a network of TOD throughout a region can strengthen the overall performance of the regional transit systems.

In the literature, the classification of TOD differs. Calthorpe (1993) identified two prototypes of TODs with qualitative attributes (e.g., location and function). One is an urban TOD where major transit network is close and therefore direct access to transit is available. Also, the urban TOD requires high residential and commercial densities and employment clusters. The other is a neighborhood TOD. The neighborhood TOD is designed for the vicinity of local or feeder bus line (10 minutes or 3 miles), allowing moderate density and local amenity needs such as parks. Dittmar and Ohland (2004) loosely classified the types of TOD, based on the role and functional characteristics in regional spaces: urban downtown, urban neighborhood, suburban town center, suburban neighborhood, neighborhood transit zone, and commuter town.

2.1.2 Historical Background

TOD is not a totally new concept of neighborhood design or urban planning. About 100 years ago, the TOD was commonplace across major cities the United States. For instance, an urban center and a suburb were linked on transit systems (e.g., streetcar and later commuter rail). While jobs were largely available inside of cites, many houses were located in suburban communities within 5-min walking distance from transit stations. Various activities took place in the vicinity of the stations (Bernick and Cervero 1997; Dittmar and Ohland 2004). As transit networks extended to further suburban areas, the geographical boundaries of cities were proportionally expanded (Bernick and Cervero 1997). The growth of suburban areas continued in this way until automobile ownership and usage were prevalent.

The way of urban design and regional planning rapidly changed from TOD to AOD with substantial roadway expansion. More and more transit lines and stations were closed and thereby transit commuters became automobile commuters. Simultaneously, many moved out from urban/suburban areas to further outside of cities. As a result,

suburban sprawl[4] and urban decay began (Bernick and Cervero 1997; Dittmar and Ohland 2004). The movement was accelerated by interstate project in the 1960s and the motor of 'American Dream' in the 1970s (Bernick and Cervero 1997). Besides, Calthorpe (1993) viewed that this movement of cities and regions was a reflection of Modernism[5]. In consequence, a number of urban transportation problems, including increase in traffic congestion and air pollution, resulted from the dominance of automobile ownership and usage and the corresponding AOD.

The TOD reappeared as means of supporting transit ridership. Since the 1970s, to mitigate increasing traffic congestion across metropolitan areas, modern transit systems were reintroduced. Examples are the San Francisco Bay Area Rapid Transit system, the Washington Metropolitan Area Transit system, and so on. However, they soon faced a lack of passengers, despite the considerable amount financial investment. To address this issue, intensive development around rail stations was suggested to ensure a sufficient number of passengers. In this sense, the TOD was viewed as a "way to reverse transit's downward spiral" (Cervero 1994). Boarnet and Compin (1999) also viewed that TOD is "an idea to use land-use planning to support rail transit." Focusing on suburban stations, large amounts of parking spaces were switched to apartment complexes.

Recently, TOD became popular as an attractive and sustainable neighborhood development and regional planning strategy. The TOD strategy is a part of the smart growth or new urbanism movement, which is a new planning paradigm. Smart growth is a set of development strategies that can "help protect our natural environment and make our communities more attractive, economically stronger, and more socially diverse" (Environmental Protection Agency). Especially due to the federal transportation legislation, government investment on alternative modes, such as transit, walking, and bicycling, increased (Dittmar and Ohland 2004). Simultaneously, an interest in land use grew as a way to shape travel demand (and traffic congestion). Smart growth highlights several design principles including mixed land uses, walkability, and compact

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[4] Reid Ewing, Rolf Pendall, and Don Chen (2002) defined sprawl as "the process in which the spread of development across the landscape far outpaces population growth," providing four characteristics of sprawl: low-density development, land use segregation, no activity centers, and limited travel choices.

[5] It is characterized as "the segregation of activities and peoples, the specialization and isolation of professions and the system they create, the centralization of ever-larger institutions, and the monopoly of certain technologies, most notably the car."

development. Examples of smart growth are traditional neighborhood developments, neo-traditional development, compact communities, and so forth. While TOD provides sustainable communities, what makes TOD different from other types of a development strategy is the fact that transit system can offer various transportation options to local residents (Calthorpe 1993), which is identical to one of the smart growth principles.

Urban revitalization is another reason for recent substantial interests in TOD. Due to suburban sprawl, the inner-city area has declined over the years. Recently, especially with light rail transit, positive consequences such as residential renewal and retail increase have been observed from several urban centers: Horton Plaza in San Diego, Pioneer Place in Portland, and Plaza in Sacramento. Therefore, city planners increasingly consider TOD as an effective tool.

2.1.3 Potential Benefits

Earlier studies have argued expected and potential benefits of implementing TOD in various ways. For example, Parker et al. (2002) listed ten critical social, economic, and environmental benefits of TOD, explaining the positive impact on the individual, community, and region level. Cervero (1994) discussed primary and secondary potential benefits, whereas Cervero, Ferrell, and Murphy (2002) summarized benefits that TOD can yield for both public (governments and communities) and private sectors. Subsequently, Cervero (2004) tabulated the benefits of TOD by class (primary vs. secondary) and primary recipient (public sector vs. private sector), pointing to the source of the benefits. Interestingly, Dittmar and Ohland (2004) discussed the expected benefits, combining with the definition of TOD. A good review on TOD benefits is also provided from elsewhere (Evans et al. 2007). The benefits of TOD (if successfully implemented) discussed in the literature are summarized as follows:

- Providing mobility choices (e.g., transit, walking, and bicycling)
- Providing housing choices (i.e., affordable housing)
- Promoting health and reducing obesity with physical activity
- Increasing private property (land and house) values
- Reducing vehicle miles traveled and traffic congestion
- Reducing negative externalities (e.g., air pollution) and energy consumption

- Mitigating urban sprawl and preserving resource lands and open space
- Increasing transit ridership and revenue gains
- Decreasing infrastructure capital and operating costs
- Boosting economic growth and increasing retail sales
- Reducing urban decline and revitalizing aging neighborhoods
- Increasing property- and sales-tax income revenues
- Enhancing sense of community and improving neighborhood quality
- Increasing security with reduction in crime

2.2 Travel/Activity Behavior and Built Environment

2.2.1 Travel Behavior

Over the past several decades, transportation researchers have intensively studied travel behavior and the underlying relationships with associated factors over space and time. Due to its complexity, the past studies have provided insights into travel behavior by various dimensions, including trip frequency, trip destinations, mode choice, and route selection as a daily travel decision. Also, trip distance and trip duration have been examined as a consequence of the decisions. Better knowledge of travel behavior have played an important role in supporting state and regional transportation planning and decision making processes (mainly for, but not limited to, infrastructure investment). To date, a substantial number of behavioral models have been developed in a diverse context. The models consistently find that travel patterns are strongly associated with various factors, including socio-demographic traits, spatial characteristics, and temporal contexts. This understanding supports travel demand modeling and analyses (Ortúzar and Willumsen 2001; Khattak et al. 2011; Wang, Khattak, and Son 2012).

As the development of information and communication technology, intelligent transportation systems emerged with various applications (e.g., advanced traveler information systems), aiming to improve the experience of individual travelers and efficiency of the transportation system. Since then, individuals have utilized travel information to make informed travel decisions such as departure times, travel modes, travel routes. The information includes travel time, incident occurrence, road work,

bridge closure, and corresponding expected delay, which can be obtained pre-trip and en route. Over the years, considerable research on travel behavior (especially whether and/or how to change intended travel plans) in response to the information has been conducted in many contexts. The studies have empirically found that travel plan changes are associated with traffic congestion (e.g., occurrence and estimated delay), travel information acquisition (e.g., source, frequency, etc.), socio-demographic characteristics (e.g., age, gender, etc.), spatial factors (e.g., network structure, congestion level, etc.), and travel contexts (Khattak and Khattak 1998; Khattak, Yim, and Stalker 1999; Wang, Khattak, and Fan 2009; Son, Khattak, and Chen 2011).

Recently, with a hope that the built environment can shape travel demand, a considerable number of planning studies have examined relationships between travel behavior and urban form (land use). While the efforts include urban shape and road network at the city or neighborhood level (Snellen et al. 2001), the built environment of residential location (with employment location) has been intensively investigated at a more micro level. To represent the built environment, several dimensions have been generated and used in literature. For example, '3D' variables (e.g., density, diversity, design) were developed and have been widely applied (Cervero and Kockelman 1997; Ewing and Cervero 2001, 2010). Especially, Cervero and Kockelman (1997) provided logical explanations of how each attribute can influence on travel patterns. Interestingly, Handy et al. (2002) suggested six dimensions: density and intensity, land use mix, street connectivity, street scale, aesthetic qualities, and regional structure. In addition, destination accessibility and distance to transit (transit accessibility) were considered (Ewing and Cervero 2001, 2010). Some dimensions are straightforward (e.g., density), while other dimensions (e.g., design) are qualitative and implicit. Therefore, not one single variable can fully characterized each dimension.

The measures of travel behavior that has been explored widely in this context are vehicle miles traveled (VMT) per capita, vehicle trips, transit trips, walk trips, and so forth. While these behaviors have been examined by focusing on non-work trip, mode choice behavior for commute trips have been intensively modeled (Cervero 2007). See Ewing and Cervero (2010) for a summary of such variables. Many studies have consistently found that residents in a higher density, more diverse, and transit/pedestrian

friendly neighborhood use automobiles less, but travel more by transit and walking. Similar findings have been confirmed when travel behavior of residents in such neighborhoods are more directly compared with conventional neighborhoods (Khattak and Rodriguez 2005).

In the research on the relationship between travel behavior and the built environment, there has been a long debate on causality. Simply put, it is not clear whether the built environment actually changes travel behavior. This is an important discussion because of the potential that urban form or land use policy can shape travel demand and subsequently mitigate traffic congestion in urban areas. If the relationship is not causal, travel behavior is a consequence of other factors. However, most studies in the past have shown only a statistical association, but not necessarily a causal relationship. Recently, some studies actually demonstrate the evidence of a causal relationship in a more sophisticated and advanced statistical method. For example, Cao, Mokhtarian, and Handy (2007) showed causal linkage with a quasi-longitudinal research design. Based on theoretical underpinning and statistical evidences, therefore, it can be said that the built environment can change travel behavior.

Another important issue that has been largely discussed in the literature is self-selection. By definition, self-selection occurs when "rational actors make optimizing decisions about what markets to participate in" (Autor 2003). In the context of the built environment and travel patterns, residential self-selection is of interest. Residential self-selection is that certain types of neighborhoods are chosen due to preferences in certain travel behavior. That is, people may select dense and mixed use neighborhoods because they are predisposed for walking and bicycling. This issue is important because, if it is true, the impact of the built environment on travel outcome can be overstated from a transportation policy perspective. Then to what degree does the residential self-selection influence on travel behavior? Cervero (2007) quantified the influence of self-selection on transit ridership (40%), using nested logit modeling. Zhou and Kockelman (2008) estimated that 42% of the differences in daily VMT per household can be attributed to self-selection between neighborhood types (rural/suburban versus CBD/urban). To date, a large number of studies have discussed methodologies to deal with residential self-selection (Bhat and Guo 2007; Mokhtarian and Cao 2008). For example, Mokhtarian and

Cao (2008) comprehensively reviewed the existing methodologies and categorized them into nine groups: direct questioning, statistical control, instrumental variables, sample selection, propensity score, joint discrete choice models, structural equation models, mutually dependent discrete choice models and longitudinal designs.

2.2.2 Activity Behavior

Over the past decades, travel demand forecasting models have rested on individual trips as a unit of analysis. As a new paradigm of travel demand analysis, however, the activity-based approach emerged, focusing on activity participation decisions with trips viewed as a special case of activity participation. Activity sequencing, household interactions and time-space dimensions become important aspects to be explored. With this trend, to some extent, a large set of studies have empirically analyzed daily activity patterns in different contexts (see Table 1).

While most empirical studies have focused on the general population of urban residents or commuters, certain population segments have also been the focus, e.g., home-workers (Lu and Pas 1999), non-workers (Lu and Pas 1999; Misra and Bhat 2000), homemakers (Chen and McKnight 2007), university students (Eom, Stone, and Ghosh 2009), and individuals 65+ years (Ziems et al. 2010). Furthermore, weekend activity patterns compared with weekday activity patterns were also analyzed (Lockwood, Srinivasan, and Bhat 2005; Zhong, Hunt, and Lu 2008). These studies examined out-of-home activities, classified into work, school, shopping, recreation, personal business, etc. Some have grouped them into subcategories such as subsistence, maintenance and recreation (Lu and Pas 1999), obligatory and discretionary (Buliung and Kanaroglou 2006), or maintenance and discretionary (Ziems et al. 2010).

Activity behaviors are quite complex to understand, partly because there are many types of daily activities and they take place over time and at different locations. To capture the complexity of observed activity patterns, various measures have been used in earlier studies, e.g., Hanson and Hanson (1981) generated and tested 51 measures to explain activity behaviors temporally and spatially, together with travel activity, including the number of stops by each activity category, by weekday and weekend, and by locations (e.g., CBD), as well as minutes spent in each activity category (see Table 1).

Recent studies have explored activity frequency, duration, sequence of activities, first or last stop (activity) of the day, and number of stops per tour (Misra and Bhat 2000). Also, a transition matrix of activity types was used to clearly show activity sequence (Misra and Bhat 2000; Eom, Stone, and Ghosh 2009). Interestingly, some studies measure daily activity behaviors in terms of space use at the household and individual level (Buliung and Kanaroglou 2006; Fan and Khattak 2008).

Activity patterns measured in different dimensions are found to be associated with demographic and socioeconomic attributes of individuals or households, but the relationships are likely context dependent. For instance, females are positively correlated to frequency, duration, or propensity of shopping activities (Hanson and Hanson 1981; Levinson and Kumar 1995; Lu and Pas 1999; Misra and Bhat 2000) while negatively related to working (Hanson and Hanson 1981; Lu and Pas 1999) and recreational (Lu and Pas 1999; Misra and Bhat 2000) activities. Moreover, the earlier stage of the life cycle is statistically associated with more frequent social activity (Hanson and Hanson 1981), as well as more time spent or higher propensity for recreation activity (Hanson and Hanson 1981; Misra and Bhat 2000). As expected, automobile ownership and availability significantly explain frequency or duration of out-of-home activities (Hanson and Hanson 1981) and some in-home activities (Levinson and Kumar 1995; Lu and Pas 1999). In addition to socio-demographics, travel behavior is both directly and indirectly related with activities (Lu and Pas 1999). Furthermore, from a time budget perspective, in-home and out-of-home activity durations must be traded-off.

Remarkably, there are a few activity behavior studies that are linked to land use patterns. However, their results are mixed. Misra and Bhat (2000) found that the land use variables did not show any statistical significance in the propensity of making specific activities, while a recent study comparing homemakers in New York and suburban areas indicated that travel and activity behavior are related with both the built environment and socioeconomic variables (Chen and McKnight 2007). The study also found that homemakers living in New York City spend more time on discretionary activities, but less time on maintenance activities, compared to those in suburbs. A gap in the literature is the lack of information about activity patterns of TOD residents over space and time, which is needed to be understood comprehensively.

Table 1. Summary of Activity Behavior Studies

Author(s)	Purpose and target	Activity category	Key measure
Hanson and Hanson (1981)	To relate urban residents' travel and daily out-of-home activity patterns with socio-demographic status and the individual's role situation	• Social • Shopping • Personal business • Work • Recreation	• Num. of stops and time spent for activity • Proportion of stops by mode
Levinson and Kumar (1995)	To understand trends in and factors affecting activity patterns among different activities of individuals by different work status and gender	• Work • Home • Shopping • Travel	• Activity duration • Activity frequency and distribution
Lu and Pas (1999)	To examine relationships among out-of-home and in-home activity participation, travel behavior, and socio-demographics	• Subsistence • Maintenance • Recreation	• Time spent on activity group
Misra and Bhat (2000)	To explore out-of-home activity behavior of non-workers, relating with individual and household socio-demographics	• Transport passenger • Personal business/ medical/dental • Social/recreation • Shopping • Home	• Num. of stops and stops per tour • First/last stops and activity of the day • Transition matrix of activity types
Frusti, Bhat, and Axhausen (2002)	To understand fixed commitments in individual activity–travel patterns, relating with socio-demographics, social roles, and work-related characteristics	• Recreation • Personal • Community • Training	• The presence of each fixed commitment
Lockwood, Srinivasan, and Bhat (2005)	To compare weekday with weekend travel-activity patterns in terms of activity participating and activity sequencing/chaining	• Work/school • Social/recreation • Meals • Shopping • Personal business • Transport passenger • Community/religious	• Frequency/duration of activity episode • Activity episode transitions/chains • First and last activity episodes of the day
Buliung and Kanaroglou (2006)	To examine the spatial characteristics of week-day household activity-travel behavior, associating with location, mobility status, and socio-demographics	• Obligatory • Discretionary	• Household activity space
Chen and McKnight (2007)	To investigate whether activity and travel behavior of homemakers differ with different types of neighborhoods and if they are attributed to the built environment	• Maintenance • Discretionary	• Activity frequency • Time use
Zhong, Hunt, and Lu (2008)	To study the differences in weekday and weekend activities in terms of participation frequencies, starting times, and durations	• Work • School • Sociality • Shopping • Eating • Exercise • Entertainment/leisure • Religious, civil, etc. • Travel • Out-of-town	• Activity participation frequency • Starting times of each activity type • Durations of each activity type
Fan and Khattak (2008)	To examine how space uses of individuals is related to urban form	N/A	• Individual daily activity space
Eom, Stone, and Kang (2010)	To analyze university students' daily activity participation and compare it across the student groups	• School/class • Meals • Study/research • Work/volunteer • Social/recreation • Family/personal	• Average activity frequency/duration • Activity sequencing • Proportion of daily activity profile
Ziems et al. (2010)	To compare the activity time allocation patterns of old individuals (age 65+) with other age groups and to quantify satisfaction of derived from the pattern	• Mandatory • Maintenance and Discretionary in-home/out-of-home • Travel • Sleep	• Average time use for in- and out-of-home activities and utility

Table 1. Summary of Activity Behavior Studies (continued)

Author(s)	Data	Method	Key findings
Hanson and Hanson (1981)	1971 Uppsala longitudinal household travel survey, Sweden (N=149 individuals)	PCA OLS	Complex behaviors of travel and activity can be viewed multi-dimensionally. Socio-demographic and individual role attributes are statistically associated with different travel-activity patterns.
Levinson and Kumar (1995)	1968 and 1987/88 metropolitan Washington, D.C. household travel surveys (N=36,958 and N=10,305 individuals)	DA OLS	Both increases in work and non-work trips lead to less time spent at home. Activity duration for home, shopping, other are associated with socio-demographic variables.
Lu and Pas (1999)	1994/95 Oregon-Southwest Washington two-day activity and travel survey (N=2,514 individuals)	SEM	Direct and indirect relationships exist among socio-demographics, time allocation of activity, and travel frequency and time. Interactions between in-home and out-of-home activity groups appear in time use.
Misra and Bhat (2000)	1990 San Francisco Bay area activity travel diary survey, CA (N=3,517 individuals)	DA BLM	Household and individual characteristics are related with activity participating and chaining, while activity sequencing is mainly determined by current activity types, not by variations of individual or household attributes.
Frusti, Bhat, and Axhausen (2002)	1999 Halle/ Karlsruhe 6-week activity travel survey, Germany (N= 361 individuals)	BLM	The determinants of fixed commitments with statistical significance are found among personal, household, and spouse variables.
Lockwood, Srinivasan, and Bhat (2005)	2000 2-day San Francisco Bay Area Travel Survey, CA (N= 50,892 individuals)	DA	Weekend activity/travel patterns are different from weekday patterns (e.g., activity purpose and travel distance). Using activity sequencing and trip-chaining behavior, activity/travel on weekends is explained.
(Buliung and Kanaroglou 2006)	1994/95 2-day Portland Household Activity-Travel Behavior Survey (N=1,609 households)	ST SRM	Between urban and suburban, urban households have less daily travel and smaller activity spaces. Statistically significant associates with household activity spaces are found.
Chen and McKnight (2007)	1997/1998 New York metropolitan area household interview survey	DA SEM	Homemakers living in New York City spend more time on discretionary activities, but less time on maintenance activities, compared to those in suburbs. Travel and activity behavior are related with built environment and socioeconomics.
Zhong, Hunt, and Lu (2008)	2001/02 Calgary household activity survey, Canada (N= about 13,000 activities)	ST MF	Weekend activities behaviors are different from their weekday counterparts. For common activity types, they tend to follow different survival functions as well as result in different parameters.
Fan and Khattak (2008)	2006 Greater Triangle region travel survey, NC (N=7,422 individuals)	SRM	Residents of densely developed neighborhoods with more retail stores and better-connected streets generally have a smaller area of daily activity space.
Eom, Stone, and Kang (2010)	2001 North Carolina State University travel survey, NC (N=843 individuals)	ST	Proportion of daily activity profile (or participation) is not significantly different across the student groups in terms of gender, educational or residential status.
Ziems et al. (2010)	2008 American time use survey (N=12,055 individuals)	URM	Older individuals show the highest values of time use utility of all age groups. Out-of-home activity engagement is important from the utility perspective.

Note: PCA=principal component analysis; OLS=ordinary least squares regression model; DA=descriptive analysis; SEM=structural equation model; BLM=binary logit model; ST=statistical test; SRM=spatial regression model; MF=model fitting; URM=utility regression model.

2.2.3 Travel/Activity Behavior and TOD

Many studies have reported that mode shares for transit are high among residents around transit stations (see Table 2). According to a recent survey of the Washington Metroplitan Area Transit Authority (2006), for example, transit trips are on average 49% around the metro stations while auto trips are 39% and the other trips, including walking and bicycling, are 14%. Notably, the reported transit modal splits vary by trip purpose, transit system and regional context; however, earlier studies consistently pointed that residents living in TOD areas undertake substantially more transit trips than those in the comparative areas (e.g., the respective region). For instance, residents near stations of several cities in California are five to seven times more likely to commute by rail transit than average workers living in their respective cities (Cervero 1994). In the case of metro stations in Arlington, Virginia, station-area residents are about 1.5 times more likely to commute by transit compared to all residents in the county (Dittmar and Ohland 2004). Lastly, mode share for transit falls as distance is farther from stations (Cervero 1994).

Given the availability of transit system, mode choice, among various dimensions of travel behavior, has been widely investigated in the context of TOD. To date, key factors found to be associated with the likelihood of traveling or commuting by transit in behavioral models are distance to subway stations, vehicle availability for household members, workplace transit proximity, and parking policy (paid vs. free parking) at workplace (Cervero 1994).

At the aggregated level, when it comes to travel behavior in TOD, ridership impacts have been studied mostly. Cervero et al. (2004) and Arrington and Cervero (2008) comprehensively reviewed and summarized the transit ridership increase in TOD. It was found that commuters in TOD typically use transit two to five times more than other commuters in the surrounding region. On the other hand, it was reported that TOD-housing results in fewer trips than in other urbanized areas that were studied by Cervero and Arrington (2008).

Other aspects of travel behavior have been studied, but in a rather limited way. Another interesting travel characteristic of TOD residents is that they have relatively fewer and shorter automobile trips than those in conventional areas featured with low density and residential use. Cervero and Arrington (2008) found that station-area

residents make 3.75 vehicle trips per TOD housing per day, which is 44% lower than trip generation estimates in practice (e.g., the ITE manual).With regard to the shorter auto use, many studies to date have utilized a measure of VMT per household. Cervero (2007) found that commuting VMT of new residents in TOD changes from 33 miles to 23.5 miles on average, with a significant decrease of 29% (Ewing and Cervero 2010). Recently, Nasri and Zhang (2013) showed that households close to transit stations have 20% and 22% less VMT, respectively, comparing between households living in TOD vis-à-vis non-TOD areas in Washington, D.C. and Baltimore metropolitan areas.

Table 2. Summary of Mode Share for the Selected Study Sites

	Author (year)	Transit system and region	Type	Station name (Number of stations)	Mode share (%) ****		
					Auto	Walk *	Transit **
All daily trips	Cervero (1993)	Bay Area Rapid Transit, CA	HRT	Pleasant Hill, Union City, Fremont, Bayfair, Lake Merritt, and South Hayward (6)	67	3	30
		Santa Clara County Transit, CA	LRT	Lick Mill, Tamien, and Almaden (3)	89	1	7
		Caltrain, Bay Area, CA	CRT	Hillsdale, San Mateo, Broadway, and Palo Alto (4)	76	7	15
		Sacramento Regional Transit, CA	LRT	Royal Oaks, Butterfield, Power Inn, and Tiber (4)	79	2	15
		San Diego Trolley, CA	LRT	Sprung St, La Mesa Blvd, and Amaya Dr (3)	86	2	12
	WMATA (2006)	Washington Metro, DC, VA, MD	HRT	Ballston, Court House, Crystal City, Friendship Heights, Silver Spring, and U-street (6)	39	14 ***	49
Work (commute) trips	Lund, Cervero, and Wilson (2004)	Bay Area Rapid Transit, CA	HRT	Pleasant Hill (1)	53	2	45
		Bay Area Rapid Transit, CA	HRT	South Hayward, Hayward, Fremont, and Union City (4)	62	1	38
		Los Angeles Metro, CA	LRT	Long Beach Transit Mall and Pacific at 5th (2)	93	3	3
		San Diego Trolley, CA	LRT	Fenton Parkway and Hazard Center (2)	85	2	13
		Caltrain, Bay Area, CA	CRT	Broadway, Mountain View, and Palo Alto (3)	82	1	17
	Dittmar and Ohland (2004)	Washington Metro, VA	HRT	Court House, Clarendon, Rosslyn, and Ballston (4)	43	11	37
	Cervero (2004)	Washington Metro, VA	HRT	Rosslyn, Court House, Clarendon, Virginia Square, and Ballston (5)	48	11	39
	Schlossberg et al. (2004)	Portland MAX, OR	LRT	Orenco, Beaverton Central, Lloyd Center, and Gresham Central (4)	75	7	14
Non-work trips	Lund, Cervero, and Wilson (2004)	Bay Area Rapid Transit, CA	HRT	Pleasant Hill (1)	82	4	15
		Bay Area Rapid Transit, CA	HRT	South Hayward, Hayward, Fremont, and Union City (4)	80	6	14
		Los Angeles Metro, CA	LRT	Long Beach Transit Mall and Pacific at 5th (2)	86	13	1
		San Diego Trolley, CA	LRT	Fenton Parkway and Hazard Center (2)	93	2	5
		Caltrain, Bay Area, CA	CRT	Broadway, Mountain View, and Palo Alto (3)	91	4	5

Notes: * Walk includes walk and bicycle trips; ** Transit includes rail and bus trips; *** It includes other trips as well; ****Mode share may not be 100 percent in total due to rounding decimals and excluding other trips; HRT=Heavy Rail Transit; LRT=Light Rail Transit; CRT=Commute Rail Transit.

2.3 Summary and Discussion

Despite a large body of literature on urban and transportation planning, travel and activity behavior in the context of TOD is not well-understood. Particularly, far less attention has been given to the activity behavior. Better knowledge of travel and activity patterns can be used to measure the benefits of land use policy. Also, a good understanding of travel and activity behavior can increase the accuracy and reliability of travel demand modeling and in turn help in making informed decisions related to transportation planning. To this end, several dimensions of travel and activity behavior need to be investigated in a holistic manner. This provides not only new and rich understanding of travel and activity behavior to the literature, but also fundamental frameworks between decision-making and consequences for future research.

To analyze the travel and activity behavior, the characteristics of TOD should be taken into account. Clearly, TOD is distinguished from other smart growth strategies (e.g., traditional neighborhood development or neo-traditional development) in a few aspects. First, TOD offers a unique neighborhood in which built and transportation environments are integrated. Second, the boundary of TOD is geographically definite (i.e., approximately 0.5 mile in distance or 10 minutes in walking from stations), around transit stations. Third, TOD is not only community development, but also regional development, linking several urban and suburban areas in a transit system. Especially, a regional level analysis can properly incorporate transit accessibility and regional connectivity into the analysis. These points need to be reflected when the relationship between travel and activity behavior and TOD is studied.

Moreover, to date, built environment attributes have been analyzed with respect to several dimensions (e.g., density, diversity, and design). Among transportation and land use attributes, however, there can be potential interactions, especially in the context of TOD. As discussed, TOD provides residents with livable and viable environment where land use is dense and mixed as well as public transit system is served. Thus, synergetic effects between land use and transit system can strongly exist, as pointed out by Cervero and Kockelman (1997). In this case, stronger study design (i.e., comparison of TOD and AOD as a whole) may be preferable. In this way, the complexity of TOD in terms of travel and activity behavior can add value to the literature.

CHAPTER 3

CONCEPTUAL FRAMEWORK AND RESEARCH DESIGN

This chapter is dedicated to present a conceptual framework that underlies this dissertation, followed by proposing a key hypothesis. Next, a study area selected for this study is explained, with the corresponding household travel survey data and several complementary data sources.

3.1 Conceptual Framework

Households and persons make various decisions on activity and travel on a daily basis. The decisions can vary from routine decisions to non-routine decisions. The former includes, for instance, activity engagement, activity duration, and travel mode. On the other hand, the latter includes activity/trip cancelation and route diversion resulting from changing activity schedules and travel plans in response to traffic information or weather conditions. Among them, this dissertation focuses on the routine travel and activity decisions and their consequences at the household, person, trip and activity levels.

Figure 1 presents a conceptual framework for travel and activity behavior as a part of three-stage of decision making processes at different temporal scales. This framework also includes not only other influential decisions such as residence and vehicle but also several other factors, based on theory and empirical findings. First, in the long run, decisions on residence, workplace, and school are determined at the household and person levels. The locations of residence, workplace, and school play an important role in travel and activity behavior as a routine anchor. Subsequently, vehicle ownership and type are decided in the mid-term. The vehicle ownership largely impacts household and personal mobility. Finally, various activity and travel choices are routinely made on a daily basis, resulting in two forms of outcomes. One is a disaggregate outcome (e.g., travel time, arrival time, etc.), which exists in the decision making process. On the other hand, the other outcome is traffic congestion and air pollution that are revealed at the aggregate level. This hierarchical decision making processes is refined from earlier discussions (Ben-Akiva and Atherton 1977; Bhat and Guo 2007; Pinjari et al. 2011; Shay and Khattak 2012). The three-stage decisions are interdependent each other. Apparently,

a later stage is conditional on decisions of the former stages. In addition to the conditionality among the stages, feedback can come into play in the process.

This study specifically focuses on daily activity and travel behavior, which is the last stage of the travel decision making process, examining how the routine activity and travel behavior is associated with influencing factors. In this structure, five groups of associates are presented: household/person attributes, the built environment and transportation system, work-related attributes, spatial contexts, and temporal contexts. Notably, factors on left hand side represent household/individual factors while space-related factors are located on right hand side.

Typically, the built environment of residential location as well as other locations (work and school) are associated with the activity and travel behavior, as suggested by earlier studies. Also, the transportation system (e.g., transit availability) is strongly related to the behavior. Notably, this study considers these aspects as a whole. As discussed, there might be interactions between the two components as TOD integrates the built environment and transportation system. Comparing travel and activity patterns of TOD and AOD can provide more clear sense of its association.

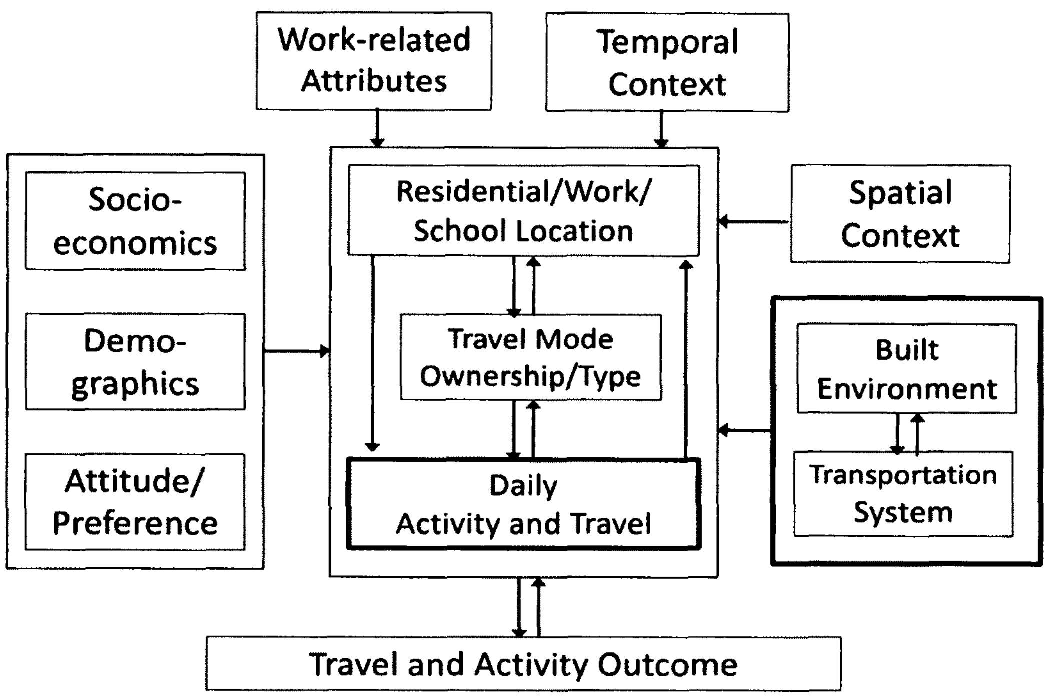

Figure 1. Conceptual Framework for Daily Activity and Travel Behavior

Socio-demographic characteristics of the household/person generally influence travel and activity behavior. Notably, socio-demographic characteristics of residents in a TOD neighborhood are unique and largely different from those of a conventional neighborhood. For example, a substantial portion of TOD residents are single, childless couples, empty nesters, and foreign immigrants (Cervero et al. 2002; Arrington and Cervero 2008). Also, households with no vehicle and/or low income are more likely to be found around transit stations. Moreover, TOD planning recently emphasized providing "affordable houses" so that low-income populations can have various choices on property near transit stations (Cervero 2007). Consequently, the diverse socio-demographic feature in TOD, together with dense and mixed land use, can result in different and potentially more complex travel activity behavior.

Another important attribute is attitude/preference. The relationship among travel and activity behavior and transportation and built environments in TOD should be carefully identified owing to residential self-selection. By definition, residential self-selection is that certain types of neighborhoods are chosen due to preference in certain travel behavior. That is, in the context of TOD, ones who prefer walking, bicycling, and using transit are more likely to choose residential locations that can support their preference. Lund, Cervero, and Wilson (2004) stated self-selection is one of the main reasons for residents to select TOD residences. For example, Cervero (1994) found that among ones who moved to TOD areas in California 56% were already transit commuters, indicating that TOD residency did not quite change the travel behavior. Similar results were found by a follow-up survey in 2003: among TOD residents, only 10% shifted their primary mode from transit to auto after moving to TOD areas (Arrington and Cervero 2008). Therefore, it is important to ensure the nature of the relationship between travel behavior and TOD areas.

Work-related attributes may be strongly related to activity and travel behavior. In urban areas, a significant portion of activity and travel are generally work-related activities and travels. Many companies operate employer-based transportation benefits, providing the employees with various options for their commuting (e.g., free parking, transit subsidy, etc.). Evidently, this can influence workers' travel and activity behavior due to transportation policies at the workplace (Cervero 1994). For example, station area

residents are more likely to commute by rail when they pay for parking at their workplaces (42%), compared with those who receive free parking (5%). Also, the availability of flexible work generally increases the use of transit (Cervero 2007).

Finally, activity and travel behavior can vary by spatial (or geographical) and temporal factors. In other words, the activity and travel behavior can be different from region to region or even from transit station to station. For example, workplace location characteristics (e.g. regional accessibility) are influential to travel decision making. Examples are a ratio of highway travel time to transit travel time (Cervero 2007) and the distance to CBD (Nasri and Zhang 2013). Similarly, the activity and travel behavior can be sensitive to day of week, month, or season.

3.2 Main Hypothesis

This study focuses on the relationship between activity and travel behavior and TOD as a whole. As pointed out earlier, a TOD neighborhood is quite distinct from an AOD neighborhood in terms of the built and transportation environments. TOD is uniquely or conceptually an interesting place to live and work, where a sustainable built environment and transit system are provided with a great level of transit accessibility and regional connectivity. The main hypothesis is that activity and travel behavior is different between residents of TOD (0.5 mile buffer around the transit stations) and those of AOD (relatively low density and mainly residential use). To examine the behavioral difference in activity and travel, this study identifies six dimensions of daily activity and travel behavior. The six dimensions and the corresponding questions to be answered are as follows:

- Activity[6] location and trip length: Do TOD residents participate in local activities more? Do they make shorter trips?
- Travel mode use in trip frequency and travel distance: Do TOD residents drive less but use transit and walk more?
- Time use by activity type and location: Do TOD residents spend more time on out-of-home activities in TOD areas?

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[6] This study focuses on out-of-home activity that are taken place outside the home but excluding travel.

- Location choice and sequence for their activities: Are TOD resident more likely to choose and sequence of activity locations centered on TOD areas?
- Commute time variations: Are TOD residents' travel times less likely variant over space when they use subway or walk?
- Schedule delay (i.e., on-time arrival at work): Do TOD residents tend to arrive at work on time when using subway or walking?

Each aspect of activity and travel behavior is separately discussed in the remainder of dissertation. In each chapter, each aspect of travel and activity behavior is proposed with *a priori* expectations and tested.

3.3 Study Area

The study area is the Washington, D.C. metropolitan region (National Capital Region), encompassing the District of Columbia and parts of Maryland and Virginia (see Figure 2). The metropolitan region includes 22 jurisdictions, which are home to 5,756,612 people and 2,139,192 households residing in 4,146,132 acres, according to 2010 US census (US Census Bureau 2010). Notably, intensive transit systems (e.g., subways and buses) run in the study area. There are three transit agencies (Washington Metropolitan Area Transit Authority, Maryland Transit Administration, and Virginia Railway Express), providing subway and commuter rail services over 11 lines and 131 stations. According to the TOD database (Center for Transit-Oriented Development), 601,102 people and 307,734 households reside near transit stations, i.e., bounded by 0.5 mile Euclidean distance buffer, which account for 10% and 13% of the regional population and households, respectively, over an area of 51,607 acres (about 1% of the total area).

This study focuses on 86 subway stations operated by the Washington Metropolitan Area Transit Authority (WMATA) located inside of the Capital Beltway (Interstate 495). Then, the boundary of TOD areas is geographically confined by setting a 0.5 mile buffer in Euclidean distance around the transit stations. The distance is equivalent to about 10-15 minutes of walking. This physical boundary has been commonly acknowledged over the decades. While this study adopted this conventional definition, the 0.5 mile buffer was empirically analyzed, indicating that 85% of subway

users who access to a station on foot are located in 0.5 mile buffer area from transit stations. Throughout this dissertation, TOD residents refer to households or individuals who reside in the defined TOD areas.

Figure 2. Study Area of the Washington, D.C. Metropolitan Region
(Source: http://www.mwcog.org/transportation/tpb/jurisdictions.asp)

3.4 Behavioral Data

This study extracted detailed data on socio-demographics and 24-hr activity-travel profiles from the 2008 household travel survey (N=11,436) in the Washington, D.C. metropolitan region (National Capital Region Transportation Planning Board Metropolitan Washington Council of Governments 2010). The survey was conducted from February 2007 through April 2008. Interestingly, this survey is methodologically different from a conventional random-digit-dial (RDD) telephone-based travel survey (e.g., National Household Travel Survey), owing to the use of emerging residential mailing address-based sampling. Unlike the conventional RDD survey, sampled households were initially contacted and recruited by a letter sent to the corresponding

address. Next, telephone contact and recruitment was attempted for those who did not respond to the mail contact and whose landline telephone number was available. In this way, a number of mobile phone-only households (about 30%) were included in the survey. This population segment is largely missed in a RDD survey and thereby a non-coverage error is a concern. This issue is discussed in detail in Chapter 4.

Data collection employed a two-stage computer-aided telephone interview methodology. In the first stage, from recruited households, the survey gathered data on socio-demographics at the household (e.g., household size, vehicle ownership, housing status, etc.), person (e.g., age, race/ethnic, work status, etc.), and vehicle (e.g., model, year, etc.) levels. In the second stage, a travel dairy was mailed to those households agreeing to report their 24-hr travel and activity profiles on weekdays (e.g., travel origin, destination, mode, purpose, departure time, arrival time, etc.). Shortly after the assigned travel day given to each household, another telephone interview was made to retrieve the travel and activity data. If and only if all members participated in the two stages of data collection and all required data were fully retrieved, this household was counted as a usable one and included in the final dataset.

To increase the response rate, a quite substantial amount of incentive ($50) was offered to households only when they were mobile phone-only households and fully completed the survey. Additionally, advanced letters, multiple contacts, and follow-up calls were appropriately made. However, a relatively low survey response rate of 6%-10% was reported. Note that the response rate for conventional travel surveys ranges from 20%-30% (Khattak and Rodriguez 2005; Federal Highway Administration 2011). The low response rate is partly due to the nature of the address-based sampling method; there is no guarantee that households receiving a contact letter may not have actually opened or checked that letter, as opposed to a large number of contact mails sent In this sense, the response rate seems reasonable.

Overall, this survey provided a rich and suitable behavioral dataset for this study. Notably, the survey covered a population segment of mobile phone-only households, who are more likely to reside in urban areas, especially more transit accessible and walkable/bikable areas, that have not been well represented in the past surveys (Blumberg and Luke 2011; Son, Khattak, and Kim 2013). Besides, this survey

oversampled high density and mixed use areas twice more than low density areas to obtain sufficient numbers of sample for each stratum through a stratified random sampling method. The study area was stratified into 42 geographic strata, taking into account jurisdiction (counties/cities) boundary and land use density (high/mixed and low). Therefore, this survey included a relatively large portion of residents exposed to high density urban environment (perhaps make more transit and walking trips) and, taken together, the survey sample is fairly representative of the population. Other errors and reasonableness were checked, showing the data set is valid and appropriate. More details on error checking and the validity of the survey data is discussed in Chapter 4.

While attributes of households, persons, vehicles, and trips/activities were linked to each other for various analyses in this study, several additional data sources were processed and incorporated into the survey dataset. First, this study synthetically assigned (i.e., geo-imputed) household locations and trip origins and destinations, given the geographic location information of the census block level. Then, the synthetic longitudinal-latitudinal coordinates were coded to the households and both trip ends. The census block is fine enough to geo-impute household and trip locations. This information was used when identifying TOD residents and computing more accurate time and distance to stations. Second, using Google Maps, trip distance (and duration) information from home and work to the closest transit station were extracted. This transportation network-based information provided more realistic measurement then Euclidean distance.

In this study, the statistical software R (R Development Core Team 2012) was used for data processing, statistical computation, and spatial analyses. While many available packages and functions in the R are mainly utilized, codes were written when there is no available function for the required analysis.

CHAPTER 4

ASSESSING THE VALIDITY OF THE TRAVEL SURVEY DATA

This chapter assesses the validity of the household travel survey data for this study, focusing on non-coverage and measurement errors. Some of the contents and discussion documented in this chapter are presented in scientific journal papers (Son, Khattak, and Kim 2013; Son et al. 2013).

4.1 Introduction

Household travel surveys are generally used to 1) understand travel and activity behavior of the population of interest over time and space, and 2) support regional and national transportation decision-making. The surveys aim to collect randomized and representative samples from the target population while measuring travel data accurately and precisely. Such samples and data are essential in order to make correct statistical inferences about the travel-activity behavior of the population and to perform more reliable and reasonable travel demand forecasting. To this end, potential errors that can occur during the survey process need to be identified. Also, if any errors are found, the validity of the behavioral data needs to be checked appropriately when conducting applied research.

In principle, four major sources of errors can occur in household travel surveys (an error and a bias are interchangeably used herein): sampling, non-coverage, non-response, and measurement errors (Transportation Research Board's Travel Survey Methods Committee (ABJ40); Ortúzar and Willumsen 2001; Stopher 2008).

First, a sampling error is the variation of survey estimates generated by using random samples rather than the total population—it is computed by dividing the standard deviation by the square root of sample size. This error does not affect the central tendency of estimates; rather it addresses the amount of inaccuracy when using sample statistics to estimate population parameters.

Second, a non-coverage error occurs when not all population segments are included in a sampling frame. This error becomes problematic if survey estimates between the covered and non- or under-covered groups are significantly different. The

error resulting from the limited representativeness of a sample can unintentionally lead to incorrect understanding of travel and activity behavior of the target population and conclusions about transportation decisions. Recently, travel survey communities are concerned about the non-coverage error coming from the miss of mobile phone-only households in the conventional RDD landline telephone sampling (McGuckin and Contrino 2012).

Third, a non-response error appears if responding households are systematically different from non-respondents. It is apparent that not all sampled households participate in travel surveys because some of them are not contacted in the first place. Even if contacts are made successfully, a group of households or individuals refuse to participate in the surveys. For example, younger, older, and larger households, households from more densely populated areas, and households without a car were found to be relatively less responsive (Roux and Armoogum 2011). Typically, the non-response error is suspected when a response rate is low.

Last, a measurement error is defined as the difference between an actual value and a measured value. In the context of household travel surveys, such inaccuracy can be made by both interviewers and interviewees in any steps of the daily travel data collection process. It is well-known that the number of trips undertaken tends to be measured with an error, i.e., they are normally underreported by survey respondents (Clarke, Dix, and Jones 1981; Bricka and Bhat 2006; Son et al. 2012).

This study assessed the validity of the household travel survey of the Washington, D.C. area (HTS-DC), focusing on non-coverage and measurement errors. The non-coverage error is of interest, as mobile phone-only households are not typically included in landline telephone-based surveys, while the proportion of mobile phone-only households is rapidly increasing. Next, the measurement error of this survey was examined. The accuracy of measurement for key travel variables is a major concern as household travel surveys generally depend on self-reporting of survey respondents. To examine the measurement error, other household travel survey data was analyzed together. Overall, the assessment ensured that the validity of the survey dataset and the research results of this study.

4.2 Non-coverage Error

4.2.1 Mobile Phone-Only Households

Recently, travel survey communities are concerned about the non-coverage error. This is because mobile phony only households account for 31.6% of national households in January to June 2011, according to estimates from the National Health Interview Survey (Blumberg and Luke 2011), but conventional RDD landline telephone travel surveys do not include the increasing number of mobile phone-only households. Another reason is that mobile phone-only households are different from landline telephone households in terms of socio-demographic and geographic characteristics. For instance, mobile phone-only households are more likely to be single-person households and to reside in rented units and/or city centers. In addition, the members of the mobile phone-only households are more likely to be younger, students, and/or minorities (e.g., Hispanics), to earn lower income, and/or to own no vehicle. Moreover, their houses are more likely closer to downtown and to transit stops or stations (Link et al. 2007; Tucker, Brick, and Meekins 2007; Sen, Zmud, and Arce 2009; Lachapelle, Weiner, and Noland 2012).

Given that the socio-demographic and geographic characteristics between a mobile phone-only sample and a landline telephone are different, an arising question is whether their behavioral responses are also different. To answer the question, Link et al. (2006) compared health survey estimates of the households of mobile phone-only with those for the households with a landline phone. The study found that public health indicators differ by the type of telephone access in the households. Later, Link et al. (2007) analyzed the RDD landline and mobile phone surveys, and they arrived at the same conclusion. In a recent transportation study, Lachapelle, Weiner, and Noland (2012) examined whether the cell phone-only household samples walked more frequently (using reported frequency of walking over the past month). They found that the mobile phone-only household members tend to walk more frequently than the counterpart because of different socio-demographic characteristics. These findings suggest that non-coverage errors can most likely be present if mobile phone-only households are not included in household travel surveys.

4.2.2 Objectives and Methodology

This study first assessed the representativeness of the survey data to the population by comparing with the 2010 US Census data. Through the residential address-based sampling method, this survey included both landline telephone households and mobile phone-only households, which had not been collected in conventional travel surveys. Thus, the survey dataset was expected to be more representative, addressing the non-coverage issue. Second, this study more comprehensively explored whether the travel behavior of mobile phone-only households differ from those of households with landline telephones, extending to automobile, transit, and walking. Importantly, the non-coverage error becomes problematic if survey estimates between the covered and non- or under-covered groups are significantly different. To this end, the mobile phone-only sample (N=2,988) and the landline telephone sample (N=7,774) were identified and compared. Figure 3 displays locations of each household group, followed by each density distribution. Figure 4 shows mobile phone households are more concentrated in downtown Washington, D.C.

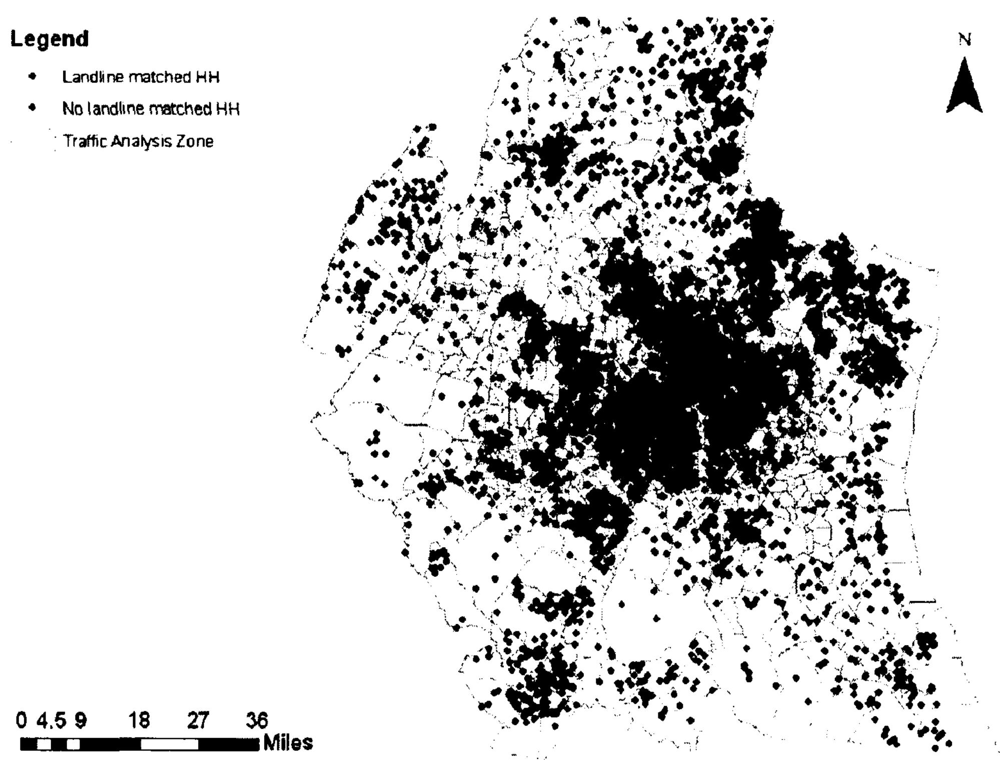
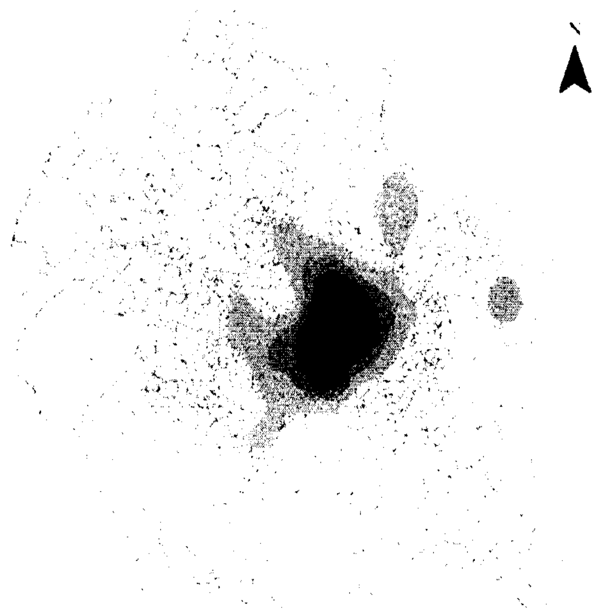
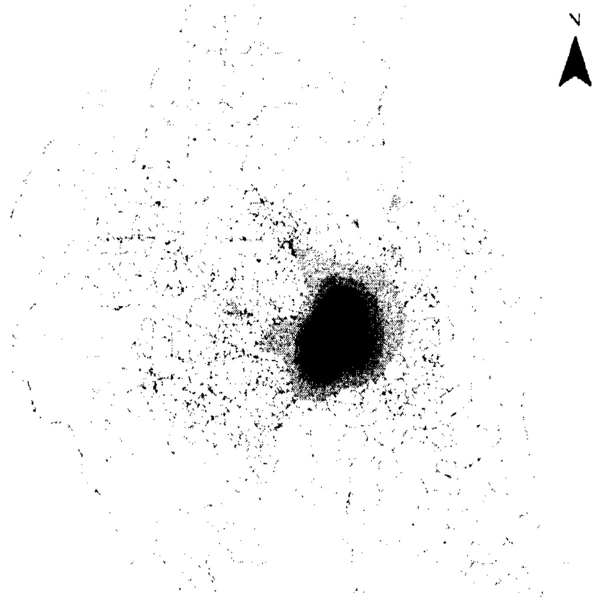


Figure 3. Comparison of Landline Telephone and Mobil Phone-Only Household Locations



(a) Landline Telephone Sample



(b) Mobile phone-only Sample

Figure 4. Comparison of Kernel Density Plots for the Two Sample Groups

4.2.3 Comparing Socio-Demographics

Key socio-demographic variables are significantly different between landline telephone and mobile phone-only households. Table 3 shows that the mobile phone-only group consists of relatively higher proportion of single person-households (41% vs. 30%) than the landline group. Additionally, the mobile phone-only sample is more likely to have zero vehicle-households as well as to live in multi-family and rental housing (Son,

Khattak, and Kim 2013). At the person level, the mobile phone-only group has relatively more individuals with age between 19-34 years (29% vs. 11%) and African American/Asian/Hispanic races. Furthermore, Son, Khattak, and Kim (2013) show that working status and commute modes are also different between the two groups. More employees and transit commuters are observed in the mobile phone-only sample. These results are largely consistent with earlier studies (Sen, Zmud, and Arce 2009; Lachapelle, Weiner, and Noland 2012).

Table 3. Sample Characteristics of Households and Persons (%)

Variable	Category	Landline telephone	Mobile phone-only	Pooled sample	2010 Census
Household size	1	30.0	41.0	33.1	26.3
	2	37.5	35.6	37.0	30.5
	3	14.3	11.5	13.5	16.7
	4	12.2	8.4	11.2	14.6
	5+	5.9	3.5	5.3	11.8
Gender	Male	47.2	45.6	46.8	48.8
	Female	52.8	54.4	53.2	51.2
Age group	0-18	21.9	20.1	21.5	26.5
	19-34	10.5	29.3	15.2	21.4
	35-44	14.0	17.2	14.8	14.9
	45-54	17.9	15.3	17.2	15.5
	55-64	18.2	11.1	16.4	11.4
	65+	17.5	7.0	14.8	10.2
Race/ethnicity	African American	11.6	26.1	15.3	24.0
	Asian	3.7	7.0	4.5	8.8
	Hispanic	3.8	5.1	4.1	6.0
	White	78.0	60.0	73.5	57.9
	Others	2.8	1.8	2.6	3.3

Note: Landline telephone household sample (N=7,774); Mobile phone-only household sample (N=2,988); Individuals in landline telephone household sample (N=17,757); Individuals in mobile phone-only household sample (N=5,949).

This survey data better represents to the target population by including both mobile phone-only households and landline telephone households. The inclusion of the mobile phone-only group increases younger persons aged 19 to 34 years (from 11% to 15%) and African Americans (from 12% to 15%). A comparison with the 2010 US Census data shows that the pooled sample is closer to the population in terms of their

makeup at the person level: younger persons aged 19 to 34 years (deviation from 10% down to 6%) and African Americans (deviation from 13% to 9%). Given that these population segments are traditionally known as hard-to-reach groups, these changes are a fairly substantial improvement. However, at the household level, the pooled samples are not well representative to the population, with a slightly high overrepresentation of single- and two-person households. This overrepresentation is partly due to generous incentive offers and the strict household retrieval, as explained in Chapter 3, and it is taken into account in further analyses in this study.

4.2.4 Comparing Travel Behavior

Travel behavior is compared between the landline telephone and mobile phone-only samples, indicating there is a systematic difference. Table 4 and Table 5 show average trip frequency per household by travel mode according to the household size. For all household sizes, more transit trips are found in the mobile phone-only group over the landline phone group. Similarly, the mobile phone-only sample has more walking trips than landline phone sample, except when the household size is five or more. On the other hand, differences in total and automobile average trip frequencies between the two groups vary by the household size. The higher trip frequency is found in the mobile phone-only group for the households with fewer members, while the landline phone group has higher trip frequency when the household size is three or more. Between the two samples, therefore, systematic differences likely exist.

Consequently, results indicate that travel estimates, especially for transit and walking trip frequency, are well represented in this survey data, with the inclusion of mobile phone-only households. By comparing the landline telephone household sample and the pooled sample, the extent of potential non-coverage errors on travel estimates in travel surveys can be quantified, supposing that the mobile phone-only household group is not included. Results suggest that the omission can substantially underrepresent transit and walking trips (about 20% to 30%) when household size is one or two (see Table 4 and Table 5). These values were computed by dividing the deviation between the average trip frequency of the landline sample and mobile phone sample by the average trip frequency of the mobile phone sample. In sum, the non-coverage error cannot be ignored,

supporting that the use of the survey data, obtained through address-based sampling and recruiting, is valid for this dissertation.

Table 4. Average Trip Frequency by Household Size and Travel Mode (Unweighted)

	Total trip frequency			Auto trip frequency		
Household size	Landline sample	Mobile phone	Pooled sample	Landline sample	Mobile phone	Pooled sample
1	3.49	4.24	3.74	2.62	2.79	2.68
2	6.86	7.23	6.96	5.87	5.49	5.77
3	10.14	10.50	10.22	8.56	8.69	8.60
4	14.07	12.88	13.82	11.53	10.12	11.24
5+	17.99	16.04	17.63	14.70	13.08	14.40
Total	7.86	7.17	7.67	6.50	5.41	6.19
	Transit trip frequency			Walking trip frequency		
Household size	Landline sample	Mobile phone	Pooled sample	Landline sample	Mobile phone	Pooled sample
1	0.36	0.64	0.46	0.43	0.72	0.53
2	0.38	0.82	0.49	0.51	0.80	0.59
3	0.51	0.62	0.53	0.69	0.83	0.72
4	0.43	0.74	0.50	1.04	1.16	1.06
5+	0.38	0.60	0.42	1.28	0.73	1.18
Total	0.40	0.71	0.48	0.62	0.80	0.67

Note: The pooled sample includes both landline telephone and mobile phone-only samples.

Table 5. Average Trip Frequency by Household Size and Travel Mode (Weighted)

	Total trip frequency			Auto trip frequency		
Household size	Landline sample	Mobile phone	Pooled sample	Landline sample	Mobile phone	Pooled sample
1	3.48	4.23	3.83	2.76	2.93	2.84
2	6.85	7.23	7.00	6.04	5.72	5.92
3	10.09	10.49	10.22	8.67	8.90	8.75
4	13.98	13.03	13.69	11.63	10.56	11.30
5+	17.99	16.22	17.47	14.71	13.28	14.29
Total	9.03	8.02	8.65	7.61	6.34	7.13
	Transit trip frequency			Walking trip frequency		
Household size	Landline sample	Mobile phone	Pooled sample	Landline sample	Mobile phone	Pooled sample
1	0.30	0.57	0.43	0.35	0.66	0.50
2	0.32	0.71	0.47	0.40	0.69	0.51
3	0.46	0.54	0.49	0.59	0.69	0.62
4	0.37	0.64	0.45	0.91	1.00	0.94
5+	0.38	0.70	0.47	1.26	0.88	1.15
Total	0.35	0.62	0.46	0.60	0.73	0.65

Note: The pooled sample includes both landline telephone and mobile phone-only samples.

4.3 Measurement Error

4.3.1 Trip Underreporting

The accuracy of measurement for key travel variables is a major concern, as household travel survey data generally are collected through self-reporting by survey respondents. A large body of literature has found that trips reported or recorded in a household travel survey tend to be underestimated (Clarke, Dix, and Jones 1981; Son et al. 2012). Compared with the number of vehicular trips detected by Global Positioning System (GPS) devices, usually 10-35% of total vehicular trips were not reported in conventional travel diaries (Wolf 2004). The groups who tend to underreport are young, male, low income, less educated, and unemployed individuals. Also, individuals making many trips and traveling long distances were associated with higher likelihood of trip underreporting. In addition, certain trips were less likely reported in a trip diary, such as trips of short duration and a discretionary nature. Trips made at the end of the day tended to be underreported (Bricka and Bhat 2006; Stopher, FitzGerald, and Xu 2007; Son et al. 2012). Trip underreporting occurs for several reasons, including incomplete recall, memory decay, insufficient understanding, unwillingness to report, and carelessness. Also, response burden due to poor survey instrument design, lengthy questionnaire, and/or insufficient instruction can cause trip underreporting in household travel surveys (Clarke, Dix, and Jones 1981; Son et al. 2012). These findings indicate that measurement errors can prevalently occur in conventional travel surveys; therefore, importantly, the errors need to be checked.

4.3.2 Objectives and Methodology

This section examines how well the 2008 household travel survey of the Washington, D.C. metropolitan region (HTS-DC) captured travel behavior, particularly, focusing on trip frequency. As critical information for travel demand analysis, reported trips can be used to estimate the amount of trips at present and in the future. To examine the measurement error, this study compared a subset of the survey data with the corresponding 2009 National Household Travel Survey Virginia Add-on (NHTS-VA) data (Federal Highway Administration 2011). The NHTS-VA was conducted over the

Virginia state from March 2008 through May 2009 (N=15,231 households). The measurement error can be checked by comparing reported trips of travel diary with the corresponding GPS-record trips. However, the GPS data was not available in this study. Moreover, trip frequency information obtained from GPS travel surveys are not necessarily ground truth mainly because GPS-based surveys can fail to record actual trips due to operational failure or trip-detection algorithms can also create inherent errors (Bricka et al. 2012).

Table 6 compares the methodology of the two large scale household travel surveys. The most remarkable difference between the two surveys is survey sampling. NHTS-VA used list-assisted RDD sampling, while HTS-DC adopted ADD sampling while the data collection was consistently processed with CATI technology. Another interesting difference is the survey instrument applied in both surveys. NHTS-VA used a comprehensive and relatively long questionnaire from Section A (Telephone Number Screening) to Section N (Collection of Odometer Readings). NHTS-VA collected large socio-demographic and travel/activity information as well as attitudinal questions about walking and biking. Compared to NHTS-VA, HTS-DC was more concise and short (i.e., 10 items in the questionnaire and some extensive questions in the interview), focusing on travel and activity behavior information.

Table 6. Comparison of NHTS-VA and HTS-DC

	NHTS-VA	HTS-DC
Area	State of Virginia	National Capital Region
Period	March 2008 – May 2009	February 2007 - April 2008
Sampling	Landline telephone RDD	Residential mailing address
Stratification	13 strata by Metropolitan Planning Organization	43 strata by jurisdiction & density type
Interview	Computer assisted telephone interview	Computer assisted telephone interview
Incentive	Household ($5); travel dairy ($2)	Household with no landline phone ($50)
Target age	Age 5+	All ages
Travel day	Monday to Sunday (start at 4 AM)	Monday to Friday (start at 3 AM)
Instrument	Comprehensive and long	Concise and short
Sample size	15,231 *	11,436
Response rate	28%	8%

Note: A travel day includes holidays. * It includes both the Virginia add-on sample (N=14,584) and the national sample (N=647).

The reason to choose the NHTS-VA is that both surveys were conducted in a similar timeframe. Also, they collected a household sample from Northern Virginia (see the area hashed in blue in Figure 5). Note that there are large portions of the mixed land use areas with good transit service and multiple activity centers. The study area was carefully selected by considering geographical overlap and sampling stratification. Notably, the study area was one of the thirteen strata in NHTS-VA. On the other hand, the area was stratified into eight strata in HTS-DC, taking into account jurisdiction boundaries and land use density (high and low). The high density represents mixed land use while the low density largely indicates residential areas. This common overlap area allows controlling for geographical attributes.

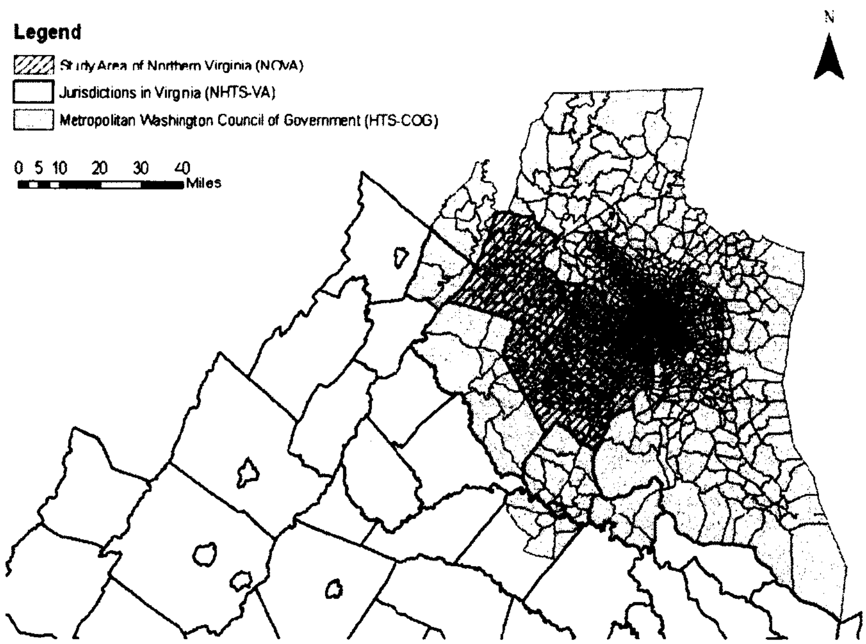


Figure 5. The Common Overlap Area in Northern Virginia (Hashed in Blue)

4.3.3 Comparing Trip Frequency

This section compares the reported trip frequency of the two surveys (see Table 7). Corresponding to the overlap area, two subsamples of 429 and 2,469 households were extracted from the NHTS-VA and HTS-DC datasets, respectively. Note that unweighted data were used for both groups and the households reporting weekday trips were only focused very squarely. Compared with 7.80 trips in the HTS-DC subsample, the mean of the reported household trip frequency is 13.7% higher in the NHTS-VA subsample (8.87

trips). The average trip frequency between the two groups is statistically different (two-sample t-test, $p<0.01$) for all cases. Additional comparisons were made for each travel mode. The largely distinctive average frequencies are found in transit and walk/bike trips between the two subsamples. Compared to the HTS-DC subsample, in the NHTS-VA subsample, fewer transit trips (about 34%) were observed, while relatively more walking trips (about 119%) were observed. These differences consistently appear at the person level, which indicates that measuring transit and walking trips can be systematically different between the two surveys.

Many factors are associated with the differences in reported trip frequency. They include households' socio-demographics and residential locations, as well as travel days. Notably, a different survey instrument design can result in different trip measurement (Son et al. 2012). As reviewed, NHTS-VA adopted a more comprehensive survey instrument, while HTS-DC used a shorter instrument focusing on socio-demographics and a travel diary. This study investigated a potential but systematic measurement difference in the two subsamples, taking these factors into account. In this study, a direct comparison between actual trips and reported trips was not made. Instead, the difference was captured by comparing the two surveys in terms of trip frequency. This is because survey respondents are unlikely to over-report their trips; rather, they are more likely to underreport their trips due to failure to recall or survey burden. When targeted population and study area is in common and other factors are controlled, therefore, it can be said that a survey that has fewer reported trips would involve higher measurement error.

Table 7. Comparison of Average Trip Frequency by Survey

	NHTS-VA			HTS-DC			Mean Diff (%)
	N	Mean	SD	N	Mean	SD	
Household	429	8.87	6.28	2,469	7.80	6.09	13.7
Auto		7.10	5.40		6.56	5.62	8.2
Transit		0.23	0.77		0.35	0.86	-34.3
Walking		1.16	1.97		0.53	1.41	118.9
Person	954	3.99	2.54	5,350	3.60	2.52	10.8
Auto		3.19	2.46		3.03	2.57	5.3
Transit		0.10	0.47		0.16	0.56	-37.5
Walking		0.55	1.12		0.27	0.83	103.7

Note: Diff (%) = (NHTS-VA – HTS-DC)/HTS-DC*100.

To identify and quantify a potential measurement error between the two subsamples, statistical models were specified and estimated. To capture the extent of trips differently measured by the two survey instruments, count (e.g., Poisson and negative binomial) regression models were used, as they can account for the nature of trips (i.e., non-negative integer). The count regression model can avoid the bias that possibly occurred by an ordinary least squares regression, given the positive and low counts for the dependent variables. The Poisson and negative binomial regression models are discussed below (Cameron and Trivedi 1998; Greene 2003).

Let Y_i denote the number of trip frequency for the i^{th} individual, $Y_i = 0,1,2,...$ Then, the number of trips undertaken on the assigned day follows a Poisson distribution,

$$P(Y_i = y_i|X_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}$$

$$E(y_i|X_i) = Var(y_i|X_i) = \lambda_i = e^{\beta X_i}$$

where λ_i is expected trip frequency for individual i; $y_i!$ denotes the factorial of y_i; X_i is a vector of independent variables; and β is a vector of parameters.

As specified, this model requires that the conditional mean of the trip frequency equals the conditional variance. However, Table 7 indicates that the mean and variance of trips by each mode differ significantly. For such data, a negative binomial regression is appropriate, by relaxing the mean-variance equality assumption. To allow for unexplained randomness in λ_i by specifying:

$$\ln \lambda_i = \beta X_i + \varepsilon_i$$

where ε_i is the error term, which reflects heterogeneity of data as well as a specification error such as omitted independent variables. The negative binomial regression model specifies that

$$P(Y_i = y_i|X_i) = \frac{\Gamma[(1/a) + y_i]}{\Gamma(1/a)y_i!}\left[\frac{1/\alpha}{(1/\alpha) + \lambda_i}\right]^{1/\alpha}\left[\frac{\lambda_i}{(1/\alpha) + \lambda_i}\right]^{y_i}$$

$$E(y_i|X_i) = \lambda_i = e^{\beta X_i}$$

$$Var(y_i|X_i) = E(y_i|X_i)[1 + \alpha E(y_i|X_i)]$$

where λ_i is expected trip frequency for individual i, $y_i!$ denotes the factorial of y_i, X_i is a vector of independent variables, and β is a vector of estimated parameters. Remarkably, α is an over-dispersion parameter, which allows for mean-variance inequality.

A log-likelihood function for the Poisson and negative binomial regression, respectively, is

$$\ln L = \sum[-\lambda_i + y_i X_i \beta - \ln y_i!],$$

$$\ln L = \sum \ln(\Gamma(y_i + \frac{1}{a})) - \sum \ln(y_i!) - N \ln \Gamma(\frac{1}{a}) + N(\frac{1}{a}) \ln(1 - \frac{\lambda_i}{1/a + \lambda_i}) + \sum y_i \ln(\frac{\lambda_i}{1/a + \lambda_i}),$$

where λ_i is expected trip frequency for individual i, $y_i!$ denotes the factorial of y_i, X_i is a vector of independent variables, and β is a vector of estimated parameters; α is an over-dispersion parameter; N is the number of observations.

For independent variables, the survey indicator variable was added to provide the statistical significance of the potential deviation related to the survey instrument. In addition, several control variables were included: household socio-demographics and residential locations (according to geographical stratification in HTS-DC). Finally, the model used pooled data of the two household subsamples. To ensure the validity of the models, the underlying assumptions for the statistical models were checked (e.g., high collinearity among independent variables) and found to be satisfactory.

Table 8 summarizes the negative binomial regression reported trip frequency models for total, auto, transit, and walking trips, with 2,898 household observations (see Table 7). All models are statistically significant ($p<0.01$) with reasonable goodness-of-fit measures (pseduo-R^2). The over-dispersion parameters are statistically significant at the 5% level, suggesting the negative binomial regression models appropriately capture inequality of means and variances of dependent variables. Most variables are statistically significant at the 5% level. The signs of the coefficient values are mostly consistent with expectations, while the magnitudes are appropriate. The models reasonably estimated the

control variables of household socio-demographics, geographical context variables, and temporal context variables. They are not discussed in this chapter; however, the associations found from these models are used throughout the dissertation.

Indicator variables are of interest. Results suggest that total and auto trips are not significantly reported between the two subsamples (Model 4-1 and Model 4-2, respectively). The magnitudes of the difference in transit and walking trips are relatively large. While the difference of the transit trip is not statistically significant (Model 4-3), the walking trip shows a statistical difference between the two subsamples at the 5% level (Model 4-5). Specifically, Model 4-5 indicates that HTS-DC captured 66.3% ($=1-e^{-1.090}$) fewer walking trips than NHTS-VA. A coefficient value of each variable can be interpreted in Incident Rate Ratio (IRR), indicating that the effect of a unit change in an independent variable on a multiplicative scale, holding others constant. Given that the different survey instruments, as discussed previously, the difference in reported walking trips can be viewed as a measurement error resulting from the HTS-DC (i.e., diary instructions and the presence of walking questions in the instrument).

Two additional models were estimated to examine the impact of the measurement error on this study of travel and activity behavior of residents between TOD and AOD. An interaction term of the survey instrument and TOD residence was added to the transit and walking trip models. Results show that the interaction terms are not statistically significant at the 5% level (Model 4-4 and Model 4-6, respectively), implying that the measurement error on reported trip frequency is not necessarily observed from respondents of TOD residents only; rather, the measurement error tends to be equally found at both TOD and AOD residents. Therefore, despite the presence of measurement errors on walking trips in the HTS-DC data, this survey data can be carefully used for this study with a caution.

Table 8. Summary of Trip Frequency Models by Travel Mode

Dependent variable / Independent Variable	Model 4-1 Total trips	Model 4-2 Auto trips	Model 4-3 Transit trips	Model 4-4 Transit trips	Model 4-5 Walking trips	Model 4-6 Walking trips
Constant	0.813 ***	0.393 ***	-1.469 *	-1.438 *	-0.442	-0.431
Household socio-demographics						
Household size	0.246 ***	0.219 ***	0.059	0.050	0.525 **	0.524 *
Household size squared	-0.033 ***	-0.030 **	-0.017	-0.017	-0.069 **	-0.068 *
Num. of members aged 5-18	0.335 ***	0.307 ***	0.107	0.109	0.395 ***	0.397 ***
HH members aged 19-34	0.204 ***	0.217 ***	0.210	0.213	0.146	0.147
HH members aged 35-44	0.260 ***	0.243 ***	0.474 **	0.476 **	0.331 *	0.332 *
HH members aged 45-54	0.232 ***	0.229 ***	0.490 **	0.490 **	0.172	0.172
HH members aged 55-64	0.269 ***	0.266 ***	0.562 ***	0.561 ***	0.294 *	0.294 *
Num. of members aged 65+	0.248 ***	0.301 ***	-0.076	-0.076	-0.151	-0.151
Num. of vehicles	0.085 **	0.217 ***	-0.930 ***	-0.929 ***	-0.258	-0.255
Num. of vehicles squared	-0.012 *	-0.025 ***	0.090 ***	0.090 ***	-0.005	-0.006
Num. of workers	0.048 **	0.028	0.380 ***	0.382 ***	0.134	0.134
Household income ($10,000)	0.002 **	0.002 **	0.002	0.002	0.001	0.001
Single-person HH(1=yes)	-0.155 **	-0.127 **	-0.246	-0.252	-0.147	-0.148
No vehicle HH (1=yes)	-0.473 ***	-2.052 ***	0.324	0.325	0.222	0.226
Spatial context						
Alexandria & High (1=yes)	-0.076 *	-0.034	-0.355 *	-0.361 *	-0.159	-0.158
Fairfax & Low (1=yes)	-0.107 **	0.027	-0.658 ***	-0.663 ***	-0.963 ***	-0.963 ***
Fairfax & High (1=yes)	-0.119 ***	0.006	-0.380 **	-0.383 **	-0.797 ***	-0.796 ***
Loudoun & Low (1=yes)	-0.151 ***	-0.002	-1.743 ***	-1.747 ***	-1.125 ***	-1.125 ***
Loudoun & High (1=yes)	-0.144 *	-0.037	-1.842 ***	-1.845 ***	-0.439	-0.440
Prince William & Low (1=yes)	-0.203 ***	-0.057	-1.167 ***	-1.170 ***	-1.133 ***	-1.131 ***
Prince William & High (1=yes)	-0.104 **	0.063	-1.411 ***	-1.417 ***	-1.094 ***	-1.097 ***
Temporal context						
Tuesday (1=yes) ****	0.019	0.017	-0.051	-0.051	-0.052	-0.053
Wednesday (1=yes)	0.014	-0.008	0.283 ***	0.287 ***	0.063	0.064
Thursday (1=yes)	0.063 *	0.023	0.332 ***	0.335 ***	0.100	0.101
Friday (1=yes)	0.081 **	0.081 **	0.087	0.087	0.066	0.066
Mar-Jun (1=yes) *****	0.131 ***	0.109 ***	0.339 **	0.339 **	0.502 ***	0.502 ***
Jul-Oct (1=yes)	0.118 ***	0.086 ***	0.303 **	0.303 **	0.428 ***	0.428 ***
Indicator						
HTS-DC survey (1=yes)	0.042	0.112	0.497	0.477	-1.090 ***	-1.104 ***
TOD residence (1=yes)	0.035	-0.095 **	0.442 ***	0.207	0.478 ***	0.370
HTS-DC* TOD (1=yes)	-	-	-	0.254	-	0.123
Summary statistics						
Num. of observations	2898	2898	2898	2898	2898	2898
Over-dispersion parameter	0.171 ***	0.285 ***	3.951 ***	3.949 ***	3.701 ***	3.701 ***
Log likelihood (constant)	-8841	-8504	-1953	-1953	-2778	-2778
Log likelihood (full)	-7965	-7773	-1824	-1824	-2612	-2621
Log likelihood ratio χ^2	1752 ***	1449 ***	258 ***	258 ***	314 ***	314 ***
Pseudo-R^2	0.099	0.086	0.066	0.066	0.060	0.060

Note: * p<0.10; ** p<0.05; *** p<0.01; **** Monday is a base; ****** Arlington & High density is a base.

4.4 Summary and Discussion

Behavioral data on travel and activity is generally obtained from household travel surveys. Survey errors can be found; therefore, it is important to check in order to understand travel and activity behavior more accurately and to draw a conclusion properly. This study comprehensively examined the validity of the household travel survey data for the Washington, D.C metropolitan area, indicating that the survey is valid and appropriate for this study in the following reasons.

First, the HTS-DC data is fairly representative of the population of interest. Recently, a non-coverage error due to mobile phone-only households is a large concern. They are not well represented in household travel surveys, consisting of relatively more single-person households, younger individuals, and Blacks/Asians/Hispanics. Through address-based sampling, the survey data included a large set of the mobile phone-only sample (27%). This study showed that the HTS-DC data is more representative of the population by including the mobile phone-only households. Moreover, this study quantified the potential non-coverage errors on travel behavioral estimate. Focusing on alternative modes and small households (one or two members in a household), this suggests that the error is significant; therefore, should not be ignorable.

Second, although a measurement error was detected on walking trips in the HTS-DC data, the data can be used for this dissertation research without further handling. This is mainly because this study found that the underreporting consistently presents between TOD and AOD residents. This study checked the measurement error on trip frequency as trip under-reporting can generally occur in a household travel survey. Interestingly, trip frequency measured in the HTS-DC was compared with another survey of NHTS-VA, conducted in similar time window, focusing on the overlap area. Statistical models were estimated to identify and quantify a measurement, finding that walking trip frequency is much less in the HTS-DC (66%). The difference partly resulted from diary instructions and the presence of walking/bicycling questions in the survey instrument.

CHAPTER 5

COMPARING ACTIVITY LOCATION AND MODE USE BEHAVIOR WITH A MATCHED PAIR ANALYSIS

This chapter discusses activity location and travel mode use behavior of residents in a transit-oriented development (TOD) neighborhood. Their behavior is spatially and statistically compared with that of residents in a matched auto-oriented development (AOD) neighborhood. Partial results and discussions documented in this chapter are presented in a conference paper (Son, Khattak, and Choi 2014).

5.1 Introduction and Motivation

Recently, TOD has gained popularity among urban and transportation planning agencies as a sustainable development strategy. Owing to its potential benefits, more than 1,500 TOD projects are underway or newly proposed across metropolitan cities in the United States. While demand for TOD has been increasing rapidly, a full spectrum of travel and activity behavior in the TOD context has not been well captured in the literature, excepting transit ridership and mode choice behavior. Therefore, a better understanding of other dimensions of travel and activity patterns is needed, focusing on residents in TOD. This will not only fill a gap in the literature on urban and transportation planning, but also the findings can support TOD as a sustainable policy.

Over the last decade, a sustainable land development strategy (e.g., traditional neighborhood) has been analyzed in term of travel behavior, suggesting that residents in such developments tend to drive less and walk more. Given that the presence of good transit accessibility and a sustainable built environment, i.e. high density, mixed land use, and alternative mode-friendly streets, interactions between transportation systems and the built environment are expected in the context TOD. However, this has not been well captured in the literature on planning, although more empirical studies on TOD can support and justify this transportation and land use policy. Also, discussion of TOD as a sustainable development strategy is needed. For this reason, this study particularly focuses on activity location and mode use behavior, which are related to the benefits of TOD and then can be translated into performances of policy evaluation.

5.2 Hypotheses

This chapter tests two hypotheses for activity and travel behavior at the community or neighborhood level. The first hypothesis is that activity locations of residents of TOD neighborhoods are expected to differ from those of AOD neighborhoods. Compared to AOD residents, therefore, TOD residents will make more local trips (within a TOD boundary) because TOD can provide the residents with livable environments that are walk/bicycle friendly, higher density, and mixed use. These attributes can play important roles in taking place diverse activities (e.g., working, shopping, and social/recreation) around transit stations, which allows TOD residents to have improved accessibility to daily activities. Consequently, more trips in shorter length will be observed from the residents of TOD neighborhoods, compared to the AOD counterparts, and thereby their trip length distribution will be different from each other.

The second hypothesis to test in this chapter is that travel mode use behavior of residents is expected to be different between TOD and AOD neighborhoods. The mode use in this context is daily trip frequency and travel distance at the household level. Auto uses (both in frequency and distance) of TOD households are fewer and shorter, while alternative modes (e.g., transit and walking) are more frequently used. Also, longer travel distance for transit and walking are expected for TOD households than AOD households. Land use in TOD neighborhoods is typically dense and mixed, allowing the residents to participate in their activities nearby. This area is also served by a public transit system, featuring better accessibility and connectivity. Therefore, auto trips will be largely replaced by non-motorized trips, and perhaps additional walking and transit trips will be induced.

5.3 Methodology and Data Extraction

5.3.1 Neighborhoods Selection

To test these speculations, this study employed the transportation decision-making structure conceptualized in an earlier chapter. As noted, travel and activity behavior is conditional on residence/work/school location and vehicle ownership, associating with other factors. To reflect transportation systems and the built environment in the residence

location, this study tightly compared activity and travel behavior of residents in a matched pair of TOD and AOD neighborhoods. In this way, stronger conclusions can be drawn. Two critical issues were carefully taken into account in this study. First, this study assesses how many activities TOD can internally capture from activities undertaken by TOD residents; therefore, the locations will be spatially analyzed and compared. Second, self-selection is highly suspected in this circumstance, based on theory and empirical findings. To understand the impact of TOD attributes more accurately, this issue was accounted for this chapter.

Among the several candidate neighborhoods of TOD in the Washington, D.C. metropolitan area, the Rosslyn-Ballston Metrorail Corridor in Arlington, Virginia, was selected (see Figure 6). The corridor is located right across the Potomac River from Washington, D.C., consisting of five metro stations on Orange line: Rosslyn, Courthouse, Clarendon, Virginia Square, and Ballston stations. Offices and retail shops are centered on the stations. Average weekday ridership (passenger boarding only) for the stations was collectively 44,806 in 2012 (Washington Metropolitan Area Transit Authority 2013).

As a successful example of TOD, this corridor has been nationally and internationally recognized (Bernick and Cervero 1997; Cervero, Ferrell, and Murphy 2002; Cervero 2004; Dittmar and Ohland 2004; Evans et al. 2007). In the 1960s and 1970s, the Rosslyn station area was an auto-oriented city, with high-rise office buildings and major commercial centers. Also, the built form was widely spaced with narrow sidewalks on the street. Similarly, the Ballston station area was originally low density commercial corridor, prospering throughout the 1950s and 1960s. However, during the 1970s, major retailers left and population declined as the commercial district was aging and new suburban areas were developed. In the late 1970s, as the Orange line was extended from Rosslyn to Ballston in 1979, the redevelopment—centered on the stations—started with the new planning concept: TOD. Through the collaboration among regional stakeholders such as Arlington County and WMATA, the TOD initiative was successfully implemented. For example, substantial dwelling units were added around the Rosslyn station. And access to the transit station was improved. In Ballston, a mixture of offices, retails, housing, and hotels was concentrated around the station. Taken together,

the Rosslyn-Ballston Metrorail Corridor had been transformed into transit-oriented communities.

To match the selected TOD neighborhood (a group of right bottom circles in Figure 6), an AOD neighborhood in the vicinity of the TOD community was chosen (a left top circle in Figure 6). Because this neighborhood has been channeled into an area with well-defined boundaries, surrounding low-density single-family neighborhoods have been preserved. The selected AOD area is supported by major freeways (e.g., George Washington Memorial Parkway and Custis Memorial Parkway). Consequently, the proximity to downtown in Washington, D.C. and major employment centers in Virginia was carefully controlled.

Table 9 presents socio-demographic and land use measures across the two selected neighborhoods. Compared to the conventional neighborhood, density and land use characteristics in the TOD neighborhood are higher and mixed (i.e., residential use is 71% and commercial use is 29%). Household and population density in the TOD neighborhood is 5.6 and 3.7 times higher, respectively. Notably, in the TOD site, there are substantial amount of jobs (70,192 vs. 9,329), which are higher than its population, indicating that land use in the TOD is mixed and compact. It also suggests that the TOD area attracts many workers not only inside but also outside out the neighborhood. Management and professional occupations account for 76% of the total jobs, while service, sales, and office jobs are 19% in the selected TOD area.

5.3.2 Sample Characteristics

Corresponding to the two selected neighborhoods, a sample of 315 households was prepared for comparative analysis. For TOD and AOD neighborhoods, 185 and 130 households were extracted from the survey dataset, respectively. Note that young individuals (age 19-34) are slightly underrepresented (about 10 %) and single-member households are overrepresented to some extent, compared to 2010 US Census figures (US Census Bureau 2010). Table 10 compares descriptive statistics by neighborhood, indicating that socio-demographic characteristics and travel behavior are significantly different from each other. With 1.61 individuals per household, households in the TOD

neighborhood have about 32% fewer people than households in the AOD neighborhood. These statistics are quite similar to 2010 Census data—see Table 9.

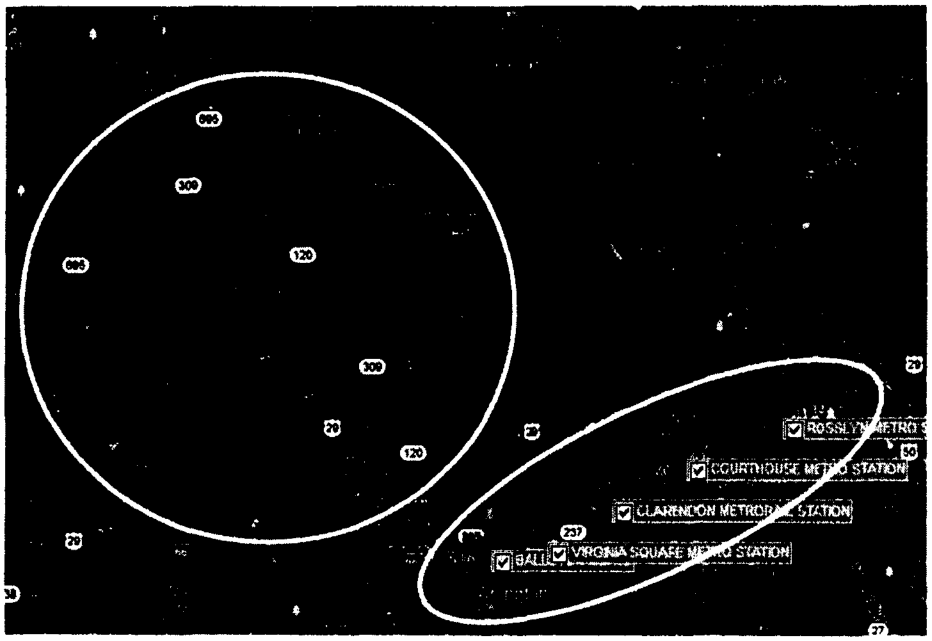


Figure 6. Two Selected Neighborhoods in Arlington, Virginia
TOD (right bottom circle) and AOD (left top circle)
(Source: http://toddata.cnt.org/, not to scale)

Table 9. Comparison of the Selected Neighborhoods

Variable	TOD neighborhood	AOD neighborhood
Total Households	28,774	12,588
Total Population	51,157	33,881
Average household size (population/household)	1.78	2.69
Total Jobs *	70,192	9,329
Management and professional occupations	76%	44%
Service, sales and office occupations	19%	53%
Other occupations	5%	3%
Total Area (acres)	1,833	4,506
Household Density (households/acres)	15.70	2.79
Population Density (population/acres)	27.91	7.52
Job Density (jobs/acres)	38.29	2.07
Average block size (acres/ block)	4.53	7.80

Note: All data are based on 2010 unless indicated; * 2009 data.

Sources: TOD database (http://toddata.cnt.org/); OnTheMap (http://onthemaps.ces.census/gov/); 2010 Census (http://2010.census.gov/2010census/).

Likewise, households in the TOD neighborhood own 1.20 vehicles on average, which are about 40% fewer than those in the AOD neighborhood. Their average household incomes, reported in categories and converted to the middle value, are about \$100,000 and about \$130,000 in the TOD and AOD, respectively. Interestingly, the majority of responding households in the TOD neighborhood live in multi-family houses (75%). In contrast, single-family houses are dominant for household samples in the conventional neighborhood (83%). Relatively more workers and younger individuals (aged 19-34) are found at the TOD households, while more students are found from the AOD households.

Table 10. Descriptive Statistics for the Extracted Samples by Neighborhood

		TOD neighborhood		AOD neighborhood	
		Mean	SD	Mean	SD
Household level	Household size	1.61	0.87	2.35	1.20
	1 person (%)	58		25	
	2-3 persons (%)	38		55	
	4+ persons (%)	4		19	
	Vehicle ownership	1.20	0.75	1.96	0.84
	0 vehicles (%)	14		2	
	1 vehicle (%)	57		25	
	2+ vehicles (%)	39		73	
	Household income (\$10,000)	10.37	5.04	13.08	5.69
	Less than \$75,000 (%)	32		22	
	\$75,000 to \$150,000 (%)	51		49	
	\$150,000 and more (%)	17		39	
	Housing type				
	Single family detached (%)	16		83	
	Single family attached (%)	9		5	
	Multi-family (%)	75		12	
Person level	Gender				
	Male	51		47	
	Female	49		53	
	Age	40.74	19.76	44.68	23.58
	00-04 (%)	5		5	
	05-18 (%)	6		18	
	19-34 (%)	31		8	
	35-44 (%)	17		14	
	45-54 (%)	17		14	
	55-64 (%)	12		24	
	65+ (%)	11		18	
	Professions				
	Student (%)	8		21	
	Worker (%)	72		54	
	Others (%) *	20		25	

Note: TOD households and persons (N=185 and N=298, respectively); AOD households and persons (N=130 and N=306, respectively); * Others include retirees, homemakers, and the unemployed.

5.4 Activity Location and Trip Length

5.4.1 Activity Location Analysis

This section examines the first hypothesis of the difference in activity locations between TOD and AOD residents. To test this hypothesis, this study identified out-of-home activity by purpose and location. Out of 1,080 and 1,236 activities in total, made by TOD and AOD residents, out-of-home activities commonly account for 64% of total activities (see Table 11), with more nonwork-related activities among out-of-home activities. As expected, TOD residents make higher proportion of work-related activities (24%) than the AOD residents (15%), but make smaller proportion for nonwork-related activities (40% vs. 49%).

Table 12 shows the location of out-of-home activities by residence location and activity type, indicating that activity locations are overall different between TOD and AOD residents. A majority of the work activities (80% and more) were not commonly found in either the TOD or AOD neighborhoods. The TOD neighborhood captured a similar amount of work-related activities from TOD and AOD residents (15% and 16%, respectively). However, the AOD neighborhood only captured few the AOD residents' work activities (4%), while the TOD residents rather selected other neighborhoods more for their work activities. For nonwork activities, both TOD and AOD neighborhoods similarly captured the activities of their local residents (38% and 37%). However, the AOD residents' activities in the TOD neighborhood accounts for 13%, while 9% for vice versa, noting that the TOD residents do not locate their activities in the AOD neighborhood as often as the AOD residents do in the TOD neighborhood. Also, taken together, while both TOD and AOD residents participate in a relatively close distance, the TOD residents choose outside neighborhoods more than the AOD for their activities.

Table 11. Activity Location and Type by Neighborhood

Activity		TOD neighborhood		AOD neighborhood	
		N	%	N	%
Total		1,080	100	1,236	100
In-home		392	36	440	36
Out-of-home	Work-related	258	24	189	15
	Nonwork-related	430	40	607	49

Note: Activities of individuals aged 0-4 were not included.

Table 12. Activity Type and Location by Neighborhood (Out-of-Home Activity Only)

Activity type	Activity location	TOD neighborhood		AOD neighborhood		P-value *
		N	%	N	%	
Work-related	Total	258	100	189	100	0.001
	TOD	38	15	31	16	0.199
	AOD	1	0	7	4	-
	Other	219	85	151	80	0.001
Non-work related	Total	430	100	607	100	0.001
	TOD	163	38	81	13	0.362
	AOD	38	9	227	37	0.001
	Other	229	53	299	49	0.001

Note: Activities of individuals aged 0-4 were not included; * P-value was derived from permutation tests with nearest neighborhood method (Schilling 1986; Rizzo 2008; Corral-Rivas et al. 2010).

Figure 7 presents spatial distributions of out-of-home activities by residence location and activity type, in line with Table 12. The X-axis and Y-axis represent longitude and latitude, respectively. Each dot represents an out-of-home activity location. The areas clustered by groups of black triangles and red circles represent the TOD and AOD neighborhood, respectively. Blue dots are any outside activities (neither in the TOD or AOD). The spatial distributions of work-related activity locations seem to be quite similar between TOD and AOD residents. Another interesting observation is that outside activities participated by the TOD residents are more likely to be clustered whereas those of the AOD residents are spread over the study area.

To statistically test whether the spatial distributions of out-of-home activity location differ by activity type and residential locations, permutation tests with the nearest neighbor method were jointly used. This test consists of two steps. In the first step, the nearest neighbor statistic quantifies the similarity of two spatial distributions between zero to one. The zero means a perfect mix while one represents the complete separation of two distributions. In the second step, a permutation distribution of the statistic is generated with a large number of resampling.

The permutation test can be applied in a variety of statistics because it does not require a specific population distribution (e.g., normality), providing fairly accurate p-values. The p-value from the permutation test is called the achieved significance level, also known as the empirical p-value (see the last column of Table 12). More detailed information is below.

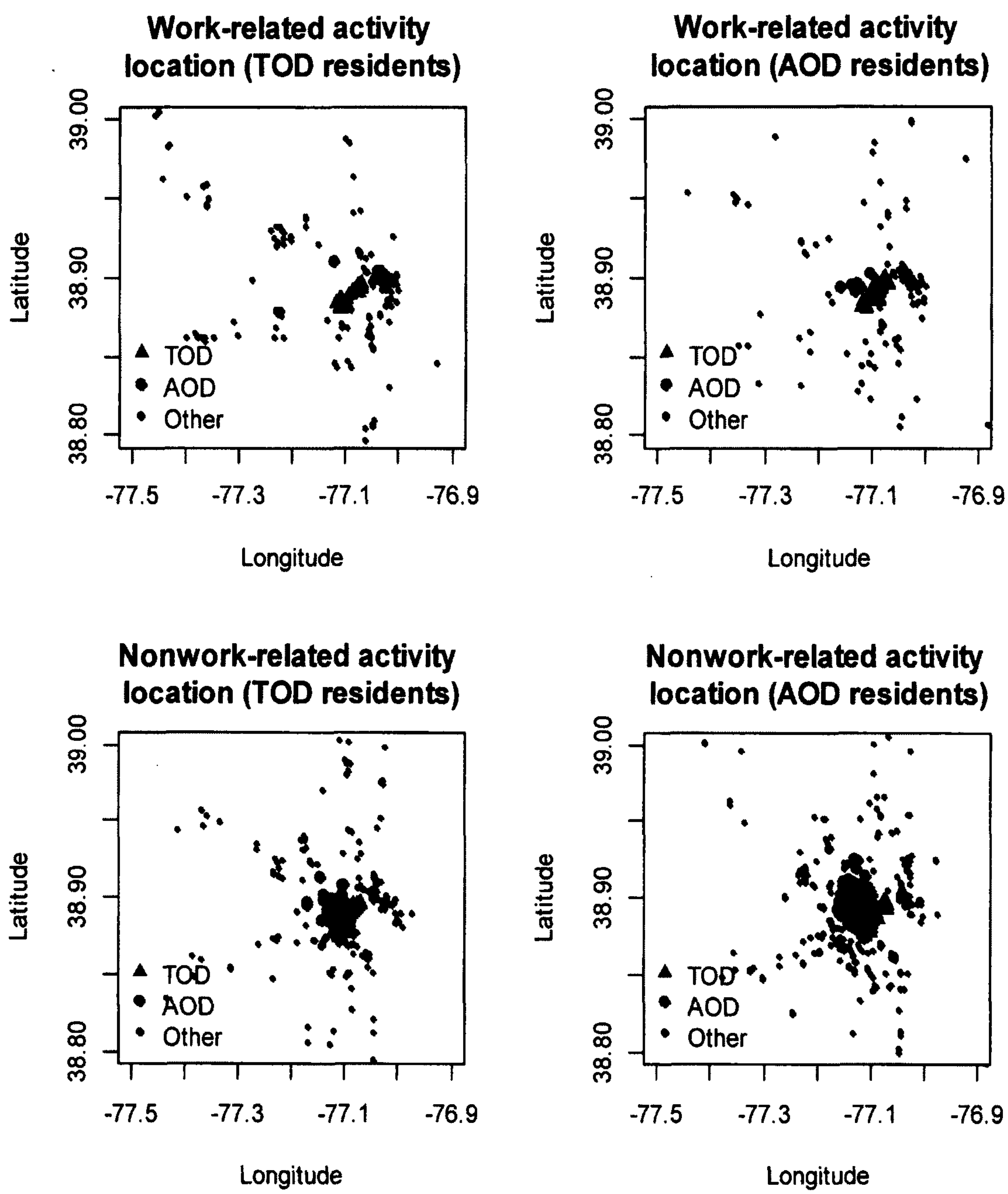


Figure 7. Distributions of Activity Location by Type and Residence

To test for independence of two spatial distributions, first, a nearest neighbor method is useful for multivariate two-sample distribution problems, especially when two distributions are continuous. The nearest neighbor test is based on ordered distances between sample elements. Suppose $X=\{X_1, \ldots, X_{n1}\}$ and $Y=\{Y_1, \ldots, Y_{n2}\}$, where $X_i, Y_j \in R^d$, and $d \geq 1$, are independent random samples, and $Z=\{X_1, \ldots, X_{n1}, Y_1, \ldots, Y_{n2}\}$, where $n=n_1+n_2$, is a pooled sample. Then, the nearest neighbor statistic is defined by

$$T_{n,k} = \frac{1}{nk}\sum_{i=1}^{n}\sum_{r=1}^{k} I_i(r), \tag{1}$$

where

$T_{n,k}$ = k^{th} nearest neighbor statistic ($0 \le T_{n,k} \le 1$),

$I_i(r)$ = indicator function ($I_i(r)$=1, if Z_i and r^{th} nearest neighbor of Z_i belong to the same sample X or Y; $I_i(r)$=0, otherwise),

n = the total number of sample elements (n=n_1+n_2),

k = the number of nearest neighbors,

i = 1, …, n, and

r = 1, …, k.

In general, the k^{th} nearest neighbor statistic in Formula (1) measures the proportion of first through k^{th} nearest neighbor coincidences. The overall nearest neighbor statistic $T_{n,k}$ ranges from 0 to 1. Large values of $T_{n,k}$ support the alternative hypothesis that two distributions are different. In other words, zero means they are a perfect mix while one represents that two distributions are completely separated.

Due to the unknown probabilistic distribution of the nearest neighbor statistic, a permutation test was used to assess the equality of two distributions. The permutation test compares the observed test statistic, $T_{n,k}$, with a permutation distribution of the statistic with a large number of resampling. The permutation test can be applied in a variety of statistics because it does not require a specific population distribution (e.g., normality), but does provide fairly accurate p-values. The p-value from the permutation test is called the achieved significance level (ASL), also known as the empirical p-value. It is computed as follows:

$$P(\hat{\theta}^* \ge \hat{\theta}) = \binom{n}{n_1}^{-1} \sum_{j=1}^{\binom{n}{n_1}} I(\hat{\theta}^{(j)} \ge \hat{\theta}), \tag{2}$$

where

$\hat{\theta}^{(j)}$ = the computed statistic for the j^{th} replicate,

$\hat{\theta}$ = the observed test statistic with the original sample,

$\hat{\theta}^*$ = the distribution of replicates (permutation distribution),

n = the total number of elements in a pool sample Z,

n_1 = the number of elements in either sample of X or Y, and

j = $1, \ldots, \binom{n}{n_1}$.

To construct a permutation distribution, a random sample with n_1 elements is drawn without replacement from the n elements in the pooled sample Z. There is the $\binom{n}{n_1}$ number of different ways to partition the pooled sample Z into two subsets of size n_1 and n_2. From the two subsets, a statistic $\hat{\theta}^{(j)}$ is computed for each replicate. Finally, the permutation distribution is constructed. By comparing the observed nearest neighbor test statistic with this permutation distribution, the ASL or empirical p-value is computed. With these, the null hypothesis can be rejected when ASL < 0.05 or failed to reject when ASL > 0.05. This is called a permutation test.

This study considers the null hypothesis that the spatial distributions of the two household samples are not different from each other. To do this, the number of nearest neighbors, k, was set to 3, and the number of permutations was 1,000. The 'boot' and 'ann' functions in the 'boot' and 'yaImpute' packages, respectively, were used for computation in the statistical software R.

Results show that the distributions of work-related activities are statistically different at the 1% significance level (see Table 12). Likewise, the distributions of nonwork-related activities are also statistically different at the 1% significance level, indicating that activity locations chosen between TOD and AOD residents are different. More tests were conducted by activity location. Interestingly, the statistical tests show that there is no significant difference in distribution of activity locations within the TOD neighborhood for both work and nonwork activities (black triangles in Figure 7). However, for both work and nonwork activity locations when they are neither TOD nor AOD, the distributions of activities are significantly different (blue dots in Figure 7).

5.4.2 Trip Length Analysis

This section analyzes trip length and its distribution at the individual trip level, continuing to test the first hypothesis. Given that the TOD residents located a substantial amount of activities within the TOD neighborhood, as shown in the preceding section, trip length distributions are expected to be different between the TOD and AOD residents, with a higher proportion of shorter trips of the TOD residents.

Table 13 compares trip length by activity type and residence neighborhood. A total of 1055 and 1208 trips were identified for the TOD and AOD residents, respectively. Surprisingly, average trip length (total and work-related trips) of the TOD residents is longer than that of AOD residents. This is because the average value can be largely sensitive to an extreme value. Therefore, trip length distributions were analyzed (see Table 14).

Table 13. Descriptive Statistics for Trip Length by Type and Neighborhood

	TOD neighborhood			AOD neighborhood		
	N	Mean	SD	N	Mean	SD
Total	1055	4.43	5.94	1208	3.85	4.27
Work-related	384	6.68	7.46	263	6.16	5.36
Non-work related	671	3.14	4.37	945	3.21	3.66

Note: Max distance is set to 30 miles.

Table 14. Comparison of Trip Length Distributions by Type and Neighborhood

Activity type	Trip length	TOD neighborhood		AOD neighborhood		p-value *
		N	%	N	%	
Work-related	Total	384	100	263	100	0.006
	0-0.5	47	12	24	9	
	0.5-1.5	32	8	19	7	
	1.5-5	149	39	85	32	
	5-10	80	21	100	38	
	10-20	42	11	27	10	
	20+	34	9	8	3	
Non-work related	TOD	671	100	945	100	0.001
	0-0.5	177	26	168	18	
	0.5-1.5	160	24	213	22	
	1.5-5	215	32	374	40	
	5-10	78	12	155	16	
	10-20	30	4	28	3	
	20+	11	2	7	1	

Note: Activities of age 0-4 were not included; * P-value was derived from K-S tests.

Notably, TOD residents undertake shorter trips (less than 0.5 miles) more than the AOD counterparts (12% vs. 9% for work-related trips and 26% vs. 18% for non-work trips), as shown in Figure 8. Moreover, the proportion of other length of work trips (0.5-5.0 mile) is also higher the TOD residents. However, in work trips of TOD residents, 9% of them are longer than 20+ miles, which is the reason for the larger average trip lengths for total and work-related trips.

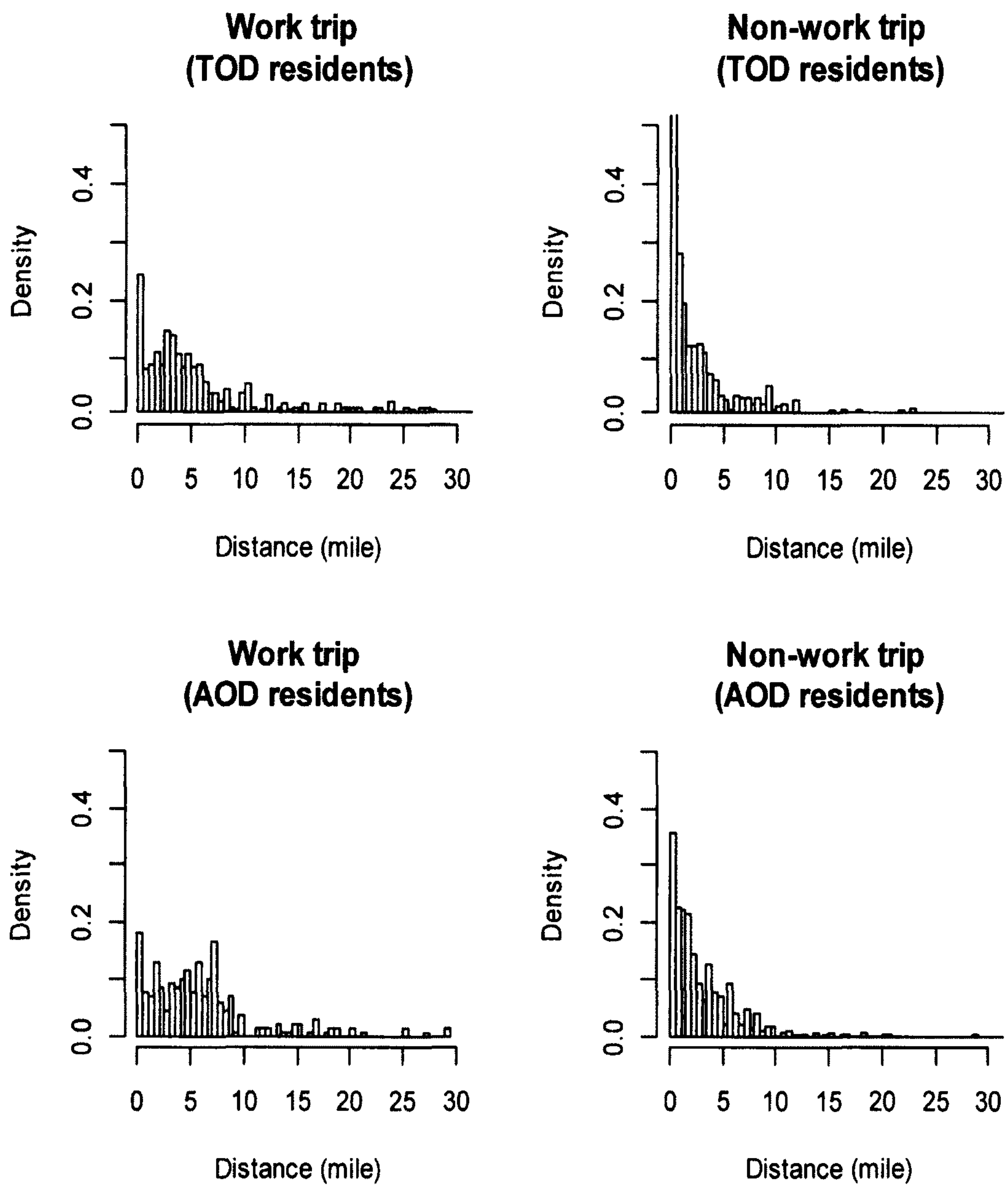


Figure 8. Comparision of Trip Length Distributions by Type and Residence

To examine the difference of two trip length distributions, a two sample Kolmogorov-Smirnov (K-S) test was performed. As a nonparametric test, the K-S test compares the cumulative distributions of two sample groups. The K-S test provides D statistic, which represents the maximum difference in distance between the two cumulative distributions. Corresponding to the D statistic and the sample sizes, p-value is calculated. If the p-value is small, it can be concluded that the two sample groups are drawn from different distributions.

Results suggest that trip length distributions are significantly different between the TOD and AOD residents (see Figure 9). Table 14 shows that D statistic for work trip distributions is 0.137 (the corresponding p-value=0.006) and D statistic for nonwork trip distributions is 0.125 (the corresponding p-value<0.001), rejecting the null hypothesis of no difference in distribution. The statistical evidence shows that more trips with shorter length are found for TOD residents, which supports the first hypothesis.

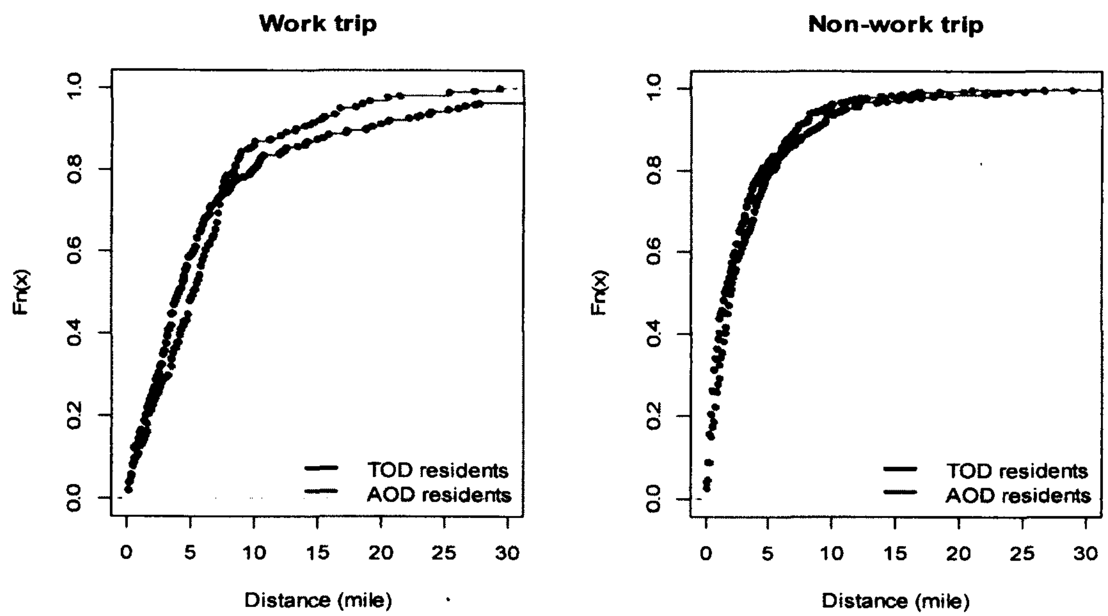


Figure 9. The K-S Test for Trip Length Distributons by Type

5.5 Mode Use: Frequency and Distance

5.5.1 Descriptive Analysis

Focusing on trip frequency and travel distance, this section compares travel mode use behavior between the TOD and AOD households. A household is generally used as a unit of travel demand analysis. All trips undertaken by an individual of age 5 or above only were analyzed. The descriptive analysis indicates that households in the TOD neighborhood make fewer auto trips but more transit and walking trips (Table 15). And, this is true for travel distance. With regard to trip frequency, households in the TOD neighborhood undertake 5.84 trips per day, compared with 9.51 trips in the AOD. Notably, auto trip rates in the TOD are 3.34, which are similar to vehicle trip rates of TOD household found in other studies (3.55 trips/day) (Cervero and Arrington 2008). For mode share by neighborhood, in the AOD neighborhood, 84% of the total trips are auto trips, while 57% in the TOD are auto trips. By contrast, mode share for transit and walking accounts for 18% and 21% of the total trips in the TOD neighborhood, respectively, while the AOD has substantially lower shares for transit (5%) and walking (9%). Note that transit trips include both subway and local bus trips. With respect to travel distance and duration, significantly shorter auto use in distance and time and longer use of alternative modes are observed from the TOD households.

Table 15. Descriptive Statistics for Mode Use Behavior by Neighborhood (Household Level)

		TOD neighborhood (N=185)		AOD neighborhood (N=130)	
		Mean	SD	Mean	SD
Trip frequency (trips/day)	Total	5.84	4.03	9.51	6.21
	Auto	3.34 (57%)	3.85	7.95 (84%)	5.95
	Transit	1.04 (18%)	1.37	0.44 (5%)	0.97
	Walking	1.23 (21%)	2.07	0.87 (9%)	1.59
Travel distance (miles/day)	Total	26.28	27.81	36.00	25.87
	Auto	18.91	24.74	31.72	24.64
	Transit	4.76	7.08	3.07	7.11
	Walking	0.54	1.00	0.30	0.70

Note: N=the number of households; SD=standard deviation; Statistics for 'Bike' and 'Other' are not presented, but included in 'Total' trip; Trips of age 0-4 were not included.

5.5.2 Statistical Modeling

To test the second hypothesis of difference in mode use behavior between the TOD and AOD neighborhoods, behavioral models were estimated. In the conceptual framework, it was discussed that activity and travel behavior is influenced by socio-demographic attributes, work-related attributes, attitude/preference, the built environment and transportation system attributes, and temporal attributes. Note that a TOD indicator variable represents both built environment and transportation system attributes as a whole. Econometric models are specified as follows:

$$Y1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 TOD + \beta_5 \hat{u} + \varepsilon \qquad (1)$$

$$Y2 = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 BE + u \qquad (2)$$

where

$Y1$ = daily household trip frequency and travel distance,

$Y2$ = daily household travel duration,

X_1 = a set of socio-demographic variables,

X_2 = a set of work-related variables,

X_3 = a set of temporal variables,

TOD = an indicator variable (1=TOD resident, 0=otherwise),

BE = a set of built environment variables,

β, γ = a set of parameters, and

ε, u = error terms.

This study carefully took into account attitude toward or preference to travel behavior to avoid endogeneity bias in a statistical model, which can be caused by residential self-selection. As reviewed, self-selection represents households' predisposition for transit-oriented living (i.e., easy transit access and walk-friendly streets) that consciously sorts into residential areas near transit stations. This implies the increase of transit use and walking activity may not result from the TOD attributes; thus, the impact of the residential neighborhood on travel behavior can be misleading. From a statistical point of view, the independent variable (TOD in this case) can be highly

correlated with the error term (ε) if endogeneity results from lifestyle preference. When the independence assumption between an independent variable and an error term does not hold, estimated parameters are no longer unbiased and consistent. Rather, the parameter of *TOD* is likely to be overestimated than the true parameter value due to the positive correlation.

To control for the endogeneity that occurs from the residential self-selection, this study adopted a two-step estimation procedure. First, the econometric model 1 regresses household travel duration on socio-demographic, work-related, temporal variables as well as built environment variables. Note that the built environment variables tested in the first step were housing types (e.g., multi-family home and single family attached) and walking distance and duration from home to the nearest subway station, which can largely represent the land use characteristics. The walking distance and duration (between of the closest subway station and household location) were extracted from Google Maps plugging in their geocodes. In the second step, the residuals obtained from the econometric model 2 were added to the econometric model 1 in that the residual can largely reflect attitude factors (e.g., predisposition for a transit- and pedestrian-friendly environment). The travel duration can be viewed as a consequence of households' trip making behavior; therefore, the variable is likely associated with the preference for a certain travel mode and built environment. That is, if a household prefers to use transit and walking, it would probably choose TOD areas to live, resulting in having longer travel duration for them.

There are several well-known approaches to addressing the residential self-selection. First, a statistical control method can reduce the influence by adding a set of attitudinal variables to a statistical model. The attitudinal variables are measures of preference for residential and travel choices, which can be obtained from targeted surveys. In this approach, the predisposition attitude is removed from an error term, thus any correlation between the residential neighborhood variable (TOD) and the error term (ε) can be controlled. Unfortunately, attitudinal variables are not available from the survey dataset in this study. Typically, such information is not readily available in household travel surveys, as well as this survey dataset.

Second, using an instrumental variable can deal with the endogeneity bias. This approach consists of two stages. In the first stage, the residential neighborhood variable (TOD) is regressed on a set of instrumental variables that are highly correlated with the endogenous variable (TOD), but not correlated with the error term (ε). In the second stage, the residential neighborhood variable (TOD) is replaced by its predicted variable ($\widehat{TOD}$) and then the model 2 is re-estimated, assuming that the predicted variable is uncorrelated with the error term (ε). In this study, several candidate variables including housing types (e.g., multi-family) that are expectedly highly correlated with the residence in a TOD neighborhood, were tested, but they did not satisfy the two strong criteria mentioned above. As pointed out, finding suitable instrument variables is challenging in practice, despite its theoretical appeal (Wooldridge 2000). Therefore, this study employed the two-step method in this context as an ad-hoc approach.

To estimate the models, this study applied count regression, relating daily trip frequency at the household level with the associating factors. For travel distance, this study used log-transformed regression method. The count regression model can reflect the nature of trip frequency (i.e., non-negative integer), as shown in Figure 10. In addition to the advantages mentioned in Chapter 4, the count regression can account for observed heterogeneity (Cameron and Trivedi 1998; Winkelmann 2008). The results can be easily interpreted in terms of trip frequency. Among several count models, negative binomial regression models were estimated to address the inequality of means and variances of the dependent variable. Zero-inflated count models can be applied to handle the substantial number of zeroes[7]; however, the sample size is too small to employ such models in this analysis. For the models for daily travel distance behavior, the travel distances were log-transformed after adding one to the dependent variables to adjust for the skew in distributions (see Figure 10), which is widely used in practice. Walking trips are much shorter than auto and transit trips, requiring a finer analytic resolution. To estimate parameters of the models, a maximum likelihood estimation technique was used in the generalized linear model framework.

[7] 24% of households did not make an auto trip on the assigned travel day; 66% for transit trips; 64% for walking trips.

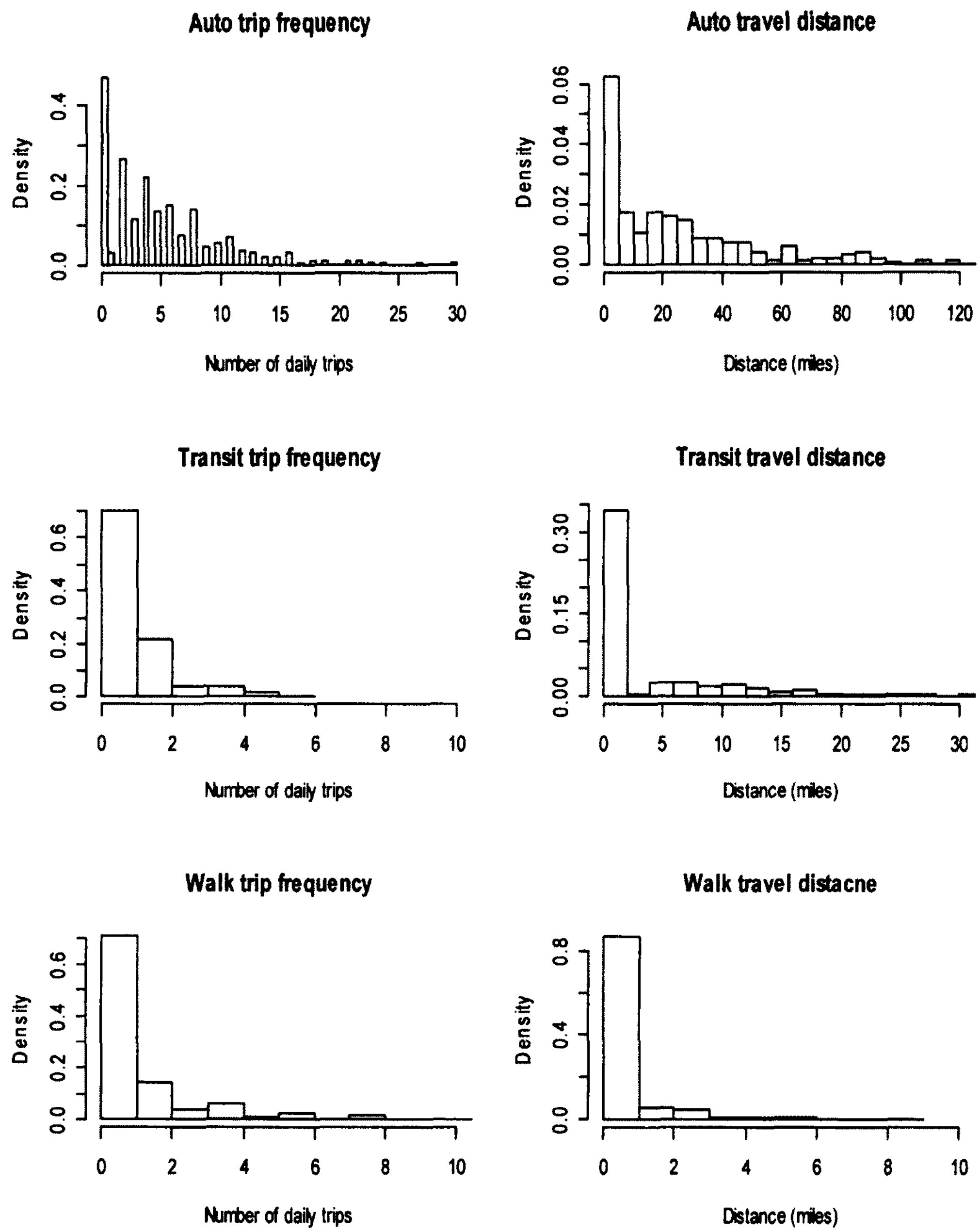


Figure 10. Trip Frequency and Travel Distance Distributions by Mode

5.5.3 Results and Interpretation

Table 16 and Table 17 summarize parameter estimates of trip frequency and travel distance regression models. For each model, two sets of models were presented—without and with residual inclusion. The models with residual addressed residential self-selection. All models are statistically significant at the 5% level, with reasonable goodness-of-fit scores (Pseudo-R^2). In the negative binomial models, the over-dispersion

parameter (alpha) is also found to be significant, indicating the inequality of means and variances of dependent variables. The signs of the parameter estimates are consistent with *a priori* expectations, while the magnitudes are appropriate. Each coefficient value can be interpreted by exponentiating the estimated parameters.

Results show that mode use behavior in trip frequency and travel distance is significantly associated with socio-demographic variables, as expected. Depending on the travel mode, the association results in various magnitudes and forms. For example, trip frequency and household size are positively associated, indicating that the presence of an additional household member can increase auto trips by 35% ($=e^{0.306}-1$) and they make 39% ($=e^{0.329}-1$) more transit trips, and 38% ($=e^{0.323}-1$) more walking trips, all else being equal. Interestingly, household size squared and the vehicle ownership squared variables are used to capture a non-linear relationship with the dependent variables. In addition, the interaction between household size and vehicle ownership was tested in the auto travel distance models and found to be significant.

In addition, several work-related variables (e.g., work location and transportation benefits) are significantly related to the frequency and distance models. For instance, a household with more workers who work near transit stations (i.e., within 0.5-mile buffer) are positively associated with more transit trips—the presence of an additional worker can increase transit trips by 105% ($=e^{0.717}-1$). With regards to the transportation benefits, a set of variables were tested: the number of workers with free parking, with transit/vanpool subsidy, with bike/pedestrian facilities, and with no benefit per household. Results suggest that more workers receiving transit/vanpool subsidy in a household are negatively related with auto trips and distance, but positively related to more transit trips and distance. Similarly, walking trips and distance are found to be positively related to the presence of bicycle/pedestrian facilities or services at workplace. These results are consistent with earlier findings in the context of mode choice behavior (Cervero 1994, 2007).

The models include a set of temporal variables. Interestingly, several variables show statistical significance. For example, transit trips are positively related to the Thursday dummy variable, indicating that survey respondents tend to undertake more transit trips on Thursday, compared to Monday. Interestingly, fewer transit trips and

shorter transit distance were observed for Jan-Feb, which could indicate a seasonable variance. However, for the same period, relatively more walking trips and distance were captured, which points out the systematic transition between the two modes. The models well captured this behavior and controlled for.

The most important finding is that the mode use behavior is statistically different between the TOD and AOD residents. In the trip frequency models, the coefficients of the TOD variable with the residual term suggest that households in TOD neighborhoods undertake 30% ($=1-e^{-0.356}$) fewer auto trips but 61% ($=e^{0.477}-1$) and 57% ($=e^{0.457}-1$) more trips by transit and walking, respectively, compared to households in the AOD neighborhood. Similarly, the travel distance models indicate that, with the residual term, households in TOD neighborhoods undertake 35% ($=1-e^{-0.430}$) shorter auto distances but 25% ($=e^{0.221}-1$) and 12% ($=e^{0.111}-1$) longer travel distances by transit and walking, respectively, compared to households in the AOD neighborhood. In terms of the magnitude of differences, TOD attributes have stronger influences on transit and walking than driving for trip frequency while for travel distance that influence is reversed.

These values are relatively conservative estimates TOD association. The modeling results show that all residual variables are statistically significant at the 1% level. Also, the goodness-of-fit measures are better when the residual term is present in the model. The results indicate that unobserved factors are strongly associated with travel behavior. As discussed earlier, the unobserved factors can include attitudes toward using a particular travel mode or having a particular lifestyle (i.e., residential self-selection). However, the factors can also include built environment variables which were not included in the first step model. For these reasons, the parameter estimates for TOD likely capture the minimum impacts of TODs on travel behavior.

This study additionally estimated two separate auto trip and distance models by using households that own at least one vehicle (N=287). This is because households with no vehicle cannot make any auto trips and distance; therefore, including such households may cause systematic bias. Results show that the models without no-vehicle households do not show substantial difference, compared to the models with pooled households. This indicates that there is no significant bias resulting from the inclusion of no-vehicle households in this context.

Table 16. Trip Frequency Model Results by Travel Mode

Independent variable \ Dependent Variable	Auto trip frequency				Transit trip frequency		Walking trip frequency	
	Model 5-1		Model 5-2		Model 5-3		Model 5-4	
	WR	R	WR	R	WR	R	WR	R
Parameter estimates								
Constant	**-0.600**	**-0.378**	-0.031	0.053	**-1.623**	**-1.607**	-0.815	**-1.409**
Socio-demographics								
Household size	0.246	0.175	**0.414**	**0.306**	**0.369**	**0.329**	**0.405**	**0.323**
Household size squared	-0.027	-0.021	-0.044	**-0.035**	-	-	-	-
Num. of vehicles	**1.729**	**1.547**	**0.976**	**0.992**	**-0.452**	**-0.367**	**-0.434**	**-0.297**
Num. of vehicles squared	**-0.320**	**-0.282**	**-0.172**	**-0.170**	-	-	-	-
Household income ($10,000)	-0.005	-0.005	-0.005	-0.005	**-0.066**	**-0.072**	**0.049**	**0.044**
Student in household (1=yes)	**0.348**	**0.449**	0.265	**0.399**	-0.474	-0.344	0.077	0.110
Worker in household (1=yes)	0.050	0.076	-0.017	0.014	-	-	-	-
Work-related variable								
Workers working in TOD	-	-	-	-	**0.723**	**0.717**	0.029	0.072
Workers with free parking	0.134	0.097	**0.171**	**0.125**	-0.046	-0.157	-	-
Workers with transit subsidy	**-0.313**	**-0.347**	**-0.286**	**-0.329**	**0.768**	**0.735**	-	-
Workers with pedbike facilities	-0.095	-0.075	-0.113	-0.079	-0.263	-0.231	0.265	0.272
Workers with no benefit	0.098	0.035	0.111	0.053	**0.440**	**0.412**	-	-
Temporal context								
Tuesday (1=yes)	0.164	0.112	0.176	0.119	-0.160	-0.243	-0.034	0.111
Wednesday (1=yes)	0.042	0.075	0.047	0.077	0.071	-0.011	0.071	0.220
Thursday (1=yes)	0.119	0.089	0.138	0.110	**0.581**	**0.440**	-0.317	-0.144
Friday (1=yes)	0.260	**0.211**	0.165	0.140	0.165	0.049	-0.431	-0.176
Mar-May(1=yes)	-0.027	0.014	0.024	0.036	**0.799**	**0.854**	-0.166	0.049
Jun-Oct (1=yes)	0.126	0.051	0.128	0.057	**0.737**	**0.756**	-0.553	-0.229
Nov-Dec (1=yes)	0.025	-0.027	0.016	-0.034	0.638	**0.831**	-0.390	-0.333
Indicator variable								
Residing in TOD (1=yes)	**-0.377**	**-0.356**	**-0.391**	**-0.362**	**0.482**	**0.477**	**0.670**	**0.457**
Residual	-	**0.006**	-	**0.005**	-	**0.006**	-	**0.039**
Summary Statistics								
Num. of observations	315	315	287	287	315	315	315	315
Over-dispersion parameter	**0.361**	**0.092**	**0.320**	**0.069**	**0.716**	**0.463**	**2.355**	**0.991**
Likelihood ratio $\chi 2$	**218**	**395**	**158**	**336**	**96**	**119**	**126**	**131**
Log-likelihood (Constant)	-865	-865	-809	-809	-380	-380	-429	-429
Log-likelihood (Full)	-755	-667	-733	-642	-332	-321	-413	-363
Pseudo-R^2	0.126	0.228	0.095	0.208	0.119	0.157	0.004	0.153

Note: Bold face denotes significance at p-value<0.1; WR means a model with without a residual term; R means a model with a residual term.

Table 17. Travel Distance Model Results by Travel Mode

Independent variable \ Dependent Variable	Auto travel distance				Transit travel distance		Walking travel distance	
	Model 5-5		Model 5-6		Model 5-7		Model 5-8	
	WR	R	WR	R	WR	R	WR	R
Parameter estimates								
Constant	**0.809**	**0.760**	**1.464**	**1.412**	0.176	0.180	0.096	0.116
Socio-demographics								
Household size	0.207	0.209	0.147	0.152	0.132	**0.131**	**0.146**	**0.146**
Num. of vehicles	**0.857**	**0.871**	**0.459**	**0.475**	**-0.184**	**-0.185**	**-0.120**	**-0.124**
Household size * vehicles	**-0.123**	**-0.124**	-0.053	-0.055	-	-	-	-
Household income ($10,000)	**0.029**	**0.030**	**0.028**	**0.028**	**-0.033**	**-0.033**	0.005	**0.006**
Student in household (1=yes)	0.376	**0.391**	0.338	0.354	-0.190	-0.191	-0.122	**-0.127**
Worker in household (1=yes)	0.194	0.177	0.107	0.090	-	-	-	-
Work-related variable								
Workers working in TOD	-	-	-	-	**0.504**	**0.505**	0.004	0.005
Workers with free parking	**0.551**	**0.544**	**0.578**	**0.572**	-0.005	0.006	-	-
Workers with transit subsidy	**-0.554**	**-0.561**	**-0.536**	**-0.542**	**0.685**	**0.686**	-	-
Workers with pedbike facilities	-0.065	-0.062	-0.058	-0.054	**-0.316**	**-0.316**	**0.109**	**0.110**
Workers with no benefit	0.016	0.013	0.086	0.084	**0.196**	**0.197**	-	-
Temporal context								
Tuesday (1=yes)	0.030	0.024	0.059	0.055	-0.062	-0.062	0.086	**0.088**
Wednesday (1=yes)	0.011	0.016	-0.060	-0.055	0.091	0.090	0.042	0.039
Thursday (1=yes)	0.029	0.025	0.058	0.056	**0.537**	**0.538**	0.012	0.013
Friday (1=yes)	0.127	0.130	0.035	0.039	-0.012	-0.013	0.014	0.014
Mar-May(1=yes)	-0.160	-0.160	-0.097	-0.095	**0.328**	**0.329**	-0.079	-0.080
Jun-Oct (1=yes)	0.047	0.045	0.043	0.042	**0.430**	**0.431**	**-0.170**	**-0.171**
Nov-Dec (1=yes)	0.033	0.032	0.033	0.031	**0.407**	**0.407**	**-0.114**	**-0.114**
Indicator variable								
Residing in TOD (1=yes)	**-0.494**	**-0.430**	**-0.518**	**-0.457**	**0.226**	**0.221**	**0.127**	**0.105**
Residual	-	**0.010**	-	**0.011**	-	**0.014**	-	**0.014**
Summary Statistics								
Num. of observations	315	315	287	287	315	315	315	315
Likelihood ratio $\chi 2$	**168**	**374**	**102**	**285**	**107**	**456**	**36**	**330**
Log-likelihood (Constant)	-589	-589	-515	-515	-506	-506	-194	-194
Log-likelihood (Full)	-505	-403	-463	-372	-451	-278	-177	-27
Pseudo-R^2	0.142	0.317	0.100	0.277	0.108	0.451	0.092	0.848

Note: Bold face denotes significance at p-value<0.1; WR means a model with without a residual term; R means a model with a residual term.

5.6 Summary and Discussion

This chapter tightly compared the two aspects of activity and travel behavior: activity location and travel mode use. To test the difference in such behavior between TOD residents with AOD residents, a matched pair of TOD and AOD neighborhoods carefully was selected (i.e., the Rosslyn-Ballston Metrorail Corridor and its vicinity area in Arlington, Virginia), which allows controlling for regional accessibility.

First, this study found that the activity locations of the TOD residents are significantly different from AOD residents. The spatial comparisons of out-of-home activities show that TOD residents participated in more activities within the TOD neighborhood than the AOD counterparts. Also, the statistical tests indicate that the TOD resident had significantly higher proportion of shorter trips (0-0.5 miles), which probably resulted from the activity location selection behavior. These are clear evidences that TOD can make the residents' trips shorter in distance by capturing their activities into the TOD neighborhood whose land use is dense and mixed. In addition, their external activity location and trip distances are found to be different from those of the AOD residents.

Second, mode use behavioral models suggest that households in the TOD neighborhood on average make substantially fewer and shorter automobiles trips while using transit more and longer. Also, the TOD residents walk more frequently and longer. The resulting differences in travel behavior are still pronounced, even after considering resident self-selection, which was found by an ad-hoc approach proposed in this study. These behavioral differences can be translated into policy benefits and used as quantitative guidelines. Several associated factors discussed in the conceptual structure were found to be significant. The models confirm the importance of commuting programs that companies operate in a metropolitan area. Some actually influence the mode use (e.g., free parking, transit subsidy, etc.). This travel outcome is partly due to the ease access to transit, high walkability, and compact/mixed land uses in the TOD neighborhood.

CHAPTER 6

COMPARING TIME USE AND LOCATION CHOICE BEHAVIOR FROM A REGIONAL PERSPECTIVE

6.1 Introduction

Transportation planning agencies, e.g., metropolitan planning organizations, generally use travel demand models for transportation planning, especially for making informed infrastructure investment and improvements, as well as transportation policy decisions. Over the past decades, forecasting and analyzing travel demand has been based on individual trips, made by households and people, as a unit of analysis. However, this has been conceptually criticized by the view that a trip is actually derived from activities. In addition, other limitations are that trip-based models only limitedly account for interactions among travel decision makers (i.e., household members) or travel-related decisions (e.g., destination and mode choice). Moreover, the conventional trip-based approach does not fully account for time/space aspects (or constraints). Although the recent interest in reflecting spatial aspects of land use, trip-based travel demand models weakly account for them. Taken together, real world travel decision making are imperfectly represented (Bhat and Koppelman 1999; McNally and Rindt 2007).

An activity-based approach emerged as a new paradigm of travel demand analysis. The activity-based approach more fully takes into account travel as a derived demand, focusing on activity participation decisions with trips viewed as a special case of activity participation. Recently, activity sequencing, household interactions, and time-space dimensions have been importantly explored. This behaviorally appealing and broader approach is finding greater application in the field, with development of activity-based land use-transportation model systems (e.g., TRANSIMS, UrbanSim, and MATSim).

Responding to this research trend, this chapter aims to better understand travel and activity behavior in the context of TOD, which has not been investigated intensively. The reason for this is mainly because of increasing demand for TOD as a sustainable urban design, and meeting the need of appropriate methodology. Among many dimensions of activity behavior, this chapter particularly explores time use and location

choice behavior for out-of-home activities undertaken by TOD residents, from a regional perspective. The findings can help travel demand modelers continue to improve activity-based modeling and provide a sounder basis for integration of land use and transportation. A detailed analysis of TOD residents is also beneficial to transit and urban planning agencies in measuring performances and determining policy actions as they face greater interest and demand for TODs across the country.

6.2 Hypotheses

The next two hypotheses in this dissertation are that time use behavior for out-of-home activities between TOD and AOD residents is different at the person level, while their activity location choice and sequence is also distinct at the activity and trip level. Unlike the case in Chapter 5, this chapter focuses on not just a single/local neighborhood but a subset of the region encompassing all 86 Metro stations. Specifically, TOD residents are expected to spend more time within TODs. Moreover, it is expected that TOD residents choose TODs for their planned activities, and better sequence their activities centered on and bounded by TODs, compared to AOD residents. As discussed, TOD can provide residents with diverse activity opportunities (e.g., work and social activities) with a greater accessibility. Also, TODs are regionally connected each other by public transit system. Consequently, areas near subway stations (TOD areas) will act as "the core of daily activities" for the residents. On the other hand, for the AOD residents, the TODs will act "a routine anchor." That is, they spend substantial time on working at the TOD areas on a daily basis but engage in other activities not around TOD areas. Therefore, their activity location choice and sequence behavior are expected to be different.

Additionally, this section examined whether the time use and location choice behavior is identical for all AOD residents. Notably, the proximity to TODs can play an important role in this context. In other words, the activity behavior can be differently associated with the distance from a subway station to a residential location. In this regard, after dividing AOD areas into two groups based on the proximity to TOD areas, this section tested the behavioral differences between the two groups as well.

6.3 Methodology and Data Extraction

6.3.1 Study Area Selection and Comparison Groups

This section extended the scope of comparative analysis to regional TODs with the focus of an inner area of the Washington, D.C. metropolitan region surrounded by Capital Beltway (Interstate 495). This area is almost identical to the area covered by 86 WMATA transit stations. This study divided this area into three groups: TOD, AOD close to TOD (AOD-C), and AOD far from TOD (AOD-F). The TOD was defined as an area bounded by 0.5-mile buffer of each subway station (small inner circles), which is consistent to the previous chapter. Next, additional circular spatial buffers were created from the metro stations, with the distance of 0.5-mile to 1.5-mile (larger outer circles). This was referred to the AOD-C. Finally, the remaining area is referred to AOD-F. Corresponding to each group, a set of household sample was identified and extracted from survey dataset. As a result, 1,911, 2,524, and 2,980 households that fall in each group are prepared to compare time use and location choice behavior in the context of residence location. Then, they were aligned for comparison across the three groups.

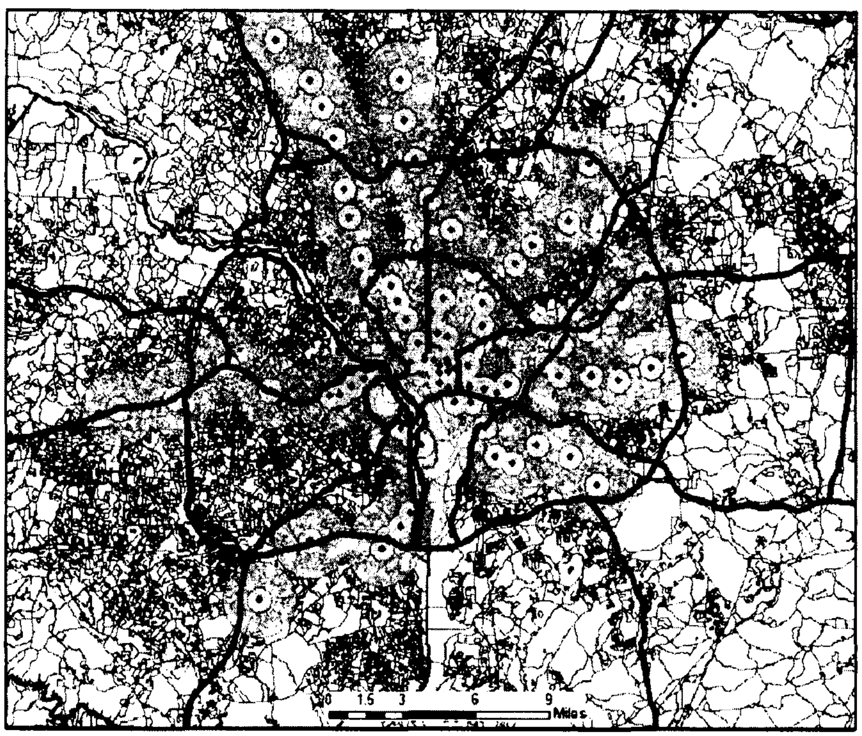


Figure 11. Three Residential Groups by Distance to Transit Stations
(TOD in green, AOD-C in pink, and AOD-F)

6.3.2 Sample Characteristics

Table 18 summarizes socio-demographic characteristics of the three comparison groups: TOD, AOD-C, and AOD-F. Comparison of household characteristics shows that there are substantially higher proportions of single person-households (49%) and zero vehicle-households (23%) in the TOD, compared to the other two groups. In addition, the TOD households consist of more low-income residents (less than $29,999) and multi-family house dwellers. As a residence location moves from the TOD area to the AOD area, a household has more members, workers, vehicles, and income. Table 19 shows that, at the person level, the individuals residing in the TOD have relatively more individuals aged 19-34 (25%) and employees (71% out of individuals aged 16 and above) than the other groups. Interestingly, in the outer TOD, a relatively higher ratio of African American is found. Overall, the socio-demographics are largely different by residence group.

Table 18. Sample Characteristics by Residence Group at the Household Level (%)

Variable	Category	TOD (N=1,911)	AOD-C (N=2,524)	AOD-F (N=2,980)
Household size	1	49	39	32
	2	34	35	37
	3	10	13	14
	4+	7	13	17
Number of workers	0	23	23	22
	1	47	44	41
	2	28	30	33
	3+	2	3	4
Number of vehicles	0	23	8	4
	1	51	43	36
	2	21	37	42
	3+	5	12	18
Household income	Less than $29,999	13	11	7
	$30,000 - $49,999	16	15	13
	$50,000 - $99,999	33	33	34
	$100,000 - $149,999	24	24	29
	$150,000 or more	14	17	17
Housing type	Single family detached	21	52	58
	Single family attached	21	19	19
	Multi-family	58	29	23

Table 19. Sample Characteristics by Residence Group at the Person Level (%)

Variable	Category	TOD (N=3,174)	AOD-C (N=4,934)	AOD-F (N=6,291)
Gender	Male	46	45	46
	Female	54	55	54
Age	5-18	9	16	17
	19-34	25	15	15
	35-44	17	15	15
	45-54	16	18	18
	55-64	16	19	18
	65+	17	17	17
Race/ethnicity	African American	21	25	17
	Asian	4	4	7
	Hispanic	5	4	5
	White	68	65	68
	Others	2	2	3
Work status (among age 16+)	Employed	71	66	66
	Retired	18	19	20
	Disabled	3	3	2
	Homemaker	3	5	6
	Unemployed	2	2	2
	Student	3	5	4

Note: Individuals of age 0-4 were not included.

6.4 Time Allocation by Activity and Location

6.4.1 Descriptive Analysis

This section compares daily time use at the person level across the residence groups. Table 20 shows that residents in the TOD spend more time on out-of-home activities and travel. The travel means any movement linking two consecutive activities as well as transportation-related activities such as the pick-up/drop-off someone. On average, individuals residing in the TOD spend 400 minutes on out-of-home activities, which are about 30 minutes longer than the others. Similarly, individuals residing in TOD areas spend slightly longer time for their travel. Therefore, the TOD residents stay at home about 30 to 40 minutes less than the other groups.

Table 21 presents that time used for out-of-home activities breaks down into activity types and locations. The TOD residents, on average, spend more time on working (67%), but less time on school-related activities (9%) than the other groups, while, interestingly, the distribution of time use for the rest of the activities is very similar, regardless of residence locations. Notably, the TOD residents spend more time within

TOD areas than the AOD residents do within AOD areas. TOD residents use more than 60% of time for out-of-home activities over TOD areas, while the two other groups spend 47% and 31%, respectively. Another interesting finding is that the AOD-C residents do not allocate a majority of their time for the AOD-C areas; rather they spend a great amount of time (about 50%) within the TOD areas. Also, the AOD-F residents spend relatively more time over TOD areas rather than AOD-C, although outer TOD is closer to them. This indicates that time use over urban space is complex. In addition, urban residents spend a substantial amount of their time within TOD areas, though their size only accounts for about 1% of the region. Therefore, this section focuses on time spend for TOD areas, examining who uses their time at TOD areas and with what activities. This is a unique aspect of this study, compared to the literature reviewed in Chapter 2.

Table 20. Daily Time Use by Residence Location (Person Level)

	TOD (N=3,174)			AOD-C (N=4,934)			AOD-F (N=6,291)		
	Mean	SD	%	Mean	SD	%	Mean	SD	%
Total	1440	-	100	1440	-	100	1440	-	100
In home	941	287	65	970	284	67	982	291	68
Out-of-home activity	400	258	28	374	251	26	368	257	26
Travel	98	101	7	96	109	7	89	91	6

Note: SD=Standard deviation; Individual of age 0-4 are not included.

Table 21. Time Use by Activity Type and Residence Location (Person Level)

	Category	TOD (N=3,174)	AOD-C (N=4,934)	AOD-F (N=6,291)
Total	Total (minutes/person)	400	374	368
activity type	Work (%)	67	59	60
	School (%)	9	16	16
	Shopping (%)	3	4	4
	Social/Recreational (%)	9	10	9
	Personal Business (%)	7	7	6
	Meal (%)	3	3	3
	Other (%)	2	1	2
Activity location	TOD (%)	65	47	31
	AOD-C (%)	21	34	23
	AOD-F (%)	14	19	46

6.4.2 Statistical Modeling

Behavioral models were estimated to test the third hypothesis that time allocation behavior is different among TOD, AOD-C, and AOD-F residents. As discussed, this section specifically focuses on time spent within TOD areas, examining the relationship with influencing factors discussed in conceptual structure. In line with earlier studies (Buliung and Kanaroglou 2006; Chen and McKnight 2007), the out-of-home activities were initially grouped by their characteristics (e.g., obligatory and discretionary). Then, the obligatory activities were further divided into two categories in this study. Overall, this section analyzed three categories: work, school, and discretionary (consisting of shopping, social/recreational, personal business, meal, and other). Econometric models are specified as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 TOD + \beta_6 AODC + \varepsilon \qquad (1)$$

where

Y = time spent within TOD areas at the person level (dependent variable)

X_1 = a set of socio-demographic variables,

X_2 = a set of work-related variables,

X_3 = a set of spatial context variables,

X_4 = a set of temporal context variables,

TOD = an indicator variable (1=residing in TOD areas, 0=otherwise),

$AODC$ = an indicator variable (1=residing in AOD-C areas, 0=otherwise),

β = a set of parameters, and

ε = an error term.

Before estimating the models, each out-of-home activity category was examined. Figure 12 shows the distribution of time allocation for TOD areas, indicating that there are a significant number of observations with zero. Notably, 73% of total residents did not engage in any work activity in the TOD on their assigned day. Zero minutes for school activity in the TOD account for 97% of the total residents. Finally, for discretionary activities the percentage of residents, who spend zero time in the TOD area,

is 73% of the total residents. If a substantial proportion of zero is not handled properly in statistical models, bias can occur.

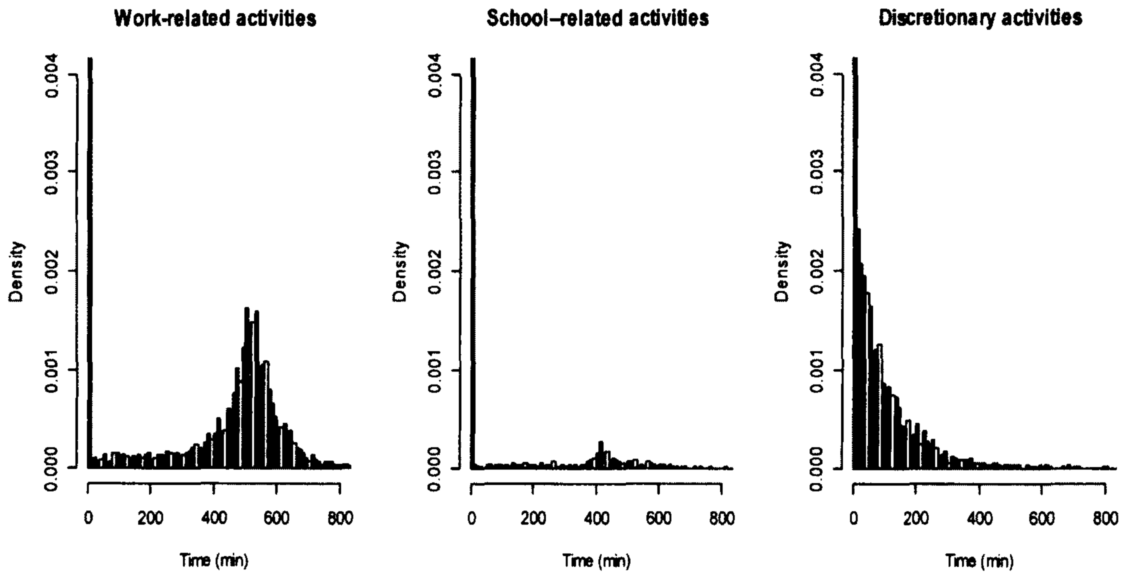


Figure 12. Distributions of Time Allocation for TOD Areas by Activity Type

To address this issue, a two-part model has been widely applied. The two-part model views the data with excess zeros with two different mechanisms (Min and Agresti 2002; Madden 2008).

Let Y_i denote the time spent within TOD for the i^{th} individual, $Y_i = 0,1,2,\ldots$ X is a vector of independent variables. Then, the probability of observing Y_i>0 follows conditional mean of Y_i

$$E[Y_i|X] = P[Y_i > 0|X] \times E[Y_i|Y_i > 0, X]$$

The first part of the two-part model can be derived from a binary model. The probability of having a positive value

$$P[Y = 1|X] = F(X'\beta)$$

where F is the cumulative density function.

Conditional on a positive value, the second part assumes a log-normal distribution; that is

$$\ln[Y|Y > 0] = X'\beta + \varepsilon$$

where ε is distributed as $N(0, \sigma^2)$.

In this context, activity participation and actual time use given that an activity is undertaken are separately modeled. The two components have different parameters which can explain their different behavior. More specifically, the first part estimates the probability of participating in a certain out-of-home activity. Conditional on the engagement of the activity, in the second part, the model regresses activity duration on explanatory variables. That is, observations that their activity duration is greater than zero are only used in the second part. Generally, the dependent variable is log transformed to ensure its positivity in the second part. In this study, for the participation model, binary probit models were estimated, while log-transformed regression models were estimated for time spent in TOD areas. In the model estimation, strong correlations among variables of interest are carefully examined. To estimate parameters of the models, the likelihood function for the two-part model is

$$L = \prod_{y_i=0} P(y_i = 0) \prod_{y_i>0} P(y_i > 0) f(y_i|y_i > 0)$$

$$L = \prod_{y_i=0} [1 - F(X'\beta)] \prod_{y_i>0} \frac{1}{1 + e^{X'\beta}} \sigma^{-1} \phi \left(\frac{\ln y_i - X'\beta}{\sigma} \right)$$

6.4.3 Results and Interpretation

Table 22 to Table 24 presents the two-part model estimation results for time use of obligatory (work-related and school-related, respectively) and discretionary activities with 14,399 individuals. Note that the dependent variables are time allocated for TOD areas only. For the time allocation models for work and school activities, those who actually participated in such activities were only included in the model. The models adequately fit the data while the models are statistically significant at the 5% level. Factors associated with out-of-home time use behavior are largely consistent with *a priori* expectations. Most of the coefficients are statistically significant at the 5% level.

As noted, the first part can be viewed as activity participation (referring to an activity participation model in the text), while the second part represents actual time spent (referring to a time use model). Each model shows coefficient values and the corresponding marginal effects that represent the amount of change in the dependent variable in a more intuitive way. The marginal effects were calculated at means of the independent variables, holding all other variables at their means. When an independent variable is categorical, the difference in the predicted probabilities between the categories is the marginal effect.

The work activity participation model (see Table 22) shows that TOD residents are more likely to work in a TOD area, compared to AOD-C and AOD-F residents (Model 6-1). Their likelihoods are 11% and 7%, respectively. Between AOD-C and AOD-F, the AOD-C residents are 4% more likely to engage in working activities within the TOD areas. Given the proximity to the workplace, it is understandable that the TOD residents have a higher likelihood. Although there are significant differences in the likelihood among the three groups, actual time allocation for work in TOD does not vary across the group (Model 6-2). This indicates that work schedules are fixed with the average duration of 8 hours.

In the work participation and time use models (see Table 22), several interesting variables are found. With regard to workplace flexibility, the models show that ones who actually telecommuted were less likely to participate in and spend time on work activity within TOD areas, noting that it is effective to reduce work trips or schedule their work time more flexibly. Surprisingly, residents in Washington, D.C. do not necessarily participate in TOD work activity more than Fairfax residents, despite the proximity to their workplaces and/or more chances to engage in such activities. Significant temporal context variables are Tuesday, Wednesday, and Thursday with higher engagement in working activity and longer working hours than Friday. This temporal pattern is not only true in the context of TOD, but also (perhaps) true for all areas.

The school activity participation and time allocation models (see Table 23) are similar to the work activity models in several aspects. TOD residents are more likely to participate in school activities taking place within TOD area, compared to AOD-C and AOD-F residents (Model 6-3). Similarly, actual time allocation for school-activity around

TOD does not vary across the group (Model 6-4); rather, they are more strongly related to individuals' jobs. As expected, students are more likely to engage in school activities and spend more time on them. Interestingly, the retired are also quite involved in school-related activities. Also, the school activity participation and time allocation behavior differ by spatial and temporal context.

The discretionary activity models (see Table 24) show more sophisticated behavior in activity engagement and time allocation. Similar to the other activity categories, TOD residents are more likely to participate in discretionary activities taking place within TOD area, compared to the other resident groups (Model 6-5). However, notably, they spend less time on the discretionary activities in TOD areas, which is different from *a priori* expectation. There may be trade-off, meaning proximity to and duration of activities. Retired people, homemakers, and the unemployed are more likely to involve discretionary activities with longer activity hours, as expected. The discretionary activities are not only spatial and temporal contexts but also they are the activity context. This means that individuals who actually participate in work or school activities tend to have discretionary activities in the TOD areas, while spending less time on the activities, pointing to the interaction between out-of-home activities. Among the discretionary activities, social and recreational activities are longer while the duration for shopping is shorter, which is expected to be long. This can imply that shopping activity in the context of TOD might be different from other areas (e.g., shopping malls at suburban areas in auto-oriented and conventional development).

Table 22. Two-Part Model Results for Work-related Activities

Independent Variable \ Dependent Variable	Work-related activity				
	Model 6-1			Model 6-2	
	Activity participation			Time use	
	Coefficient value	Marginal effect	z-statistic	Coefficient value	t-statistic
Constant	-2.490 ***	-	-10.490	5.562 ***	32.378
Socio-demographic variable					
Household size	-0.035 *	-0.013	-1.937	-0.010	-1.026
Single member (1=yes)	0.122 **	0.047	2.346	0.013	0.484
Num. of vehicles	-0.047 **	-0.018	-2.179	-0.014	-1.209
No vehicle (1=yes)	0.146 **	0.057	1.862	0.045	1.292
Gender (1=male)	0.084 ***	0.032	2.588	0.003	0.191
Age (years old)	0.005	0.002	0.568	-0.002	-0.441
Age squared (years old)	0.000	0.000	-0.966	0.000	-0.285
Household Income ($10,000)	0.016 ***	0.006	4.608	0.006 ***	3.312
Work/school context variable					
Full time student (1=yes)	-0.263 ***	-0.098	-2.62	-0.182 ***	-2.982
Part time student (1=yes)	0.016	0.006	0.222	-0.013	-0.358
Num. days telecommunicated	-0.162 ***	-0.063	-11.166	-0.143 ***	-14.713
Num. current jobs	-0.045	-0.017	-0.773	-0.127 ***	-4.073
Hours of work (hr/week)	0.016 ***	0.006	14.079	0.006 ***	8.400
Regional context variable					
Residential location					
Washington, D.C. (1=yes)	-0.280 ***	-0.105	-4.302	-0.114 ***	-3.636
Montgomery County (1=yes)	-0.202 ***	-0.077	-3.333	-0.014	-0.465
Prince George's County(1=yes)	-0.152 **	-0.058	-2.417	-0.012	-0.392
Arlington County (1=yes)	-0.264 ***	-0.099	-3.965	-0.032	-0.968
Alexandria City (1=yes)	-0.170 **	-0.066	-2.07	-0.057	-1.400
Workplace location					
Washington, D.C. (1=yes)	2.486 ***	0.785	20.605	0.628 ***	4.829
Montgomery County (1=yes)	1.577 ***	0.553	12.643	0.536 ***	4.070
Prince George's County(1=yes)	1.206 ***	0.443	9.353	0.444 ***	3.293
Arlington County (1=yes)	2.333 ***	0.646	18.163	0.602 ***	4.569
Fairfax County (1=yes)	0.355 ***	0.140	2.751	0.086	0.618
Alexandria City (1=yes)	1.563 ***	0.605	11.041	0.402 ***	2.915
Temporal context variable					
Monday (1=yes)	-0.015	-0.006	-0.292	0.017	0.628
Tuesday (1=yes)	0.111 **	0.043	2.165	0.059 **	2.195
Wednesday (1=yes)	0.110 **	0.042	2.115	0.059 **	2.198
Thursday (1=yes)	0.136 **	0.053	2.475	0.036	1.283
Jan-Apr (1=yes)	0.015	0.006	0.397	0.014	0.685
May-Aug (1=yes)	0.016	0.006	0.387	0.014	0.724
Indicator variables					
TOD resident (1=yes)	0.280 ***	0.110	5.759	-0.021	-0.831
AOD-C resident (1=yes)	0.110 ***	0.043	2.792	-0.031	-1.477
Summary statistics					
Num. of observations	8,563			3,796	
Likelihood ratio $\chi 2$	3,471 ***			574 ***	
Log-likelihood (Constant)	-5,880			-3,027	
Log-likelihood (Full)	-4,144			-2,740	
Pseudo-R^2	0.295			0.095	

Note: * p<0.10; ** p<0.05; *** p<0.01; A base for residential area is 'Fairfax County'; A base for workplace location is 'other areas in VA'; A base for temporal context variables is "Friday' and 'Sep-Dec', respectively; * looking for a job ** not looking for a job.

Table 23. Two-Part Model Results for School-related Activities

Independent Variable \ Dependent Variable	School-related activity				
	Model 6-3			Model 6-4	
	Activity participation			Time use	
	Coefficient value	Marginal effect	z-statistic	Coefficient value	t-statistic
Constant	-2.901 ***	-	-10.217	5.701 ***	19.649
Socio-demographic variable					
Household size	-0.029	-0.004	-0.911	0.029	0.904
Single member (1=yes)	-0.085	-0.013	-0.526	-0.336 **	-2.149
Num. of vehicles	-0.002	0.000	-0.053	-0.059	-1.271
No vehicle (1=yes)	0.037	0.006	0.253	0.160	1.274
Gender (1=male)	0.095	0.015	1.477	0.071	1.140
Age (years old)	0.044 ***	0.007	3.722	-0.013	-1.111
Age squared (years old)	-0.001 ***	0.000	-4.464	0.000	0.029
Household Income ($10,000)	0.011	0.002	1.626	0.010	1.529
Job-related variable					
Retired (1=yes)	1.493 ***	0.453	3.737	-0.292	-0.486
Disabled (1=yes)	-0.211	-0.028	-0.343	0.299	0.486
Homemaker (1=yes)	-3.695	-0.088	-0.044		
Unemployed * (1=yes)	0.216	0.039	0.334	0.806	1.287
Unemployed, ** (1=yes)	-4.083	-0.085	-0.015		
Student (1=yes)	0.441 ***	0.061	3.764	0.222 **	2.029
Regional context variable (residence)					
Washington, D.C. (1=yes)	0.975 ***	0.230	7.857	-0.073	-0.572
Montgomery County (1=yes)	0.331 ***	0.057	3.007	-0.006	-0.047
Prince George's County(1=yes)	0.266 ***	0.046	2.216	-0.140	-1.015
Arlington County (1=yes)	0.343 ***	0.064	2.463	-0.103	-0.676
Alexandria City (1=yes)	0.283	0.053	1.358	0.039	0.174
Temporal context variable					
Monday (1=yes)	0.146	0.024	1.286	-0.027	-0.230
Tuesday (1=yes)	0.189	0.032	1.642	0.093	0.803
Wednesday (1=yes)	0.229 **	0.036	2.036	0.173	1.513
Thursday (1=yes)	0.218 *	0.037	1.838	-0.035	-0.286
Jan-Apr (1=yes)	-0.027	-0.004	-2.235	-0.108	-1.305
May-Aug (1=yes)	-0.213 **	-0.031	0.362	0.017	0.232
Indicator variables					
TOD resident (1=yes)	0.804 ***	0.175	7.856	0.039	0.367
AOD-C resident (1=yes)	0.660 ***	0.118	7.991	0.115	1.215
Summary statistics					
Num. of observations	3,010			388	
Likelihood ratio χ2	395 ***			101	
Log-likelihood (Constant)	-1,156.			-389	
Log-likelihood (Full)	-958			-338	
Pseudo-R^2	0.171			0.130	

Note: * p<0.10; ** p<0.05; *** p<0.01; a base for job-related variable is 'Employed'; a base for residential area is 'Fairfax County'; A base for temporal context variables is "Friday' and 'Sep-Dec', respectively.

Table 24. Two-Part Model Results for Discretionary Activities

Independent Variable \ Dependent Variable	Discretionary activity				
	Model 6-5			Model 6-6	
	Activity participation			Time use	
	Coefficient	Marginal	z-statistic	Coefficient	t-statistic
Constant	-1.496 ***	-	-10.549	3.777 ***	21.353
Socio-demographic variable					
Household size	-0.080 ***	-0.024	-5.614	-0.007	-0.320
Single member (1=yes)	0.096 **	0.03	2.462	0.017	0.338
Num. of vehicles	-0.041 **	-0.013	-2.363	-0.008	-0.303
No vehicle (1=yes)	-0.031	-0.009	-0.583	0.128 **	2.029
Gender (1=male)	0.006	0.002	0.226	-0.121 ***	-3.730
Age (years old)	0.016 ***	0.005	3.774	-0.009	-1.504
Age squared (years old)	0.000 ***	0.000	-5.109	0.000	1.493
Household Income ($10,000)	0.017 ***	0.005	6.369	-0.003	-0.862
Job-related variable					
Retired (1=yes)	0.319 ***	0.082	3.909	0.286 ***	3.815
Disabled (1=yes)	-0.013	-0.024	-0.113	0.258 **	2.079
Homemaker (1=yes)	0.173 *	0.034	1.866	0.191 **	1.933
Unemployed * (1=yes)	0.292 **	0.074	2.559	0.358 **	2.914
Unemployed ** (1=yes)	-0.136	-0.057	-0.681	0.448 *	1.792
Student (1=yes)	-0.115	-0.054	-1.036	0.375 **	2.912
Work/school context variable					
Full time student (1=yes)	-0.110	-0.032	-1.380	-0.104	-0.993
Part time student (1=yes)	0.013	0.004	0.216	0.119	1.522
Num. days telecommunicated	0.063 ***	0.019	5.020	0.027 *	1.737
Hours of work (hr/week)	-0.006 ***	-0.002	-5.310	0.000	-0.367
Regional context variable					
Washington, D.C. (1=yes)	0.725 ***	0.251	16.119	0.084	1.292
Montgomery County (1=yes)	0.563 ***	0.188	14.298	-0.055	-0.887
Prince George's County(1=yes)	0.265 ***	0.086	6.187	-0.106	-1.540
Arlington County (1=yes)	0.564 ***	0.197	11.417	0.048	0.674
Alexandria City (1=yes)	0.248 ***	0.076	3.891	-0.113	-1.217
Temporal context variable					
Monday (1=yes)	-0.136 ***	-0.041	-3.533	-0.175 ***	-3.478
Tuesday (1=yes)	-0.016	-0.005	-0.418	-0.192 ***	-3.900
Wednesday (1=yes)	-0.158 ***	-0.048	-4.029	-0.104 **	-2.027
Thursday (1=yes)	-0.081 **	-0.024	-1.969	-0.088 *	-1.651
Jan-Apr (1=yes)	-0.024	-0.007	-0.835	-0.104 ***	-2.706
May-Aug (1=yes)	0.067 **	0.021	2.114	-0.098 **	-2.390
Indicator variables					
TOD resident (1=yes)	0.682 ***	0.233	18.772	-0.161 ***	-3.232
AOD-C resident (1=yes)	0.438 ***	0.140	14.571	-0.170 ***	-3.816
Activity-related variable					
Work (1=yes)	0.316 ***	0.097	9.850	-0.266 ***	-6.230
School (1=yes)	0.210 ***	0.069	2.742	-0.062	-0.608
Meal (1=yes)				0.802 ***	19.874
Personal business (1=yes)				0.682 ***	17.931
Shopping (1=yes)				0.089 **	2.414
Social/Recreational (1=yes)				1.368 ***	34.413
Other (1=yes)				1.066 ***	11.745
Summary statistics					
Num. of observations	14,399			3,841	
Likelihood ratio $\chi 2$	2,318			1,739	
Log-likelihood (Constant)	-8,351			-6,183	
Log-likelihood (Full)	-7,192			-5,313.	
Pseudo-R^2	0.138			0.140	

Note: * p<0.10; ** p<0.05; *** p<0.01; a base for job-related variable is 'Employed'; a base for residential area is 'Fairfax County'; A base for temporal context variables is "Friday' and 'Sep-Dec', respectively.

6.5 Location Choice and Sequence

6.5.1 Descriptive Analysis

Regarding the fourth hypothesis, this section compares location choice and sequence behavior at the trip level across the residence groups defined earlier. Notably, who chooses an activity within TOD areas and sequences their activities among TOD areas is an interesting question given that transit systems link local TODs with regional TODs, offering the residents greater commuting/travel options. Also, mixed land use allows residents to participate in activities with alternative transportation modes (walking and bicycle).

Using corresponding activity data for each residence group, Table 25 compares activity type and location across the residence group: TOD, AOD-C, and AOD-F. Notably, residents in the TOD participate in moderately more work activities (35%) than the other groups. By contrast, residents in other groups engage in more school activities (8%), while the rest of the activities are quite similarly involved across the residence group. This similarity is very similar to time use behavior (see Table 21) in the previous section. As hypothesized, the TOD residents choose more activities within TOD areas (66%) while the AOD-C and AOD-F residents do for within their local areas (33% and 61%, respectively). However, the AOD-C residents choose more activities in TOD areas not their local areas (33% vs. 43%). Also, the AOD-F residents similarly choose their activity locations between the TOD and AOD-C areas, although the AOD-C areas are closer to them (21% vs. 18%).

Table 26 shows sequence of activity and location. There is moderately more work-shop and work-meal activity sequences by the TOD residents. This is in line with a finding of the previous section (Model 6-5), noting that one with participation in a work activity in TOD areas is more likely to engage in a discretionary activity. Nevertheless, overall distributions of other activity sequences are fairly similar to each other. Notably, the location sequence behavior is quite different from one group to another. For example, while the TOD residents sequence TOD locations more than 50%, the AOD-F to AOD-F sequence accounts for 47% of all sequences made by the AOD-F residents. However, the sequence of activity locations are quite mixed for the residents of the AOD-C areas

Together with findings above, this indicates that time use over urban space is complex, and, in particular, TOD areas are the most frequently used spaces in urban areas.

Table 25. Activity Type and Location by Residence Location (%)

	Category	TOD (N=7,104)	AOD-C (N=10,401)	AOD-F (N=12,686)
Activity type	Work	35	31	30
	School	4	8	8
	Shopping	22	22	23
	Social/Recreational	12	13	13
	Personal Business	16	17	16
	Meal	9	8	7
	Other	2	2	2
Activity location	TOD	66	43	21
	AOD-C	20	33	18
	AOD-F	14	24	61

Note: Only activities that individuals (age 5+) participated in were included.

Table 26. Activity Sequence and Location by Residence Location (%)

	Category	TOD (N=3,149)	AOD-C (N=4,403)	AOD-F (N=5,120)
Activity type sequence	Work-Shop	16	15	13
	Work-Meal	15	10	11
	Shop-Shop	10	9	12
	PerBus-Shop	8	10	12
	Work-Work	8	10	8
	Work-PerBus	9	8	7
	PerBus-PerBus	4	5	5
	Work-SocRec	5	4	4
	SocRec-Meal	3	2	3
	Shop-SocRec	4	6	6
	PerBus-Meal	3	3	3
	Meal-Shop	3	3	4
	Other	10	14	14
Activity location sequence	TOD – TOD	56	32	14
	TOD – AOD-C	15	19	8
	TOD – AOD-F	6	7	9
	AOD-C – AOD-C	8	15	7
	AOD-C – AOD-F	6	12	14
	AOD-F – AOD-F	9	15	47

Note: Only activities that individuals (age 5+) participated in were included.

6.5.2 Statistical Modeling

To understand the location choice and sequence behavior of the residents of the study area, statistical models were estimated. The models can be also used to test the fourth hypothesis on the different location choice and sequence behavior between TOD and AOD residents. The first dependent variable of interest is whether or not the next activity location is TOD. If the next activity location is TOD, the dependent variable was coded with one; otherwise, it was coded with zero. The second dependent variable is whether two consecutive activity locations are TOD areas. Similar to the first dependent variable, in this case, the dependent variable was coded with 1 only if the next two locations are TODs. This study estimated random effect binomial probit models to explore the linkage of location choice and location sequence behavior with associated factors. The random effect can capture the correlation between errors, as an individual can make several location choices and sequences. Econometric models are specified as follows:

$$Y^* = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 TOD + \beta_6 AODC + \varepsilon \qquad (2)$$

$$Y^* = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 X_4 + \gamma_5 TOD + \gamma_6 AODC + v + u \qquad (3)$$

$Y = 1\ if\ Y^* > 0, and\ 0\ otherwise$

where

Y	=	a binary dependent variable (location choice and sequence)
X_1	=	a set of socio-demographic variables,
X_2	=	a set of work-related variables,
X_3	=	a set of spatial context variables,
X_4	=	a set of temporal context variables,
TOD	=	an indicator variable (1=residing in TOD areas, 0=otherwise),
$AODC$	=	an indicator variable (1=residing in AOD-C areas, 0=otherwise),
β, γ	=	a set of parameters, and
ε, v, u	=	error terms,

To allow for ε to be freely correlated within an individual, but uncorrelated across individuals, the error term in model 3 specifies

$$\varepsilon = v + u$$

where v is the unobserved individual specific heterogeneity. If v is unrelated to independent variables, this is called the random effect model. In this case, a conditional distribution $f(v|X)$ is not dependent on independent variables, X. If v and X are correlated, this is called the fixed effect model. As noted, this study focused on the random effect model.

The likelihood function is

$$L = \int_{-\infty}^{\infty} \left[\prod P(Y_i = y_i|X\beta + v)\right] f(v)dv.$$

6.5.3 Results and Interpretation

Table 27 and Table 28 summarize the results of two random effect binary probit models for activity location choice and sequence, with 30,191 and 12,672 observations, respectively. The observations are only for out-of-home activity locations. Both best-fitting models are statistically significant at the 1% level. The model fits are adequate, indicating that location choice and sequence behavior are well captured. In the models, most factors associated with out-of-home activity location choice and sequence behavior are statistically significant and largely consistent with expectations. Marginal effects are presented in order to help interpret the coefficient values in a more intuitive way. As explained in the previous section, the marginal effects were calculated at means of the independent variables, holding all other variables at their means.

The most interesting finding is that TOD residents are strongly associated with participating in activities in TODs and sequencing their locations within TODs. The activity location choice model suggests that TOD residents are 25% more likely to locate themselves to participate in an activity, compared to the AOD-F groups, and 13% more likely than the AOD-C residents, all else being equal (Table 27). In the activity sequence model, the TOD residents are more likely to sequence their activities within TOD; the

likelihood is higher by 16% and 10% than the other groups, respectively, holding other variables constant (Table 28). This implies that, for TOD residents, TOD areas play an important role in their daily activities. That is, TOD residents center on TOD areas for their daily activities and travels. The magnitudes estimated can be (perhaps) the impact of high levels of connectivity and accessibility and mix of land uses on location choice and sequence.

In the activity location choice model (Table 27), most socio-demographic variables are statically significant with a moderate magnitude. Individuals with fewer members and vehicles in the household are less likely to participate in activities within TODs. Also, employees, students, and retirees are two largest population groups who choose TOD areas as a location for their activity engagement. Further, males tend to choose their activities around TODs more than females, all else being equal. Several spatial and temporal context variables need to be mentioned. A substantial amount of participants of activities in TOD departs from Fairfax County to Washington, D.C. and Arlington County, which can represent regional traffic flows. Moreover, choosing TOD areas for the activities is slightly higher (about 3%) when one participated in activities from July to September, compared to October to December. Also, main activities in TOD areas are strongly associated when they are work, meal, and shopping related activities.

In the activity location sequence model (Table 28), there are several socio-demographic characteristics significantly associated with engaging activities within TOD areas. They include fewer/no vehicles, male, and more income. Employees, retirees, and interestingly homemakers are more likely to sequence their activities in TOD areas, compared to individuals with other jobs. Many spatial and temporal context variables show statistical significance. Monday and Thursday activities as well as mid-day activities are more likely to be linked around TOD areas. Particularly, strong spatial dependence is statistically found from Washington, D.C. and Arlington County in the context of sequence activity locations. Discretionary and obligatory (e.g., work and school-related) activities are more likely to sequenced within TODs. These findings reflect the characteristics of TOD design, which are higher densities and mixed land use, and regional connectivity through transit system. Also, location and sequence of activities are directly linked with travel distance and mode choice. .

Table 27. Activity Location Choice Model Results

Independent variable \ Dependent variable		Activity location (1=TOD) – Model 6-7: Coefficient value	Marginal effect	z-statistic
Constant		-3.599		-19.610
Socio-demographic variable	Household size	-0.023	-0.008	-1.570
	Single member (1=yes)	0.038	0.013	0.920
	Num. of vehicles	-0.071 ***	-0.024	-3.880
	No vehicle (1=yes)	0.070 **	0.024	2.120
	Gender (1=male)	0.083 ***	0.028	3.220
	Age (years old)	0.010 **	0.003	2.000
	Age squared (years old)	0.000 ***	0.000	-2.820
	Household Income ($10,000)	0.016 ***	0.006	5.960
	Employed (1=yes)	0.237 ***	0.081	2.670
	Retired (1=yes)	0.164 **	0.056	1.680
	Disabled (1=yes)	-0.167	-0.057	-1.180
	Homemaker (1=yes)	0.030	0.010	0.270
	Unemployed (1=yes)	0.018	0.006	0.140
	Student (16+) (1=yes)	0.249 ***	0.085	2.800
Spatial context variable	Ori: Washington, D.C. (1=yes)	0.137	0.047	1.500
	Ori: Montgomery County (1=yes)	0.042	0.014	0.450
	Ori: Prince George's County(1=yes)	0.030	0.010	0.320
	Ori: Arlington County (1=yes)	0.085	0.029	0.890
	Ori: Fairfax County (1=yes)	0.335 ***	0.114	3.590
	Ori: Alexandria City (1=yes)	0.198 *	0.068	1.890
	Des: Washington, D.C. (1=yes)	3.153 ***	1.077	34.790
	Des: Montgomery County (1=yes)	1.976 ***	0.675	21.330
	Des: Prince George's County(1=yes)	1.312 ***	0.448	13.690
	Des: Arlington County (1=yes)	2.512 ***	0.858	26.580
	Des: Fairfax County (1=yes)	0.064	0.022	0.660
	Des: Alexandria City (1=yes)	1.538 ***	0.525	15.030
Temporal context variable	Jan-Mar (1=yes)	0.016	0.006	0.460
	Apr-Jun (1=yes)	0.024	0.008	0.630
	Jul-Sep (1=yes)	0.075 ***	0.025	2.040
	Monday (1=yes)	-0.023	-0.008	-0.560
	Tuesday (1=yes)	-0.010	-0.004	-0.260
	Wednesday (1=yes)	-0.035	-0.012	-0.870
	Thursday (1=yes)	-0.041	-0.014	-0.950
	Arrive from 5 AM to 9 AM (1=yes)	0.014	0.005	0.210
	Arrive from 9 AM to 2 PM (1=yes)	0.096	0.033	1.410
	Arrive from 2 PM to 8 PM (1=yes)	0.006	0.002	0.090
Activity-related variable	Meal (1=yes)	0.491 ***	0.168	5.350
	Personal business (1=yes)	0.266 ***	0.091	3.030
	School (1=yes)	-0.007	-0.002	-0.060
	Shopping (1=yes)	0.435 ***	0.148	5.010
	Social/Recreational (1=yes)	0.134	0.046	1.500
	Work (1=yes)	0.740 ***	0.253	8.440
Indicator variable	Resident of TOD (1=yes)	0.832 ***	0.284	23.190
	Resident of AOD-C (1=yes)	0.400 ***	0.137	13.360
Summary Statistics	Num. of observations	30191		
	Likelihood ratio $\chi 2$	14,857 ***		
	Log-likelihood (Constant)	-20,210		
	Log-likelihood (Full)	-12,367		
	Pseudo-R^2	0.388		
	Variance term	0.495 (0.703)		

Note: * p<0.10; ** p<0.05; *** p<0.01; A reference for job status is a student (16<); for destinations is the other areas; for months is Oct-Dec; for day of week is Friday; for the arrival time is 8PM-5AM; for the activity is others; for the indicator is a resident of AOD-F.

Table 28. Activity Location Sequence Model Results

Independent variable \ Dependent variable		Location sequence (1=TOD-TOD) – Model 6-8 Coefficient value	Marginal effect	z-statistic
Constant		-5.720 ***		-18.288
Socio-demographic variable	Household size	-0.078 **	-0.009	-2.309
	Single member (1=yes)	-0.035	-0.004	-0.405
	Num. of vehicles	-0.159 ***	-0.019	-3.905
	No vehicle (1=yes)	0.149 **	0.018	2.184
	Gender (1=male)	0.091	0.011	1.627
	Age (years old)	0.013	0.002	1.261
	Age squared (years old)	0.000 **	0.000	-2.110
	Household Income ($10,000)	0.029 ***	0.004	4.902
	Employed (1=yes)	0.886 ***	0.106	4.385
	Retired (1=yes)	0.885 ***	0.106	4.018
	Disabled (1=yes)	0.463	0.055	1.452
	Homemaker (1=yes)	0.791 ***	0.094	3.134
	Unemployed (1=yes)	0.476	0.057	1.600
	Student (16+) (1=yes)	0.380 *	0.045	1.673
Spatial context variable	Ori: Washington, D.C. (1=yes)	2.284 ***	0.272	16.031
	Ori: Montgomery County (1=yes)	1.319 ***	0.157	9.044
	Ori: Prince George's County(1=yes)	0.807 ***	0.096	5.196
	Ori: Arlington County (1=yes)	1.975 ***	0.236	13.368
	Ori: Fairfax County (1=yes)	-0.244	-0.029	-1.509
	Ori: Alexandria City (1=yes)	0.716 ***	0.085	4.303
	Des: Washington, D.C. (1=yes)	2.558 ***	0.305	16.995
	Des: Montgomery County (1=yes)	1.633 ***	0.195	10.683
	Des: Prince George's County(1=yes)	0.924 ***	0.110	5.811
	Des: Arlington County (1=yes)	1.967 ***	0.235	12.680
	Des: Fairfax County (1=yes)	-0.279	-0.033	-1.620
	Des: Alexandria City (1=yes)	0.836 ***	0.100	4.954
Temporal context variable	Jan-Mar (1=yes)	0.088	0.011	1.148
	Apr-Jun (1=yes)	0.096	0.011	1.187
	Jul-Sep (1=yes)	0.179 **	0.021	2.270
	Monday (1=yes)	0.226 **	0.027	2.565
	Tuesday (1=yes)	0.075	0.009	0.854
	Wednesday (1=yes)	0.042	0.005	0.466
	Thursday (1=yes)	0.146	0.017	1.583
	Arrive from 5 AM to 9 AM (1=yes)	0.131	0.016	1.363
	Arrive from 9 AM to 2 PM (1=yes)	0.540 ***	0.064	6.199
	Arrive from 2 PM to 8 PM (1=yes)	0.094	0.011	1.106
Activity-related variable	Discretionary-Discretionary (1=yes)	-0.133 **	-0.016	-2.087
	Discretionary-Obligatory (1=yes)	0.219 ***	0.026	3.642
	Obligatory-Discretionary (1=yes)	0.098 *	0.012	1.712
Indicator variables	Resident of TOD (1=yes)	0.917 ***	0.333	12.265
	Resident of AOD-C (1=yes)	0.320 ***	0.125	4.802
Summary statistics	Num. of observations	12,672		
	Likelihood ratio $\chi 2$	6,610 ***		
	Log-likelihood (Constant)	-7,815		
	Log-likelihood (Full)	-4,510		
	Pseudo-R^2	0.422		
	Variance term	1.562 (0.454)		

Note: * p<0.10; ** p<0.05; *** p<0.01; A reference for job status is a student (16<); for destinations is the other areas; for months is Oct-Dec; for day of week is Friday; for the arrival time is 8PM-5AM; for the activity is Obligatory to Obligatory; for the indicator is a resident of AOD-F.

6.6 Summary and Discussion

This chapter explored activity participation and time use of out-of-home activities as well as location choice and sequence, which are not well understood in the context of TOD. Particularly, out-of-home activities undertaken within TOD areas in the region were focused at the person, trip, and activity levels. To better understand the connection between the activity behavior and other influencing factors, comprehensive behavioral models were estimated. The models answered the following questions: Who tends to participate in and spends time on TOD activities? Who tends to choose and sequences their locations around TOD areas to engage activities? Finally, are these behaviors different between TOD and AOD residents?

The time use (and activity participation) behavior for out-of-home activities was captured with the two-part models, which can handle two decision-making mechanisms more insightfully. Results show that the TOD residents are more likely to participate in our-of-home activities (e.g., work, school, and discretionary activities) undertaken in the TOD areas, compared to the other two resident groups. This is probably attributed to the TOD's greater proximity to work and home as well as transit connectivity and accessibility given to those who live in the vicinity. With regard to time use patterns, the times allocated for the work and school activities shows no statistical differences across the resident group, noting that time use patterns is perhaps strongly associated with the nature of activities (i.e., fixed schedule). The study found trade-off between proximity to destination and activity duration for the discretionary activities.

This study found that TOD residents have a higher propensity to choose the TOD areas for their activity locations, compared with the two other resident groups. This result is consistent to the activity participation behavior at the person level, discussed earlier this chapter, while the location choice and sequence behavior was modeled at the activity or trip level. This study also found that chances of sequencing the out-of-home activities near subway stations are higher when one lives in the TOD areas than other two residential areas. In the context of relatively mature land use in TOD in the study area, they allow relatively easy

access to amenities in the vicinity of a TOD without driving and with reasonable distances (i.e., proximity), while the transit system can easily transport people to other TOD areas (i.e., accessibility and connectivity) with other alternative modes.

CHAPTER 7

COMPARING COMMUTING BEHAVIOR IN THE CONTEXT OF GEOGRAPHICAL TRAVEL TIME RELIABILITY

7.1 Introduction and Motivation

Generally, travelers desire to have more reliable transportation service. They want to avoid delay resulting from traffic congestion and to match their actual arrival time with their desired times window (Iteris/Berkeley Transportation Systems et al. 2013). However, travel times for specific roadway segments, routes, or trips vary by time of day and day of week. This is partly because unexpected delays can occur anytime on freeways and highways from diverse sources such as traffic incidents, adverse weather, roadwork, work zones, special events, inadequate capacity, fluctuating demand, and traffic control devices (Texas Transportation Institute and Cambridge Systems Inc. 2006; Kwon et al. 2011). To meet travelers' desire, travel time reliability is of interest in transportation agencies in the United States.

Federal Highway Administration defines the travel time reliability as "the consistency or dependability in travel times, as measured from day-to-day and/or across different times of the day" (Texas Transportation Institute and Cambridge Systems Inc. 2006). As a means of traffic management, the travel time reliability has been actively applied. For example, national traffic congestion and reliability monitoring systems include the reliability as a critical performance measure to monitor nation-wide traffic congestion status across the country (Federal Highway Administration 2013). By monitoring the travel time reliability for major corridors in a region, regional traffic managers attempt to provide more reliable transportation service to the roadway user, e.g., commuters, shippers, and freight carriers (Cambridge Systematics and Texas Transportation Institute 2005). Moreover, through advanced traveler information systems, useful information such as the 95% reliable travel times is provided to individual travelers in the Seattle, Houston, and Chicago areas (Washington State Department of Transportation 2011). Studies suggest that the information on the travel time reliability can assist travelers in making more informed decisions, e.g., better schedules for their trips and mode/routes to take (Abdel-Aty, Kitamura, and Jovanis

1995; De Palma, Khattak, and Gupta 1997; Bhat and Sardesai 2006; Tilahun and Levinson 2010).

Although the concept of travel time reliability is dominantly used by traffic operation and management, this can be more broadly applied in other areas. In this regard, this chapter explores reliability of commuting at transportation planning and land development standpoints. Focusing on morning commutes, this study examined travel time reliability, e.g., travel time variation and schedule delay, across travel modes and over urban space. To date, studies on travel time reliability have mainly focused on auto travel and/or major corridors. In contrast, this study quantified the travel time reliability across multi-modes using commuters' origin-destination travel time in the regional context. The key question to be answered in this chapter is whether TOD residents can have better travel time reliability compared with residents of conventional auto-oriented developments.

7.2 Hypotheses

This study hypothesized that TOD residents can have different travel time reliability compared with AOD residents (the fifth hypothesis). Particularly, a higher level of reliability in commuting time is greatly expected for TOD residents. The reason for this is because TOD can offer the residents alternative travel modes, e.g., walking and transit (mainly subway), which are acknowledged as much more reliable modes than automobiles. Evidently, the speed of walking is relatively constant (3.0 to 3.5 feet per second[8] or equivalently 2.0 to 2.4 mile per hour). While there are some variations across individuals, individuals of a similar age and stature can walk at similar speeds. Moreover, in a metropolitan area, subway system runs at fixed schedule (almost no congestion) and the service in peak hours is fairly frequent, e.g., less than 5 minutes. Thus, subway and walking commuters can easily schedule their commute times quite accurately on a daily basis. On the contrary, auto and transit (e.g., local bus) commuters are perhaps exposed to more uncertainty for their commuting trips. The uncertainty can result from traffic

[8] This walking speed is guideline for calculating pedestrian crossing time of traffic signals from Manual of Uniform Traffic Control Devices (Federal Highway Administration 2009). Depending on the proportion of elderly people, 3.0 feet per second can be used (Transportation Research Board 2010).

incidents, adverse weather, work zones, special events, inadequate capacity, and fluctuating demand in the case of freeways (Kwon et al. 2011). Traffic control devices, e.g., traffic signals, can additionally influence the variability of travel times on arterials (Mazloumi, Currie, and Rose 2010).

Another reason is that TOD provides a good level of proximity and/or connectivity to local and regional employment clusters. Notably, the nature of mixed land use in TOD allows employment centers to be located within the neighborhood. Thus, residents can walk to their workplaces within TOD boundaries and return home with a fairly short commute distance. In addition, TOD neighborhoods are generally connected to major central business districts by transit systems in metropolitan areas. The residents can conveniently commute by subway, accessing and egressing on foot, which do not require park-and-ride or kiss-and-ride. Also, feeder or local buses are not involved as a part of commute.

Given that subway and walking commute times are more reliable (less variant) on a daily basis, arrival time as travel behavioral outcome might differently result between TOD residents and AOD residents (the sixth hypothesis). This study subsequently tested another hypothesis that actual arrival time of subway and walk commuters are more likely to fall in-line with their desired times of arrival (perhaps before work starting time) than auto and transit users. Therefore, less schedule delay is highly expected for subway and walk commuters in TOD neighborhoods. Also, they are less likely to be late for work if they depart home early enough. The mismatch always costs money and time. Late arrivals are especially perceived as more onerous. These aspects of the travel time reliability are tested in this study.

7.3 Data Extraction and Methodology

7.3.1 Data Extraction

From the survey dataset, a total of 10,757 commute trips were identified, consisting of direct trips from home to work (N=9,179) and chained trips (N=1,578) that stopped by some place in the middle of a journey to work. Table 29 summarizes the pooled sample of the commute trips. The average commuting distance is 13.4 miles,

while the average commuting duration is 38.6 minutes. If chained trips are not properly considered, trip distance and duration can be underestimated. Their medians are 9.5 miles and 32.0 minutes, respectively, noting that the distributions are skewed to the right (mean>median). A dominant commuting mode is automobile including drive alone and shared ride (78% in total), while the shares for transit are 16% and walking are 4%. The shares for transit and walking are higher than national estimates (Santos et al. 2011). A majority of commuting trips were undertaken during morning peak hours (79%). The commuting trips heading for TOD areas account for 42%, while 14% of commuting trips are between TOD areas. Recall that in this study, the physical boundary of TOD was defined by setting a 0.5 mile buffer around the transit stations (about 10-15 minutes on foot).

Table 29. Descriptive Statistics for Commute Trips (N=10,757)

Variable	Category	%	Mean	Median	Standard deviation
Distance (mile)	0-8	44	13.4	9.5	12.6
	8-16	26			
	16-24	14			
	24+	16			
Duration (minute)	0-20	29	38.6	32.0	25.4
	20-40	33			
	40-60	23			
	60+	15			
Travel Mode	Auto	78	-	-	-
	Transit	16	-	-	-
	Walk	4	-	-	-
	Other	2	-	-	-
Departure time (%)	Morning peak (5-10)	79	-	-	-
	Off peak (10-16)	9	-	-	-
	Evening peak (16-20)	2	-	-	-
	Other	10	-	-	-
Origin and destination (%)	Non-TOD to Non-TOD	52	-	-	-
	TOD to Non-TOD	6	-	-	-
	Non-TOD to TOD	28	-	-	-
	TOD to TOD	14	-	-	-
Month (%)	Jan-Mar	30	-	-	-
	Apr-Jun	20	-	-	-
	Jul-Sep	25	-	-	-
	Oct-Dec	25	-	-	-

7.3.2 Comparing Groups

To test the two hypotheses posed in this chapter, this study compared overall four groups: subway and walk commutes of TOD residents vs. auto and transit commutes made by AOD residents. This comparison focused on all commute trips that are destined to a workplace in TOD areas (86 stations) in the Washington, D.C metropolitan region. Notably, the subway commutes are limited to walking access to and egress from the stations, while the transit commutes include local bus and subway trips with any means of access and egress. For example, the transit trips can consist of walk-bus-walk, auto-bus-walk, walk-bus-subway-walk, auto-subway-walk, and so on, so the transit group and the subway group are mutually exclusive in terms of trip origin and access/egress mode. In examining travel time reliability between the four groups, the study compared commuting time from home to work and arrival time at workplace. To this ends, several reliability measures were reviewed in the proceeding section and then appropriate measures were selected and applied.

7.3.3 Reliability Measures

In practice, travel time reliability is measured in several ways. The measures include the 90th or 95th percentile travel time, standard deviation, coefficient of variation, percent variation, buffer time (or index), planning time (or index), travel time index, misery index, skew statistic, width, frequency of congestion, and on-time arrival (van Lint and van Zuylen 2005; Cambridge Systematics et al. 2008; Pu 2011; Iteris/Berkeley Transportation Systems et al. 2013). The 90th or 95th percentile travel time, the standard deviation, and the coefficient of variation are convenient measures commonly used in the classic mathematical and statistical framework. The 90th or 95th percentile travel time quantifies as the worst delay on corridors or routes. The standard deviation of travel time shows dispersion from the average travel time as a convenient measure in the classic mathematical and statistical framework. The coefficient of variation is the ratio of the standard deviation of travel time to the average travel time, providing a normalized measure of dispersion. Next, the percent variation can express the

coefficient of variation as a percentage of the average travel time by multiplying the quantity by 100.

Some measures can be more useful information for travelers to determine their departure times for the commutes: the buffer time, the buffer index, the planning time, the planning time index. The buffer time is the difference between the 90th or 95th percentile travel time and average travel time, suggesting information on the extra time needed to ensure to arrive at destination on time with 95% probability. If the buffer time is divided by the average travel time, it becomes the buffer index. Similarly, planning time is an addition of adding average travel time and buffer time, representing how much total time is needed for planned trips. The planning time index is computed as the 90th or 95th percentile travel time by dividing by the free-flow travel time, while the travel time index uses average travel time for the numerator, indicating that the average additional time required during peak hours compared to off-peak hours. They suggest extra time or total time needed to ensure arrival at a destination on time (Washington State Department of Transportation 2011).

Travel time distribution can be skewed especially at the onset of congestion. In this case, the misery index and skew statistic are more robust measures. The misery index is the difference between the average of the longest travel times (typically 0.5% to 5%) and the average travel time, normalized by the average travel time. The skew statistic is the ratio of the distance between the difference of the 90th and 50th percentile to that of between the 50th and 10th percentile. Complementarily, the width of travel time distribution is used, the range of travel times between the 90th and 10th percentile divided by the median.

Finally, the frequency of congestion is the percent of time or days that travel times exceed a predetermined threshold (e.g., 200% of the free-flow travel time). While most measures mainly focus on capturing the variability of travel time, arrival time can be directly used. For example, the on-time arrival represents the percent of time or days that travelers arrive before an acceptable lateness threshold (e.g., 100%-130% of the average travel time).

7.4 Average Commuting Time

7.4.1 Reliability Measures

To compare commuting times between TOD and AOD residents, this study selected a set of descriptive travel time reliability measures: standard deviation, skew statistic, and coefficient of variation. As discussed, the standard deviation measures dispersion of travel time distribution as a simple and straightforward way in the statistical framework. Next, the skew statistic shows the range of the travel time distribution above the median over the ranges below. When a travel time distribution is highly skewed, the skew statistic can work properly, as it is based on median and percentile values (van Lint and van Zuylen 2005). Finally, the coefficient of variation was selected because it can be a good mathematical proxy for several other reliability measures (Pu 2011). This is a normalization of dispersion by mean of travel time distribution. Each measure is formulated as follows:

$$Standard\ deviation = \sqrt{\frac{1}{N-1}(T_i - \bar{T})^2} \tag{1}$$

$$Skew\ statistic = \frac{T_{90} - T_{50}}{T_{50} - T_{10}} \tag{2}$$

$$Coefficient\ of\ variation = \sqrt{\frac{1}{N-1}(T_i - \bar{T})^2}\ /\ \bar{T} \tag{3}$$

where N= the number of trips, T_i = travel time for trip i, $\bar{T}$ = the average travel time, T_{10}=10th percentile travel time, T_{50}=50th percentile travel time, and T_{90}=90th percentile travel time.

The larger value in all selected measures consistently represents that travel time distribution is a wider spread, indicating that commuting times are more varying over time and space. With higher values, the last two measures represent the more right-skewed travel time distribution; therefore, commuting time is unreliable. Interestingly, if the skew statistic is one, this indicates the distribution is symmetric. When the distribution is symmetric, the coefficient of variation becomes zero.

To date, these measures have been typically applied for freeway segments or corridors (van Lint and van Zuylen 2005; Rakha, El-Shawarby, and Arafeh 2010), as part of travel (e.g., journey to work). Also, earlier studies mainly based travel time on estimates from a set of segments in the field, unless GPS data was collected (Yazici, Kamga, and Mouskos 2012). However, this study attempted to apply these measures for individuals' commute trips from door to door, which each origin and destination pair is identified. Also, these measures were used to compare travel time reliability by travel mode from a regional perspective. Note that as their travel distances vary across commuters, travel distances were, therefore, carefully controlled for.

7.4.2 Descriptive Analysis

Table 30 presents a comparison of commute times by automobile, transit, subway, and walking. For the comparison, all trips that began at home but did not stop in the middle of the trip were selected (not chained trips). Also, this analysis included commutes of distances less than 13 miles, as most subway trips fall in this range. This refinement yielded a total of 1,478 commuting trips. Results show that auto users spend 28.25 minutes on commuting while subway riders use 36.56 minutes on average. The average commuting time for subway is about 8 minutes longer because subway trips involve walk access/egress as well as waiting (and also transferring) at stations. The average commuting time of transit users is longest (49.50 minutes) among the modes. On the other hand, commuting by walk only takes 13.72 minutes on average. From the regional perspective, this shows that living in TODs allows the residents to save commute times. This is because that TOD provides residence and employment opportunities within walking distance and the nature of mixed use in TOD can result in shorter commuting time. The comparison is was also carried out for each distance group: 0-3 mile, 3-6 mile, 6-9 mile, and 9-13 mile, in order to make the comparison more meaningful. For all distance groups, auto commute times are shorter by 10 to 20 minutes than other groups, excepting for walking commute times.

Subsequently, travel time variability was compared. As expected, the variation of travel time becomes larger as the travel distance is longer (see Table 30). This is mainly because the probability experiencing any delay becomes higher as the travel distance is

longer. Also, this comparison indicates that subway and walking commute times have less variation than the auto and transit counterparts, for the same distance interval. For instance, for distance between 6 to 9 miles, the standard deviation for subway commute time (9.46 minutes) is much shorter than auto (13.33 minutes) and transit (14.54 minutes). This means that the variation in subway commuting time including access/egress to subway stations and waiting (and transferring) at stations is smaller than that of auto and transit using freeways/highways. As mentioned, unexpected delay can occur on freeways/highways caused by incidents, roadwork, and so on. Interestingly, commuting by walk is not only shorter in time but also less variant. When variation of walking was computed, a majority of the variation (6.89 minutes) is probably due to the difference in proximity to workplace within TOD areas. Other travel time reliability measures also indicate that subway commuting is more reliable (see Table 30). The findings suggest that TOD 1) provides more reliable travel modes and 2) allows commuting trips to be more predictable.

Figure 13 displays travel time distributions by travel mode and distance group. For the all groups, the distributions of subway commuting times are consistently less skewed (almost normally distributed) while the travel time for other modes are likely log-normally distributed. Notably, the variation of subway commuting times with distance less than 3 miles is slightly larger than that of auto, partly because of a relatively high proportion of access/regress and waiting time (i.e., out-of-vehicle travel time) over the total travel time. Some distributions (e.g., distance 9-13 mile) are bi-modal, partly due to transfer in the case of subway trips or route choice (freeway vs. arterial) in the case of auto trips. These also support the reliability of subway commuting over auto and transit commuting, although there is tradeoff between travel time and its variability.

Figure 14 presents travel time reliability by measure and distance group, consistently indicating that subway commuting is more reliable. Recall that the skew statistic represents the degrees of the variability of travel time distribution using median and percentile values, while the coefficient of variation is a normalized measure of dispersion, showing the extent of the variability of travel times with respect to the mean. The variability becomes larger as the travel distance is longer with respect to the standard deviation (Figure 14a); however, the dispersion of the variability reduces after

normalized by mean of travel time distribution as travel distance (Figure 14c). As opposed to the standard deviation and the coefficient of variance, the skew statistics are fairly sensitive (Figure 14b).

Table 30. Descriptive Statistics for Commute Trips by Mode and Distance Group

Travel Distance (mile)	Auto commutes (departing from AOD and arriving at a workplace in TOD)					
	N	Mean	Median	SD	SS	CV
Total	887	28.25	25	15.30	1.43	0.54
0-3	180	15.63	15	9.36	1.20	0.55
3-6	266	23.92	20	11.90	2.53	0.47
6-9	241	33.44	30	13.33	1.50	0.37
9-13	200	39.12	35	15.52	1.91	0.39
Travel Distance (mile)	Transit commutes (departing from AOD and arriving at a workplace in TOD)					
	N	Mean	Median	SD	SS	CV
Total	369	49.50	47	16.94	1.47	0.34
0-3	43	35.47	35	10.59	1.00	0.28
3-6	107	42.63	41	13.56	1.50	0.29
6-9	102	51.48	50	14.54	1.21	0.26
9-13	117	59.23	55	17.37	1.81	0.26
Travel Distance (mile)	Subway commutes (departing from TOD and arriving at a workplace in TOD)					
	N	Mean	Median	SD	SS	CV
Total	161	36.56	35	11.27	1.58	0.31
0-3	38	31.66	31.5	10.67	0.92	0.31
3-6	70	33.46	32.5	9.16	1.10	0.25
6-9	35	41.17	40	9.46	1.20	0.22
9-13	18	37.22	37.5	10.96	0.72	0.20
Travel Distance (mile)	Walk commutes (departing from TOD and arriving at a workplace in TOD)					
	N	Mean	Median	SD	SS	CV
Total	61	13.72	12	6.89	1.87	0.50

Note: SD=standard deviation; SS=skew statistic; CV=coefficient variation.

Table 31. Statistical Test Results for Travel Time Variation

Travel distance (mile)	Auto vs. Subway		Transit vs. Subway		Auto vs. Walk		Transit vs. Walk	
	F-stat.	*p-value*	F-stat.	*p-value*	F-stat.	*p-value*	F-stat.	*p-value*
0-3	0.765	0.267	0.984	0.955	4.903	0.000	6.052	0.000
3-6	1.688	0.016	2.195	0.001	-	-	-	-
6-9	1.984	0.019	2.361	0.006	-	-	-	-
9-13	2.407	0.038	3.018	0.012	-	-	-	-

7.4.3 Statistical Tests

This study statistically tested the underlying hypothesis. F-test for equality of two variances was used with the standard deviation measure (variance= standard deviation squared). The null hypothesis was set that the variations of auto and transit commuting times are similar to that of subway. Table 31 summarizes statistical test results (two sample F-tests). The results show that the variation in commuting times among auto, transit, and subway are not statistically different for short distances (e.g., less than 3 miles). However, for the other distance groups, the test shows that the variations are significantly different at the 5% significance level, rejecting the null hypothesis. This suggests that subway and walking commuters can have more reliable journey to work on a daily basis in the TOD context, based on commuting behavioral data collected over the year and over the study area.

This study found that the difference in commuting time variation among the travel modes becomes larger as travel distance is longer. On average, the variation of subway commutes is smaller in time by 3 to 5 minutes over auto and transit commutes. Interestingly, the benefit of less variation in commuting time can be larger if more detailed information on subway commutes is given. Specifically, the total subway commute time consists of access time, waiting time, in-vehicle travel time, transferring time (if made), and egress time. In this study, access and egress times vary across commuters in TOD areas, ranging from 0 to 10 minutes. Therefore, if the variation in subway commute time were computed after excluding the portion of access/egress times ($=\sqrt{s^2_{\text{total time}} - s^2_{\text{access time}} - s^2_{\text{egress time}}}$), the variation of subway commutes would become smaller than numbers shown in Table 30. In turn, the difference in travel time variability would become much larger than 3 to 5 minutes between subway commuters and auto and transit commuters.

There is clear statistical evidence that commuting by subway and walking in TOD areas has less variation in travel time, compared to auto and transit commuting. This can be translated into the residents' benefit from living in TOD neighborhoods. Notably, the subway runs at a fixed schedule (with almost no congestion) and the service in peak hour is fairly frequent. With the subway system, TODs are normally connected to central

business districts and major employment clusters in a region. Evidently, the speed of walking is quite constant across individuals for commute trips. Also, TODs provide a built and transportation environment where residential and commercial uses are mixed with a great level of walkability. Taken together, therefore, TODs can provide reliable commuting options to the residents, compared to auto-oriented neighborhoods. Especially, commuting can be shorter and more reliable by residing in TODs when residents make the journey-to-work by walking.

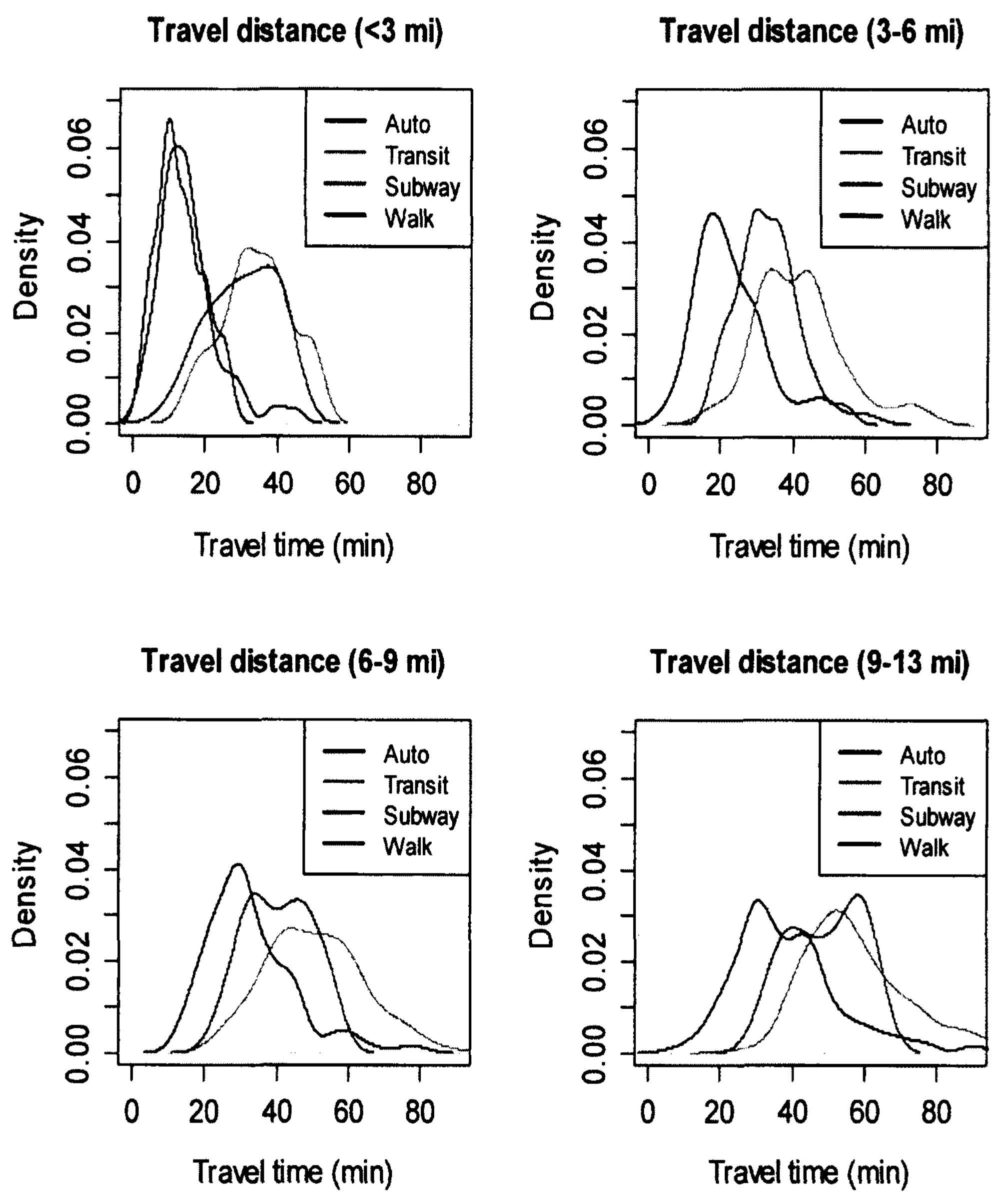


Figure 13. Comparison of Travel Time Distributions by Mode and Distance

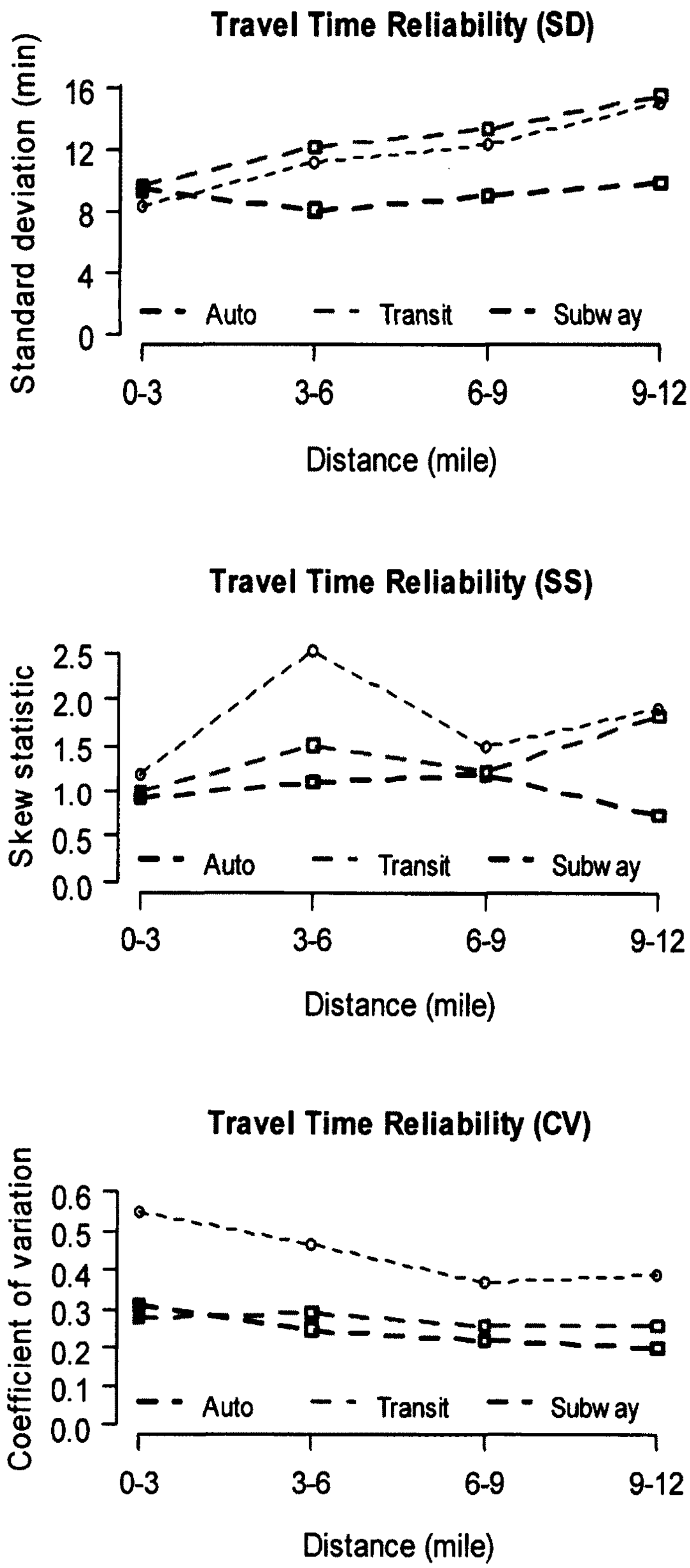


Figure 14. Comparison of Travel Time Reliability by Mode, Distance, and Measure
(a) standard deviation, (b) skew statistic, and (c) coefficient of variation

7.4.4 Sensitivity Analysis

To ensure the validity of the results, sensitivity tests were performed by increasing the size of an interval by 0.5 mile from 1 mile to 3.5 mile. Figure 15 shows the comparisons results for standard deviations by different intervals. The X-axis represents the size of distance interval while the Y-axis shows the standard deviation for commuting trips. While more fluctuation is observed for the smaller intervals, overall patterns are similar: 1) the longer commute distance and the more variation; 2) subway commute times are less variant. Therefore, the results obtained from the 3.0-mile interval can be valid.

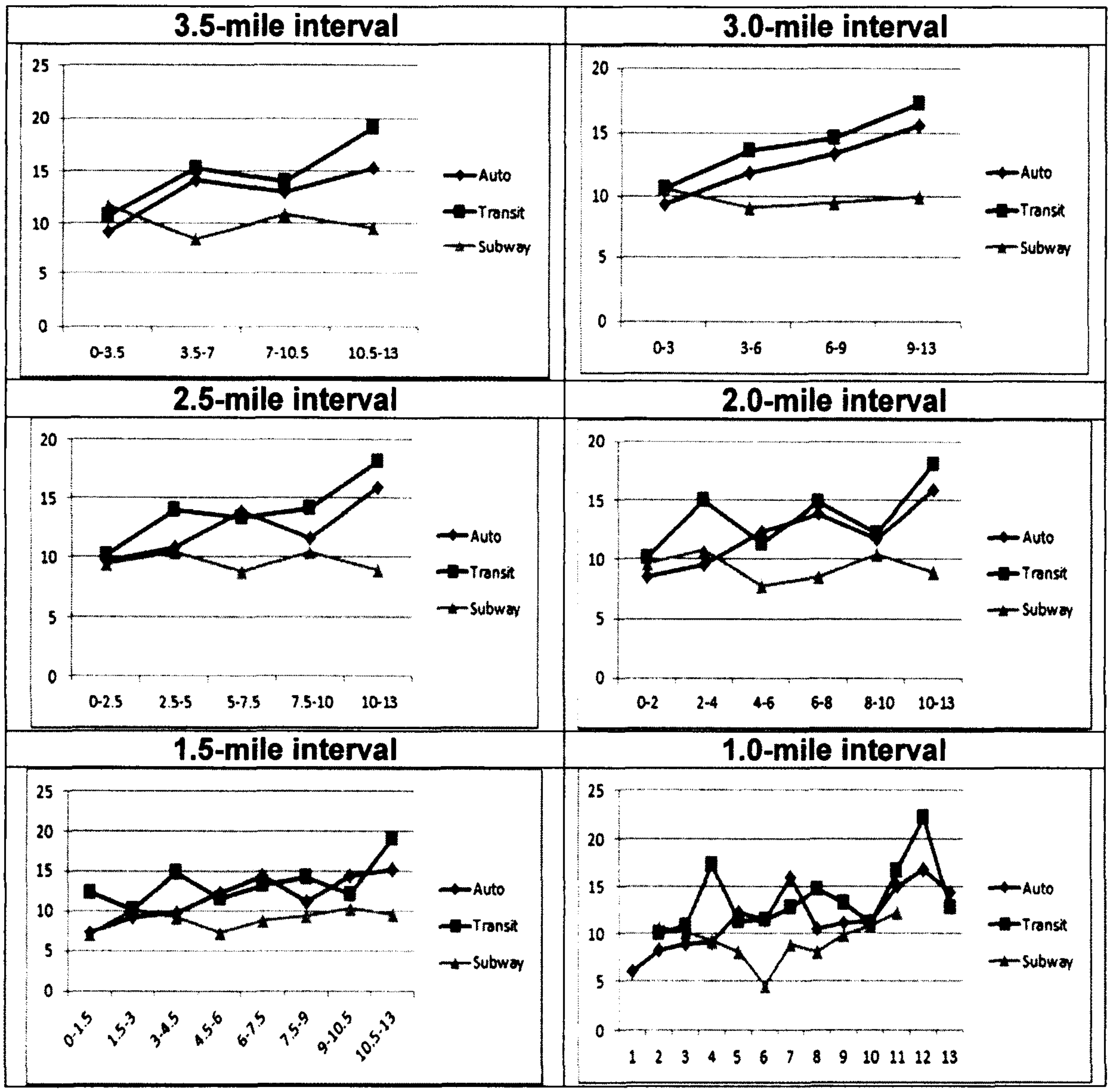


Figure 15. Comparison of Travel Time Variations by Distance Interval

7.5 Arrival Time for Commuting Trips

7.5.1 Descriptive Analysis

This section shows tests for the sixth hypothesis that actual arrival time of subway and walk commuters (TOD residents) are more likely to fall in-line with their desired times of arrival than auto and transit users (AOD residents). The previous section shows that subway and walking commute times of TOD residents are more reliable (less variant) than auto and transit counterparts of AOD residents, given the similar travel distance. Therefore, the likelihood of schedule delay for subway and walk commuters in TOD neighborhoods is expected to be less. In other words, more subway and walk commuters can arrive at the workplace before the work starts than auto and transit users living in AOD areas. Presumably, walking commuters are rarely late for work, as travel time for walking is highly expected and not much uncertainty can be encountered by a pedestrian.

This study first examined the distributions of arrival time by a group. Four groups were compared in this study: automobile commuters residing in AOD areas, transit (local bus and subway) commuters residing in AOD areas, subway commuters residing in TOD areas, and walking commuters residing in TOD areas. The transit commuter (the second group) may or may not transfer several modes to travel to the workplace, while the subway commuter represents walking access/egress and riding subway as a primary mode. The corresponding survey data was extracted for each group.

Figure 16 presents the distribution of arrival time at work (workplace is in TOD areas) by travel mode and residence location, which was defined in the previous section. Numbers on the X-axis represent arrival time at work, while the Y-axis shows the frequency of commuters. This shows that a majority of trips are concentrated just before every 30 minutes from 7:30 AM to 9:30 AM, regardless of the group. In addition, right after every 30-minute, there are not many commuters arriving at work. This well represents the pattern of arrival in the morning rush hours.

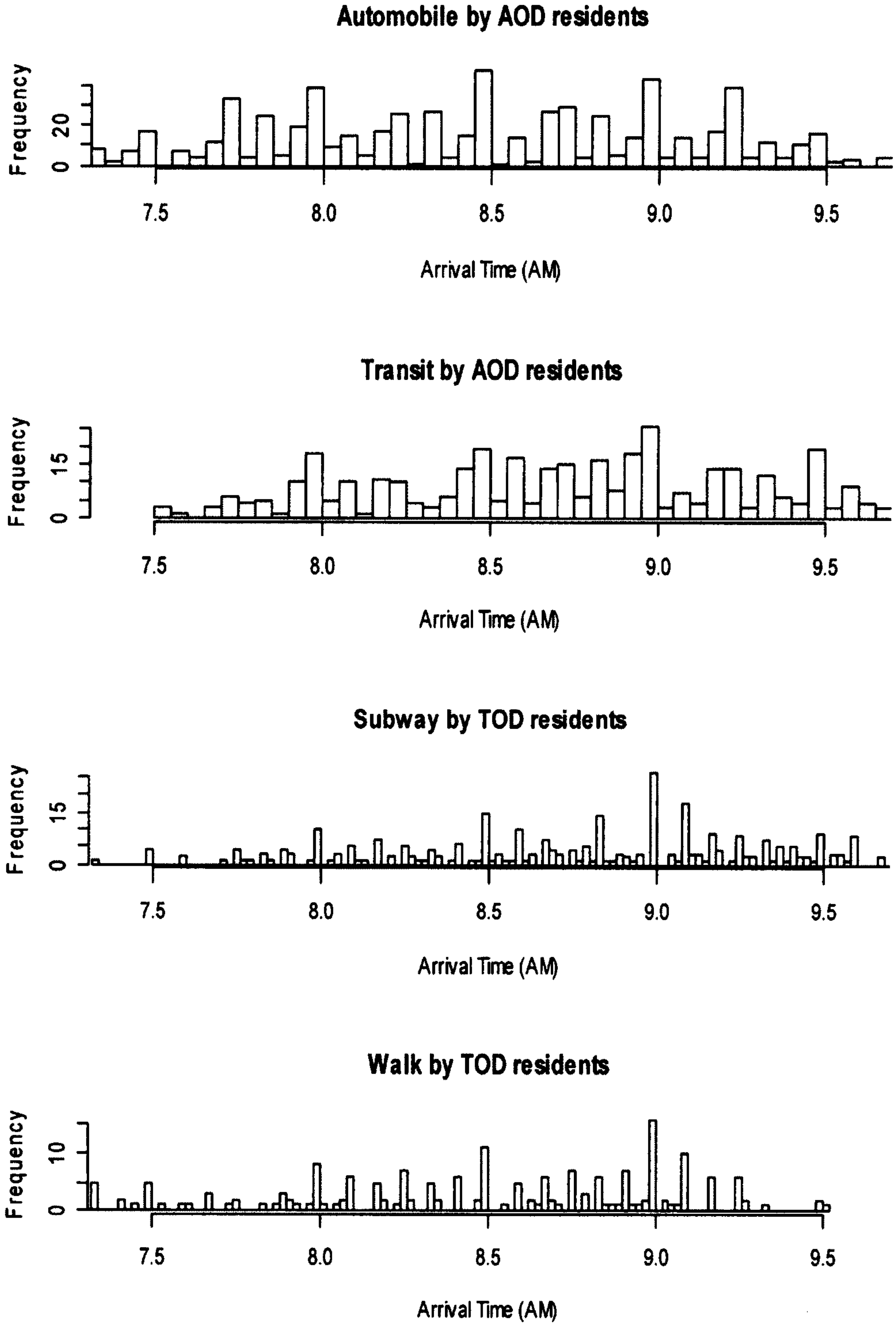


Figure 16. Distributions of Arrival Time at Work by Mode and Residence

7.5.2 Statistical Modeling

To test the sixth hypothesis, a statistical model was estimated, capturing the likelihood of lateness (or schedule delay) of commute trips for each group (according to travel mode and residence type). To estimate the model, a binary dependent variable was created using two sets of information captured in the survey: 'end trip time' at work from the trip-level data and 'typical work start time for a job' from the person-level data. If an arrival time at work is earlier than the work start time, a binary variable was coded as zero. By contrast, if the former is later than the latter, the dependent variable was coded with one. Next, four sets of variables were added to the model: socio-demographic attributes, commuting attributes, temporal and spatial context variables, and travel mode/residence indicators, in consistent with the conceptual structure demonstrated in Chapter 3. The econometric model is specified as follows:

$$Y^{*} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 TM + \varepsilon \quad (1)$$

Y=1 if Y^{*}>0 and 0 otherwise

where

Y^{*}	=	a unobserved (latent) variable,
Y	=	a binary dependent variable (1=late; 0=otherwise),
X_1	=	a set of socio-demographic variables,
X_2	=	a set of commute-related variables,
X_3	=	a set of spatial/temporal variables,
TM	=	a set of indicator variables for travel mode,
β	=	a set of parameters, and
ε	=	an error term.

Given the dichotomous nature of the dependent variable, a binary probit model was chosen. The probability that an individual chooses alternative 1 and 0, respectively, is:

$$P(Y = 1|X) = \int_{-\infty}^{X'\beta} \phi(t)dt = \Phi(X'\beta),$$

$$P(Y=0|\boldsymbol{X}) = \int_{X'\beta}^{\infty} \phi\,(t)dt = 1 - \Phi(X'\beta),$$

where $\phi(\cdot)$ is a standard normal distribution, $\Phi(\cdot)$ is a cumulative normal distribution, $\boldsymbol{X}$ is a vector of independent variables. To estimate parameters of the binary probit model, a maximum likelihood estimation technique was utilized. For the normal distribution, the log-likelihood function is written as

$$\ln L = \sum\nolimits_{Y=0} \ln[1 - \Phi(X'\beta)] + \sum\nolimits_{Y=1} \ln \Phi(X'\beta).$$

To compute marginal effects, the following equation can be used for continuous variables at their means

$$\frac{\partial E[y|X]}{\partial \boldsymbol{X}} = \left\{\frac{dF(X'\beta)}{d(X'\beta)}\right\}\beta = \phi(X\beta)\beta.$$

For dummy variables, marginal effects for X_i can be computed with the difference in probability when a variable $X_i$from 0 to 1 with all other variables at their means.

When processing data, one issue was identified. A substantial portion of individuals are late simply because they depart too late from home to work, given the distance between the house location and work location. This may be because they did not report their work start time correctly or actually left home late. In any case, the late arrival at work is associated with variation of commute time by mode and residence. Also, the reason for lateness cannot be properly captured. Thus, those individuals who cannot arrive at work before the work starting time due to the late departure time were excluded from the dataset in the next step. First, this study obtained 'minimum travel time' between an origin (home) and a destination (work) from Google Maps for each trip. As noted, their longitude and latitude were geo-imputed at the census block level, which is fine enough for this study, as discussed in Chapter 3. Next, for each individual, if the addition of departure time and minimum travel time is beyond the work start time, this

individual was not included into modeling. In this way, erroneous observations were removed and a set of data was ready for estimation (N=1,114 commute trips).

7.5.3 Results and Interpretation

Table 32 summarizes estimation results and presents the estimated coefficients of the best-fitting binary probit model with 1,114 observations. The model is statistically significant at the 1% level, with reasonable model fits. Sign and magnitude are also consistent with prior expectations, indicating that behavior of arrival at work is relatively well captured. Results show that departure time and commute distance are strongly related to the likelihood of schedule delay. That is, the later to leave home, the more likely to arrive late at workplace in TOD areas. The likelihood of arriving late at work increases steadily with the length of a commute trip. The model indicates that 1 mile increase in commute distance is associated with 2.4% higher chance of the schedule delay. Commutes on Monday tend to experience lateness; however, the statistical significance is weak.

In addition, the late at work is a spatial context, noting that an individual traveling to Washington, D.C. is 16.4% more likely to experience lateness at work, compared to that of Prince Georges County, MD. This can be explained by the transportation network design (more complex as approaching to downtown). The most important finding is that, among travel modes, those commuting with subway and walking are less likely to be late to work by 6.7% and 11.2%, respectively, compared to automobile commutes; however, the significant difference between automobile commutes and transit commutes is not found. These findings are consistent with the hypothesis and support for subway and walking as a reliable travel mode and TOD areas that can provide subway accessible and walk friendly environment.

Table 32. Statistical Model Results for Arrival at Work

Independent variable \ Dependent variable	Arrival (1=late arrival; 0=otherwise)		
	Coefficient value	Marginal effect	z-statistic
Constant	-0.482		-0.620
Socio-demographic variable			
Age	-0.002	-0.001	-0.671
Gender (1=male)	-0.058	-0.016	-0.655
Work-related variable			
Fixed work hour (1=yes)	0.031	0.009	0.352
Chained work trip (1=yes)	-0.177	-0.050	-1.300
Temporal context variable			
Work start time	-0.123 *	-0.035	-1.611
Monday (1=yes)	0.575	0.194	1.106
Tuesday (1=yes)	0.071	0.020	0.475
Wednesday (1=yes)	-0.008	-0.002	-0.054
Thursday (1=yes)	0.007	0.002	0.049
Spatial context variable			
Commute distance (mile)	0.084 ***	0.024	3.420
Commute distance squared (mile)	-0.002 ***	-0.001	-2.606
Washington, D.C. (1=yes)	0.659 ***	0.164	2.315
Montgomery County (1=yes)	0.516	0.168	1.332
Arlington County (1=yes)	0.434	0.122	1.266
Fairfax County (1=yes)	0.593	0.202	0.916
Alexandria City (1=yes)	0.575	0.194	1.106
Indicator variable			
Transit (1=yes)	0.001	0.000	0.006
Walk (1=yes)	-0.475 ***	-0.112	-2.572
Subway (residing in TOD) (1=yes)	-0.258 ***	-0.067	-1.979
Summary Statistics			
Num. of observations	1114		
Likelihood ratio $\chi 2$	-61.882 ***		
Log-likelihood (Constant)	-580		
Log-likelihood (Full)	-549		
Pseudo-R2	0.053		

Note: * p<0.10; ** p<0.05; *** p<0.01; 'Friday' is a base; 'Prince Georges County, MD' is a base; 'Auto' is a base.

7.6 Summary and Discussion

This chapter investigated new aspects of behavior in TOD. This section compared their travel time reliability among four groups set by travel mode and residence location (i.e., subway and walk commutes of TOD residents vs. auto and transit commutes made

by AOD residents), focusing on the commuting trips during morning peak hours. In terms of travel time reliability, variance of commute time and arrival time at work (schedule delay), were tightly examined. The corresponding measures of travel time reliability were selected from the literature. Using commuters' origin-destination (door-to-door) travel time in the regional context, this section tested for more reliable journey to work (commute time and arrival time) for the subway or walking commuters over the automobile and transit users.

The findings suggest that residents in TOD areas who use subway and walk as a commute mode, can commute more reliably. Specifically, this study found that the variation of subway commute trips is smaller in time, on average, by 3 to 5 minutes over auto and transit commute trips. As expected, the difference in variation between subway commuting time and auto and transit commuting time becomes larger as travel distance increases. This is partly because subway and walking are relatively reliable travel modes as opposed to auto and bus, which are highly exposed to unexpected delays in urban areas due to traffic incidents, adverse weather, etc. In addition, this is attributed to the fact that TOD areas offer proximity to local employment clusters to residents in transit/pedestrian friendly environment.

With regard to the sixth hypothesis, the key finding from this model is that TOD residents who use subway and walking as a commute mode are less likely to be late at work than automobile and transit counterparts of AOD residences. The model, capturing the behavior of schedule delay at work, suggests that subway and walk groups are less likely late at work by 6.7% and 11.2%, respectively, compared to automobile and transit commuters, holding other variables (e.g., travel distance, departure time, etc.) constant. The fact that subway and walking commute times are more reliable (less variant and more on-time arrival for TOD residents over auto or transit commuters of AOD residents) on a daily basis can clearly supports that TOD can be a desirable residential place to live and work because of its integrated mixed land use and public transit provision.

TODs are considered a sustainable solution to addressing a number of contemporary urban problems. This study suggests that implementing TOD can also benefit residents by providing better travel time reliability. That is, TOD residents can have smaller variability in commute time by choosing subway and walk for their

commute modes. This is a new insight into the personal benefits that TOD residents can have as opposed to TOD benefits in terms of a return from public investment. The findings support transit and urban planning agencies in providing a measure of performance in TOD and attracting more residents to TOD neighborhoods. Also, the study results are relevant to applied researchers interested in understanding travel-related behavior, e.g., residential location choice. Overall, this study provides an interesting aspect of travel behavior of TOD residents (i.e., travel time reliability) and contributes by exploring and quantifying the reliability benefits of TOD.

CHAPTER 8
CONCLUSIONS AND IMPLICATIONS

This chapter summarizes key findings of this dissertation along with limitations. Also, this chapter provides implications of research findings for transportation benefits of transit-oriented development (TOD), travel demand modeling, and geographical travel time reliability. Finally, this dissertation ends with stating future studies.

8.1 Summary

As a sustainable transportation and land development strategy, TOD plays an important role in providing residents a livable environment across urban and suburban space. At the neighborhood level, a TOD community can be alternative mode friendly, higher density, and mixed use, offering a great level of accessibility to work and social activities in the proximity of residence. At the regional level, transit systems can link these neighborhoods and provide regional connectivity, allowing the residents to travel to their destinations and participate in various activities. However, travel and, especially, activity behavior in the context of TOD is under-researched, despite the recent increasing demand in the public sector and its unique and integrated built and transportation environments.

To fill the gap in the literature, the travel and activity behavior was empirically explored in this study, in comparison with auto-oriented development (AOD). Considering the needs of land use policy evaluation and recent interests in activity-based travel demand modeling, several dimensions of the activity and travel behavior were established and investigated, including 1) activity location and trip length, 2) trip frequency and travel distance, 3) time use for out-of-home activities, 4) location choice and sequence, 5) the mean and variance of commute time, and 6) arrival time (or schedule delay) at work. The key question to be answered in this dissertation is whether travel and activity behavior of residents in TOD areas are different from AOD areas, which features relatively low density and mainly residential use. And, how are they different?

This study used state of the art behavioral data collected from the Washington, D.C. metropolitan region (N=11,436). Notably, this survey adopted a residential mailing address-based sampling method so that a substantial number of mobile phone-only households were recruited to avoid potential non-coverage errors, which is a recent concern in travel survey community. The validity of the survey dataset was carefully checked, indicating that the survey data is fairly representative of the population of interest. Also, measurement errors due to trip under-reporting were identified; however, the assessment suggests the survey data can be used for this dissertation research without further handling. With the rich set of behavioral data, rigorous statistical models were estimated at the household, person, trip, and activity levels, focusing on varying geographical scopes from a local neighborhood to the entire region.

Using a matched pair of the TOD neighborhood of the Rosslyn-Ballston Metrorail Corridor (geographically bounded by 0.5 mile buffer created from subway stations) and the AOD neighborhood in the vicinity, this study compared activity location and resulting trip distance. Results show that the TOD captured out-of-home activities more internally and therefore individual trip distances of the TOD are shorter on average, as desired. With regard to the mode use behavior, behavioral models suggest that the households in the TOD neighborhood undertake substantially fewer automobile trips (30%) but more transit and walking trips (61% and 57%, respectively), compared to those in the AOD neighborhood. Also, households in TOD neighborhood drive shorter distances but travel longer with public transit and walking. These behavioral differences, taken together, can be translated into expected transportation benefits of TOD.

Subsequently, from a regional perspective, activity participation and time use as well as location choice and sequence were compared among residents of TOD (0-0.5 miles from subway stations), AOD close to TOD (0.5-1.5 miles), and AOD far from TOD (1.5+ miles). The key finding is that the residents of the TOD areas have higher propensity to participate in the activities taking place in the TOD, compared to the other two resident groups. However, times allocated for work and school-related activities, with schedules that are relatively fixed, are not significantly different. Another finding is that the TOD residents are more likely to choose the TOD area for their next and

following activities. At a destination choice standpoint, this indicates that strong spatial dependence exists along with TOD areas, which partly resulting from the TOD attributes.

Finally, in terms of travel time reliability, commuting behavior was compared across the region. For commuting time, particularly, subway and walking commuters who reside in the TOD areas were compared to auto and transit (subway + local bus) commuters who live in the AOD areas. Results show that the variation of subway commute time is smaller, on average, by 3 to 5 minutes than auto and transit commutes, when the distance between work and home is greater than 3 miles. To capture the lateness (schedule delay) at work of commuters by travel mode and residence area, a behavioral model was estimated. Results suggest that TOD residents who use subway and walking are more likely to arrive at work on time than auto and transit commuters who reside the conventional AOD areas, pointing to the TOD residents' benefit of travel time reliability when they choose subway and walk as their commute mode.

In summary, the comprehensive and intensive analyses on six aspects of activity and travel behavior answer the research question posed in this dissertation. Travel and activity behavior of the residents in the TOD areas is significantly different from the AOD counterparts in many aspects. Particularly, the TOD residents tend to use less automobile, but more alternative modes (e.g., transit and walking). Moreover, their daily lives are centered on the TOD areas, participating in more out-of-home activities and spending more time within the TOD areas. Finally, the TOD residents who use subway or walk to work can commute more reliably. The main reason is partly attributed to the built and transportation environments of TOD areas that are higher density and mixed use as well as transit/alternative mode friendly. Also, transit accessibility and regional connectivity contribute to such behavioral differences. These findings support the linkage between travel and activity behavior and the integrated characteristics of TOD.

8.2 Limitations

This dissertation has several limitations. First, the analyses of this study are limited to one single metropolitan area of Washington, D.C., which has more government job clusters supported by extensive public transportation systems (e.g., 3 system operators and 11 lines). Also, a relatively large portion of land is developed in high

density and mixed use. Thus, the study area may not be fully representative of other metropolitan areas in the United States and accordingly, the results should be carefully transferable. Chapter 4 focused on TOD neighborhoods in Arlington, Virginia, especially, the Rosslyn-Ballston Metrorail Corridor. This area may not be fully representative of other TOD areas across the country. Thus, the research results should be viewed with caution. Second, this study is also limited by the use of household travel survey data. There are well-known non-sampling errors in such surveys that include non-coverage, non-response, and measurement errors. Although the survey greatly included cell phone-only households with an address-based sampling method (as analyzed in Chapter 4), there are still an under-covered population segment (e.g., household with no telephone). Moreover, the relatively high levels of incentives may have motivated certain groups (e.g., lower income) to respond to the survey more than others. Measurement errors on walking trips were also found. Although this study carefully examined the validity, underreported trips (and, therefore, activities missed) may influence the results to some extent, along with some unobserved measurement errors on reported departure and arrival times. And additional errors may come from the data processing (e.g., travel distance estimation) in the survey. Third, another limitation of this study is the use of random assigned (geo-imputed) household locations and trip origins and destinations, combined with the Google Maps application. From them, a set of travel distance and duration information was extracted. Although the geo-imputation was based on census block, which is fine enough, and Google Maps is the now widely used in practice, there might be random errors impacting the results of this study. Nevertheless, the results are reasonable and show no obvious biases.

8.3 Implications

8.3.1 Sustainable Transportation and Urban Planning

Taking the right direction in urban development and transportation infrastructure is important partly because once it is implemented, a significant change is almost impossible or (if it is even possible) it requires substantial cost. As a new paradigm of the direction, this study suggests TOD, which can offer an alternative to conventional

development patterns in transportation and urban planning. This study demonstrated how these propositions can be achieved. For example, TOD can capture more trips internally, shorten trip distances, reduce automobile trips, and promote transit/walking trips. Clearly, the reduction in auto use can directly alleviate traffic congestion and air quality deterioration while saving enormous costs for roadway investment and maintenance in transportation planning. Certainly, the benefits are not limited to the local scale. To achieve region-wide sustainability, TOD can be a skeleton ("building block" or "centerpiece") of regional development, balancing compact community/neighborhoods with employment clusters at the regional scale. By adding/expanding regional public transit systems (e.g., subway or bus-rapid-transit) and integrating with sustainable land use principles, urban and transportation planning agencies can design a comprehensive regional structure.

TOD is a sustainable urban and transportation planning strategy; however, what is challenging is to implement TOD. To operationalize TOD in metropolitan areas, the transit system can be introduced where land use are already mixed and compact. For example, university campuses in urban areas and neighborhoods developed in smart growth principles (e.g., traditional development neighborhood and neo-traditional neighborhood) can be promising areas. Specifically, universities provide a livable and conducive environment for students to participate in diverse activities such as classes, work, and other social activities around campuses (Wang, Khattak, and Son 2012). While alternative modes (e.g., public transit, walking, and bicycling) are relatively available around campuses, many still commute and experience problems like traffic congestion and parking shortage. In this sense, the provision of transit system can alleviate such problems for student commuters. This can be beneficial to residents around campus who travel downtown or to major activity clusters in the region. Alternatively, there are many smart growth neighborhoods that have been recently developed in the United States. These neighborhoods can be connected to major urban areas with a transit system. By providing alternative modes of transportation the residents, they can have more commuting options and simultaneously, public agencies can achieve their policy goals sustainably.

Another approach is to develop existing neighborhoods near transit stations (e.g., about 0.5 mile radius) and make them dense, diverse, and pedestrian friendly, if they are not yet developed so. In the study area of Washington, D.C., there are still several subway stations whose neighborhoods are low-density and single-used. For example, a place for park-and-ride facilities can be replaced by affordable housing and office buildings gradually. For community/neighborhood design, a set of design guidelines are available (Calthorpe 1993). This "transit-adjacent development" can be potentially replaced by harmonizing land use with transit system, which can continue enhancing the transportation benefit of TOD greatly.

8.3.2 Travel Demand Modeling

An activity-based approach is a new paradigm in travel demand analysis, taking into account travel as a derived demand. This behaviorally appealing and broader approach is now widely researched and applied in the field. It focuses on activity participation decisions with trips viewed as a special case of activity participation. Also, activity sequencing, household interactions, and time-space dimensions become important aspects of interest. This study provides a great understanding of activity behavior in the context of TOD, which has not been understood well in many ways. Above all, at a location choice standpoint, there is strong geographical dependency among local and regional TOD areas in the time-space use behavior. This study found that TOD residents are more likely to participate in activities within the TOD and vicinity. Also, TOD residents are more likely to sequence their activities within the constrained space of TOD. These can be reflected into current activity-based modeling efforts.

Another implication for travel demand models is about a spatial unit of analysis. In general, a traffic analysis zone is widely used for the analysis unit. However, as mentioned in this study, TOD is geographically confined by about 0.5 mile from stations (therefore, the size of TODs in the study areas accounts for 1% of the total area), but various activities take place in unique built and transportation environments. Moreover, as subway stations are typically located on the borderline between two traffic analysis zones or their intersections, the spatial aspect of TOD as the core of activities are not

represented in travel demand models. In this regard, travel demand models may consider TOD as one separate zone or a center of zone. This can capture travel and activity behavior more realistically and will improve modeling effort in a way that reflects individuals' behavioral of location choice.

8.3.3 Geographical Travel Time Reliability

From a regional space and multi-modal perspective, discussion of travel time reliability can be extended. To date, travel time reliability has been independently studied in public transportation and traffic management. In public transportation, the reliability of travel time by bus or subway has been widely analyzed over the fixed route while traffic management focuses on freeway/highway segment(s) from day to day. The reliability can be measured spatially and multi-modally. In this sense, TOD areas are good geographic locations in the region where travel time reliability can be achieved. The reason for this is that, in TOD areas, a subway is well served and travel on foot is available, depending on the distance to activity locations. Notably, these two modes are very reliable in terms of travel and arrival times, as demonstrated in this study, which compares entire commute trips (door-to-door) by residential location.

The findings of study can be used as a marketing strategy. To ensure that TOD becomes a successfully policy, TOD needs to attract attention from both public and private markets. In this regard, the research results imply that geographically reliable transportation service can be a new benefit of TOD. The more reliable commutes can be a marketing tool to advertise TOD as residential neighborhoods as well as employment clusters. While more intensive studies are needed, this study provides the empirical evidence as a starting point.

This view on the travel time reliability can be applied in more individual contexts. With the purpose of providing better (or more reliable) transportation service, travel time reliability has assessed as a system performance from a system manager's perspective. From transportation system users' perspectives, the travel time reliability can be considered as a key factor in individuals' mode choice behavior. Not to mention, the travel time reliability can be included to capture residential location choice behavior.

Thus, geographical travel time reliability can be measured in this manner, providing more meaningful information to travelers (or commuters) as well as researchers.

8.4 Further Study

Several future research directions are identified in the following. First, a more integrated and comprehensive analysis is needed to fully understand travel and activity behavior in the context of TOD, accommodating other key decisions such as residence and work locations as well as vehicle ownership and type. Second, studies on better TOD design (an integrated built and transportation environment) that can maximize its benefits are beneficial at the neighborhood and regional level in practice. Third, geographical travel time reliability can be more comprehensive and tightly studied with better measurements. The measurements can be obtained from more direct and explicit questions in the survey instrument. Also, more accurate behavioral data collected from GPS-enabled mobile phones could potentially provide more accurate results for the travel time reliability analysis.

REFERENCES

Abdel-Aty, Mohamed A., Ryuichi Kitamura, and Paul P. Jovanis. "Investigating Effect of Travel Time Variability on Route Choice Using Repeated-Measurement Stated Preference Data." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1493 (1995): 39-45.

Arrington, G. B., and Robert Cervero. *Effects of Tod on Housing, Parking, and Travel.* Washington, D.C.: Transportation Research Board, 2008.

Autor, David H. "Lecture Note: Self-Selection — the Roy Model." http://economics.mit.edu/files/551.

Ben-Akiva, Moshe, and Terry J. Atherton. "Methodology for Short-Range Travel Demand Predictions: Analysis of Carpooling Incentives." *Journal of Transport Economics and Policy*, no. 3 (1977): 224-61.

Bernick, Michael, and Robert Cervero. *Transit Villages in the 21st Century.* New York: McGraw-Hill, 1997.

Bhat, Chandra R., and Frank S. Koppelman. "Activity-Based Modeling of Travel Demand." Chap. 3 In *The Handbook of Transportation Science*, edited by R.W. Hall. 35-61. Norwell, Massachusetts: Kluwer Academic Publishers, 1999.

Bhat, Chandra R., and Jessica Y. Guo. "A Comprehensive Analysis of Built Environment Characteristics on Household Residential Choice and Auto Ownership Levels." *Transportation Research Part B: Methodological* 41, no. 5 (2007): 506-26.

Bhat, Chandra R., and Rupali Sardesai. "The Impact of Stop-Making and Travel Time Reliability on Commute Mode Choice." *Transportation Research Part B: Methodological* 40, no. 9 (2006): 709-30.

Blumberg, Stephen. J, and Julian. V. Luke. "Wireless Substitution: Early Release of Estimates from the National Health Interview Survey, January–June 2011." http://www.cdc.gov/nchs/data/nhis/earlyrelease/wireless201112_tables.htm.

Boarnet, Marlon G., and Nicholas S. Compin. "Transit-Oriented Development in San Diego County." *Journal of the American Planning Association* 65, no. 1 (1999): 80-95.

Bricka, Stacey G., and Chandra R. Bhat. "Comparative Analysis of Global Positioning System-Based and Travel Survey-Based Data." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1972 (2006): 9-20.

Bricka, Stacey G., Sudeshna Sen, Rajesh Paleti, and Chandra R. Bhat. "An Analysis of the Factors Influencing Differences in Survey-Reported and Gps-Recorded Trips." *Transportation Research Part C: Emerging Technologies* 21, no. 1 (2012): 67-88.

Buliung, Ron N., and Pavlos S. Kanaroglou. "Urban Form and Household Activity-Travel Behavior." *Growth and Change* 37, no. 2 (2006): 172-99.

Calthorpe, Peter. *The Next American Metropolis : Ecology, Community, and the American Dream.* New York: Princeton Architectural Press, 1993.

Cambridge Systematics, Inc., Dowling Associates, Inc., System Metrics Group, Inc., and Texas Transportation Institute. *Cost-Effective Performance Measures for Travel Time Delay, Variation, and Reliability*. Transportation Research Board, 2008. http://onlinepubs.trb.org/Onlinepubs/nchrp/nchrp_rpt_618.pdf

Cambridge Systematics, Inc., and Texas Transportation Institute. "Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation." FHWA Office of Operations, U.S. Department of Transportation. http://www.ops.fhwa.dot.gov/congestion_report/

Cameron, A. Colin, and Pravin K. Trivedi. *Regression Analysis of Count Data.* Cambridge, UK; New York, NY, USA: Cambridge University Press, 1998.

Cao, Xinyu, Patricia L. Mokhtarian, and Susan L. Handy. "Do Changes in Neighborhood Characteristics Lead to Changes in Travel Behavior? A Structural Equations Modeling Approach." *Transportation* 34, no. 5 (2007): 535-56.

Center for Transit-Oriented Development. "Tod Database." Center for Transit-Oriented Development, http://toddata.cnt.org/.

Cervero, R. , and G. B. Arrington. "Vehicle Trip Reduction Impacts of Transit-Oriented Housing." *Journal of Public Transportatoin* 11, no. 3 (2008): 1-18.

Cervero, Robert. "Ridership Impacts of Transit-Focused Development in California : Report to the California Department of Transportation and the University of

California Transportation Center." Berkeley, Calif.: University of California at Berkeley, Institute of Urban and Regional Development, 1993.

———. "Transit-Based Housing in California: Evidence on Ridership Impacts." *Transport Policy* 1, no. 3 (1994): 174-83.

———. "Transit-Oriented Development's Ridership Bonus: A Product of Self-Selection and Public Policies." *Environment & Planning A* 39, no. 9 (2007): 2068-85.

———. *Transit-Oriented Development in the United States : Experiences, Challenges, and Prospects.* Washington, D.C.: Transportation Research Board, 2004.

Cervero, Robert, and Michael Duncan. "Walking, Bicycling, and Urban Landscapes: Evidence from the San Francisco Bay Area." *American Journal of Public Health* 93, no. 9 (2003): 1478-83.

Cervero, Robert, Christopher Ferrell, and Steven Murphy. *Transit-Oriented Development and Joint Development in the United States : A Literature Review.* Washington, D.C.: Transportation Research Board, 2002.

Cervero, Robert, and Kara Kockelman. "Travel Demand and the 3ds: Density, Diversity, and Design." *Transportation Research Part D: Transport and Environment* 2, no. 3 (1997): 199-219.

Chen, Cynthia, and Claire E. McKnight. "Does the Built Environment Make a Difference? Additional Evidence from the Daily Activity and Travel Behavior of Homemakers Living in New York City and Suburbs." *Journal of Transport Geography* 15, no. 5 (2007): 380-95.

Clarke, Mike, Martin Dix, and Peter Jones. "Error and Uncertainty in Travel Surveys." *Transportation* 10, no. 2 (1981): 105-26.

Committee on Physical Activity, Health, Transportation, and Land Use,. "Does the Built Environment Influence Physical Activity?: Examining the Evidence." Washington D.C.: Transportation Research Board, 2005.

Corral-Rivas, José Javier, Christian Wehenkel, Hermes Alejandro Castellanos-Bocaz, Benedicto Vargas-Larreta, and Ulises Diéguez-Aranda. "A Permutation Test of Spatial Randomness: Application to Nearest Neighbour Indices in Forest Stands." *Journal of Forest Research* 15, no. 4 (2010): 218-25.

De Palma, André, Asad Khattak, and Deepak Gupta. "Commuters' Departure Time Decisions in Brussels, Belgium." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1607 (1997): 139-46.

Dittmar, Hank, and Gloria Ohland. *The New Transit Town : Best Practices in Transit-Oriented Development*. Washington, DC: Island Press, 2004.

Environmental Protection Agency. "About Smart Growth." http://www.epa.gov/dced/about_sg.htm.

Eom, Jin Ki, John R. Stone, and Sujit K. Ghosh. "Daily Activity Patterns of University Students." *Journal of Urban Planning and Development* 135, no. 4 (2009): 141-49.

Eom, Jin Ki, John R. Stone, and Kyungwoo Kang. "Empirical Case Study of Spatial-Temporal Student Activity Population." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2157 (2010): 11-21.

Evans, John, Richard Pratt, Andrew Stryker, and Richard Kuzmyak. "Traveler Response to Transportation System Changes. Chapter 17, Transit Oriented Development." Washington, D.C.: Transportation Research Board, 2007.

Ewing, Reid, and Robert Cervero. "Travel and the Built Environment." *Journal of the American Planning Association* 76, no. 3 (2010): 265-94.

———. "Travel and the Built Environment: A Synthesis." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1780 (2001): 87-114.

Fan, Yingling, and Asad Khattak. "Urban Form, Individual Spatial Footprints, and Travel: Examination of Space-Use Behavior." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2082 (2008): 98-106.

Federal Highway Administration. "2009 National Household Travel Survey User's Guide." 2011.

———. "Manual of Uniform Traffic Control Devices." 2009.

———. "Urban Congestion Reports." http://ops.fhwa.dot.gov/perf_measurement/ucr/index.htm.

Frusti, Teresa, Chandra R. Bhat, and Kay Axhausen. "Exploratory Analysis of Fixed Commitments in Individual Activity—Travel Patterns." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1807 (2002): 101-08.

Greene, William H. *Econometric Analysis.* Prentice Hall, 2003.

Handy, Susan L., Marlon G. Boarnet, Reid Ewing, and Richard E. Killingsworth. "How the Built Environment Affects Physical Activity: Views from Urban Planning." *American Journal of Preventive Medicine* 23, no. 2 (2002): 64-73.

Hanson, Susan, and Perry Hanson. "The Travel-Activity Patterns of Urban Residents: Dimensions and Relationships to Sociodemographic Characteristics." *Economic Geography* 57, no. 4 (1981): 332-47.

Iteris/Berkeley Transportation Systems, Inc., Kittelson & Associates, Inc., National Institute of Statistical Sciences, University of Utah, Rensselaer Polytechnic Institute, Joseph Schofer of Northwestern University, and Asad Khattak of Planitek. "Establishing Monitoring Programs for Travel Time Reliability." In *Strategic Highway Research Program (SHRP 2) Reliability Project L02*: Transportation Research Board, 2013.

Khattak, Aemal, and Asad Khattak. "Comparative Analysis of Spatial Knowledge and En Route Diversion Behavior in Chicago and San Francisco: Implications for Advanced Traveler Information Systems." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1621 (1998): 27-35.

Khattak, Asad., and Daniel Rodriguez. "Travel Behavior in Neo-Traditional Neighborhood Developments: A Case Study in USA." *Transportation Research Part A: Policy and Practice* 39, no. 6 (2005): 481-500.

Khattak, Asad, Xin Wang, Sanghoon Son, and Paul Agnello. "Travel by University Students in Virginia." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2255 (2011): 137-45.

Khattak, Asad, Youngbin Yim, and Linda Stalker. "Does Travel Information Influence Commuter and Noncommuter Behavior?: Results from the San Francisco Bay Area Travinfo Project." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1694 (1999): 48-58.

Kwon, Jaimyoung, Tiffany Barkley, Rob Hranac, Karl Petty, and Nick Compin. "Decomposition of Travel Time Reliability into Various Sources." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2229 (2011): 28-33.

Lachapelle, Ugo, Marc Weiner, and Robert Noland. "Are Cell Phone Samples Needed for Studies of Walking Activity?". *Transportation Research Record: Journal of the Transportation Research Board*, no. 2285 (2012): 56-65.

Levinson, David, and Ajay Kumar. "Activity, Travel, and the Allocation of Time." *Journal of the American Planning Association* 61, no. 4 (1995): 458-70.

Link, Michael W., Michael P. Battaglia, Martin R. Frankel, Larry Osborn, and Ali H. Mokdad. "Address-Based Versus Random-Digit-Dial Surveys: Comparison of Key Health and Risk Indicators." *American Journal of Epidemiology* 164, no. 10 (2006): 1019-25.

———. "Reaching the U.S. Cell Phone Generation." *Public Opinion Quarterly* 71, no. 5 (2007): 814-39.

Lockwood, Allison, Sivaramakrishnan Srinivasan, and Chandra Bhat. "Exploratory Analysis of Weekend Activity Patterns in the San Francisco Bay Area, California." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1926 (2005): 70-78.

Lu, Xuedong, and Eric I. Pas. "Socio-Demographics, Activity Participation and Travel Behavior." *Transportation Research Part A: Policy and Practice* 33, no. 1 (1999): 1-18.

Lund, Hollie, Robert Cervero, and Richard W. Wilson. "Travel Characteristics of Transit-Oriented Development in California." 2004.

Madden, David. "Sample Selection Versus Two-Part Models Revisited: The Case of Female Smoking and Drinking." *Journal of Health Economics* 27, no. 2 (2008): 300-07.

Mazloumi, E., G. Currie, and G. Rose. "Using GPS Data to Gain Insight into Public Transport Travel Time Variability." *Journal of Transportation Engineering* 136, no. 7 (2010): 623-31.

McGuckin, Nancy, and Heather Contrino. "Hard to Reach Groups in Household Travel Surveys." Sub-Committee on Household Surveys, 2012

McNally, Michael G., and Craig R. Rindt. "The Activity-Based Approach." In *Handbook of Transport Modelling*, edited by Kenneth John Button and David A. Hensher. 53-69. New York: Elsevier Science B.V., 2007.

Min, Yongyi, and Alan Agresti. "Modeling Nonnegative Data with Clumping at Zero: a Survey." *Journal of Iranian Statistical Society* 1, no. 1 (2002): 7-33.

Misra, Rajul, and Chandra R. Bhat. "Activity-Travel Patterns of Nonworkers in the San Francisco Bay Area: Exploratory Analysis." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1718 (2000): 43-51.

Mokhtarian, Patricia L., and Xinyu Cao. "Examining the Impacts of Residential Self-Selection on Travel Behavior: A Focus on Methodologies." *Transportation Research Part B: Methodological* 42, no. 3 (2008): 204-28.

Nasri, Arefeh, and Lei Zhang. "Analysis of Transportation-Oriented Development in Washington, Dc, and Baltimore Metropolitan Areas." Paper presented at the 92nd Annual Meeting of Transportation Research Boards, Washington D.C., 2013.

National Capital Region Transportation Planning Board Metropolitan Washington Council of Governments. "2007/2008 TPB Household Travel Survey: Technical Documentation." 2010.

Ortúzar, Juan de Dios, and Luis G. Willumsen. *Modelling Transport*. 3rd ed. Chichester New York: J. Wiley, 2001.

Parker, Terry, Mike McKeever, G. B. Arrington, and Janet Smith-Heimer. "Statewide Transit-Oriented Development Study: Factors for Success in California's Transit-Oriented Development." 2002.

Pinjari, Abdul, Ram Pendyala, Chandra R. Bhat, and Paul Waddell. "Modeling the Choice Continuum: An Integrated Model of Residential Location, Auto Ownership, Bicycle Ownership, and Commute Tour Mode Choice Decisions." *Transportation* 38, no. 6 (2011): 933-58.

Pu, Wenjing. "Analytic Relationships between Travel Time Reliability Measures." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2254 (2011): 122-30.

R Development Core Team. "R: A Language and Environment for Statistical Computing." R Foundation for Statistical Computing, http://www.r-project.org/.

Rakha, Hesham, Ihab El-Shawarby, and Mazen Arafeh. "Trip Travel-Time Reliability: Issues and Proposed Solutions." *Journal of Intelligent Transportation Systems* 14, no. 4 (2010): 232-50.

Reid Ewing, Rolf Pendall, and Don Chen. "Measuring Sprawl and Its Impacts." Smart Growth America, 2002.

Rizzo, Maria L. *Statistical Computing with R / Maria L. Rizzo*. Chapman & Hall/Crc Computer Science and Data Analysis Series. Boca Raton : Chapman & Hall/CRC, 2008.

Roux, Sophie, and Jimmy Armoogum. "Calibration Strategies to Correct Nonresponse in a National Travel Survey." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2246 (2011): 1-7.

Santos, Adella., Nancy. McGuckin, H.Y. Nakamoto, Danielle. Gray, and Susan. Liss. "Summary of Travel Trends: 2009 National Household Travel Survey." Washington D.C.: Federal Highway Administration, 2011.

Schilling, Mark F. "Multivariate Two-Sample Tests Based on Nearest Neighbors." *Journal of the American Statistical Association* 81, no. 395 (1986): 799.

Schlossberg, M., N. Brown, E. Bossard, and D. Roemer. "Using Spatial Indicators for Pre- and Post-Development Analysis of Tod Areas: A Case Study of Portland and the Silicon Valley." Mineta Transportation Institute, 2004.

Sen, Sudeshna, Johanna Zmud, and Carlos Arce. "Efficiency and Effectiveness of Cell Phone Samples in Transportation Surveys." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2105 (2009): 44-50.

Shay, Elizabeth, and Asad Khattak. "Household Travel Decision Chains: Residential Environment, Automobile Ownership, Trips and Mode Choice." *International Journal of Sustainable Transportation* 6, no. 2 (2012): 88-110.

Snellen, Danielle, Theo Arentze, Aloys Borgers, and Harry Timmermans. "Impact of Urban Setting on Activity-Travel Patterns: Comparison of Performance Indicators with Quasi-Experimental Design Data." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1780 (2001): 1-8.

Son, Sanghoon, Asad Khattak, and Ju-Yin Chen. "Comparative Analysis of University Students' Acquisition and Use of Travel Information." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2243 (2011): 46-54.

Son, Sanghoon, Asad Khattak, and Keechoo Choi. "Comparing Travel Behavior between Transit-Oriented Developments and Automobile-Oriented Developments: A

Matched Pair Analysis." Paper presented at the 93rd Annual Meeting of Transportation Research Boards, Washington D.C., 2014.

Son, Sanghoon, Asad Khattak, and Nak-Kyeong Kim. "Noncoverage Errors in Travel Surveys Due to Mobile Phone-Only Households." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2354 (2013): 29-39.

Son, Sanghoon, Asad Khattak, Xin Wang, Paul Agnello, and Ju-Yin Chen. "Quantifying Key Errors in Household Travel Surveys." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2354 (2013): 9-18.

Son, Sanghoon, Asad Khattak, Xin Wang, and Ju-Yin Chen. "Transferring Telephone-Based National Household Travel Survey to the Internet." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2285 (2012): 91-99.

Stopher, Peter, Camden FitzGerald, and Min Xu. "Assessing the Accuracy of the Sydney Household Travel Survey with Gps." *Transportation* 34, no. 6 (2007): 723-41.

Stopher, Peter R. *Standardized Procedures for Personal Travel Surveys*. Washington, D.C.: Transportation Research Board, 2008.

Texas Transportation Institute and Cambridge Systems Inc. "Travel Time Reliability: Making It There on Time, All the Time." FHWA Office of Operations, U.S. Department of Transportation. http://ops.fhwa.dot.gov/publications/tt_reliability/

Tilahun, Nebiyou Y., and David M. Levinson. "A Moment of Time: Reliability in Route Choice Using Stated Preference." *Journal of Intelligent Transportation Systems* 14, no. 3 (2010): 179-87.

Tim Lomax, David Schrank, Shawn Turner, Lauren Geng, Yingfeng Li, and Nick Koncz. "Real-Timing the 2010 Urban Mobility Report." Texas Transportation Institute, 2011.

Transportation Research Board. "HCM 2010: Highway Capacity Manual." Washington D.C. , 2010.

Transportation Research Board's Travel Survey Methods Committee (ABJ40). "The on-Line Survey Manual: A Dynamic Document for Transportation Professionals " http://www.travelsurveymanual.org/.

Tucker, Clyde, J. Michael Brick, and Brian Meekins. "Household Telephone Service and Usage Patterns in the United States in 2004: Implications for Telephone Samples." *Public Opinion Quarterly* 71, no. 1 (2007): 3-22.

US Census Bureau. "American Factfinder Fact Sheet." http://www.census.gov/.

van Lint, J., and H. van Zuylen. "Monitoring and Predicting Freeway Travel Time Reliability: Using Width and Skew of Day-to-Day Travel Time Distribution." *Transportation Research Record: Journal of the Transportation Research Board*, no. 1917 (2005): 54-62.

Wang, Xin, Asad Khattak, and Yingling Fan. "Role of Dynamic Information in Supporting Changes in Travel Behavior." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2138 (2009): 85-93.

Wang, Xin, Asad Khattak, and Sanghoon Son. "What Can Be Learned from Analyzing University Student Travel Demand?". *Transportation Research Record: Journal of the Transportation Research Board*, no. 2232 (2012): 129-37.

Washington Metroplitan Area Transit Authority. "2005 Development-Related Ridership Survey." 2006.

Washington Metropolitan Area Transit Authority. "FY 2012 Metrorail Boarding by Station. "http://www.wmata.com/pdfs/planning/FY12_Historical_Ridership_By_Station.pdf.

Washington State Department of Transportation. "Seattle Area Travel Times: Plan Your Commute - 95% Reliable Travel Times." http://www.wsdot.com/Traffic/Seattle/TravelTimes/95reliable.aspx.

Winkelmann, Rainer. *Econometric Analysis of Count Data*. Springer, 2008.

Wolf, Jean. "Applications of New Technologies in Travel Surveys." In *7th International Conference on Travel Survey Methods*. Playa Herradura, Costa Rica, 2004.

Wooldridge, Jeffrey M. *Introductory Econometrics : A Modern Approach*. Cincinnati, OH: South-Western College, 2000.

Yazici, M., Camille Kamga, and Kyriacos Mouskos. "Analysis of Travel Time Reliability in New York City Based on Day-of-Week and Time-of-Day Periods."

Transportation Research Record: Journal of the Transportation Research Board, no. 2308 (2012): 83-95.

Zhong, Ming, John Hunt, and Xuewen Lu. "Studying Differences of Household Weekday and Weekend Activities: A Duration Perspective." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2054 (2008): 28-36.

Zhou, Bin, and Kara Kockelman. "Self-Selection in Home Choice: Use of Treatment Effects in Evaluating Relationship between Built Environment and Travel Behavior." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2077 (2008): 54-61.

Ziems, Sarah, Karthik Konduri, Bhargava Sana, and Ram Pendyala. "Exploration of Time Use Utility Derived by Older Individuals from Daily Activity-Travel Patterns." *Transportation Research Record: Journal of the Transportation Research Board*, no. 2156 (2010): 111-19.

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