Title
Analysis of Complex Travel Behavior: A Tour-based Approach

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Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Analysis of Complex Travel Behavior: A Tour-based Approach

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Transportation Science

by

Rezwana Rafiq

Dissertation Committee:
Professor Michael G. McNally, Chair
Professor Wilfred Recker
Professor Jean-Daniel Saphores

2019

DEDICATION

To

my parents, husband, and son

in recognition of their sacrifice, support, and unconditional love

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ACKNOWLEDGMENTS

At first, all praises belong to the most gracious, the most merciful, the almighty Allah for giving me the blessing, the strength, and the chance in completing my PhD dissertation.

I would like to express my deepest gratitude to my advisor, Professor Michael G. McNally, for being a tremendous mentor for me. It has been an honor for me to be his PhD student. I would like to thank him for his constant guidance, thoughtful suggestions, and strong encouragement towards the successful completion of the thesis. I gratefully acknowledge all of his contributions of time, valuable ideas, and funding supports that make my PhD life productive and a memorable endeavor. His constructive comments and criticisms from diversified angles on various transportation issues enrich my knowledge and way of thinking. Being a PhD student while being a mother of one has been very challenging for me. I would like to express my sincere gratitude to my advisor for giving me the flexibility of time in doing research that helped me a lot in balancing my research work and family life.

I would like to thank my committee members, Professor Wilfred Recker and Professor Jean-Daniel Saphores for their great support and advice. I also gratefully acknowledge their lecture classes on various statistical data analysis techniques in transportation that made a strong foundation for my research work. I would like to express my gratitude to the late Professor Jennifer Buher Kane (who was in my initial dissertation committee before her sad demise), Professor Jae Hong Kim, and Professor R. Jayakrishnan for their valuable comments during my PhD qualification exam. I want to thank Professor Stephen Ritchie for giving me a chance to work in a summer project on freight transport, which offered a different experience in my PhD. I took a course on Structural Equation Modeling (SEM) with Professor John R. Hipp that helped me enormously to build a solid foundation on SEM that I extensively used in my dissertation.

Professor Hipp also helped me out with his valuable comments and suggestions when I encountered various problems in applying SEM in my research. Thank you, Professor Hipp.

I would like to express my sincere gratitude to Dr. Suman Kumar Mitra for being a wonderful mentor. I want to thank him for his insightful comments, guidance, and motivations in my research work. I would like to thank Professor Mohammad Al Faruque (of ECE at UCI) and his wife Mrs. Nahid Chowdhury for their inspiration and encouragement. I am also grateful to Tanjeeb and Faiza for giving their kind support. I am thankful to Rizvi Bhai (one of my cousins living in Irvine) and Afrin Bhabi for their hospitality and taking care of me and my family. I would also like to thank all of my Bangladeshi friends in Irvine, especially Tania, Naila, Dida Apu, Asha, Sabur Bhai, Samia, Anagh, Nilima, Dia, Rashid, Al Amin Bhai, and Aftab. I want to express special thanks to Gigi (Manal Mehawed) for taking good care of my son in her daycare.

I would like to thank Dr. Jared Sun and Ms. Cam Nguyet Tran for their kind administrative supports in the Institute of Transportation Studies (ITS). I am also thankful to my ITS lab mates and friends: Koti, Lu, Yunwen, Karina, Chenying, and Xuting. I am immensely appreciative of the staff of Verano Graduate Housing Community, where my family and I lived quite peacefully and with great comfort for the entire duration of five years of my Ph.D. at UCI.

I would like to express my deepest homage to my parents (Father: A. T. M. Rafiqul Hoque, Mother: Shabnam Chowdhury), brother (Mohammad Raihan Rafiq), mother-in-law, and other family members, whose continuous inspiration, sacrifice, love, and blessings encouraged me to complete the thesis successfully. Last but not the least, I want to sincerely acknowledge the sacrifice and love of my son, Aaraf Rizwan Yusuf and my husband, Dr. Md. Yusuf Sarwar Uddin who are always very supportive, caring, and patient for me. They are my source of strength and encouragement in this endeavor.

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- **Rafiq, R.** and McNally, M. G. (2018). "Modeling the structural relationships of activity-travel participation of working women", *Transportation Research Record*, 0361198118784135.
- **Rafiq, R.** and Mitra, S. K. (2018). "Shared school transportation: determinants of carpooling as children's school travel mode in California", *Transportation*, 1-19.

- Rahman, M. M., Barua, U., Khatun, F., Islam, I., and **Rafiq, R.** (2018). "Participatory Vulnerability Reduction (PVR): an urban community-based approach for earthquake management", *Natural Hazards*, 93(3), 1479-1505.
- Zannat, K. E., Ahmed, T., Mitra, S. K., **Rafiq, R.** et al. (2014). "Parking Demand and Supply Analysis of Major Shopping Centers in Dhaka: A Case Study of New Market Shopping Center along Mirpur Road", *Journal of Bangladesh Institute of Planners*, Vol. 6, pp. 161-172.
- Labib, S. M., Rahaman, Z. and **Rafiq, R.** (2014). "Sustainable transportation system for sustainable city climate: An ecological footprint approach for transportation sustainability measure in Dhaka, Bangladesh" Proceedings of 3rd International Conference on Recent Trends in Engineering and Technology (ICRTET 2014), published by Elsevier Science and Technology, Maharashtra, India, March 28-30.
- **Rafiq, R.**, Alam, S., Rahman, M. and Islam, I. (2014). "Conserving wetlands: Valuation of Indirect Use Benefits of a Wetland of Dhaka", *International Journal of Environmental Science and Development*, Vol. 5, No. 1, pp. 64-69.
- Uddin, Y. S. and **Rafiq, R.** (2014). "Citizen Assisted Environmental Pollution Measurements in Developing Cities", *International Journal of Environmental Science and Development*, Vol. 5, No. 1, pp. 70-76.
- Shakil, S. H., Ananya, T. H., Hasan, M. U. and **Rafiq, R.** (2014). "Does Distribution of Schools Matter in Human Development? - A Case Study of Bangladesh", Sustainability and Economics E-journal, *Social Science Research Network (SSRN)*, Vol. 3 (2), pp. 1-13.
- **Rafiq, R.** and Khan, M. R. (2011). "Ecological City Building: A Movement Towards an Eco-Friendly City", published by LAP LAMBERT Academic Publishing House (http://www.amazon.com/Ecological-City-Building-Movement-Eco-Friendly/dp/3843385211).

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- **Rafiq, R.** and McNally, M.G. (2019). "Activity-Travel Behavior Before and After the 2009 Recession", *Irvine Symposium on Emerging Research in Transportation* (*ISERT*), Irvine, CA, Jan 18-19.

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- **Rafiq, R.** and McNally, M.G. (2019). "Changes in Activity-Travel Behavior of Workers Before and After the 2009 Recession", in *Transportation Research Board (TRB) Annual Meeting*, Washington D.C., Jan 13-17.
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- **Rafiq, R.** and McNally, M.G. (2018). "Modeling the Structural Relationships of Activity-Travel Behavior of Working Women", in *Transportation Research Board (TRB) Annual Meeting*, Washington D.C., Jan 7-11.
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- **Rafiq, R.** and Islam, I. (2013). "Recreational Value of a Wetland of Dhaka: An Application of Travel Cost Method", in *12th International Asian Urbanization Conference on Urban Dynamics, Environment and Health: Challenges for Twenty First Century*, Banaras, India, Dec 28-30.
- Rahman, M. M., Mohiuddin, H. and **Rafiq, R.** (2013). "Urban Concentration in Bangladesh: Role of Small and Medium Sized Urban Centers", in *12th International Asian Urbanization Conference on Urban Dynamics, Environment and Health: Challenges for Twenty First Century*, Banaras, India, Dec 28-30.
- **Rafiq, R.**, Alam, S., Rahman, M. and Islam, I. (2013). "Conserving wetlands: Valuation of Indirect Use Benefits of a Wetland of Dhaka", in *International Conference on Environmental Pollution and Prevention (ICEPP 2013)*, organized by Asia Pacific Chemical, Biological and Environmental Engineering Society, Melaka, Malaysia, Oct 5-6.
- **Rafiq, R.,** Islam, I. and Rahman, M. (2013). "Economic valuation of demarcated western floodplains of Dhaka", in *International Conference on "Bridging the Policy Action Divide: Challenges and Prospects for Bangladesh*, organized by Bangladesh Development Initiatives (BDI) and Center for South Asia Studies, UC Berkeley, California, USA, Feb 22-24.

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- “**University Grand Commission Scholarship**” for highest CGPA in the Faculty of Architecture and Planning, Bangladesh University of Engineering and Technology
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ABSTRACT OF THE DISSERTATION

Analysis of Complex Travel Behavior: A Tour-based Approach

By

Rezwana Rafiq

Doctor of Philosophy in Transportation Science

University of California, Irvine, 2019

Professor Michael G. McNally, Chair

Complex travel behavior places travel in a broader context than in the conventional trip-based approach. The activity-based approach provides an analysis framework that positions travel decisions as dependent on a collection of activities that form an agenda for participation and, therefore, cannot be properly analyzed on individual trip basis. The basic units of analysis for activity-based approaches are *tours*, which can be defined as sequences of trips and activities that begin and end at the same location. In this dissertation, I apply a tour-based approach to analyze complex travel behavior from three perspectives: sustainability, technology, and economics.

First, I examine the complex travel behavior of workers, who utilize a sustainable transport option, namely public transit. I identify dominant patterns of work tours and analyze factors affecting tour choice using Structural Equation Modeling (SEM). The results obtained by using the 2017 National Household Travel Survey dataset suggest that 80 percent of work tours consist of seven dominant tours and that tour choice is influenced by a set of socio-demographic, built environment, and activity-travel characteristics. Second, the complex travel behavior of people who use technology-enabled ride-hailing services, such as Uber/Lyft, is explored. In particular, I identify heterogeneous groups of ride-hailing users by using Latent Class Analysis,

analyze the activity-travel patterns of each of these groups, and discuss the ramifications of that behavior to policy directives.

Lastly, I explore the travel behavior of workers, again in terms of tours, when they are exposed to an economic downturn, the 2007-2009 recession. I apply multi-group SEM to analyze changes in tour choice during the recession (2009) compared to pre- (2006) and post-recession (2012) years. Using American Time Use Survey data, this study shows that activity-travel relationships and their role in tour choices differed significantly in the recession year. The results of this study provide insights into potential changes in worker's travel demand during a recession, which would contribute to building better pattern choice sets in tour-based models.

The common thread throughout this dissertation is the development of a framework for analyzing complex travel behavior under disruptive changes due to environment, technology, and economics forces.

CHAPTER 1: Introduction

Complex travel behavior places travel in a broader context than in the conventional single-trip based approach. Such travel behavior can be analyzed by using an activity-based approach. The core concept of this approach is that travel demand is a derived demand. More specifically, travel decisions are driven by a collection of activities that form an agenda for participation and, therefore, it cannot be properly analyzed on individual trip basis. The process of assembling a travel-activity pattern (whether in pre-travel planning or in real time) and the choice attributes of each component can only be understood within the context of the entire agenda. The basic unit of activity-based approach is *tours*, which can be defined as a sequence of trips and activities that begins and ends at the same location. In this dissertation, I analyze complex travel behavior of people by using a tour-based approach.

The fundamental difference between the activity- or tour-based approach and the trip-based approach is that the latter considers travel as a collection of unlinked or independent *trips* ignoring the interrelationships among the choice of time, destination, and mode of different trips. In contrast, the tour-based representation can capture the interdependency and consistency among various temporal, spatial, and modal attributes of trips within a particular tour and can provide an understanding of how people allocate their time to pursue different activities and travel subject to time constraints over the whole day. Moreover, a tour-based approach facilitates the prediction of individual-level responses towards the changes in various travel demand management policies, such as congestion pricing, alternative work schedule. Such kind of individual-level prediction is not possible in the trip-based approach since the demand models under this approach are developed at an aggregate level. Again, trip-based models can accommodate a limited set of socio-demographic variables and capture the effects at household or traffic analysis zones (TAZ)-level whereas tour-based models can accommodate a wide range of socio-demographic characteristics and predict the effects at individual-level who actually make the activity-travel decisions. Therefore, activity-based models are better equipped in forecasting both short-term and long-term changes in travel demand in response to the changes in the socio-demographic composition and the travel environment.

In this dissertation, I apply a tour-based approach to analyze complex travel behavior of people from *three* relevant perspectives, namely sustainability, technology, and economics. First, I examine the complex travel behavior of workers who utilize a *sustainable* transport option, namely public transit. The complexity of travel behavior has changed over time and is often manifested by an increasing tendency to chain trips for different purposes. Private vehicles often offer greater flexibility of travel, which tends to increase the demand for private vehicle ownership and usage. This rising use of private vehicles has some negative implications, such as congestion, air pollution, and energy consumption while public transit is considered a sustainable transport mode to effectively mitigate these adverse consequences. To make public transit ridership more attractive and consequently to reduce the use of private vehicles, it is imperative to identify the existing tour patterns of transit commuters.

I, therefore, identify the dominant patterns of work tours made by transit commuters and analyze the attributes of these tours using a set of activity-travel analytics. I also characterize the transit commuters based on their work tour choice and analyze the factors that determine the choice of work tours. The structural relationship among the different factors affecting the tour choice is modeled using SEM and the effects are analyzed based on the 2017 National Household Travel Survey (NHTS) dataset. The results of this study can provide better insights on identifying the transit commuters who have complex travel needs and can explain how they meet their needs while utilizing transit in their work tours. It can help transit authorities to find out the potential target market who have complex travel needs and to formulate better land use and transit operating policies to foster higher usage of this sustainable transportation option.

Second, from *technology* perspective, I analyze the complex travel behavior of people who use technology-enabled ride-hailing services (e.g. Uber/Lyft). Here, travel behavior is analyzed in two distinct but related aspects: tours and patterns. Tours represent the dominant sequence of activities and trips whereas patterns are used to capture the grouping or clustering of ride-hailing users based on their travel behavior indicators. The user clusters are identified by using Latent Class Analysis (LCA). This analysis is conducted based on the 2017 NHTS dataset. The results of this study can help ride-hailing operators to find out and address the travel needs of various heterogeneous groups of potential market users who will show different responses to policy directives.

Lastly, I explore the travel behavior of people, again in terms of tours, when they are exposed to an *economic* downturn, i.e. specifically the most recent 2007-2009 recession. In particular, I investigate whether a worker changed his/her tour pattern during the recession. I apply multi-group Structural Equation Modeling (SEM) on the American Time Use Survey (ATUS) data to analyze changes in tour choice during the recession (2009) compared to pre- and post-recession years (2006 and 2012 respectively). The results of this study provide valuable insights on possible changes in worker's travel demand during an economic downturn, which would contribute to building better pattern choice sets in tour-based models.

The common thread throughout this dissertation is the development of a framework for analyzing complex travel behavior under disruptive changes due to environment, technology, and economics forces.

This dissertation is organized in the following way. The next two chapters contain the observations on the work tours of transit commuters. Chapter 2 describes the dominant work tours and detail analysis of each of these tours and Chapter 3 summarizes the factors that govern the choice of a particular type of work tour. Chapter 4 outlines the activity-travel patterns (tours) of ride-hailing users. Chapter 5 describes the changes in tour choice behavior of workers when they are exposed to changes in the economy. Finally, conclusions, limitations, and future research directions are provided in Chapter 6.

CHAPTER 2: Tour Formation of Public Transit Commuters

2.1 Introduction

The complexity of travel behavior has changed over time as travelers respond to different activity demands and to the changing supply environment, measured by congestion, cost, and emerging technologies. Complexity in travel behavior is often manifested by an increasing tendency to chain trips for different purposes for increased efficiency in time management. Travelers seek more flexible travel modes to complete their complex travel demand. Private vehicles often offer greater flexibility of travel, which tends to increase demand for private vehicle ownership and usage. This rising use of private vehicles has some negative implications, such as congestion, air pollution, and energy consumption while public transit is considered as a sustainable transport mode to effectively mitigate these adverse consequences (Federal Highway Administration, 2002). However, with operations on fixed routes and fixed schedules, public transit offers lower accessibility and mobility services than private vehicles. The question of interest is to what extent can public transit accommodate complex travel needs, particularly in chaining non-work activities before, during, or after work activities.

I analyze the complex travel behavior of workers who utilize public transit in some portion of their work commute. The activity-based approach is a paradigm that considers the full complexity of travel behavior to better understand and thus improve travel forecasting models (Chung *et al.*, 2004; Doherty *et al.*, 2002). The core concept of the paradigm is that travel demand is a derived demand, which implies that the demand for travel is created to participate in out-of-home activities. The basic units of analysis of this approach are individual and household travel-activity patterns that explicitly incorporate the revealed patterns of activities and travel over a specified time period (often a single day) (McNally and Rindt, 2008). Each pattern reflects the range of attributes defining daily activities and trips, including the type, location, mode, timing and duration, and sequence of all travel and activities (Ren and Kwan, 2009).

A fundamental difference between the activity-based approach and the conventional trip-based approach is that the latter considers travel as a collection of unlinked or independent *trips* ignoring the interrelationships among the choice of time, destination, and mode of different trips (Pinjari and Bhat, 2011). But travel decisions are driven by a collection of activities that form an agenda for participation and, therefore, it cannot be properly analyzed on individual trip basis. The process of assembling a travel-activity pattern (whether in pre-travel planning or in real time) and the choice attributes of each component can only be understood within the context of the entire agenda (McNally and Rindt, 2008). The activity-based approach addresses these issues by using full patterns (in theory) or *tours* (in practice) as a basic unit of analysis, with a tour being defined as a sequence of trips and activities that begins and ends at the same location. If a tour contains at least one work activity location, it is called *work tour*. The tour-based representation can capture the interdependency and consistency among various temporal, spatial, and modal attributes of trips within a particular tour (Pinjari and Bhat, 2011) and can provide an understanding of how people allocate their time to pursue different activities and travel subject to time constraints (24 hours a day) over the whole day.

In this study, I conduct an empirical analysis of work tours of individuals who utilize public transit within their work tours. I refer to these travelers as public transit commuters. A number of dominant patterns of work tours made by transit commuters are identified and analyzed in detail using a set of activity-travel analytics, such as temporal distribution of trips, activity purposes and duration, modal distribution, modal sequence, and frequency of transit with other modes. This empirical analysis can lead to a better understanding of how non-work activities and trips are linked to work trips, to evaluate current transit services and to adjust the travel needs of users accordingly, and to realize how transit commuters can modify their activity-travel pattern under various policy constraints.

2.2 Literature Review

The increasing complexity of modern life can lead to increased time poverty, which in turn can increase the tendency of travelers exploring opportunities to chain non-work activity purposes within a work tour to reduce travel and time costs and to gain efficiency in activity participation (McGuckin *et al*., 2005; Hensher and Reyes, 2000; Levinson and Kumar, 1995; Bianco and Lawson, 1996). However, increasing the number of complex work tours can also increases the reliance on more flexible travel modes (Hensher and Reyes, 2000), such as private vehicles that can allow much flexibility and convenience to the commuters to schedule either planned or spur of the moment non-work activities within the work tour under spatial and temporal constraints (Lee and McNally, 2003). Hensher and Reyes (2000) found in Sydney, Australia that the likelihood of public transit usage decreases with the change of a tour from simple to complex. In addition, the authors identified different household level socio-economic and demographic factors that influence the utility of a simple or complex tour (work or non-work) yielded from either car or public transit. Similar results were found by Wallace *et al.* (2000) who claimed that tours made by public transit are less complex than the tours taken by cars. Krygsman et al. (2007) investigated the causal relationships between travel mode choice (car or public transit) and the insertion of intermediate activities before, in between, or after a work activity within a work tour in Netherlands. The authors concluded that the inclusion of an intermediate stop for non-work activity before or after work tends to decrease public transit utility and increase car utility. They also found that in a majority of home-based work tours, activity decisions are made before making a decision on mode of travel. This claim is supported by Ye *et al.* (2007), who found that for both work and non-work tours, tour complexity drives the choice of mode rather than the mode determining the inclusion of additional activity stops within the tour. This implies that with the increasing demand to make complex tours, travelers will seek more flexible modes and, hence, public transit ridership could suffer as travelers find it difficult to connect multiple stops within a tour by transit.

In contrast, several prior studies found different relationships between tour behavior and public transit usage. Currie and Delbosc (2011) explored the tour behavior of public transit users in Melbourne, Australia. Based on univariate analyses, the authors suggested that for non-work tours, public transit chains are found to be more complex than those undertaken by car. However, the opposite relationship was found for work tours. They explained that the higher complexity of trip chains in public transit based non-work tours might be caused by the availability of a wide range of services and activities concentrated around the city center that can be easily accessed by public transit. Primerano *et al.* (2008) found that in Adelaide, Australia all forms of mass public transport tours involved higher numbers of activities compared to private car-based tours. The authors argued against the hypothesis of Hensher and Rayes (2000) that public transit is not flexible for complex trip chaining. They instead suggested that the nature of complex trip chaining behavior of public transit users is different rather than inflexible. With public transit, travelers can access a destination comprising a mix of land uses in close proximity to one another whereas travelers using a private car can access activities located at multiple destinations that are not necessarily in close proximity to each other. This statement is reinforced by Ho and Mulley

(2013). Based on Sydney household travel survey data, the authors showed that public transit tours increased with an increase in the number of activities located in close proximity to one another (yielding a *multiple purpose single destination tour*). These results suggest that chaining multiple activities in tours does not necessarily hinder public transit usage but an unfavorable spatial distribution of activity locations might do so.

In summary, previous studies addressed the interrelationships between the complexity of activities and the utility of different mode usage with a primary focus on private vehicle and public transit. In contrast, this work aims to analyze the complexity of work tours that incorporate public transit on at least one leg of the tour and, in particular, how and when public transit users incorporate different non-work activity demands within their work tours, constrained by work time commitments, transit fixed route, fixed schedules, waiting time, transfer time, and access/egress issues. To the best knowledge, this study is the first to analyze the full work tours with transit usage in different parts of the chain.

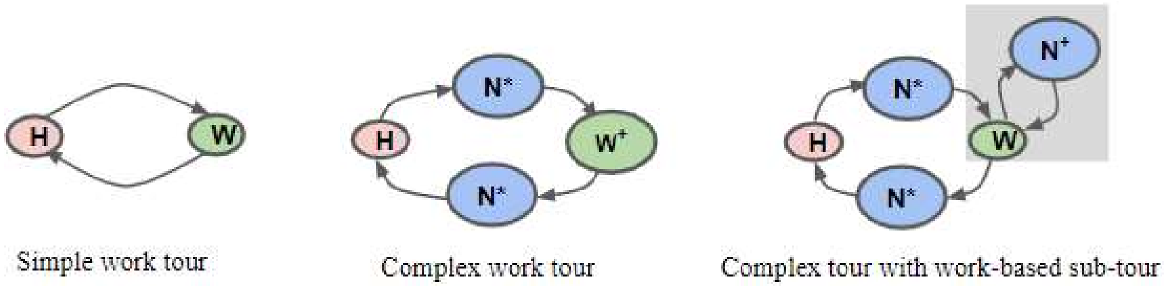
2.3 Definitions and Classification of Tours

A *tour* is a sequence of trips that starts and ends at the same location and contains one or more activities performed at single or multiple destinations (Strathman and Dueker, 1995; Ho and Mulley, 2013). If the starting and ending location in question is home, the tour is deemed a home-based tour. Since this study involves working individuals, I only consider home-based tours that contain at least one work location outside home. These are called home-based *work* tours. A home-based work tour is called a *simple work tour* if it contains exactly one work activity but no non-work activity within it. That means, a home-based simple work tour has this sequence of activities Home-Work-Home, separated by two trips in between.

On the other hand, a home-based work tour may contain non-work activity with work in the same tour. These tours are called *work-nonwork mixed* tours. In this study, these mixed tours are divided into two categories: complex work tours and complex tours with work-based sub tour. *Complex work tours* contain non-work locations other than work accessed on the way to or from work. Non-work activities are called 'way to work' non-work activities when performed after leaving home and before arriving at work. Similarly, 'way to home' non-work activities are those activities that are performed on the way to home from the workplace.

Work-based tours involve visiting non-work locations 'during work' (such as during a lunch break). When a home-based tour is combined with a work-based tour, it is referred to as *complex tour with work-based sub-tour*. Both simple and complex work tours have exactly one circuit whereas complex tours with work-based tour have two or more circuits, i.e. one circuit between home and work, and (minimum) one circuit with work as a base. Note that, the work-based tour is classified as a distinct one as it shows unique socio-demographic and transport properties compared to the second work tour category (non-work on the way to or from work) (Krygsman et al., 2007).

Figure 2.1 shows the general construct of these three types of tours. The difference in tour type emanates from the degree to which non-work activities are mixed with work. For instance, simple work tours do not involve any non-work at all, complex work tours involve non-work stops on the way to work and/or on the way to home, and work-based tours can have non-work stops in any or all of these three ways. To represent the different types of tours, a graphical model is produced where activity locations are vertices as H (home), N(non-work) and W (work) depending on where the activity is performed and an arrow between two vertices denotes a trip between the corresponding locations.



N*: zero or any number of non-work
N+: one or more non-work
W+: one or more work
Shaded portion can repeat

Figure 2.1 General construct of home-based work tours

A tour type is a generic representation of performing work and non-work activities and can be realized in many possible ways. Any specific realization of a tour of a certain type is called a *tour pattern* or simply a *pattern*. For example, H-W-H is a pattern of realizing a home-based simple tour (which happen to be the *only* pattern for this particular type) and H-N-W-H and H-W-N-N-H are sample patterns of home-based complex tours that involve one non-work on the way to work and two non-work activities on the way to home. As a mean of representing patterns of any kind, I denote each pattern as a 3-tuple (a, b, c) where the three whole numbers (including zero) indicate the number of non-work activities involve on the way to work, on the way to home, and from work and back to work respectively. Hence, the three patterns mentioned can be denoted as (0, 0, 0), (1, 0, 0) and (0, 2, 0) respectively. These notations are used when the most dominant tour patterns are identified from data for the study group.

2.4 Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS). NHTS is the source of information about travel by US residents in all 50 states and the District of Columbia.

The data includes trips made by all modes of travel (private vehicle, public transport, pedestrian, biking, etc.) and for all purposes (work, school, shopping, recreation, etc.). The NHTS data base contains four datasets or tables: households, persons, trips, and vehicles. The household table contains socio-economic and location characteristics of surveyed households and the person table contains information about the demographic characteristics of all individuals living in those households. The trip data table lists all trips made within a 24-hour period by each household member aged 5 or older as well as trip-related attributes, and the vehicle data table contains information about vehicles available for use by households. The NHTS dataset contains 129,696 households consisting of 264,234 persons who took a total of 923,572 trips. Among them, 23.40 percent individuals (a total of 61,842) made at least one home-based work tour.

For the analysis, *home-based work tours* (HBW) are identified by individuals who are at least 18 years old, perform at least one work activity, and used public transit in at least one trip segment[1]. A choice of travel mode is treated as 'public transit' if it is any of the following: public or commute bus, city-to-city bus (greyhound, Mega bus, etc.), Amtrak/commuter rail, and subway/elevated/light rail/street car. This generates a sample of 2,448 individuals. Home-based transit work tours are formed by linking person trip sequences that start and end at home and contain at least one work activity. The result was a total of 2,454 home-based work tours (2.68 percent of total 91,635 work tours in the dataset).

Note that although *change of transportation* is recorded as an activity purpose in the survey data, it is not considered as an activity in the analysis. Because 'mode change' is a part of the whole trip to access a particular activity site and the inclusion of this type as a separate non-work activity may artificially increases the complex nature of public transit tours (Noland *et al.*,

[1] When a trip involves change of modes, each mode defines a trip segment.

2008; Ho and Mulley, 2013).

Table 2.1 Descriptive statistics of transit commuters

Variables	Mean	Std. dev.
Total respondents	2,448	
Household characteristics		
Household size	2.42	1.26
Number of household vehicles		
Number of vehicles = 0	0.23	0.42
Number of vehicles = 1	0.35	0.48
Number of vehicles > 1	0.42	0.49
Monthly household income (USD)		
Low income (less than $35K)	0.21	0.40
Middle income ($35K to $100K)	0.35	0.48
High income ($100K or more)	0.44	0.50
Home ownership (Own = 1, Others = 0)	0.54	0.50
Presence of child aged 0-17 (Yes =1, No = 0)	0.16	0.37
Number of adults	2.03	0.87
At least one vehicle per worker (Yes =1, No = 0)	0.56	0.50
At least one vehicle per licensed driver (Yes =1, No = 0)	0.57	0.50
Personal characteristics		
Age groups (Millennials: 18-38 yrs. = 1, Others = 0)	0.43	0.50
Gender (Male =1, Female = 0)	0.51	0.50
Type of employment (Full time=1, Part time=0)	0.84	0.37
Flexibility in work arrival time (Yes=1, No=0)	0.53	0.50
Multiple job status (Yes=1, No=0)	0.08	0.28
Occupation (Professional, managerial or technical = 1, Others = 0)	0.62	0.48
Educational attainment (at least have some college degree = 1, Others = 0)	0.87	0.34
Ethnicity status (Hispanic=1, Others=0)	0.11	0.31
Race (Caucasian = 1, Others = 0)	0.66	0.47
Immigration status (Yes=1, No=0)	0.23	0.42
Employment status of spouse or partner		
Has employed spouse or partner	0.48	0.50
Has non-employed spouse or partner	0.12	0.32
No spouse or partner	0.40	0.49
Captive rider: no vehicle or no driving license or give up driving for medical condition (Yes=1, No=0)	0.34	0.47
Location characteristics		
Population density (persons per sq. mile) in census block group		
Low density (0-2000)	0.18	0.38
Medium density (2000-10000)	0.41	0.49
High density (>10000)	0.41	0.49
MSA rail status (Have rail = 1, Does not have rail or household not in MSA = 0)	0.59	0.49
Distance from home to workplace (mile)	21.89	110.05
Proximity to transit station		
Trip time to transit station (min.)	9.72	8.79
Trip time from transit station (min.)	12.52	14.63

Table 2.1 summarizes the household, personal, and location characteristics of the selected transit commuters. Note that the definition of transit commuter implies that a transit mode was used in at least one trip segment of the overall home-based tour. In terms of household characteristics, transit commuters have on average two persons per household, 76 percent have a car available (42 percent have more than one) and 44 percent belong to a higher income group (annual income exceeds $100K USD). Majority of them are car sufficient households (57 percent have at least one vehicle per licensed driver). Few of these households have children aged less than or equal to 17 years (16 percent). Regarding personal characteristics, the age distribution of transit commuters is almost similar for millennials (18-38 years) and non-millennials (above 38 years). Interestingly, males and females are an equal share among transit commuters. While most transit commuters are Caucasians (66 percent), have full-time work (84 percent), have flexibility in work arrival time (53 percent) and live in metropolitan areas that have rail connections (59 percent), rather few of them are Hispanic (11 percent), immigrant (23 percent) or have multiple jobs (8 percent).

2.5 Extracting Tour Attributes from Data

For each sampled traveler, I extract and code trips using the symbols W (work), N (non-work) and H (home) based on where the trip destination's activity (except the first trip of the tour which is also defined for trip origin). The trips are placed in order of their departure times. Any two consecutive trips are separated in time by the duration of the activity performed between the trips. This generates individual tours as a sequence of trips denoted by a string triad (H, W, N). This representation is referred to as a *tour string*. An example tour string may look like this HNNWNNH, which indicates that, the individual left home and performed two non-work activities back to back and then went to work. After work, the individual made two more non-work activities and then returned home. Since I consider home-based work tours, I take those tours that start and end with home (H) and contain at least one work (W) in them. Note that a person can have one or more work tours which is reflected as two separate tours.

2.6 Identification of Dominant Work Tours

After extracting tour attributes from the data, I identify which work tour patterns appear most frequently. To ensure sufficient sample observations (at least 50) in each of these patterns, the seven most dominant patterns of tours are selected that represent 80 percent of the total work tours. While 80 percent of all home-based work tours can be classified into seven representative patterns; the remaining 20 percent of these tours are labeled as "other" and can be classified as either complex or home with work-based tours.

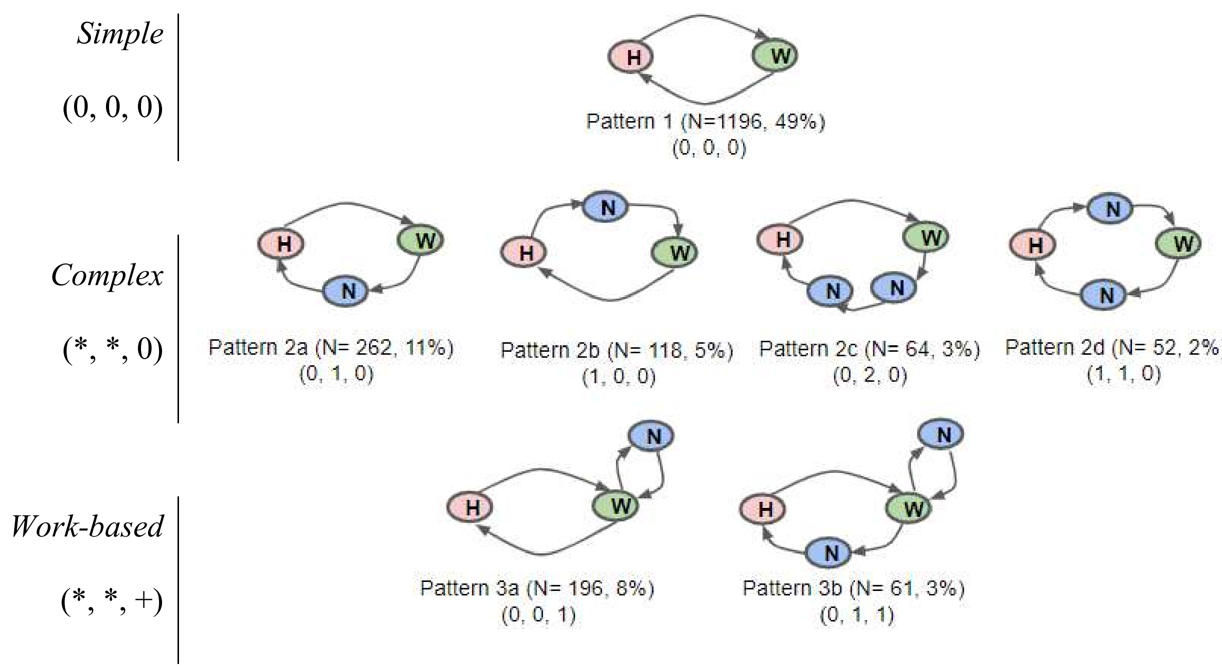


Figure 2.2 Seven dominant patterns of work tours: (1) simple work tour, (2a, 2b, 2c, 2d) complex work tour and (3a, 3b) complex tour with work-based sub-tour

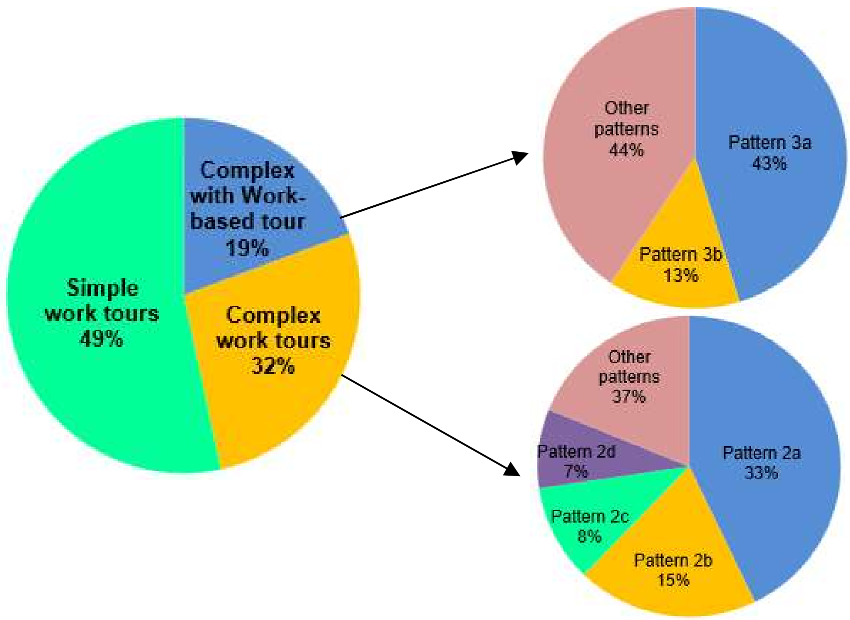


Figure 2.3 Fraction of different work tours

Figure 2.2 and 3.3 display the identified seven patterns. The simple work tour is deemed *pattern 1*. Those patterns that represents complex work tours are deemed *pattern 2,* with four sub-categories deemed as patterns 2a, 2b, 2c, and 2d based on the order of non-work activities. Last, complex tours with work-based sub-tour are deemed as *pattern 3,* with two sub-categories patterns (patterns 3a and 3b). I have also identified a complex tour pattern that consists of 70 observations (2.8 percent of total work tours). This pattern includes two work but no non-work activities. This pattern is not considered among the seven dominant patterns because NHTS data do not provide location data so it is not possible to identify the precise nature of these work activities. Therefore, these tours are considered in the analysis of the “other” category.

Figure 2.3 shows the fraction of tours for each of the three primary pattern types. A higher fraction of tours represents simple tours (49 percent). Complex work tours constitute the next most frequent group (32 percent) with sub-category pattern 2a (33 percent) and pattern 2b (15 percent) the two most frequent. This suggests that travelers who perform non-work activities as part of a work tour tend to do so primarily on the way home from work (Rafiq and McNally, 2018). Among all pattern types, complex tours with work-based sub-tour comprise 19 percent of all HBW tours, with patterns 3a and 3b constituting 43 percent and 13 percent of these tours, respectively.

2.7 Properties of Dominant Work Tours

Including a non-work stop within a work tour depends on individual activity demand (timing and duration) as well as availability of travel modes to access the activity location. Compared to more flexible travel modes, public transit usually offers less accessibility since it typically operates on a fixed route and with a fixed and often limited schedule. When a transit user makes a non-work stop within their work tour, it raises several questions:

1. Which travelers make non-work stops within their work tour?
2. When do different activity demands occur within a work tour?
3. What are the most frequent non-work activities performed by time of day?
4. How much time is spent on each of the non-work activity purposes? and
5. What modes do travelers use to access activity locations? In particular, when and where does transit tend to be utilized?

This section provides an empirical analysis of the socio-demographic and activity-travel characteristics of travelers completing each of the identified representative patterns. A set of five different activity-travel characteristics, each focusing a different aspect of activity-travel behavioral issues, are presented that address the above questions related to trips (starting time, mode, purpose) and activities (activity type, duration) involved in each pattern of tours. Note that, although each tour pattern involves a different number of trips and activities (work and non-work), the analytical means and the associated infographics used remain common to all such tour patterns. The outlines of all six social-demographics and activity-travel characteristics for each of the three tour patterns are shown in Table 2.2.

Table 2.2 Six dimensions of complex travel behavior considered

Socio-demographic characteristics	Personal (e.g. gender, age) and household-level (e.g., income, vehicle ownership) information of travelers who make tours of a certain type and their dominant socio-demographic traits
Temporal distribution of trips	An illustration of when travelers are making trips for which purposes (e.g., work, non-work, return home) throughout the whole day.
Non-work activity purpose and duration	Distribution of activity purposes and the amount of time spent in those activities for each non-work activity in a tour, if any.
Modal distribution	Distribution of transport modes for each trip involved in a tour and their durations, as well as an illustration of when those trips are started, for what purpose and by which mode.
Modal sequence	The sequence of modes used in a tour, that is, an ordered list of modes for all trips made in a tour.
Frequency of transit with other modes	An analysis showing which other modes are combined with transit in work tours of a certain type.

2.7.1 Simple Work Tour

A total of seven dominant types of work tours were identified and categorized under three broad pattern types: simple work tours (*pattern 1*), complex work tours (*pattern group 2*), and complex tours with work-based sub-tour (*pattern group 3*). This section discusses the socio-demographic and travel characteristics of travelers making simple work tours.

2.7.1.1 Socio-demographic characteristics

The distribution of socio-demographic characteristics of travelers who make simple work tours is shown in the spider plot in Figure 2.4. The prevailing socio-demographic characteristics under this category of tours are married male with higher income. They typically belong to households that have at least two workers and no children (aged between 6 and 17) and that have more than one vehicle (the individuals being the primary driver of one of those vehicles). The individuals reportedly have less flexibility regarding work arrival time.

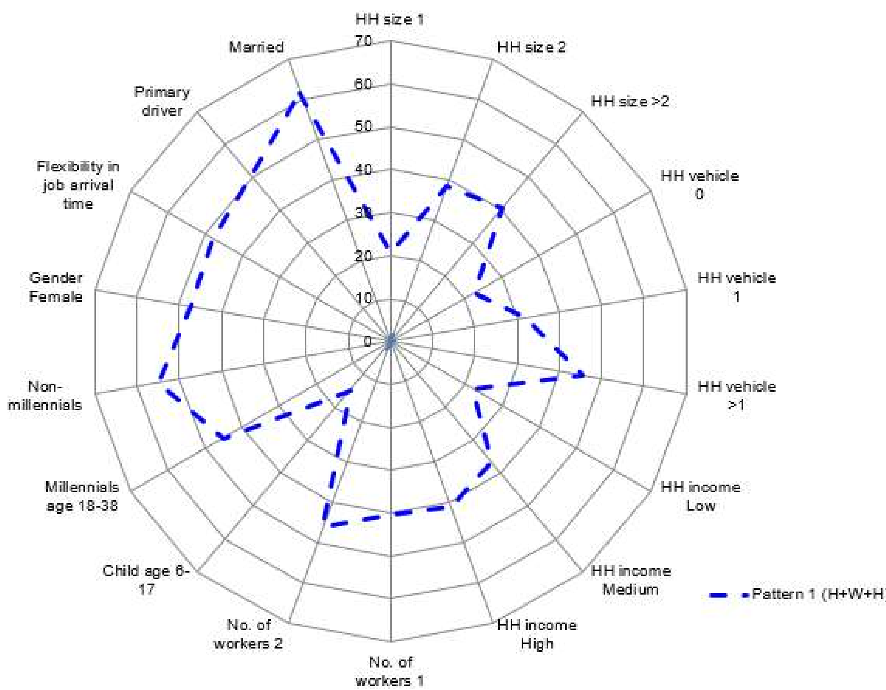
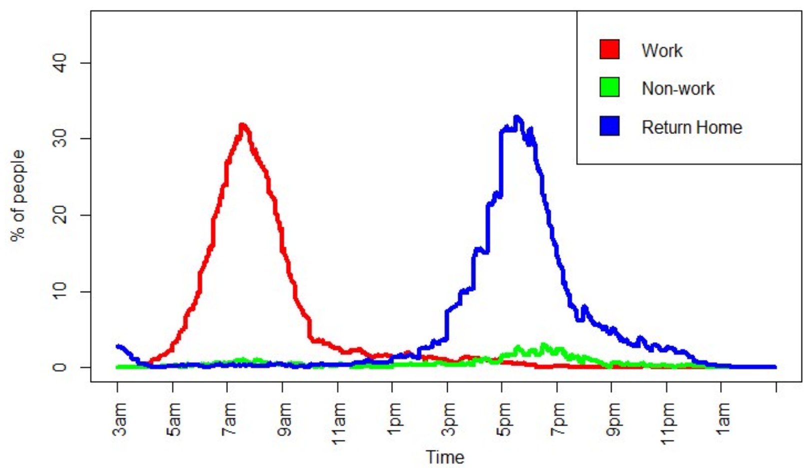


Figure 2.4 Socio-demographic characteristics of travelers in simple work tours

2.7.1.2 Temporal distribution of trips

The temporal distribution of activities or 'time in motion' of travelers of Pattern 1 is displayed in Figure 2.5. The figure shows the fraction of travelers who reported to be in a trip for work, non-work, and return to home purposes at a given time in a total 24-hours period. Note that the figure covers *all* trips made in an entire day, not only the work tour trips. For simple work tours, non-work activities are not part of the work tour but could be part of home-based non-work tours performed either before or after the work tour (only home-based work tours are analyzed in this study). For simple work tour makers, such non-work purposes can be seen in the later PM peak (3pm—7pm) and evening period.



H-W-H (n= 1196)

Figure 2.5 Time in Motion for three activity purposes in simple work tours

2.7.1.3 Modal distributions

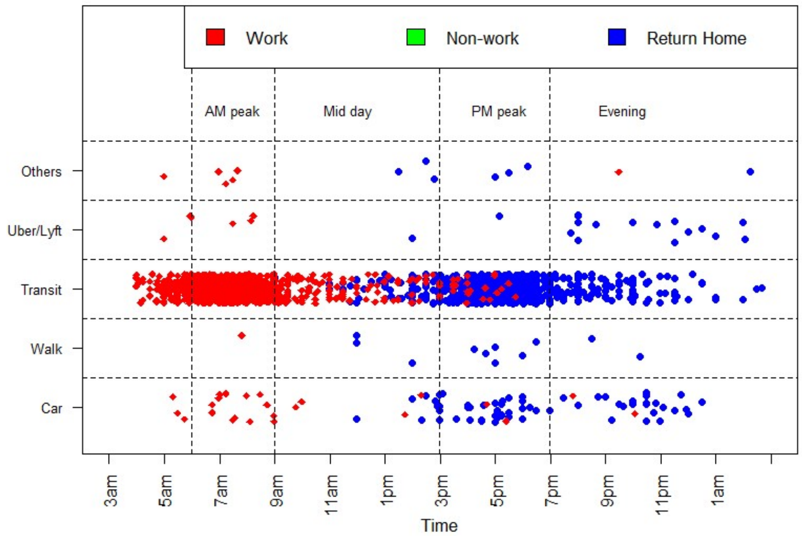
Each simple work tour has two trips: home to work and from work to return home. Table 2.3 shows the distribution of tours by modes for each of the trips in simple work tours. The table also shows the mean travel time for the associated mode. Note that, single or multiple modes can be used in a trip. If multiple modes are used, only the *primary* mode is reported in the table. The mode that took the longest travel time is considered as the primary mode. It is observed that public transit is predominantly used in both legs in most simple work tours (in about 90 percent of tours) with a mean travel duration of 63 minutes and 69 minutes for home to work and return to home trip respectively. A very small fraction of tours has their both trips made by private vehicles (~5 percent) or on foot (~1 percent).

Table 2.3 Percentage of tours and average duration for trip modes in simple work tours

	H-W-H (n= 1196)			
	Fraction of tours		Mean travel duration (min.)	
	H-W	W-H	H-W	W-H
Single mode	97.6	97.1	---	---
Multiple modes	2.4	2.9	---	---
Primary mode *				
Public transit	92.9	88.7	62.8	68.6
Walk	0.3	1.3	37.3	32.1
Private vehicle	5.3	7.9	16.4	24.5
Ride-hailing	0.7	1.3	34.0	29.1
Other	0.9	0.8	46.5	48.7

Notes: Home-based work tours are identified by individuals who used public transit in at least one trip segment. * *if multiple modes are used in a trip, only the primary mode is reported.*

Now it is understood that which trips are made by which modes, it will be interesting to know when those trips are started and how they span a 24-hour day. Figure 2.6 shows such a plot where each trip is represented by a dot and the x-axis shows the time of day when the associated trip started (trip departure time) and the y-axis shows which mode is used (depending on the mode is used, each trip/dot is placed in the corresponding y-axis band). Furthermore, dots are color coded based on the purpose which the trip is made for (red for work, green for nonwork and blue to returning home). For the sake of better illustration, the horizontal axis, i.e., the time of day, is again segmented into four conventional travel periods: AM peak (6 am to 9 am), Midday (9 am to 3 pm), PM peak (3 pm to 7 pm), and Evening (after 7 pm). From Figure 2.6, it is noticed that for simple work tours, transit demand is higher in both the AM and PM peak periods. Transit departure times tend to be earlier than for other modes (at least for travelers who use transit for at least one trip on a work tour).

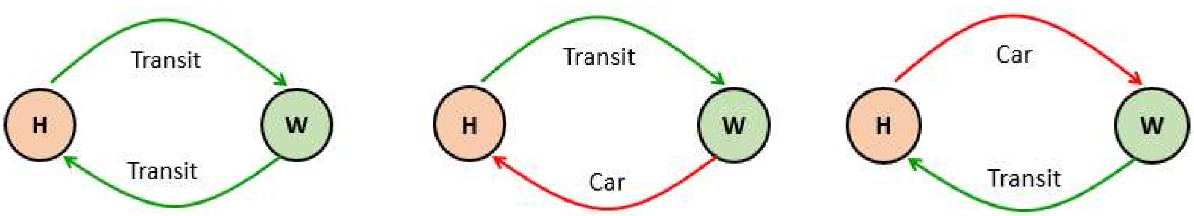


H-W-H (n= 1196)

Figure 2.6 Modal distributions by three activity purposes in simple work tours

2.7.1.4 Modal sequence by tour

While the preceding discussion focused on mode use for each trip independently, I now consider mode usage as a *sequence* within a tour to illustrate how transit commuters connect modes in their work tours. For this, I represent the modes chosen in all trips in a sequence diagram like the one shown in Figure 2.7.



Most frequent sequence (80% tours)

Second-most frequent sequence (5% tours)

Third-most frequent sequence (1% tours)

H-W-H (n= 1196)

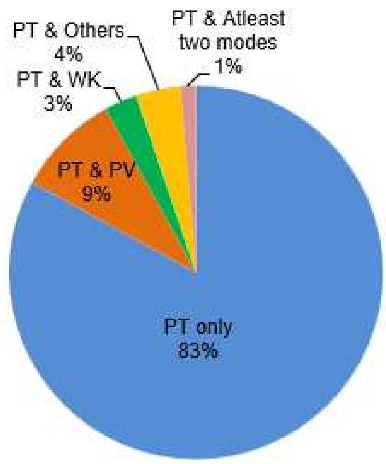
Figure 2.7 Frequent modal sequences in simple work tours

Instead of showing all sequences that may exist for tours of a certain pattern (which may be fairly large for tours involving multiple trips), I count how many times a given modal sequence appears and report only the top three frequent sequences.

The top three frequent modal sequences for simple work tours are (transit, transit), (transit, car), and (car, transit) that constitute about 80 percent, 5 percent, and 1 percent of tours respectively, as shown in Figure 2.7. That means, in about 80 percent of home-based simple tours, transit is used for both the work-bound and home-bound trips, nearly 5 percent tours involve transit in the first trip and private vehicle in the return leg, and about 1 percent tours involve the reverse mode choice. In the latter two modal sequences, travelers reported being the passenger in the car, which denotes the pick-up or drop off by family members or friends. On average travel by transit takes about 63 minutes to work in the morning peak period and about 67 minutes to return home in the evening peak period, as compared to 16 minutes and 25 minutes by private vehicle, respectively (cf. Table 2.2).

2.7.1.5 Frequency of transit with other modes

Next, I examine the frequency of transit use with other travel modes in an aggregate level. I produce a pie chart to report this. Figure 2.8 shows such a pie chart for simple work tours. Each sampled respondent used transit for at least one trip segment within the work tour, but transit was used in combination with walk (PT&WK), private vehicle (PT&PV), other modes except walk and private vehicle (PT&Others), or any two or more combinations of modes. Figure 2.8 shows that the share of transit only tours (PT only) is the largest (83 percent) for simple work tours. It will be interesting to observe how this fraction varies for *complex* tours, which is discussed in later sections.



H-W-H (n= 1196)

Figure 2.8 Frequency of transit with other modes in simple work tours

2.7.2 Complex Work Tours

This section represents the properties of the second category of tour (pattern group 2), that is complex work tour. Note again, four dominant patterns (2a, 2b, 2c, and 2d) are identified under this work tour category.

2.7.2.1 Socio-demographic characteristics

Figure 2.9 depicts the distribution of socio-demographic characteristics for pattern group 2, in reference to pattern 1. In contrast to simple work tour makers, travelers who make complex work tours are typically females with medium or high income (see Figure 2.4). They report more than two members in their household, are typically the only worker in the household, and have flexibility in their work arrival time. Their households tend to have at least one vehicle but the traveler is not considered the primary driver of that vehicle. They report to have more children between 6 and 17 years of age in their household compared to simple tour makers. A higher percentage of this group of travelers belong to the non-millennial group (age > 38 years), and a lower percentage report being married.

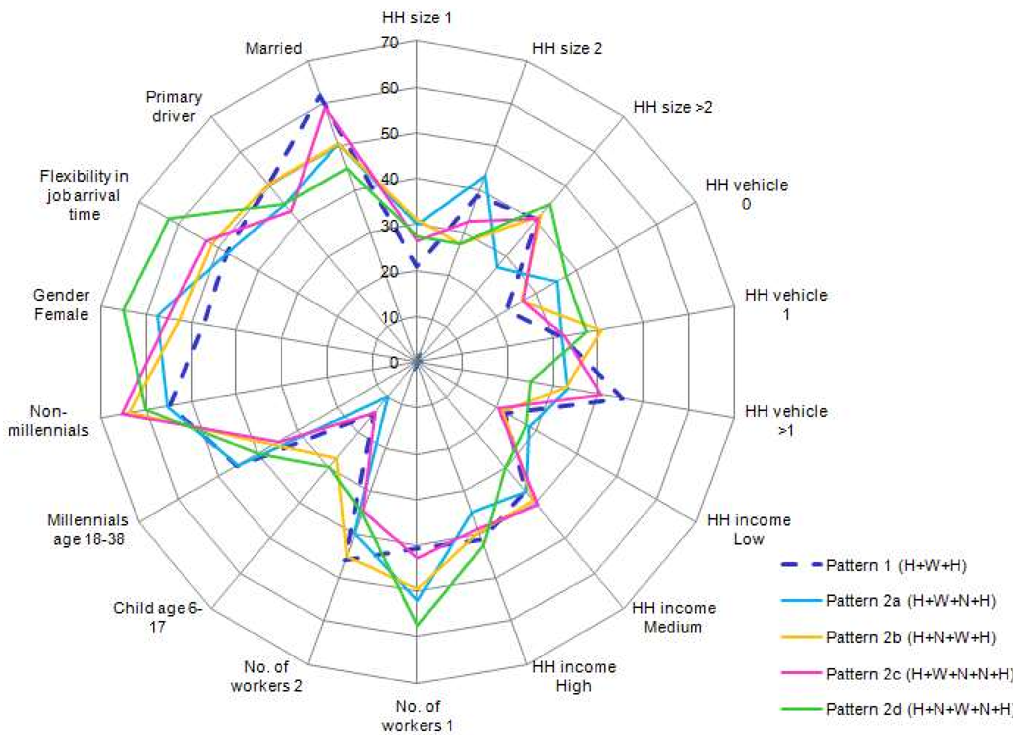
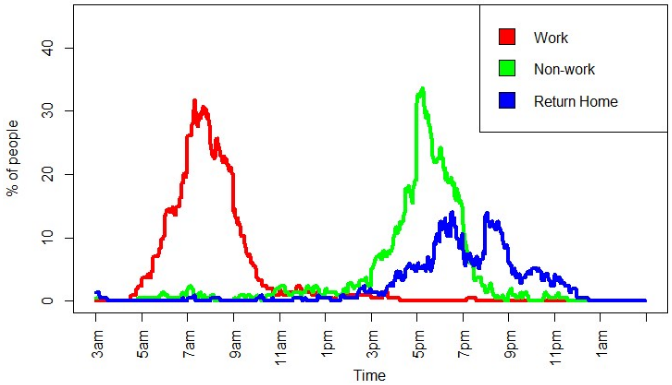


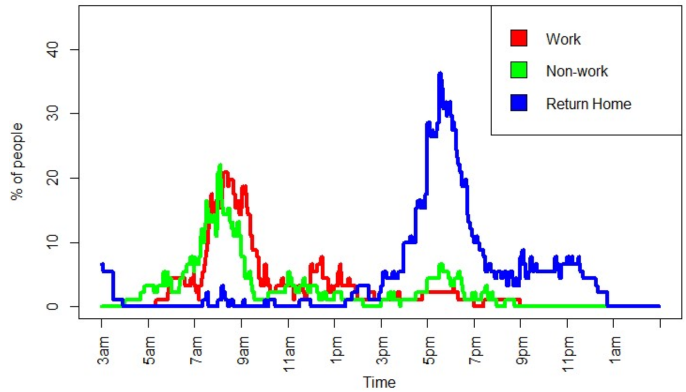
Figure 2.9 Socio-demographic characteristics of travelers in complex work tours

2.7.2.2 Temporal distribution of trips

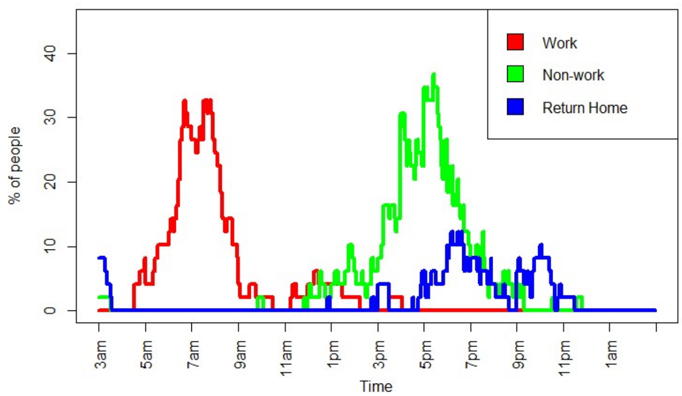
The time in motion plots for complex work tour makers are shown in Figure 2.10. Conventional patterns defined by individual activity starting times is identifiable in the first few figures but the distributions for more complex tours clearly illustrate the chaining effects before, or after work activity. The earlier initial departure time from home by travelers who make non-work activities before the work activity (Patterns 2b and 2d) is observed in Figure 2.10. Interestingly, complex tours with one non-work stop on their return home (Pattern 2a) have a bimodal distribution of return home times, peaking around 6 pm and 8 pm. This suggests that some travelers also have a home-based non-work tour that is performed after the work tour.



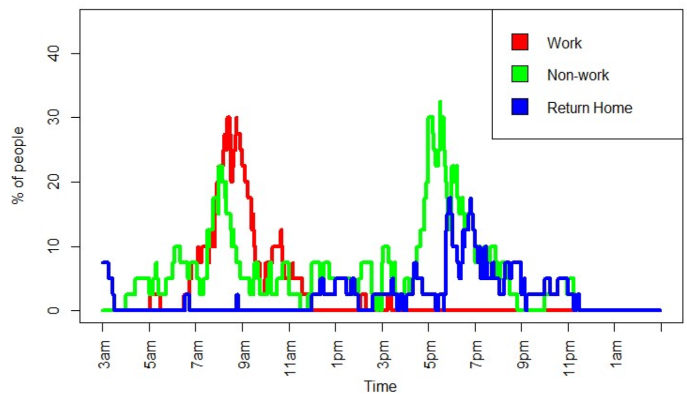
2a. H-W-N-H (n= 262)



2b. H-N-W-H (n= 118)



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

Figure 2.10 Time in Motion for three activity purposes in complex work tours

2.7.2.3 Non-work activity type and duration

A complex work tour may involve multiple trips and one or more non-work activities. To analyze complex tours in depth, I examine the mode and travel duration for each trip of a tour as well as the purposes and their durations for each non-work activities within the tour. Table 2.4 and Table 2.5 show such results for four identified patterns under pattern group 2. The tables help us understand how the distribution of modes and their durations differ (or remain similar, if so) across different trips in a certain tour pattern. Similarly, for non-work activities, they show

how non-work activity purposes and the amount of time spent on them differ across the different tour patterns, particularly when non-work activities align themselves with respect to work (before or after or both). In this subsection, I focus on attributes of non-work activities and defer the discussion on modes in the next subsection.

Table 2.4 Percentage of tours for trip modes and non-work activities in complex work tours

	2a. H-W-N-H			2b. H-N-W-H			2c. H-W-N-N-H				2d. H-N-W-N-H			
	N = 262			N= 118			N = 64				N = 52			
	H-W	W-N	N-H	H-N	N-W	W-H	H-W	W-N	N-N	N-H	H-N	N-W	W-N	N-H
Single mode	97.3	96.2	98.1	99.2	93.2	97.5	100	98.0	100	96.9	98.1	96.2	98.1	96.2
Multiple modes	2.7	3.8	1.9	0.8	6.8	2.5	0.0	1.6	0.0	3.1	1.9	3.8	1.9	3.8
Primary mode*														
Public transit	89.7	64.8	35.2	45.8	57.6	72.9	85.9	54.7	23.4	26.6	38.5	61.5	76.9	23.1
Walk	3.4	16.1	20.7	23.7	28.8	6.8	3.1	15.6	23.4	18.8	26.9	28.8	13.5	32.7
Private vehicle	4.6	16.1	39.1	29.7	12.7	12.7	6.3	18.8	48.4	51.6	30.8	7.7	7.7	38.5
Ride-hailing	1.5	1.5	4.2	0.0	0.0	5.9	3.1	6.3	3.1	3.1	1.9	0.0	0.0	1.9
Other	0.8	1.5	0.8	0.8	0.8	1.7	1.6	4.7	1.6	0.0	1.9	1.9	1.9	3.8
Non-work activity														
School/Daycare/Religious		4.6		10.2				6.3	4.7		9.6		5.8	
Medical/Dental		5.0		2.5				4.7	1.6		3.8		1.9	
Shopping/Errands		**39.5**		18.6				**34.4**	**42.2**		7.7		28.8	
Social/Recreational		14.9		5.1				12.5	14.1		1.9		13.5	
Pick up/drop off		7.7		**24.6**				12.5	4.7		**38.5**		**32.7**	
Buying Meals		16.5		**26.3**				18.8	26.6		28.8		7.7	
Others		11.9		12.7				10.9	6.3		9.6		9.6	

Notes: Home-based work tours are identified by individuals who used public transit in at least one trip segment. * *if multiple modes are used in a trip, only the primary mode is reported.*

For travelers who perform two non-work activities on the return home (*pattern 2c*), most report a shopping activity as the first non-work stop (on about 34 percent of tours), with the next most frequent non-work task being buying meals (on about 19 percent of tours). The same two non-work activity purposes dominate in their second non-work stop. With respect to activity duration, travelers spend on average about 26 to 48 minutes for shopping and about 57 to 72 minutes for buying meals (substantially greater than meals prior to work). This difference is likely due to both greater flexibility after work and the cultural nature of meals by time of day (with after work meals often involving family or friends).

Table 2.5 Average duration (minutes) for trip modes and non-work activities in complex work tours

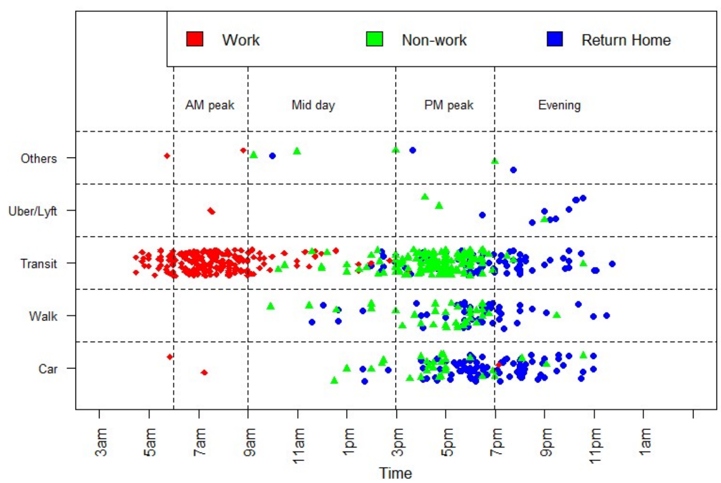
Primary mode	2a. H-W-N-H			2b. H-N-W-H			2c. H-W-N-N-H				2d. H-N-W-N-H			
	N = 262			N= 118			N = 64				N = 52			
	H-W	W-N	N-H	H-N	N-W	W-H	H-W	W-N	N-N	N-H	H-N	N-W	W-N	N-H
Public transit	56.0	54.1	51.4	47.8	58.3	65.2	55.7	59.5	35.5	44.5	56.1	49.1	51.0	47.6
Walk	24.0	14.4	18.7	11.2	10.0	31.5	19.5	11.3	10.8	21.5	9.6	8.7	15.9	15.6
Private vehicle	13.4	39.5	19.4	12.4	12.7	26.7	25.0	33.3	19.2	16.2	14.9	14.5	30.5	26.7
Ride-hailing	24.5	40.0	21.8	0.0	0.0	32.0	24.0	13.5	19.0	12.5	10.0	0.0	0.0	30.0
Other	45.0	35.3	17.5	15.0	7.0	13.5	79.0	21.7	8.0	0.0	40.0	17.0	15.0	30.0
Non-work activity														
School/Daycare/Religious		266.0		156.9				117.0	122.0		53.0		132.3	
Medical/Dental		67.7		125.3				81.7	60.0		67.5		108.0	
Shopping/Errands		37.0		20.5				25.6	47.9		5.0		24.9	
Social/Recreational		161.4		90.8				95.3	168.3		28.0		140.6	
Pick up/drop off		25.6		5.9				13.6	6.7		9.8		12.4	
Buying Meals		59.7		11.1				57.3	72.4		10.1		70.0	
Others		94.5		80.2				174.6	85.5		63.4		78.8	

With the case of two non-work activities before and after work (*pattern 2d*), it is interesting to note that the purpose of the two non-work activities seem to be negatively correlated, that means, task of a certain type performed before work has a less chance to appear again after work and vice versa. For example, shopping/errands and social/recreation happens less often before work than after work (7.7 percent vs 28.8 percent for shopping and 1.9 percent vs 13.5 percent for social) whereas buying meals patterns is the converse (28.8 percent and 7.7 percent before and after work respectively). The only exception to this trend is pick up/drop off, which occurs quite equally in both legs (38.5 percent and 32.7 percent), possibly due to picking up a child from school/daycare after work who has been dropped off before going to work.

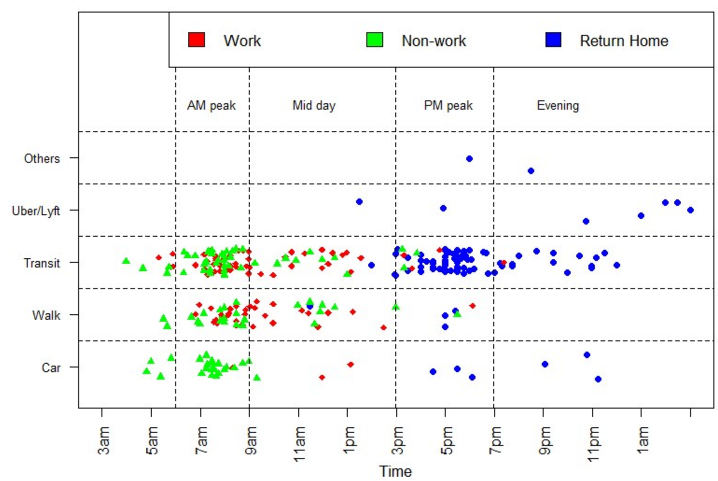
As discussed, the most dominant activity performed on the way to work is pick up/drop off. It may be worthwhile to investigate how transit commuters manage to pick up/drop off someone on their way to work or way home since use of transit often involves a change of modes (access/egress modes) and therefore, does not provide as much flexibility and convenience as a private vehicle does. A more detailed discussion is provided later.

2.7.2.4 Modal distributions

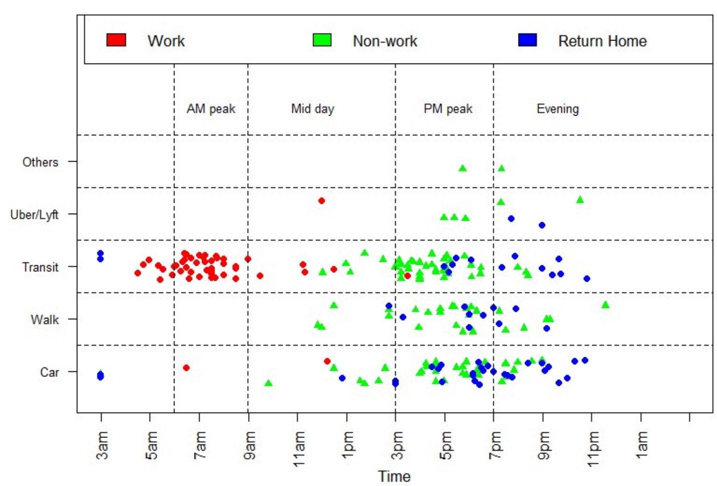
Unlike simple work tours, complex tours combine work with non-work activities in a single tour. It will be then interesting to observe which transport modes are chosen for work and non-work trips. Arguably, private vehicles provide the most flexibility in managing such needs. Thus, individuals with access to a private vehicle over the duration of a work tour would typically find it flexible and convenient to connect non-work activity demands on a work tour.



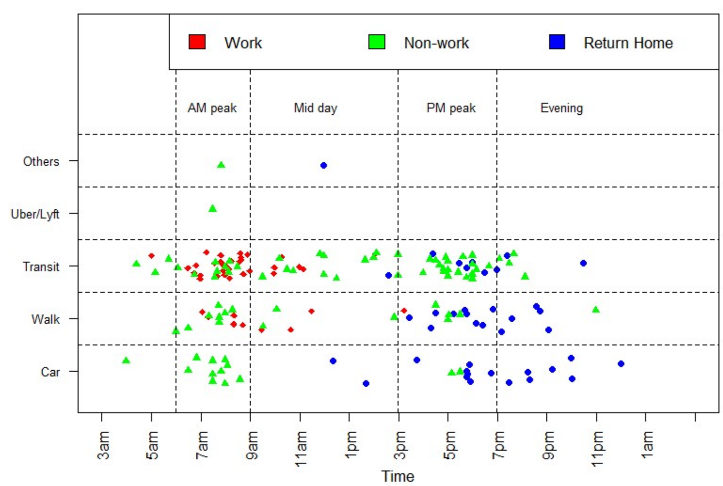
2a. H-W-N-H (n= 262)



2b. H-N-W-H (n= 118)



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

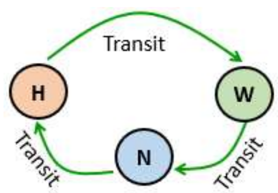
Figure 2.11 Modal distribution by three activity purposes in complex work tours

Since public transit usually operates on a fixed route with a fixed schedule, it cannot provide as much flexibility to accommodate non-work activity stops within a work tour. It may be worthwhile to investigate how travelers who use transit for at least one trip within a work tour manage to connect their non-work activities. What are the combinations of modes used within a tour? To better understand the modal distribution of trips under complex work tours, I examine the top section (unshaded) of Table 2.4 (distribution of tours by travel mode for each trip within a tour) and the 'modal distributions' plot in Figure 2.11. It is observed that travelers who have non-work activities on their way to work (pattern 2b) reflect different mode choices returning home than for travelers who perform non-work activities on the way home (pattern 2a, 2c, and 2d). Table 2.4 demonstrates that for pattern 2b transit is dominant for the return home trip, while for the other three patterns in this category, private vehicles dominate on the return home trip. It may be seen, from Figure 2.11, that very few work tours use ride-hailing services or other modes, regardless of trip purpose, when transit is also used on the tour. Last, in the two tour categories where a non-work activity occurs on the way to work (pattern 2b and 2d), a higher fraction of car and walk trips are recorded during AM peak period (Table 2.4 and Figure 2.11).

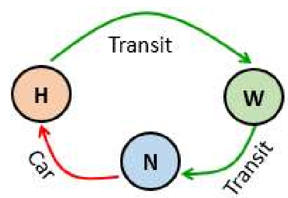
2.7.2.5 Modal sequence by tour

Figure 2.12 shows the top three most frequent modal sequences in the identified four patterns of complex tours. I also examine the average travel time spent on each trip by different modes within a tour from Table 2.5. Combined, the analysis contributes to the understanding of mode usage in activity-travel patterns in terms of activity type and temporal proximity.

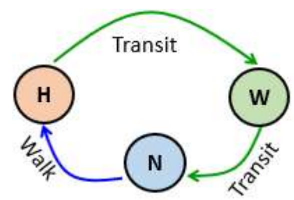
The four patterns of complex work tours show variations in the sequence of mode usage. In *pattern 2a*, transit is reported as travel mode for all the three trips in the largest fraction of tours (about 20 percent), followed by transit to work and non-work trips and then private vehicle for the return home trip (about 18 percent). In 15 percent of the tours of this pattern, transit is used for the first two trips and walk is reported for the last trip. This case may be attributed that a choice of a non-work activity in close proximity to home (19 minutes walking time (Table 2.5)).



Most frequent
sequence (20% tours)

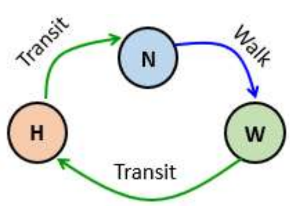


Second-most frequent
sequence (18% tours)

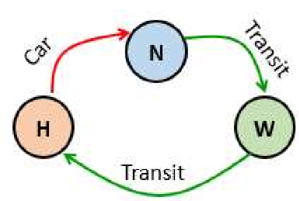


Third-most frequent
sequence (15% tours)

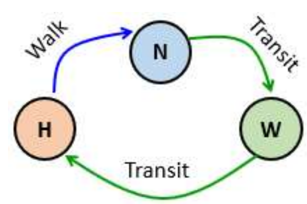
2a. H-W-N-H (n= 262)



Most frequent
sequence (17% tours)

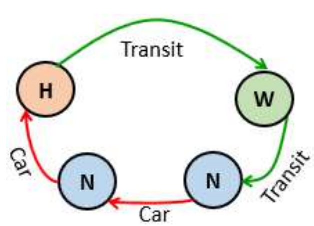


Second-most frequent
sequence (16% tours)

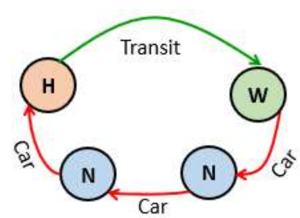


Third-most frequent
sequence (13% tours)

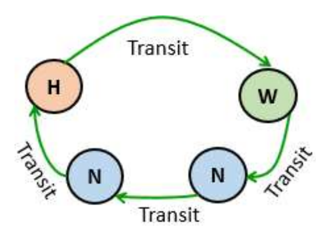
2b. H-N-W-H (n= 118)



Most frequent
sequence (20% tours)

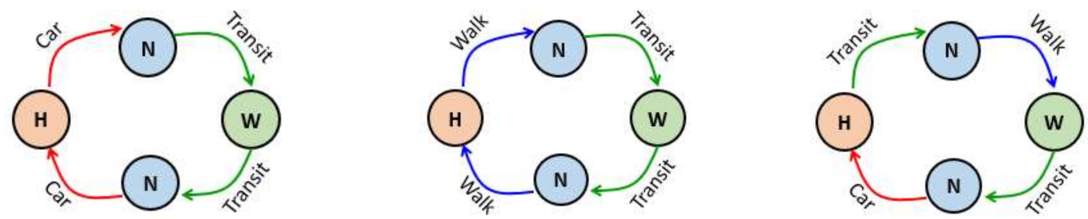


Second-most frequent
sequence (15% tours)



Third-most frequent
sequence (11% tours)

2c. H-W-N-N-H (n= 64)



Most frequent sequence (13% tours) | Second-most frequent sequence (11% tours) | Third-most frequent sequence (9% tours)

2d. H-N-W-N-H (n= 52)

Figure 2.12 Frequent modal sequences in complex work tours

In *pattern 2b*, the highest portion of tours (about 17 percent) involves transit use to a non-work activity close to work, followed by on average a 10-minute walk to work (cf. Table 2.5) to reach to their workplace. About the same portion of tours (about 16 percent) use a private vehicle for the first trip to a non-work activity, then take transit to reach the workplace (and also return home from work via transit). About 13 percent tours involve an 11-minute walk (Table 2.5) to the station, then doing one non-work activity there and taking transit for both work and return home trips. On these tours, the non-work activities include buying meals (26 percent), pick up/drop off (25 percent), or shopping (19 percent) (cf. Table 2.4). The use of private vehicle for only the first trip in the tour can have several explanations: (1) travelers are dropped off at a transit station but record it as dropping off someone; (2) travelers drop off someone at their activity location and then drive to the station; (3) travelers drive a vehicle to a station and perform a non-work activity there before taking transit to work, leaving the vehicle at the station (but not having a corresponding trip at the end of the tour); or (4) travelers drive to the station with another traveler. Uncertainty in properly recording complex travel confounds interpretation of the data.

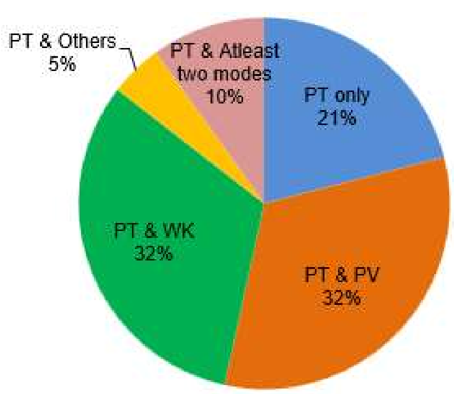
Note that neither case 1 nor case 4 represent pick up/drop off activities performed by a survey respondent. Case 1 corresponds to being dropped off by someone else and case 4 involves traveling in a private vehicle with someone to 'change mode' at station. To make further inquiries on these issues, the particular tours are analyzed where travelers choose modes in the sequence in question (private vehicle (NW) → transit (W) → transit (H)) and record the 'pick up/drop off' in their activity list. In 45 percent of the tours, people drop off a child at school by using a private vehicle for the first trip. then drive to the station, park the vehicle, and take transit to work (case 2). About 14 percent of the tours represent case 1 suggesting that people misreported the drop off activity in their activity-travel diary. On the other hand, around 21 percent of tours correspond to case 3 while no tours stand for case 4.

In *pattern 2c* where travelers make two non-work stops on their way home, 20 percent of tours use transit for the first trip to work. On the return home portion, transit can be used to travel to the first non-work location followed by a pick up by someone with a private vehicle to access the second non-work activity (which is located an average of 16 minutes from home (Table 2.5)). The final return home trip is with that vehicle. In some of the tours (about 15 percent), transit is used for only the first trip but later picked up by their household members from the workplace by private vehicle to complete the rest of the tour.

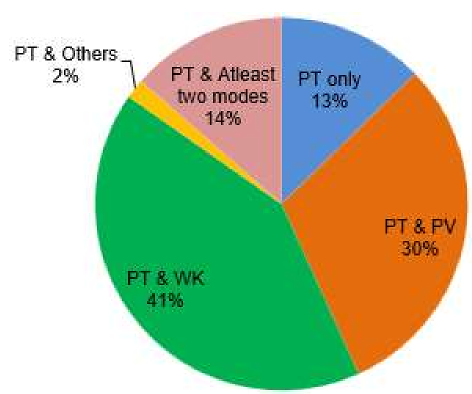
The most frequent modal sequence in *pattern 2d* is to use a private vehicle for the first and last trips (non-work activities both before and after work) and to use transit for the two middle trips (from non-work to work and the reverse from work to non-work on the way home). The most frequent non-work activity purpose recorded for both directions is drop off/pick up someone (between 33 to 39 percent of tours, Table 2.4). Similar to pattern 2b, this activity purpose invokes some interesting questions. After analyzing the tours where the non-work activity purpose was 'drop off/pick up', I conclude that in most of these tours (about 48 percent) the travelers either use private vehicle or walk to drop off children at school/daycare and then drive or walk to a station to take transit to work. After work, they reverse the morning commute (pick up and return home). It appears that some people (about 14 percent of tours) are dropped off but incorrectly report their own drop off/pick up activity in their activity list.

2.7.2.6 Frequency of transit with other modes

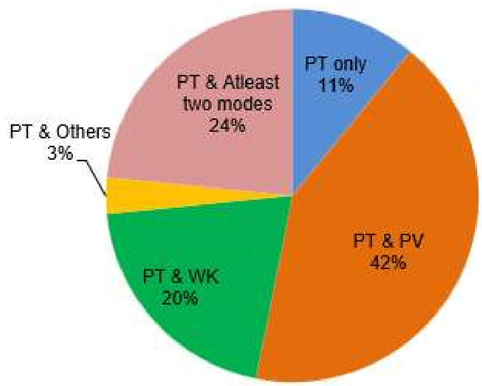
From the above analysis, it is evident that transit alone cannot meet all travel demands. While this is not surprising, what is of interest is that most transit commuters use multiple modes to access different activities within a daily work tour. Figure 2.13 depicts the proportion of tours with a combination of travel modes within a complete work tour. Note again that each sampled respondent used transit for at least one trip segment within the work tour, but transit was used in combination with walk, private vehicle, other modes except walk and private vehicle, or any two or more combinations of modes. Interestingly, as discussed earlier that when travelers simply go to their workplace and come back (simple tours), the share of transit only tours (PT only) is the largest (83 percent). But when they mix any non-work activity before or after work, the 'PT only' fraction declines and travelers tend to combine transit with other travel modes particularly private vehicles, which causes private vehicle share (PT&PV) to increase (e.g. for pattern 2c, the PT only share becomes 11 percent and PT&PV share rises to 42 percent).



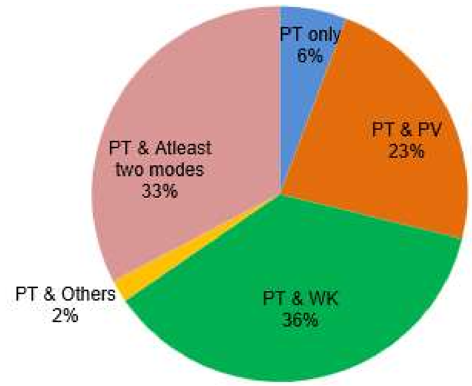
2a. H-W-N-H (n= 262)



2b. H-N-W-H (n= 118)



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

Figure 2.13 Frequency of transit with other modes in complex work tours

2.7.3 Complex Tour with Work-based Sub-tour

In this section, the socio-demographic characteristics and travel behavior of travelers who make a work-based sub-tour within a home-based tour (pattern group 3) are discussed. Note again that two dominant work tour patterns (3a, 3b) are identified representing this work-based sub-tour category.

2.7.3.1 Socio-demographic characteristics

Figure 2.14 shows the socio-demographic characteristics in a spider plot for this group, in reference to the basic pattern (pattern 1). It is found that pattern group 3 travelers are generally male, younger or millennials (age 18–38), married, and with higher incomes. Moreover, most of their households consist of two members where both of them are employed. Very few travelers in this category have child in their household. Again, this group of travelers own at least one

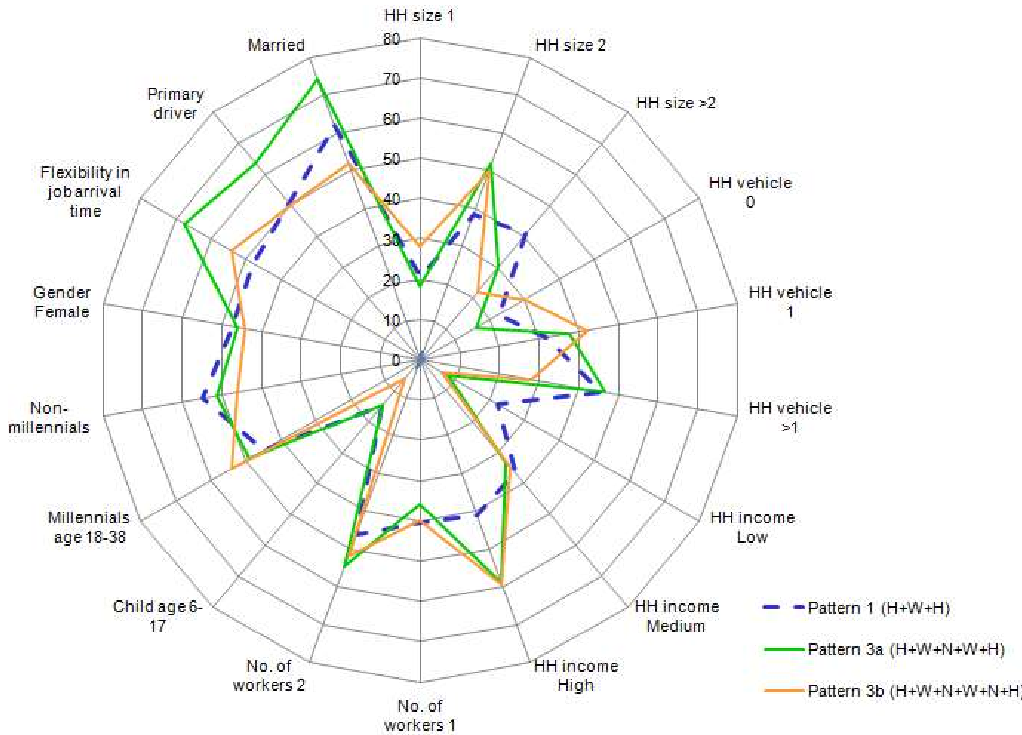
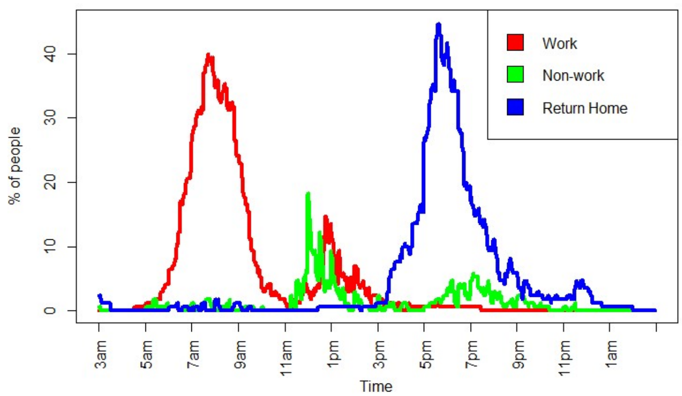


Figure 2.14 Socio-demographic characteristics of travelers in complex tours with work-based sub-tour

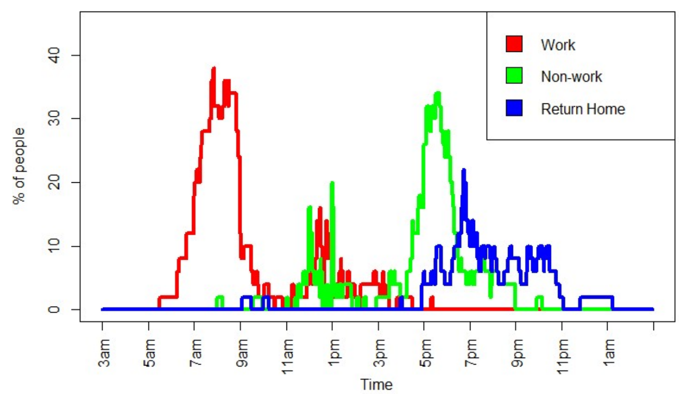
household vehicle in the household and they are considered as the primary driver of that vehicle. A much higher proportion of travelers in this group have flexibility in their job arrival time compared to simple or complex work tour makers. Furthermore, in terms of household income, a greater proportion of these travelers belong to the higher income class than the travelers from the other two tour categories. Figure 2.14 also shows that travelers in pattern 3a are more likely to be married and have higher flexibility in job arrival time than travelers in pattern 3b. The reason for reporting higher flexibility in job arrival time is perhaps due to the nature of their job (78 percent of travelers in pattern 3a reported doing professional, managerial or technical job compared to 68 percent travelers of pattern 3b).

2.7.3.2 Temporal distribution of trips

Next, I examine the time in motion plot for this tour category (Figure 2.15). Recall that the time in motion plot shows the fraction of travelers is in a trip for a given purpose at different times of a day. Since this category of tours involve making a sub-tour from workplace, the figure illustrates dual trips to work reflecting the case of accommodating a non-work activity mid-day and then return to work.



3a. H-W-N-W-H (n= 196)



3b. H-W-N-W-N-H (n= 61)

Figure 2.15: Time in Motion for three activity purposes in complex tours with work-based sub-tour

2.7.3.3 Non-work activity type and duration

For complex tours with work-based sub-tour, workers have mid-day visit to a non-work activity location from their workplace and then return to the workplace (Patterns 3a and 3b, Figure 2.15). Such behavior can be better explained by Table 2.6 and Table 2.7, which suggest that during midday in most of these tours (about 74 to 77 percent, Table 2.6), workers report to go out for lunch from their workplace, spending about 23 to 28 minutes and then returning to work (Table 2.7). In *pattern 3b*, an additional trip to a non-work location is made, often shopping (about 34 percent of tours, Table 2.6) with an average duration of about 28 minutes (see Table 2.7).

Table 2.6 Percentage of tours for trip modes and non-work activities in complex tours with work-based sub-tour

	3a. H-W-N-W-H				3b. H-W-N-W-N-H				
	N = 196				N = 61				
	H-W	W-N	N-W	W-H	H-W	W-N	N-W	W-N	N-H
Single mode	98.5	100	99.5	96.4	100	100	100	93.4	96.7
Multiple modes	1.5	0.0	0.5	3.6	0.0	0.0	0.0	6.6	3.3
Primary mode*									
Public transit	93.4	4.1	4.6	86.7	93.4	9.8	9.8	60.7	37.7
Walk	1.5	91.8	92.3	2.0	1.6	86.9	86.9	24.6	21.3
Private vehicle	5.1	2.6	3.1	8.2	3.3	3.3	3.3	13.1	34.4
Ride-hailing	0.0	0.5	0.0	1.0	0.0	0.0	0.0	0.0	6.6
Other	0.0	1.0	0.0	2.0	1.6	0.0	0.0	1.6	0.0
Non-work activity									
School/Daycare/Religious		1.5				1.6		1.6	
Medical/Dental		1.5				3.3		1.6	
Shopping/Errands		9.7				9.8		**34.4**	
Social/Recreational		2.0				1.6		18.0	
Pick up/drop off		0.5				0.0		6.6	
Buying Meals		**77.0**				**73.8**		21.3	
Others		7.7				9.8		16.4	

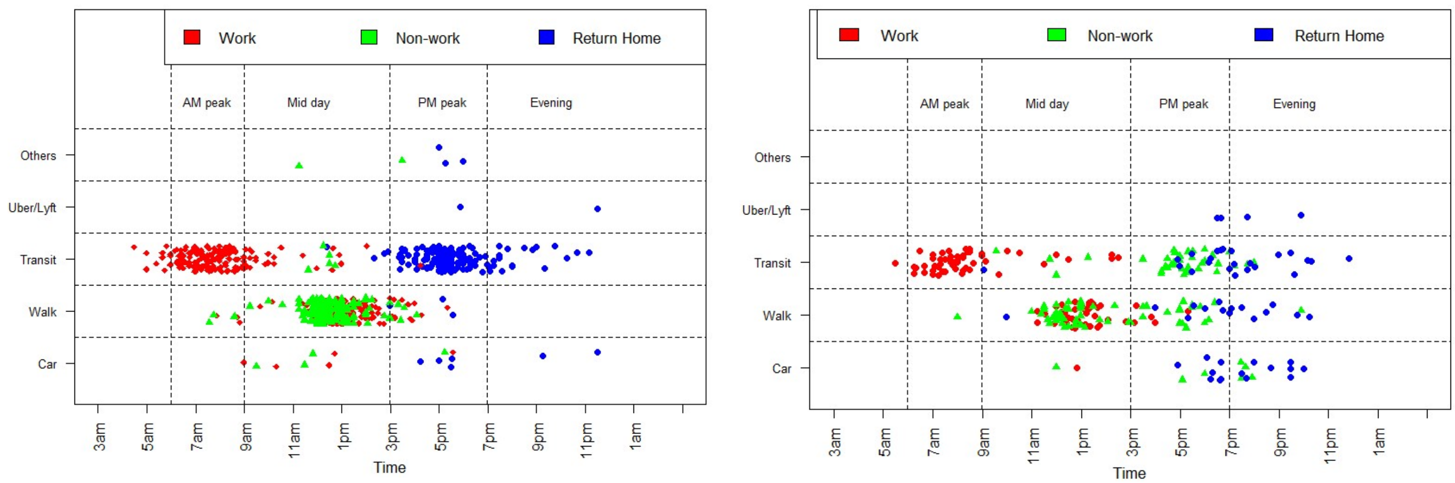
Notes: Home-based work tours are identified by individuals who used public transit in at least one trip segment. * *if multiple modes are used in a trip, only the primary mode is reported.*

Table 2.7 Average duration for trip modes and non-work activities in complex tours with work-based sub-tour

Primary mode	3a. H-W-N-W-H				3b. H-W-N-W-N-H				
	N = 196				N = 61				
	H-W	W-N	N-W	W-H	H-W	W-N	N-W	W-N	N-H
Public transit	60.2	22.1	37.1	63.0	51.0	19.7	21.5	48.3	51.3
Walk	25.0	8.2	8.3	31.3	5.0	6.9	7.6	12.3	10.5
Private vehicle	14.8	12.2	66.2	15.6	25.0	12.5	10.0	23.0	16.3
Ride-hailing	0.0	10.0	0.0	24.5	0.0	0.0	0.0	0.0	19.0
Other	0.0	12.5	0.0	43.8	21.0	0.0	0.0	19.0	0.0
Non-work activity									
School/Daycare/Religious		45.7				44.0		75.0	
Medical/Dental		65.0				42.5		50.0	
Shopping/Errands		27.5				36.7		28.0	
Social/Recreational		36.3				35.0		148.0	
Pick up/drop off		10.0				0.0		16.3	
Buying Meals		28.3				22.5		61.6	
Others		44.1				39.3		88.4	

2.7.3.4 Modal distributions

Similar to simple and complex tours, the 'modal distributions' plot is prepared for work-based tours and presented in Figure 2.16. The figure shows that transit is the dominant mode for all the trips within the tour except the midday trips to non-work activity locations. In about 87 to 92 percent of these tours, these midday trips are made by walking (see Table 2.6 and Figure 2.16). Such behavior corresponds to conventional lunch hour activity, likely in densely developed areas, such as lunch activity within walking distance of the workplace.



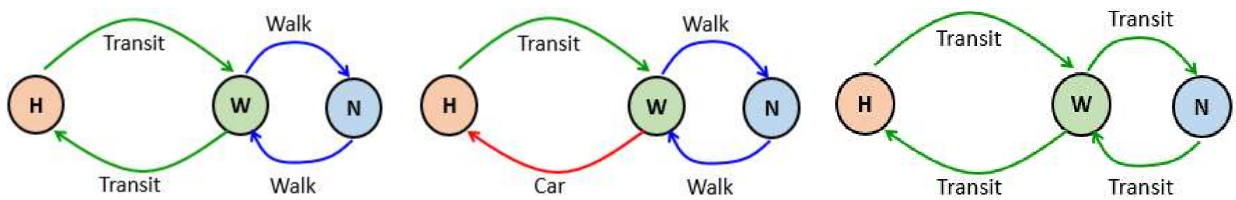
3a. H-W-N-W-H (n= 196) **3b. H-W-N-W-N-H (n= 61)**

Figure 2.16 Modal distribution by three activities in complex tours with work-based sub-tour

Again, in a very few tours, ride-hailing and other modes are used regardless of trip purpose. In *pattern 3b,* a considerable fraction of travelers (34 percent), use private vehicles for return home purpose (see Table 2.6 and Figure 2.16).

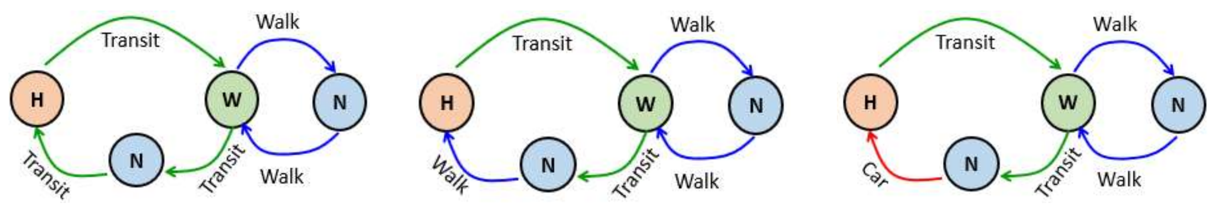
2.7.3.5 Modal sequence by tour

Figure 2.17 shows the top three most frequent modal sequences of this category of tours. While the modal sequences indicate trips are chained by which modes, I consult Table 2.7 to check the associated trip durations. It is found that the largest fraction of tours (about 77 percent of tours in pattern 3a) involves a long (on average one hour) transit commute to work, with short (average 8 min. each way) walking trips during the midday for non-work activities (mostly meals) close to the work location (these are work-based sub-tours).



Most frequent sequence (77% tours) | Second-most frequent sequence (3% tours) | Third-most frequent sequence (2% tours)

3a. H-W-N-W-H (n= 196)



Most frequent sequence (18% tours) | Second-most frequent sequence (18% tours) | Third-most frequent sequence (14% tours)

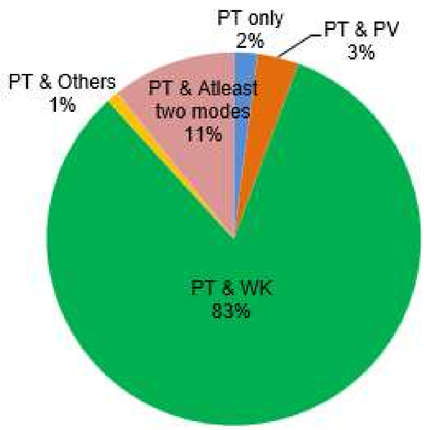
3b. H-W-N-W-N-H (n= 61)

Figure 2.17 Frequent modal sequences in complex tours with work-based sub-tour

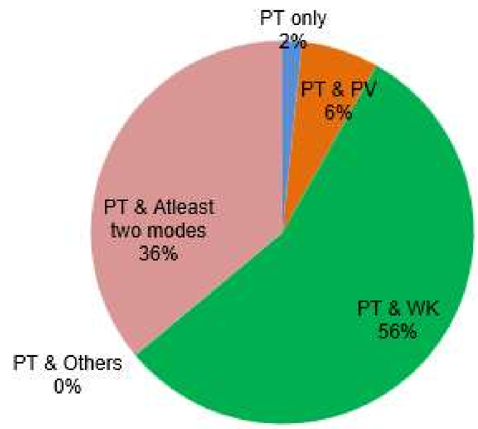
During the evening peak period, the reverse commute via transit is frequent. In pattern 3b, travelers make a 48-minutes (on average) transit commute to an additional non-work location (cf. Table 2.7) before returning home.

2.7.3.6 Frequency of transit with other modes

While observing the frequency of transit use with other travel modes in this pattern of tours it is found that the share of public transit with walk (PT&WK) is very high (cf. Figure 2.18), which is not that surprising. An interesting observation is that, for *pattern 3b*, transit use in combination with two or more other modes is high (36 percent) because in addition to walk trips at midday, other modes, mostly private vehicles, are used in the return home trip.



3a. H-W-N-W-H (n= 196)



3b. H-W-N-W-N-H (n= 61)

Figure 2.18 Frequency of transit with other modes in complex tours with work-based sub-tour

2.7.4 Comparing Three Categories of Work Tours

2.7.4.1 Socio-demographic characteristics

The socio-demographic characteristics of travelers vary over the three categories of work tours. For example, male travelers tend to make simple tours or work-based tours whereas female travelers tend to make complex work tours. Moreover, younger or millennial travelers mostly make work-based tours, while non-millennials tend toward simple or complex work tours. Travelers who make simple work tours have less flexibility regarding work arrival time compared to the other two types of tour makers. A notable result is that zero-vehicle households tend toward complex work tours more than simple tours or work-based tours.

2.7.4.2 Activity-travel behavior

In this study, all sampled tours are defined as containing a work activity and using public transit in at least one trip segment. In most simple work tours, transit is used for both the work-bound and home-bound trips, thus, the share of transit-only tours is largest for simple tours. When travelers mix their non-work activities either before or after work, the transit-only fraction declines and travelers tend to combine transit with other travel modes, particularly private vehicles. The share of public transit with walk is the largest for tours of pattern group 3 (complex tours with work-based sub-tour), with both the walk access/egress and the density proximate to the work place being the likely explanatory factors. When travelers make at least one non-work stop on the way to work (complex tours), they mostly do so to drop off a child or to buy a meal. When a non-work stop is made on the way to home, the activity tends to be buying goods or services. If travelers make a non-work stop during work (work-based sub-tours), they typically go out for lunch within walkable distance from their workplace.

2.7.4.3 Time-use behavior

To mark the differences and similarities in a broader time usage sense across the seven dominant tour patterns, an aggregate summary statistic of time spent on a work tour for work and non-work activity purposes and travel is computed. The summary is reported in Table 2.8 which provides information on the total time spent in and out of home, as well as for travel, in a full day. People making pattern 3a spent more time on travel in a day (travel time expenditure) than the people making other tour patterns. Moreover, where travelers make a non-work stop on their way to work (patterns 2b and 2d), they spend significantly less non-work activity time than for those patterns where the non-work activities are performed on the way home (patterns 2a and

2c). This can be explained by the time constraints often imposed by the work activity that follows in these patterns. As a result, these patterns mostly include short duration activities, such as pick up/drop off. Finally, with patterns 2a and 2c, people spend significantly less time at home than in other patterns. In pattern 2c with two non-work activities on the return home commute, more time is allocated to non-work than in the other patterns.

Table 2.8 Aggregate time-use statistics by identified tour types

Average Time-use	Pattern 1	Pattern 2a	Pattern 2b	Pattern 2c	Pattern 2d	Pattern 3a	Pattern 3b
Total tour duration (home to home)	10h 14m	11h 26m	9h 32m	11h 4m	10h 40m	10h 49m	11h 28m
Work duration	8h 23m	7h 58m	8h 3m	7h 29m	7h 23m	8h 5m	7h 53m
Work travel duration	55m	49m	57m	1h 1m	48m	55m	45m
Nonwork duration in work tour	0	1h 16m	34m	2h 3m	1h 6m	30m	1h 33m
Nonwork travel duration in work tour	0	49m	31m	1h 6m	1h 19m	10m	46m
Travel duration in work tour	2h 6m	2h 14m	2h 11m	2h 24m	2h 25m	2h 22m	2h 14m
Travel time expenditure in a day*[2]	2h 18m	2h 21m	2h 22m	2h 28m	2h 34m	2h 38m	2h 17m
In home activity duration in a day*	12h 53m	12h 11m	12h 36m	11h 43m	12h 41m	12h 17m	12h 9m
Out home activity duration in a day*	8h 48m	9h 27m	9h 1m	9h 48m	8h 44m	9h 4m	9h 33m

* marked variables are calculated in terms of people and other variables are calculated in terms of tours

It is hypothesized that the two home with work-based patterns, pattern 3a and 3b, with midday activity (e.g., lunch) during work are similar in structure to pattern 1 and 2a, respectively, assuming that pattern 1 and 2a might have midday activities, such as lunch or e-shopping, that did not involve leaving the workplace (and effectively increasing work duration). Figure 2.19 shows these two pairs of similar patterns. To test this hypothesis, I conducted a *Kruskal-Wallis test* only to find that no statistically significant difference in total tour duration was found between pattern 1 and 3a or between pattern 2a and 3b.

[2] Total time spent on travel in a day

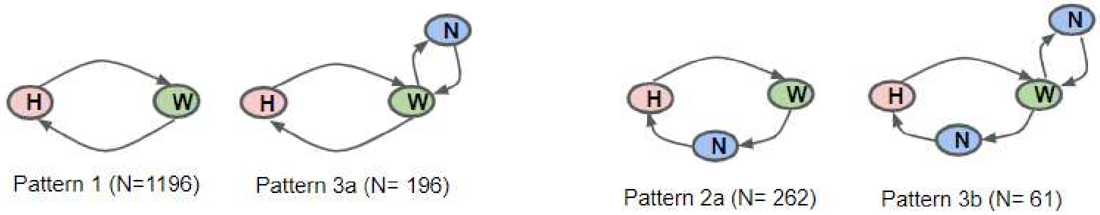


Figure 2.19 Two pairs of similar patterns

2.8 Properties of Other Work Tours

I have presented and discussed characteristics of the seven most dominant patterns of work tours that utilize public transit, together representing 80 percent of total work tours. Here, I briefly discuss the properties of the other 20 percent of work tours. This *other* category contains a total of 506 work tours with 106 unique tour patterns thus, this 20 percent of work tours is much more diverse and complex. Note that these tours cannot belong to pattern 1 (home-based simple work tours) rather belong to either pattern 2 or pattern 3 (complex tours). The average number of non-work activities performed under these tours is notably higher. Also, 60 percent of these tours reflect *complex work* tours. Among these complex tours, 42 percent tours involve two or more work but no non-work activities whereas 58 percent tours involve mixing non-work activities with work. In majority of the other tours (47 percent), non-work stops are made only on the return home. Travelers tend to combine walk with transit in making many of these work tours (44 percent) (Figure 2.20). As expected, very few travelers (3 percent) use transit for making all the trips within a tour. Again, in 37 percent tours travelers tend to use at least two other travel modes with transit.

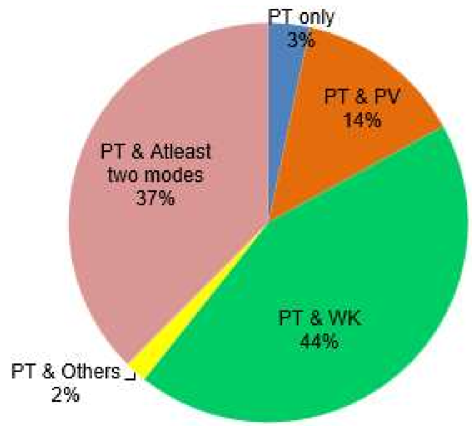


Figure 2.20 Combination of travel modes with transit in 'other' category

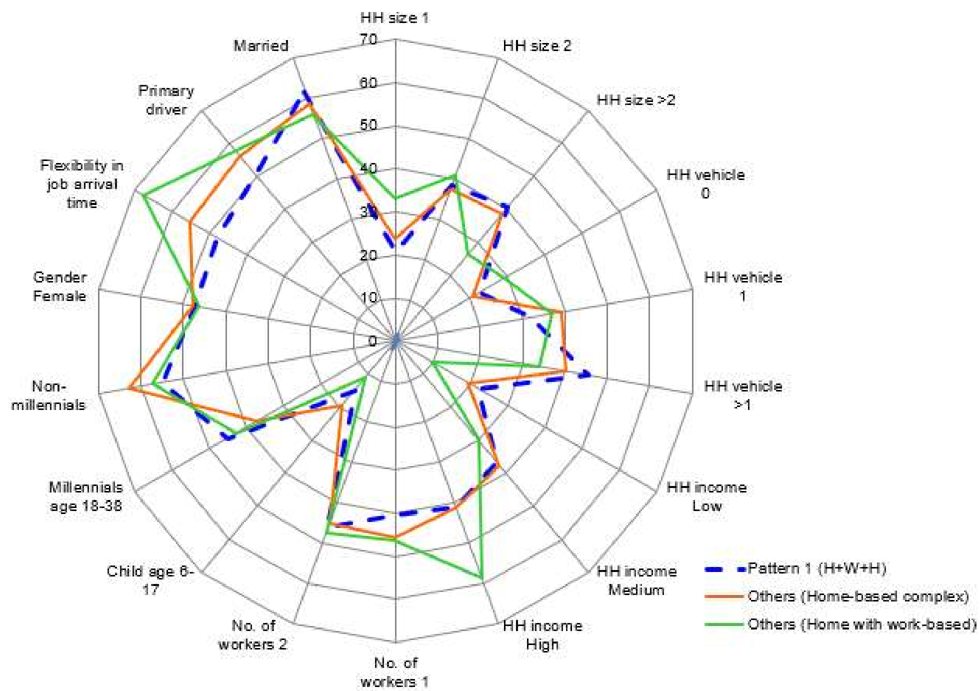


Figure 2.21 Socio-demographic characteristics of travelers making 'other' tour patterns

Figure 2.21 displays the socio-demographic characteristics of travelers who make these 'others' tours, partitioned into two groups based on which tour patterns they belong (complex tours or work-based tours). Travelers who perform both complex tours and work-based tours are in general similar to those exhibiting simple work tours. Complex work tour makers are mostly non-millennials, belong to medium or high-income group, have at least two household members in their household, and have flexibility in their job arrival time. Work-based tour makers generally belong to the higher income class, have much greater flexibility in their job arrival time than their counterparts, and most of their households consist of two members. An interesting difference between the characteristics of home with work-based tour makers who belong to the bottom 20 percent data with the same group who fall into the top 80 percent of the data is that the first group of travelers mostly represents non-millennials whereas the second one typically consists of millennials.

2.9 Conclusions and Policy Implications

This study analyzes the complex travel behavior of working individuals who utilize public transit in their work tours. Here, complex travel behavior is defined in terms of *tours.* This study aims to investigate how transit commuters manage to link non-work activities as part of work tours under limited flexibility in meeting complex travel demands. In particular, I identify dominant patterns of work tours made by transit commuters and analyze these tours using a set of activity-travel analytics, such as temporal distribution of trips, activity purposes and duration, modal distribution, modal sequence, and frequency of transit with other modes based on data from the 2017 National Household Travel Survey (NHTS).

The primary insights and key implications of this study are:

(1) *About 80 percent of work tours consist of 7 unique dominant patterns whereas the remaining 20 percent of tours demonstrate a total of 106 diverse and more complicated patterns.*

To our best knowledge, this study is the first to analyze the full work tours with transit usage in different parts of the chain so the simple categorization and analysis of tour types is considered as a contribution to theory and practice. Seven dominant work tour patterns are identified that represent 80 percent of the tours and these patterns can be placed under three broad tour categories: simple work tours, complex work tours with four sub-categories, and complex tours with work-based sub-tour with two sub-categories. Based on the choice of a particular work tour, this study identifies potential transit commuters. For example, tours performed by males tend to be more elementary than tours performed by females, who frequently link non-work activity either on the way to work or on the way to home, a result consistent with the greater range of activity responsibilities for female workers (Strathman *et al.*, 1994; McGuckin and Murakami, 1999; Kuppam and Pendyala, 2001; Rafiq and McNally, 2019). On the other hand, higher income people do not frequently make non-work stops on their way to work or to home (complex tours); instead, they tend to do so within the work hour (making work-based tours). Similarly, younger or millennial travelers mostly make work-based tours whereas non-millennials prefer to make simple or complex work tours. This information might help the transit operators to identify the potential market group and their demand of transit usage at different times in a day, which might help to better evaluate current transit services and to implement market strategies (e.g. fare structure) that can meet the complex travel needs of potential users, leading to a higher use of transit. For example, people making multiple transit stops within work tours can be provided discounted fare options such as a day pass or free transfers which might encourage commuters to use transit to reach non-work activity location along with workplace.

(2) *Transit work tours are pretty complex.*

Previous study showed that the majority of workers who use transit in their work tours are more likely to make home-based simple tours (McGuckin *et al.*, 2005). It is observed that an equal share of simple and complex work tours is made by transit commuters. Among all the work tours where transit is utilized, 49 percent represents elementary or simple tours. On the other hand, 51 percent tours involve complex tours (complex with and without sub-tours) where commuters are observed to chain either multiple works but no non-work activity (5 percent) or to mix non-work activities with work on the way to work or during work, or on the way to home (46 percent). Among these work-nonwork mixed tours, most of the travelers (60 percent) make at least one non-work stop on the way to home travel. On the other hand, 35 percent and 41 percent travelers do so on the way to work journey and during work hour respectively. While making a non-work stop on the way to work, travelers mostly drop off a child or buy a meal. Again, when a non-work stop is made on the way to home, the activity tends to be buying goods or services. If travelers make a non-work stop during work, they typically go out for lunch within walkable distance from their workplace.

Thus, it is apparent that public transit work tours are notably complex, which is partially supported by Bernardin Jr et al. (2011) who showed that, on the contrary to the common belief, public transit tours are at least as complex as tours by other modes. This tour-based analysis facilitates understanding of the interrelationships and consistencies among the choice of activities, timing, locations (proximity), duration and modes used for the full set of trips comprising a complex tour. Since public transit offers less flexibility of travel in accommodating the complex travel needs than private vehicles, the findings of this study will provide an empirical justification of evaluating the policies that can better address the complex travel demands of transit commuters.

(3) *Transit complex tours are multimodal.*

The study results suggest that when non-work activities are linked with work, transit commuters tend to be multimodal, that is, they mix other travel modes with transit. It is found that simple work tours are predominantly transit-only tours (83 percent). When travelers mix non-work activities either on the way to work or way to home, the transit-only fraction declines and travelers tend to combine transit with other flexible travel modes, particularly private vehicles as transit use is not generally conducive to do so. For example, a common non-work activity performed on the way to work is dropping off children at school. It would not be convenient for the commuters to connect such non-work activity location (e.g. schools) with home or workplace by using transit since connecting these facilities (home—non-work—workplace—home) involves multiple transfers, waiting time, or access/egress issues. To provide a convenient modal linkage, transit stations should be designed to consider parking facilities and other activity services.

(4) *Transit is utilized many ways within a work tour beyond the traditional home to work commute with a diverse set of choices at various stages of activity scheduling.*

While policies associated with public transit typically focus only on the journey to work, this study considers the complete set of trips starting and ending at home including intermediate non-work activity. Although transit use is observed to be predominantly associated with the work-end of the tour (a direct connection to or from work) due to the better transit services in employment centers, it is also noticed to be utilized at the non-work end of the tours. Identification of a variety of transit usage as part of the complex travel can provide a foundation to formulate better land use and transit-related policies to satisfy demands for the complex tours with a larger share for transit. For example, allocation of mixed land use developments at employment centers might help transit commuters to access non-work activity centers in off-peak periods within walking distance of workplaces. In addition, non-work activity centers can be allocated near the transit stations or near residences. While allocating these facilities, multiple activity centers (e.g.

shopping/grocery, restaurants) can be considered at a single location. This might reduce the number of transfers for the commuters if they utilize public transit to access various non-work activities and facilitate easier chaining of multiple activity purposes at a single location within a work tour.

The empirical analysis of this study can lead to a better understanding of how the transit commuters link non-work activities with work, which can improve our knowledge of linkages between activity and mobility. Identification of such information is very crucial and at the same time challenging for the understanding and the development of the tour- or activity-based demand models (Wang, 2015) as TRB (2007) indicated that the analytical complexity and prohibitive data demands of tour- or activity-based models enable only a small number of US transportation agencies to apply them. Note that while analyzing tour behavior of transit commuters applying an activity-based approach, it does not directly represent an activity-based (or tour-based) *forecasting* model. However, the insights of this study can be utilized to develop better tour-based models that reflect the complexity of transit use within tours.

Since location data is not provided in the NHTS data, it was not possible to analyze how the land use distribution near home, work or transit stations might influence activity choices as well as tour formation of transit commuters. Also, the travel activity scheduling of a transit commuter may be greatly influenced by the travel choices made by other individuals in the same household. This study was focused on identifying patterns in transit work tours but reserves the analysis of critical factors such as socio-demographic, location, and activity-travel attributes affecting those choices to future work.

Research has suggested that when commuters meet non-work activity demands on their way to home from work, they are less likely to make a non-work tour after returning home

(Rafiq and McNally, 2019; Bhat and Singh, 2000). The connections between tours, rather than within tours, as well as identifying the difference in complex travel behavior between bus and rail commuters, is the subject of on-going research. It would be interesting to compare the dominant patterns of work tours between transit and non-transit commuters.

2.10 References

Bernardin Jr, V. L., Swenson, A., Jiang, Z., & Grovak, M. (2011). Income effects and other new findings on complexity of transit tours. *Transportation Research Record*, *2217*(1), 38-45.

Bhat, C. R., and Singh, S. K. (2000). A comprehensive daily activity-travel generation model system for workers. *Transportation Research Part A: Policy and Practice*, 34(1), 1-22.

Bianco, M., & Lawson, C. (1996). Trip chaining, childcare and personal safety: critical issues in women's travel behavior. *In Proceedings from the second national conference on women's travel issues*. Washington DC

Chung, J. H., Kim, S., Lee, Y. K., and Choi, Y. S. (2004). Multilevel structural equation model for activity participation and travel behavior: Data from the Puget sound transportation panel. *Transportation Research Record: Journal of the Transportation Research Board*, (1898), 52-60.

Currie, G., & Delbosc, A. (2011). Exploring the trip chaining behaviour of public transport users in Melbourne. Transport Policy, *18(1)*, 204-210.

Doherty, S. T., Miller, E. J., Axhausen, K. W., and Garling, T. (2002). A conceptual model of the weekly household activity/travel scheduling process. In: E. Stern, I. Salomon, and P. Bovy (Eds.). *Travel Behaviour: Patterns, Implications and Modelling*.

Federal Highway Administration (2002). Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance. http://www.fhwa.dot.gov/policy/2002cpr/pdf/execsummary_book.pdf. Accessed Dec 24, 2018.

Hensher, D. A., and Reyes, A. J. (2000). Trip chaining as a barrier to the propensity to use public transport. *Transportation*, *27*(4), 341-361.

Ho, C. Q., & Mulley, C. (2013). Multiple purposes at single destination: A key to a better understanding of the relationship between tour complexity and mode choice. *Transportation Research Part A: Policy and Practice*, 49, 206-219.

Krygsman, S., Arentze, T., & Timmermans, H. (2007). Capturing tour mode and activity choice interdependencies: A co-evolutionary logit modelling approach. *Transportation Research Part A: Policy and Practice*, 41(10), 913-933.

Kuppam, A. R., & Pendyala, R. M. (2001). A structural equations analysis of commuters' activity and travel patterns. *Transportation*, 28(1), 33-54.

Lee, M. S., & McNally, M. G. (2003). On the structure of weekly activity/travel patterns. *Transportation Research Part A: Policy and Practice*, 37(10), 823-839.

Levinson, D., & Kumar, A. (1995). Activity, travel, and the allocation of time. *Journal of the American Planning Association*, 61(4), 458-470.

McGuckin, N., & Murakami, E. (1999). Examining trip-chaining behavior: Comparison of travel by men and women. *Transportation Research Record: Journal of the Transportation Research Board*, (1693), 79-85.

McGuckin, N., Zmud, J., & Nakamoto, Y. (2005). Trip-chaining trends in the United States: understanding travel behavior for policy making. *Transportation Research Record*, 1917(1), 199-204.

McNally, M. G., and Rindt, C. (2008). The activity-based approach. In: D. A. Hensher and K. J. Button (Eds.). *Handbook of Transport Modeling*. 2nd ed., 55-73.

Noland, R.B., Schmocker, J.D. and Bell, M.G.H. (2008). Trip chaining behaviour of older people: Effects of medical conditions and urban form. *Presented at 87th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Pinjari, A. R., and Bhat, C. R. (2011). Activity-based travel demand analysis. *A Handbook of Transport Economics*, *10*, 213-248.

Primerano, F., Taylor, M. A., Pitaksringkarn, L., & Tisato, P. (2008). Defining and understanding trip chaining behaviour. *Transportation*, 35(1), 55-72.

Rafiq R. and McNally, M. G. (2019). Changes in Activity-Travel Behavior of Workers Before and After the 2009 Recession. *Presented at 98th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Ren, F., and Kwan, M. P. (2009). The impact of the Internet on human activity–travel patterns: analysis of gender differences using multi-group structural equation models. *Journal of Transport Geography*, *17*(6), 440-450.

Strathman, J. G., Dueker, K. J., & Davis, J. S. (1994) Effects of household structure and selected travel characteristics on trip chaining. *Transportation*, 21(1), 23-45.

Strathman, J., Dueker, K. (1995). Understanding trip chaining. *Special Reports on Trip and Vehicle Attributes*, 1990 NPTS Report Series, US Department of Transportation and Federal Highway Administration.

TRB. (2007). *Metropolitan Travel Forecasting: Current Practice and Future Direction--Special Report 288* (No. 288). Transportation Research Board.

Wallace, B., Barnes, J., & Rutherford, G. (2000). Evaluating the effects of traveler and trip characteristics on trip chaining, with implications for transportation demand management strategies. *Transportation Research Record: Journal of the Transportation Research Board*, (1718), 97-106.

Wang, R. (2015). The stops made by commuters: evidence from the 2009 US National Household Travel Survey. *Journal of Transport Geography*, *47*, 109-118.

Ye, X., Pendyala, R. M., & Gottardi, G. (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B: Methodological*, 41(1), 96-113.

CHAPTER 3: Determinants of Work Tour Choice of Transit Commuters

3.1 Introduction

The increasing complexity of modern life can lead to increased time poverty, which in turn can increase the tendency of travelers exploring opportunities to chain non-work activity purposes within a work tour to reduce travel and time costs and to gain efficiency in activity participation (McGuckin *et al*., 2005; Hensher and Reyes, 2000; Levinson and Kumar, 1995; Bianco and Lawson, 1996). However, increasing the number of complex work tours can also increases the reliance on more flexible travel modes (Hensher and Reyes, 2000), such as private vehicles that can allow much flexibility and convenience to the commuters to schedule either planned or spur of the moment non-work activities within the work tour under spatial and temporal constraints (Lee and McNally, 2003). This rising use of private vehicles has some negative implications, such as congestion, air pollution, and energy consumption while public transit is considered as a sustainable transport mode to effectively mitigate these adverse consequences (Federal Highway Administration, 2002). However, with operations on fixed routes and fixed schedules, public transit offers lower accessibility and mobility services than private vehicles particularly in satisfying complex travel demand. Hensher and Reyes (2000) observed that trip chaining is the potential barrier in attracting car users to switch to public transit use, particularly for work trips. Thus, to increase the use of public transit, we need to better accommodate the chaining of non-work activities with work while utilizing public transit within a work tour. Identification of the public transit commuters[3] who meet their complex travel needs by chaining non-work activities

[3] Public transit commuters are defined as the travelers who utilize transit in any trip segment of their work tour

on the way to or from work or during work hour and the factors that influence the choice is important to facilitate such trip chaining behavior.

A considerable number of research works focused on the trip chaining behavior of commuters and identify a set of factors, such as age, gender, driving license, vehicle ownership, household structure, presence of child, and household income that affect trip chaining during the commute to or from work (Strathman *et al.*, 1994; Bhat, 1999; McGuckin and Murakami, 1999; Lu and Pas, 1999; Goulias and Kitamura, 1991; Wallace *et al.*, 2000; McGuckin and Nakamoto, 2005; Wang, 2015). Prior works that considered trip chaining behavior of *transit* users focused on variety of issues. Hensher and Reyes (2000) found in Sydney, Australia that the likelihood of public transit usage decreases with the change of a tour from simple to complex. Based on a limited number of socio-demographic variables, they regressed the utility of a simple and complex tour (work or non-work) yielded from either car or public transit usage. Krygsman *et al.* (2007) investigated the causal relationships between travel mode choice (car or public transit) and the insertion of intermediate activities before, in between, or after a work activity within a work tour in Netherlands. The authors concluded that the inclusion of an intermediate stop for non-work activity before or after work tends to decrease public transit utility and increase car utility. They also found that in a majority of home-based work tours, activity decisions are made before making a decision on mode of travel.

In contrast, Currie and Delbosc (2011) found in Melbourne, Australia that for non-work tours, public transit chains are found to be more complex than those undertaken by car. However, the opposite relationship was found for work tours. Again, Primerano *et al.* (2008) observed that in Adelaide, Australia all forms of mass public transport tours involved higher numbers of activities compared to private car-based tours. The authors argued against the hypothesis of

Hensher and Rayes (2000) that public transit is not flexible for complex trip chaining. They instead suggested that the nature of complex trip chaining behavior of public transit users is different rather than inflexible. With public transit, travelers can access a destination comprising a mix of land uses in close proximity to one another whereas travelers using a private car can access activities located at multiple destinations that are not necessarily in close proximity to each other. This statement is reinforced by Ho and Mulley (2013). Based on Sydney household travel survey data, the authors showed that public transit tours increased with an increase in the number of activities located in close proximity to one another (yielding a *multiple purpose single destination tour*). These results suggest that chaining multiple activities in tours does not necessarily hinder public transit usage but an unfavorable spatial distribution of activity locations might do so. Again, based on the onboard transit ridership survey data in Ohio, U.S. and the results of the univariate analysis Bernardin Jr *et al.* (2011) showed that transit tours are at least as complex as tours by other modes.

In summary, previous studies addressed the interrelationships between the complexity of activities and the utility of different mode usage with a primary focus on private vehicle and public transit. In contrast, this study characterizes the transit commuters based on the complexity of trip chaining they make within a work tour and assesses the impact of characteristics of commuters, household, built environment, and activity engagement on the likelihood of a commuter to choose a particular type of work tour. Here, the term *tour* is defined as a sequence of trips and activities that begins and ends at home. If a tour contains at least one work activity location, it is called *work tour*. Based on the presence of a non-work activity and its location within the tour, work tours can be categorized into the following three types. *Simple work tour* contains exactly one work but no non-work activity whereas *complex work tour* may contain one or more non-work activity on the way to work or on the way to home. Finally, *complex tours with work-based sub-tour* additionally contains one or more non-work activities during work hour. This tour choice model can provide better insights on identifying the transit commuters with a particular type of work tour and the factors that determine the tour choice, which can eventually help to predict the number of stops within a tour for each individual and then to schedule a tour in an activity-based model.

3.2 Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS). NHTS is the source of information about travel by US residents in all 50 states and the District of Columbia. The data includes trips made by all modes of travel (private vehicle, public transport, pedestrian, biking, etc.) and for all purposes (work, school, shopping, recreation, etc.). The NHTS data base contains four datasets or tables: households, persons, trips, and vehicles. The household table contains socio-economic and location characteristics of surveyed households and the person table contains information about the demographic characteristics of all individuals living in those households. The trip data table lists all trips made within a 24-hour period by each household member aged 5 or older as well as trip-related attributes, and the vehicle data table contains information about vehicles available for use by households. The NHTS dataset contains 129,696 households consisting of 264,234 persons who took a total of 923,572 trips. Among them, 23.40 percent individuals (a total of 61,842) made at least one home-based work tour.

For this analysis, I identified *public transit commuters* making work tours, that is, those individuals who are at least 18 years old, perform at least one work activity, and used public transit in at least one trip segment[4]. A choice of travel mode is treated as 'public transit' if it is any of the following: public or commute bus, city-to-city bus (greyhound, Mega bus, etc.), Amtrak/commuter rail, and subway/elevated/light rail/street car. This generates a sample of 2,448 individuals. *Home-based* transit work tours are formed by linking person trip sequences that start and end at home and contain at least one work activity. The result was a total of 2,454 home-based work tours. From the total sample observations, the travelers who visited multiple work locations (more than one) but do not mix non-work with work (126 observations) are removed. Again, I did not consider those travelers who made two work tours in a day (6 observations). After removing observations with missing information, I finally obtained a sample of 2,079 individuals for modeling purpose. Note that although *change of transportation* is recorded as an activity purpose in the survey data, it is not considered as an activity in the analysis. Because 'mode change' is a part of the whole trip to access a particular activity site and the inclusion of this type as a separate non-work activity may artificially increases the complex nature of public transit tours (Noland *et al.*, 2008; Ho and Mulley, 2013).

3.3 Tour Formation of Transit Commuters

A *tour* is a sequence of trips that starts and ends at the same location and contains one or more activities performed at single or multiple destinations (Strathman and Dueker, 1995; Ho and Mulley, 2013). If the starting and ending location in question is home, the tour is deemed a home-based tour. Since this study involves working individuals, I only consider home-based tours that contain at least one work location outside home. These are called home-based *work* tours. A home-based work tour is called a *simple work tour* if it contains exactly one work

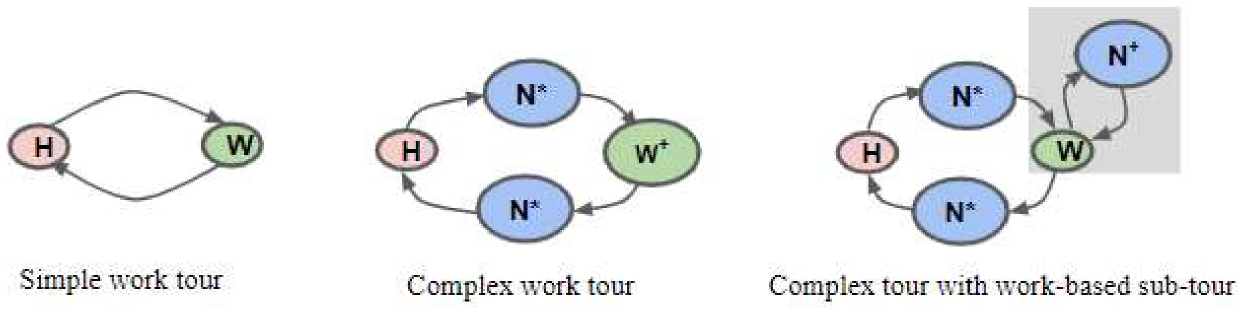
[4] When a trip involves change of modes, each mode defines a trip segment.

activity but no non-work activity within it. That means, a home-based simple work tour has this sequence of activities Home-Work-Home, separated by two trips in between.

On the other hand, a home-based work tour may contain non-work activity with work in the same tour. These tours are called *work-nonwork mixed* tours. In this study, these mixed tours are divided into two categories: complex work tours and complex tours with work-based sub tour. *Complex work tours* contain non-work locations other than work accessed on the way to or from work. Non-work activities are called 'way to work' non-work activities when performed after leaving home and before arriving at work. Similarly, 'way to home' non-work activities are those activities that are performed on the way to home from the workplace.

Work-based tours involve visiting non-work locations 'during work' (such as during a lunch break). When a home-based tour is combined with a work-based tour, it is referred to as *complex tour with work-based sub-tour*. Both simple and complex work tours have exactly one circuit whereas complex tours with work-based tour have two or more circuits, i.e. one circuit between home and work, and (minimum) one circuit with work as a base. Note that, work-based tour is classified as a distinct one as it shows unique socio-demographic and transport properties compared to the second work tour category (non-work on the way to or from work) (Krygsman *et al*., 2007).

Figure 3.1 shows the general construct of these three types of work tours. The difference in tour type emanates from the degree to which non-work activities are mixed with work. For instance, simple work tours do not involve any non-work at all, complex work tours involve non-work stops on the way to work and/or on the way to home, and work-based tours can have non-work stops in any or all of these three ways. To represent the different types of tours, I produce a graphical model where activity locations are vertices as H (home), N(non-work) and W (work) depending on where the activity is performed and an arrow between two vertices denotes a trip between the corresponding locations.



N^*: zero or any number of non-work
N^+: one or more non-work
W^+: one or more work
Shaded portion can repeat

Figure 3.1 General construct of home-based work tours

The fraction of tours for each of the three categories are shown in Figure 3.2. The figure shows that both simple work tours and work-nonwork mixed tours contribute almost equal fraction of tours. Among the mixed tours, complex tours represent higher fraction of tours (29 percent) compared to complex tours with work-based sub-tour (20 percent). Data shows that in most simple work tours, transit is used for both the work-bound and home-bound trips, thus, the

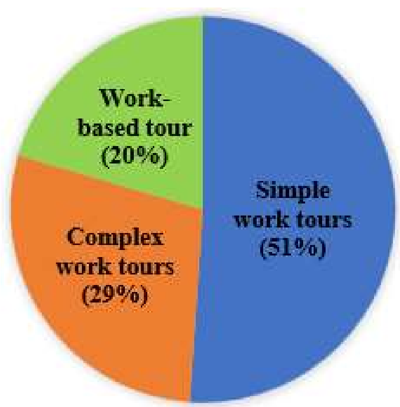


Figure 3.2 Fraction of different types of work tours

share of transit-only tours is largest for simple tours. When travelers mix their non-work activities either before or after work, the transit-only fraction declines and travelers tend to combine transit with other travel modes, particularly private vehicles. The share of public transit with walk is the largest in complex tours with work-based sub-tour, with both the walk access/egress and the density proximate to the work place being the likely contributing factors. When travelers make at least one non-work stop on the way to work (complex tours), they mostly do so to drop off a child or to buy a meal. When a non-work stop is made on the way to home, the activity tends to be buying goods or services. If travelers make a non-work stop during work (work-based sub-tours), they typically go out for lunch within walkable distance from their workplace.

3.4 Model Specification

Structural equation modeling (SEM) is a comprehensive methodological framework that can simultaneously estimate the causal relationships among a set of observed variables based on a specified model (Kaplan, 2008). That is, an SEM structural model can capture the causal influences of the exogenous variables on the endogenous variables (regression effects) and the causal influences of endogenous variables on each other. The structural model also allows to provide specifications of error-term covariances (Golob, 2003). The strength of a SEM is that in addition to find out the direct effect of one variable to another one, it can capture the indirect effect as well through other mediating variables. The summation of direct and indirect effects represents the total effect that provides valuable insights on the interrelationships between variables.

SEM is widely used in travel behavior research as it enables the analysis of complex causal relationships among a set of exogenous and endogenous variables. Golob (2003) outlined a comprehensive review of application of SEM in various travel behavior research including its use in the activity-based travel demand modeling. Several notable works include developing SEM model to find out relationships between activity participation and number of trips, number of chains, and travel time (Lu and Pas, 1999), activity participation and complexity in trip chain generation (e.g. simple, complex) (Golob, 2003), activity participation and frequency of complex work trip chains for commuters (Kuppam and Pendyala, 2001), and transportation control measures and commuters' activity-travel patterns (Fujii and Kitamura, 2000). Among the recent works, Van Acker and Witlox (2011) showed how the relationships between land use and commuting differ between work-only tours and more complex tours. Again, the relationships between work and non-work trip chaining (tours) and various mode choice are explored by Islam and Habib (2012). Several works focused on the relationships among activity participation, trip chaining, and mode choice from the context of developing countries (Yang *et al.*, 2010; Cheng *et al.*, 2019; Hadiuzzaman *et al.*, 2019).

This study identifies factors that determine the choice of work tours by conceptualizing a causal relationship among a set of socio-demographic characteristics, built environment variables, activity participation, and a particular work tour choice for the public transit commuters by using SEM for *path* model. Path models typically have three types of variables: exogenous variables, endogenous outcome variables, and endogenous mediator variables. An exogenous variable is not causally dependent on any other variables in the model. On the other hand, both of the endogenous variables are determined by the model. An endogenous outcome variable is a dependent variable with respect to other variables used in the model. Whereas, an endogenous mediator variable is independent with respect to some variables and dependent with respect to other variables in the model. This variable mediates between an exogenous variable and an endogenous outcome variable (Acock, 2013). The SEM equations for path model, conceptualized causal structure, and the list of exogenous and endogenous variables are described next.

3.4.1 The Structural Equation Modeling for Path Model

Let us denote measured exogenous variables as **X** and measured endogenous variables as **Y**. The equation for the endogenous variables is given by (Kline, 2016):

$$\mathbf{Y} = \mathbf{\Gamma X} + \mathbf{BY} + \boldsymbol{\zeta} \tag{1}$$

where **Y** is an ($m \times 1$) column vector of endogenous variable and **X** is an ($n \times 1$) column vector of measured exogenous variables.

The structural parameters are the elements of the matrices are (Golob and McNally, 1997):

- $\mathbf{\Gamma}$ — ($m \times n$) matrix of direct causal (regression) effects from the (n) exogenous variables to the (m) endogenous variables;
- $\mathbf{B}$ — ($m \times m$) matrix of causal links between the m endogenous variables; and
- $\boldsymbol{\zeta}$ — ($m \times 1$) matrix of m error terms

Equation (1) can be expressed in matrix form as (Kline, 2016):

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \cdots & \cdots & \cdots \\ \gamma_{m1} & \cdots & \gamma_{mn} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_n \end{bmatrix} + \begin{bmatrix} 0 & \cdots & \beta_{1m} \\ \cdots & \cdots & \cdots \\ \beta_{m1} & \cdots & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \cdots \\ \zeta_m \end{bmatrix} \tag{2}$$

Other parameter matrices include the covariance matrix of the measured exogenous variables $\mathbf{\Phi}$ and the covariance matrix of the error terms $\mathbf{\Psi}$, shown in Eq. (3).

$$\boldsymbol{\Phi} = \begin{bmatrix} \phi_{11} & & & \\ \phi_{21} & \phi_{22} & & \\ \vdots & \vdots & \ddots & \\ \phi_{n1} & \phi_{n2} & \cdots & \phi_{nn} \end{bmatrix} \quad \boldsymbol{\Psi} = \begin{bmatrix} \psi_{11} & & & \\ \psi_{21} & \psi_{22} & & \\ \vdots & \vdots & \ddots & \\ \psi_{m1} & \psi_{m2} & \cdots & \psi_{mm} \end{bmatrix} \tag{3}$$

For identification of system (1), **B** must be chosen such that (**I-B**) remains non-singular, where **I** is an identity matrix of dimension *m*. For an identified system, the model implied total effects of the endogenous variables on each other are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{yy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1} - \boldsymbol{I} \tag{4}$$

The total effects of the exogenous variables on the endogenous variables implied by the system are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{xy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1}\boldsymbol{\Gamma} \tag{5}$$

The model parameters of the system in the Eq. (1) are estimated using variance analysis methods, also known as *methods of moments*. The theory is that the population covariance matrix of the observed variables (Σ) can be expressed as a function of a set of parameters θ, shown in Eq. (6) (Lu and Pas, 1999).

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}\,(\boldsymbol{\theta}) \tag{6}$$

Here, θ represents the model parameters of **Γ, B, Φ,** and **Ψ.** These unknown parameters are estimated such that the difference between the sample covariance matrix *S* and the model implied covariance matrix Σ (θ) is minimized. This is achieved by minimizing a fitting function, which is a function of *S* and Σ (θ). Several estimation methods are available to identity a best fitting model. The maximum likelihood (ML) method works well when the endogenous variables have multivariate normal distribution. On the contrary, weighted least square mean and variance adjusted (WLSMV) estimator accounts for non-normally distributed data (Muthen and Kaplan, 1992).

3.4.2 The Exogenous and Endogenous Variables

The model's exogenous and endogenous mediator variables and their summary statistics for each of the three work tour types, namely simple, complex, and complex tours with work-based sub-tours are shown in Table 3.1. The variables are selected based on the relevant prior works and data availability. The *exogenous* variables include a set of household and personal level socio-demographic and economic characteristics. The *household* level characteristics include presence of child (aged 0 to 17 years), number of adult members (aged 18 years or more), presence of spouse/partner by two categories: employed or no spouse/partner (reference group) and unemployed spouse/partner, vehicle-driver ratio (total number of vehicles divided by total number of licensed drivers), and household income by three categories: low (reference group: less than \$20K), middle income (\$20K to \$60K), and high income (\$60K or more). Again, several *personal* characteristics of the travelers, such as age, gender, ethnicity, Hispanic status, immigration status, educational attainment, employment type, flexibility in job arrival time, are considered as important determinants of work tour choice. All the person level variables are represented as dummy variables in the model (detailed categories and reference groups are shown in Table 1).

On the other hand, the *endogenous mediator* variables shown in Table 1 are of two broad categories: built environment and activity-travel characteristics. The *built environment* variables include population density (persons per square mile) in the census block group of the household's home location, road network distance (miles) between home location to workplace, and proximity to or from a transit station. The last variable refers to how far a traveler needs to travel to access a transit station or to travel to a destination from a station. In this study, such proximity is captured by using travel time to or from a station instead of distance. In particular, two variables are used in the model: average travel time (minutes) to access the station from an origin (home or non-home activity locations) and average travel time (minutes) to a destination from the station.

Activity-travel characteristics of a traveler are represented by three groups of variables, such as share of household activities (work, maintenance, and discretionary) performed outside home, technology usage, mode usage, and travel party composition. The first group of variables accounts for fraction of total hours spent on various activity purposes outside home by the traveler. For example, the fraction of total household work hours by the traveler is calculated by dividing the total hours spent on work by the traveler outside home by the total hours spent on work by all the members of the household (including the traveler). The other two variables representing the fraction of total household maintenance and discretionary hours are also calculated in the same way. Note that, maintenance activities include drop off or pick up someone, buying goods (e.g. groceries), buying services (e.g. banking) or other general errands, exercise, health care visit, and religious activities whereas discretionary activities include buying meals, recreational activities (e.g. visit parks, movies, bars), visiting friends and relatives, and volunteer activities. The technology usage is denoted by two variables, such as frequency of ride-hailing app usage and frequency of online purchase in the last month. Again, the mode usage is represented by the fraction of trips made by private vehicle within the *work tour*, which is calculated by dividing the total number of trips made by private vehicle within the work tour by the total number of trips made in that tour. The last set of variables represents the fraction of trips made with household and non-household members. The fraction of trips made with household members by the traveler is calculated by dividing the total number of trips made by the traveler with household members by the total number of trips made by the traveler in a day. The fraction of trips with non-household members is calculated in the same manner. The *endogenous outcome* variable used in the model denotes the choice of a particular work tour by a transit commuter.

Table 3.1 Summary statistics of exogenous and endogenous variables

	Simple work tour	Complex work tour	Complex tour with work-based sub-tour
	n = 1062	n = 592	n = 425
	(a)	(b)	(c)
Household Characteristics			
Presence of child (aged 0-17) (%)	15.91[b]	19.76[ac]	13.18[b]
Presence of spouse/partner			
Have no spouse/partner (%)	36.91[b]	48.65[ac]	37.18[b]
Have employed spouse/partner (%)	50.09[b]	44.26[ac]	52.94[b]
Have unemployed spouse/partner (%)	12.99[b]	7.09[a]	9.88
Vehicle-driver ratio	0.80[bc]	0.70[a]	0.73[a]
Number of adult members (aged >= 18)	2.15[bc]	1.91[a]	1.89[a]
Monthly household income			
Low income (less than $20K) (%)	20.81[c]	23.82[c]	8.71[ab]
Middle income ($20K to $60K) (%)	35.88	35.14	32.00
High income ($60K or more) (%)	43.31[c]	41.05[c]	59.29[bc]
Personal Characteristics			
Millennials (aged 18-38) (%)	43.97	41.55	47.29
Male (%)	53.30[b]	44.93[ac]	53.41[b]
Have at least some college degree (%)	83.90[bc]	87.67[ac]	96.71[ab]
Immigrant (%)	24.29	20.95	20.24
Hispanic (%)	11.86[c]	10.47	7.06[a]
Caucasian (%)	64.69[c]	60.98[c]	77.88[ab]
Have flexibility in job arrival time (%)	48.12[c]	52.70[c]	65.41[ab]
Have full-time job (%)	84.65[bc]	80.74[ac]	91.29[ab]
Built Environment Characteristics			
Average midpoint of population density (persons per sq. mile) in census block group of home location (in 1000)	11.09[bc]	13.44[ac]	14.30[ab]
Distance from home to workplace (miles)	20.39[bc]	25.25[a]	14.84[a]
Proximity to transit station			
Average travel time to access the station (min.)	10.42[bc]	8.78[a]	9.28[a]
Average travel time to destination from station (min.)	13.78[bc]	10.55[a]	11.60[a]
Activity-travel Characteristics			
Fraction of total household work hours	0.76[b]	0.79[ac]	0.76[b]
Fraction of total household maintenance hours	0.10[bc]	0.52[ac]	0.39[ab]
Fraction of total household discretionary hours	0.05[bc]	0.34[ac]	0.63[ab]
Monthly frequency of ride-hailing app. usage	1.64[bc]	1.80[ac]	2.71[ab]
Monthly frequency of online purchase	3.28[bc]	3.64[ac]	4.39[ab]
Fraction of trips made with household members	0.09[bc]	0.17[ac]	0.09[ab]
Fraction of trips made with non-household members	0.07[bc]	0.12[ac]	0.16[ab]

Notes: Table shows mean values for all the variables. Mean values for binary variables are shown in percentage. All the categorical variables (except: middle income and millennials) and continuous/count variables are jointly significant at 5% significance level in χ^2 test and KW test respectively. Superscripts a, b, and c indicate that values are significantly different (at 5% significance level) from values of simple tours, complex tours, and complex tours with work-based sub-tours respectively in post-hoc tests.

3.4.3 The Conceptual Model

The conceptual structure of a SEM can be graphically depicted by a path diagram. An arrow in a diagram indicates the direct effect from one variable to other. The rectangular boxes represent exogenous and endogenous variables. Since an exogenous variable affects an endogenous variable, an arrow is directed *from* it. On the other hand, an endogenous mediator variable is influenced by some variables and affects the other variables, so an arrow is directed *to and from* it. Since an endogenous outcome variable is dependent on all the variables in the model, an arrow is directed *to* it. The conceptual structure of the proposed model is shown in Figure 3.3. In the model, household and person level characteristics are considered as the exogenous variables whereas built environment and activity-travel variables are accounted for endogenous mediator variables. Finally, the choice of three work tours: simple, complex, and complex tour with work-based sub-tours are considered as the endogenous outcome variables.

It is conceptualized that travelers' necessity to participate in various *activities* determines whether they make a simple work tour or mix non-work with work within the tour (work tour choice). For instance, it is assumed that the increasing fraction of household maintenance or discretionary hours spent by a traveler induces the choice of making a work-nonwork mixed tour (positive effect). Besides, the *built environment* characteristics (e.g. population density at residence, distance from home to workplace etc.) are anticipated to affect the work tour choice. For example, a traveler living in a denser area tends to make complex tours (positive effect). More importantly, a set of household and person level *socio-demographic and economic* factors (e.g. age, gender, ethnicity, income, presence of child etc.) are postulated to influence the choice of work tour.

Residential self-selection effects are captured in the model, the fact that people chose where to live based on their travel abilities, needs, and preferences (Mokhtarian and Cao, 2008). To capture such effect, I posit direct connections from each of the household and person level socio-demographic and economic characteristics to the residential location and surrounding built environment variables. In addition, it is conceptualized that people's activity-travel characteristics are affected by their socio-demographics and built environment characteristics.

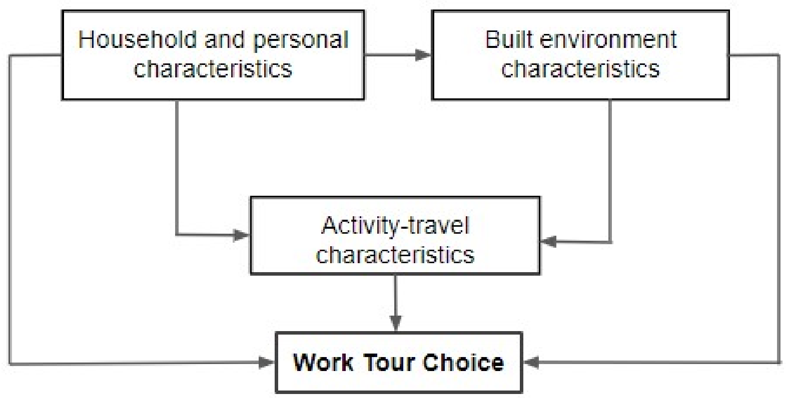


Figure 3.3 SEM conceptual structure

In the model, some error-term covariances among similar set of variables are added, for example, among the four built environment variables, between two technology usage variables, and two travel party composition in trips variables. In addition, two error-term covariances are added between the fraction of total household maintenance and the fraction of total household discretionary activities.

3.4.4 Estimation of the Model

Based on the conceptual structure (Figure 3.3), three SEM path models are estimated, with different combination of a binary outcome variable. For instance, in *Model 1* (sample size: 1,654), the outcome variable is 1 if a traveler chooses complex tour and 0 if he/she choose simple tour. The purpose of this model is to contrast the factors that affect the choice of complex tours with that of simple tours. Again, in *Model 2* (sample size: 1,487), the outcome variable is 1 if a traveler chooses complex tour with work-based sub-tour and 0 if the choice of tour is simple. This facilitates the understanding of how the factors that determine the choice of work-based sub-tours differ with the factors that influence simple work tour choice. Lastly, in *Model 3* (sample size: 1,017), a contrast between two work-nonwork mixed tours is made. That is, in this model, the outcome variable is 1 if the choice of the work tour is complex tour with work-based sub-tour and 0 if it is complex tour.

SEM path models are estimated using `lavaan` package in R. I used weighted least square mean and variance adjusted (WLSMV) estimator that works with categorical endogenous variables (one binary outcome variable in each model, which is regressed by a probit function in `laavan` (R documentation, 2018)) and that accounts for non-normally distributed data (Muthen and Kaplan, 1992). The widely used index to evaluate the model fit is χ^2 statistic that tests whether the observed covariance matrix and the model implied covariance matrix are equal. Smaller χ^2 value with high *p-value* (*p-value* > 0.05) indicates better model fit. Other model fit indices are also reported, such as Root Mean Square Error Approximation (RMSEA), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Standardized Root Mean Square Residual (SRMR). The resultant fit statistics for three models and the cut off value for the fit indices are shown in Table 3.2. It is observed that all the model fit indices indicate satisfactory fit for the three models.

Table 3.2 Model fit indices for the three SEM path models

Model fit indices	Description	Cut-off value	Model-based value		
			Model 1 (n = 1,654)	Model 2 (n = 1,487)	Model 3 (n = 1,017)
Chi-square: χ^2 (df)	A measure of the discrepancy between the observed and model-implied covariance matrices. Smaller value indicates better model fit.	$p > 0.05$	2.27 (5) $p > 0.811$	6.50 (5) $p > 0.260$	7.15 (5) $p > 0.210$
RMSEA	A measure of the amount of error of approximation per model degree of freedom, while controlling for sample size. Smaller value indicates better model fit.	< 0.05	0.000	0.014	0.021
CFI	An assessment of the improvement of the hypothesized model compared to the independence model with unrelated variables. Bigger value indicates better model fit.	> 0.95	1.00	0.99	0.99
TLI	An assessment of the improvement of the hypothesized model compared to the independence model with unrelated variables. Bigger value indicates better model fit.	> 0.95	1.02	0.99	0.97
SRMR	A measure of the mean absolute correlation residual, indicating the overall difference between the observed and predicted correlations. Smaller value indicates better model fit.	< 0.08	0.004	0.006	0.007

Kline (2016), Hu and Bentler (1999), and Van Acker and Witlox (2010)

3.5 Results and Discussion

The model results are discussed in this section by dividing the findings into three broad categories: factors that determine the work tour choice, evidence of residential self-selection, and factors that affect activity-travel characteristics. Here, unstandardized coefficients of the *direct* and *total* effects that are statistically significant are discussed. If not otherwise stated, all the mentioned effects below represent direct effects.

Table 3.3 Direct and total effects of variables on work tour choice in three SEM models

	Model 1: complex vs. simple		Model 2: complex with sub-tour vs. simple		Model 3: complex with sub-tour vs. complex	
	n = 1,654		n = 1,487		n = 1,017	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
Household Characteristics						
Presence of child						
B: 1 = if HH has child aged 0-17 years	0.073***	0.077**	0.064**	-0.027	0.015	-0.126***
Presence of spouse/partner						
B:1 = if traveler have unemployed spouse/partner	-0.056**	-0.087**	0.041	-0.027	0.101**	0.056
Vehicle-driver ratio	-0.062**	-0.105***	-0.088***	-0.149***	0.038	-0.033
Number of adult members (aged >=18 years)	0.071**	-0.122***	-0.031	-0.181***	-0.026	-0.044
Household income						
B: 1 = low income (less than $20K) (baseline)						
B: 1 = middle income ($20K to $60K)	-0.034	-0.005	0.123***	0.156***	0.138**	0.134**
B: 1 = high income ($60K or more)	0.004	0.014	0.201***	0.277***	0.220***	0.255***
Personal Characteristics						
Age of the traveler						
B: 1 = Millennials (aged 18 to 38 years)	-0.062**	-0.04	-0.044	0.039	0.012	0.076*
Gender: B: 1 if male	-0.047*	-0.091***	-0.016	-0.014	0.065*	0.065
Educational attainment						
B: 1 = have some college or higher degree	0.032	0.097***	0.141***	0.209***	0.167***	0.135**
Immigration status: B: 1 = if Immigrant	-0.03	-0.057*	0.011	0.01	0.046	0.058
Hispanic status: B: 1 if Hispanic or Latino	-0.018	-0.018	-0.052*	-0.037	0.005	-0.034
Ethnicity: B: 1 = if Caucasian	-0.051**	-0.064*	0.079***	0.117***	0.130***	0.173***
Flexibility in job arrival time						
B: 1 if have flexibility	0.043*	0.051	0.095***	0.116***	0.031	0.061
Employment type: B: 1 = if have full-time job	-0.042	-0.084**	0.046	0.027	0.132***	0.114**
Built Environment Characteristics						
Midpoint of population density in census block group of home location (persons per sq. mile)	0.100*	0.104***	0.079**	0.101**	-0.112**	-0.04
Distance from home to workplace (miles) (log)	0.026	0.027	-0.042	-0.124***	-0.119***	-0.170***
Proximity to transit station						
Average travel time to access the station (log)	-0.036	-0.065*	0.000	-0.044	0.066	0.062
Average travel time to destination from station (min.) (log)	-0.055**	-0.145***	-0.018	-0.058	0.006	0.072
Activity-travel Characteristics						
Fraction of total household work hours	0.091***	0.078**	-0.056	-0.058	-0.137***	-0.085*
Fraction of total household maintenance hours	0.460***	0.514***	0.284***	2.86	-0.063	-0.068
Fraction of total household discretionary hours	0.467***	0.466***	0.646***	0.669***	0.273***	0.308***
Monthly frequency of ride-hailing app. usage	0.011	-0.006	0.016	0.037	0.001	0.005
Monthly frequency of online purchase	0.028	0.052*	0.007	0.027	-0.003	-0.005
Fraction of trips made with household members	0.087***	0.087***	-0.065*	-0.066*	-0.117***	-0.117***
Fraction of trips made with non-household members	-0.029	-0.029	0.131***	0.131***	0.163**	0.163***
Fraction of trips made by private vehicle	0.328***	0.498***	0.178***	0.291***	-0.348***	-0.382***

Notes: 'B' stands for binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

3.5.1 Factors Affecting Work Tour Choice

3.5.1.1 Household and personal characteristics

Work tour choice is influenced by household and personal characteristics on an individual. As observed, millennials are less likely to make non-work stop on either way to work or way to home (complex) but more likely to do so during work (sub-tour) (total effect). It is also noticeable that tours performed by males tend to be more elementary (simple) than tours performed by females, who frequently link non-work activity either on the way to work or on the way to home. This is perhaps because female workers usually carryout greater range of activity responsibilities than their male counterparts (Strathman *et al.*, 1994; McGuckin and Murakami, 1999; Kuppam and Pendyala, 2001; Rafiq and McNally, 2019). In contrast, males prefer more to make non-work during work. Furthermore, an individual having at least college degree is more likely to make any kind of work-nonwork mixed tours.

Immigration status appears significantly in only model 1with implication that immigrants are more likely to make simple tours than native born people (total effect). While being Hispanic appears to be significant in only model 2, ethnicity demonstrated significant impacts on tour choice in all three models, such as Caucasians are found to be less likely to make complex tours but more likely to make complex with sub-tours. Employment characteristics, such as fulltime vs part time, flexibility in job arrival time, influence tour choice: full-time workers apparently prefer making simple tours compared to mixing work with nonwork (total effect), whereas travelers who have flexibility in arriving their jobs are more likely to make work-nonwork mixed tours than simple tours.

Presence of spouse (both employed and non-employed), children and other adults significantly affect the work tour choice. In particular, a traveler having unemployed spouse/partner are more likely to make simple tours than complex (Model 1) compared to the traveler who either do not have spouse or have employed spouse/partner. But these group of travelers are more interested to make work-based sub-tours (Model 3) than their counterpart. On the other hand, individuals having children at home tends to prefer make to complex tours (Model 1) over simple tours, perhaps because those individuals might take their child to daycare or school or complete shopping for their child within a work tour and thus have fewer opportunities to make separate non-work tours. Between two complex tours (Model 3), they tend to make non-work less during work hour than on the way to work or way to home compared to the travelers who do not have child (total effect). With the increase of the number of adults in households, travelers tend to make more simple tours and do not mix work with non-work activities. This might be due to the presence of other adult household members who might take care of essential non-work household activities (e.g., taking a child to school/daycare, grocery shopping).

Another important household characteristic affecting tour choice is household income and the presence and prevalence of vehicles at the household. However, household income does not appear significant in model 1, that means it does not significantly contribute in determining the likelihood of making complex tours over simple tours (Wang, 2015). It shows significant effects in the other two models. Results show that both middle- and higher-income travelers are more likely to make work-based sub-tours compared to low-income travelers. Moreover, travelers from households with a higher vehicle to driver ratio are prone to make simple tours (effect in Model 1 and Model 2), which is because more vehicle per driver in the household might give the traveler higher flexibility to make separate non-work tours after returning home.

3.5.1.2 Built environment characteristics

Built environment characteristics affect people's choice of certain work tour. Travelers living in denser areas (higher population density near the residence) are more likely to make any kind of complex tours than simple tours (effect in Model 1 and Model 2), perhaps because they can easily perform non-work activities on their way to home near home location (due to dense neighborhood). As distance to work increases the chance to further travel from workplace to a non-work location declines hence tours to and from workplace reduces (effect in Model 2 and Model 3). Proximity to the transit station appears significant in only the Model 1. It shows that with the increase of the average travel time to or from the stations reduces the tendency of making complex tours.

3.5.1.3 Activity-travel characteristics

Tour choice of an individual depends on his/her activity-travel characteristics, such as share of household activities (work, maintenance and discretionary) performed outside home, technology usage, mode usage, and travel party composition. With the increase of the fraction of total household work hours made by a traveler, the tendency of making complex tours increases (Model 1) but complex with sub-tours decreases (Model 3). On the other hand, increase of the fraction of total maintenance hours contribute to make any kind of work-nonwork mixed tours than simple work tours. Similarly, the increase of the fraction of total household discretionary hours cause to make work-nonwork mixed tours than simple tours. Discretionary stops are more likely to be made during work hour (buying lunch during midday) (Model 3). Technology usage such as monthly frequency of ride-hailing app usage or online shopping do not significantly affect the choice of work tours.

Interestingly, who accompany a trip affects the tour choice. For example, when individuals make trips with household members accompanied with them, their chance of making complex tours increases and the tendency of making work-based sub-tours declines. Conversely, with the increase of the fraction of trips made with non-household members, the chance of making work-based sub-tours increases. Non-work stops made on the way to work or on way to home, are more likely to be made with household members to drop off/pick up someone from the same household. On the other hand, a non-work stop made during work hour is more likely to be made with co-workers (non-household members) for lunch. The use of private vehicle in the work tour appears discernable effects in all the three models. With the increase of the fraction of trips made by private vehicle, the tendency to make any kind of work-nonwork mixed tours increases (model 1 and model 2). While comparing the two work-nonwork mixed tours, the increasing fraction of private vehicle usage decreases the chance of making work-based sub-tours compared to complex tours (model 3).

3.5.2 Residential Self-selection

Residential self-selection refers to people's social-demographics attributes affecting their choice of where they live (residence) and the characteristics of the surrounding built environment (e.g., population density, distance to and from work and transit station). The tour choice model demonstrates the presence of residential self-selection in all the three models. It turns out that traveler's personal characteristics, such as age and household characteristics, such as presence of child, number of adults, vehicle-driver ratio, and income are important residential self-selection factors in tour choice modeling. For instance, millennials, people with higher educational qualification, immigrant, Hispanics, middle- and high-income households are more likely to live in a denser area. In contrast, male travelers, non-millennials, people who have flexibility in job arrival time and people from households having children and adults at home with higher vehicle to driver ratio are less likely to live in a denser residential area. Most of the results are consistent except a few. For example, high income households tend to live in residential areas with lower population density. But the model results show the opposite. However, similar result was found in a study by Mitra and Saphores (2017).

Again, distance from home to work location is influences by a set of socio-demographic characteristics. Most of the effects appear positive, except a few. For example, age has negative effect on the distance from home to workplace, which implies that millennials tend to work at a location that is not very far from the residence than non-millennials. The indicators representing the proximity to the station also appears to be significantly affected by the socio-demographic characteristics but at a limited scope. For instance, millennials tend to access or egress the transit stations close to their home or non-home activity locations. On the other hand, travelers with high household income and higher number of household vehicles per driver tend to travel longer distance (longer trip time) to access the station or egress from the station.

3.5.3 Factors Affecting Activity-Travel Characteristics

Household and personal characteristics influence individual's activity-travel characteristics in their way to influencing the tour choice. Millennials tend to contribute less fraction of household work hour than non-millennials. As expected, men tend to contribute higher proportion of work hour and lower fraction of maintenance hour in the household. With the increase of the number of adults in the household, the work and maintenance load of the traveler diminishes. Similar

Table 3.4 Residential self-selection results for three SEM models

	Model 1: complex vs. simple				Model 2: complex with sub-tour vs. simple				Model 3: complex with sub-tour vs. complex			
	n = 1,654				n = 1,487				n = 1,017			
	Population density	Distance to work	Travel time to station	Travel time from station	Population density	Distance to work	Travel time to station	Travel time from station	Population density	Distance to work	Travel time to station	Travel time from station
Household Characteristics												
Presence of child												
B: 1 = if HH has child aged 0-17	-0.072***	0.050**	0.005	0.023	-0.102***	0.083***	0.054**	0.063**	-0.076***	0.083***	0.056*	0.018
Presence of spouse/partner												
B:1 = if traveler have unemployed spouse/partner	-0.037	0.038	0.064***	0.074***	-0.035	0.056**	0.059**	0.038	-0.016	0.051	0.012	0.071**
Vehicle-driver ratio	-0.360***	0.237***	0.099***	0.078***	-0.359***	0.241***	0.091***	0.074**	-0.468***	0.253***	0.140***	0.129***
Number of adult members (aged >=18)	-0.056**	0.071***	0.026	0.040*	-0.042*	0.096***	0.046	0.090***	-0.098***	0.058*	0.039	0.098***
Household income												
B: 1 = low income (less than $20K) (baseline)												
B: 1 = middle income ($20K to $60K)	0.184***	0.059*	-0.011	0.022	0.144***	0.022	0.002	0.006	0.235***	0.074	-0.071	-0.058
B: 1 = high income ($60K or more)	0.229***	0.191***	0.099**	0.110**	0.224***	0.182***	0.095**	0.047	0.314***	0.166***	0.01	0.003
Personal Characteristics												
Age of the traveler												
B: 1 = Millennials (aged 18 to 38)	0.057**	-0.113***	-0.061**	-0.045*	0.060**	-0.120***	-0.098***	-0.112***	0.033	-0.131***	-0.085***	-0.084**
Gender: *B: 1 if male*	-0.063***	-0.003	-0.008	-0.011	-0.045*	0	0.016	0.009	-0.078***	0.024	-0.031	-0.047
Educational attainment												
B: 1 = have some college or higher degree	0.050**	0.044*	-0.011	-0.003	0.052**	0.029	-0.004	-0.007	0.077**	0.025	0.018	0.02
Immigration status: B: 1 = if Immigrant	0.086***	0.046*	0.001	-0.004	0.089***	0.019	-0.002	-0.016	0.091***	0.018	-0.011	0.013
Hispanic status: B: 1 if Hispanic or Latino	0.125***	-0.02	-0.026	0.04	0.116***	-0.021	-0.022	0.018	0.120***	-0.021	-0.029	0.068**
Ethnicity: B: 1 = if Caucasian	-0.033	-0.03	-0.017	-0.056**	-0.007	-0.013	0.01	-0.03	0.026	-0.058	-0.011	-0.038
Flexibility in job arrival time												
B: 1 if have flexibility	-0.036	-0.03	-0.027	-0.022	-0.045*	-0.078***	-0.022	-0.033	-0.059*	-0.083**	-0.063*	-0.047
Employment type: B: 1 = if have full-time	0.004	0.042*	0.024	0.051*	-0.02	0.072***	0.028	0.068**	0.019	0.053*	0.014	0.071**

Notes: 'B' stands for binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 3.5 Direct and total effects of variables on activity-travel characteristics in model 1

	Model 1: complex vs simple work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Household Characteristics																
Presence of child																
B: 1 = if HH has child aged 0-17 years	-0.033*	-0.032*	-0.023	-0.006	-0.082***	-0.076***	-0.015	-0.027	0.018	0.014	0.119***	0.157***	-0.03	-0.007	0.108***	0.115***
Presence of spouse/partner																
B:1 = if traveler have unemployed spouse/partner	0.266***	0.273***	0	-0.033	-0.015	-0.02	-0.016	-0.019	-0.037	-0.038	-0.004	-0.053**	-0.003	-0.008	-0.051*	-0.054*
Vehicle-driver ratio	-0.027	-0.009	-0.036	-0.048**	-0.041	-0.057**	-0.049*	-0.093***	0.037	0.026	-0.056*	-0.009	-0.001	0.039	0.097***	0.140***
Number of adult members (aged >=18 years)	-0.544***	-0.538***	-0.212***	-0.197***	-0.074	-0.124***	-0.055*	-0.067**	-0.031	-0.032	0.090***	0.148***	-0.045	-0.065**	-0.008	-0.005
Household income																
B: 1 = low income (less than $20K) (baseline)																
B: 1 = middle income ($20K to $60K)	-0.095***	-0.100***	-0.051	-0.019	0.018	0.021	0.043	0.051	0.099**	0.105**	0.045	0.058	-0.094***	-0.087***	0.05	0.02
B: 1 = high income ($60K or more)	-0.224***	-0.223***	-0.128***	-0.087**	0.065	0.049	0.163***	0.168***	0.253***	0.262***	0.088**	0.111***	-0.111***	-0.098**	0.065	0.02
Personal Characteristics																
Age of the traveler																
B: 1 = Millennials (aged 18 to 38 years)	-0.091***	-0.099***	-0.033	-0.018	0.029	0.033	0.219***	0.231***	0.107***	0.107***	0.052**	0.073***	0.086***	0.090***	0.026	0.022
Gender: B: 1 if male	0.042**	0.045**	-0.059**	-0.074***	0.017	0.005	-0.029	-0.035	-0.043*	-0.044*	-0.006	-0.016	-0.053**	-0.055**	-0.04	-0.03
Educational attainment																
B: 1 = have some college or higher degree	0.003	0.002	0.057**	0.067***	0.04	0.050**	0.028	0.029	0.081*	0.083*	0.007	0.005	-0.014	-0.009	0.009	0.002
Immigration status: B: 1 = if Immigrant	-0.043**	-0.045**	-0.067**	-0.057**	0.002	-0.005	-0.034	-0.03	-0.058**	-0.054*	-0.015	-0.013	-0.003	-0.003	0.006	-0.006
Hispanic status: B: 1 if Hispanic or Latino	-0.001	-0.006	0.024	0.033	-0.051**	-0.042*	0.015	0.026	-0.018	-0.016	-0.016	-0.025	0.013	0.005	0.012	-0.011
Ethnicity: B: 1 = if Caucasian	-0.017	-0.017	0.002	0	0.006	0.002	-0.022	-0.022	0.064**	0.064**	-0.059**	-0.061**	-0.002	-0.012	-0.037	-0.026
Flexibility in job arrival time																

	Model 1: complex vs simple work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
B: 1 if have flexibility	-0.004	-0.005	0.027	0.027	-0.017	-0.014	0.027	0.024	0.070***	0.068***	0.015	0.017	-0.026	-0.029	-0.005	0.002
Employment type: B: 1 = if have full-time job	0.018	0.021	-0.014	-0.019	-0.048**	-0.053***	-0.003	-0.004	0.045	0.045	-0.012	-0.025	0.01	0.002	-0.015	-0.021
Built Environment Characteristics																
Midpoint of population density in census block group of home location (persons per sq. mile)	-0.033	-0.029	0.113***	0.085***	0.044	0.037*	0.084***	0.085***	0.032	0.035	-0.023	-0.067**	-0.009	-0.045	-0.143***	-0.143***
Distance from home to workplace (miles) (in log)	0.03	0.031	0.015	0.016	-0.017	-0.014	-0.065***	-0.065***	0.018	0.018	-0.016	-0.02	0.023	0.021	-0.001	-0.001
Proximity to transit station																
Average travel time to access the station (min.) (in log)	0.022	0.022	-0.032	-0.031	-0.052*	-0.053**	0.025	0.024	0.007	0.007	0.015	0.017	-0.036	-0.038	0.014	0.014
Average travel time to destination from station (min.) (in log)	0.012	0.015	-0.049*	-0.075***	0	-0.021	-0.001	0.001	-0.024	-0.022	-0.046*	-0.084***	0.053*	0.023	-0.119***	-0.119***
Activity-travel Characteristics																
Fraction of total household work hours			-0.042	-0.042	0.04	0.035		0.002			-0.109***	-0.107***	0.028	0.034		
Fraction of total household maintenance hours					0.119	0.119		0			-0.029	-0.026	-0.040*	-0.026		
Fraction of total household discretionary hours				0				0.002*			0.03	0.03	0.123***	0.123***		
Monthly frequency of ride-hailing app. usage			-0.033	-0.033		-0.004						0.001		0.001		
Monthly frequency of online purchase			0.047**	0.047**		0.006		0				-0.001		-0.001		
Fraction of trips made with household members				0		0	-0.009	-0.009						0		
Fraction of trips made with non-household members				-0.001		0	0.022**	0.022**				0				
Fraction of trips made by private vehicle	-0.030*	-0.030*	0.198***	0.199***	0.109	0.132***	-0.013	-0.01	-0.019	-0.019	0.320***	0.321***	0.255***	0.263***		

Notes: 'B' stands for binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 3.6 Direct and total effects of variables on activity-travel characteristics in model 2

	Model 2: complex tour with work-based sub-tour vs. simple work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Household Characteristics																
Presence of child																
B: 1 = if HH has child aged 0-17	-0.012	-0.005	-0.063*	-0.071**	0.174	-0.084***	0.02	-0.002	-0.004	-0.008	0.064***	0.070***	-0.014	-0.02	0.018	0.02
Presence of spouse/partner																
B:1 = if traveler have unemployed spouse/partner	0.275***	0.281***	-0.014	-0.036	0.027	-0.041	-0.03	-0.036	-0.04	-0.04	0.019	-0.019	-0.006	-0.029	-0.034	-0.035
Vehicle-driver ratio	-0.016	-0.004	-0.005	-0.027	0.019	-0.041*	-0.062**	-0.129***	0.034	0.018	-0.005	0.024	0.015	0.035	0.047**	0.063***
Number of adult members (aged >=18 years)	-0.569***	-0.562***	-0.182***	-0.167***	0.559	-0.167***	-0.090***	-0.106***	-0.053*	-0.053*	0.065**	0.112***	-0.046	-0.057**	0.007	0.002
Household income																
B: 1 = low income (less than $20K) (baseline)																
B: 1 = middle income ($20K to $60K)	-0.112***	-0.112***	-0.018	-0.012	0.131	0.067*	0.051	0.066*	0.126**	0.136**	0.054	0.044	-0.115***	-0.117***	-0.03	-0.044*
B: 1 = high income ($60K or more)	-0.239***	-0.231***	-0.046	-0.043	0.327	0.143***	0.178***	0.195***	0.286***	0.306***	0.091**	0.074*	-0.098**	-0.098**	-0.046	-0.078***
Personal Characteristics																
Age of the traveler																
B: 1 = Millennials (aged 18 to 38 years)	-0.094***	-0.106***	-0.008	0.015	0.062	0.066***	0.235***	0.247***	0.144***	0.144***	0.036	0.061**	0.065***	0.085***	0.027	0.033
Gender: *B: 1 if male*	0.054***	0.056***	-0.014	-0.021	0.091	0.031	-0.034	-0.038	-0.027	-0.03	-0.017	-0.026	-0.029	-0.028	-0.019	-0.016
Educational attainment																
B: 1 = have some college or higher degree	0.012	0.014	0.083***	0.079***	-0.239	0.079**	0.017	0.024	0.065	0.07	0.021	-0.002	0.021	0.016	-0.054***	-0.060***
Immigration status: B: 1 = if Immigrant	-0.013	-0.015	-0.01	-0.004	0.008	-0.022	-0.003	0.007	-0.008	-0.002	-0.042*	-0.034	-0.001	0	0.039*	0.031
Hispanic status: B: 1 if Hispanic or Latino	-0.006	-0.009	0.024	0.03	-0.11	-0.008	0.055**	0.071***	0.009	0.015	0.015	0.013	0.003	0.002	0.018	0.008
Ethnicity: B: 1 = if Caucasian	0.012	0.01	0.04	0.042*	-0.126	0.034	0.031	0.031	0.056*	0.055*	-0.02	-0.013	-0.013	-0.004	0.015	0.018
Flexibility in job arrival time																
B: 1 if have flexibility	0.009	0.006	0.036	0.038*	-0.131	0.015	0.028	0.029	0.075***	0.070**	-0.008	-0.007	0.008	0.009	-0.021	-0.012

	Model 2: complex tour with work-based sub-tour vs. simple work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Employment type: B: 1 = if have full-time job	0.007	0.013	-0.006	-0.015	0.024	-0.013	-0.001	-0.006	0.024	0.025	-0.033	-0.047*	0.014	0.007	-0.019	-0.024
Built Environment Characteristics																
Midpoint of population density in census block group of home location (persons per sq. mile)	-0.013	-0.009	0.033	0.027	-0.079	0.045*	0.133***	0.138***	0.059**	0.061**	-0.04	-0.068***	-0.032	-0.048*	-0.090***	-0.090***
Distance from home to workplace (miles) (in log)	0.014	0.016	-0.038	-0.043*	0.064	-0.088***	-0.086***	-0.083***	0.030*	0.031*	-0.014	-0.033	-0.001	-0.03	-0.052**	-0.052**
Proximity to transit station																
Average travel time to access the station (min.) (in log)	0.039*	0.039*	-0.038	-0.04	0.107	-0.037	0.038	0.037	-0.002	-0.002	0.014	0.008	-0.04	-0.049*	-0.007	-0.007
Average travel time to destination from station (min.) (in log)	0.039*	0.041*	-0.021	-0.026	0.038	-0.046*	0.005	0.01	-0.004	-0.003	-0.061**	-0.078***	0.037	0.017	-0.042**	-0.042**
Activity-travel Characteristics																
Fraction of total household work hours			-0.043	-0.043	0.176	0.011		0.003			-0.091***	-0.091***	-0.024	-0.022		
Fraction of total household maintenance hours					3.852	3.852		0.009			-0.001	0.007	-0.003	0.662		
Fraction of total household discretionary hours				0				0.002			0.002	0.002	0.173***	0.173***		
Monthly frequency of ride-hailing app. usage			0.007	0.007		0.028						0		0.005		
Monthly frequency of online purchase			0.007	0.007		0.027		0				0		0.005		
Fraction of trips made with household members				0		-0.001	-0.035	-0.035						0		
Fraction of trips made with non-household members				0		0	0.013	0.013				0				
Fraction of trips made by private vehicle	-0.038	-0.038	0.086***	0.087***	-0.219	0.110***	-0.036	-0.043	-0.022	-0.022	0.323***	0.326***	0.267***	0.287***		

Notes: 'B' stands for binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Table 3.7 Direct and total effects of variables on activity-travel characteristics in model 3

	Model 3: complex tour with work-based sub-tour vs. complex work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Household Characteristics																
Presence of child																
B: 1 = if HH has child aged 0-17	-0.013	-0.012	-0.075**	-0.060*	-0.226***	-0.241***	-0.003	-0.027	0.05	0.04	0.137***	0.210***	-0.054	-0.046	0.120***	0.146***
Presence of spouse/partner																
B:1 = if traveler have unemployed spouse/partner	0.317***	0.319***	-0.024	-0.054	-0.083*	-0.054	-0.025	-0.029	-0.047	-0.053	0.023	-0.027	0.005	0.004	-0.028	-0.028
Vehicle-driver ratio	-0.027	-0.021	-0.071*	-0.044	0.035	0.013	-0.003	-0.105**	0.018	-0.027	-0.072*	0.005	0.008	0.095***	0.240***	0.367***
Number of adult members (aged >=18 years)	-0.561***	-0.560***	-0.373***	-0.323***	-0.188	-0.228***	-0.07	-0.091*	-0.012	-0.025	0.046	0.215***	-0.078*	-0.078**	0.047	0.064*
Household income																
B: 1 = low income (less than $20K) (baseline)																
B: 1 = middle income ($20K to $60K)	-0.113***	-0.113***	-0.015	-0.003	0.088	0.07	0.053	0.077	0.123	0.137*	0.023	0.03	-0.052	-0.065	-0.002	-0.047
B: 1 = high income ($60K or more)	-0.227***	-0.224***	-0.136**	-0.126**	0.121	0.100*	0.217**	0.249**	0.294***	0.303***	0.067	0.069	-0.086	-0.111**	-0.08	-0.142**
Personal Characteristics																
Age of the traveler																
B: 1 = Millennials (aged 18 to 38 years)	-0.108***	-0.112***	-0.102***	-0.099***	0.086	0.077**	0.234***	0.259***	0.134***	0.147***	0.056*	0.088***	0.163***	0.183***	0.023	0.012
Gender: *B: 1 if male*	0.060**	0.061**	-0.058*	-0.060*	0.065	0.068*	-0.005	-0.023	-0.049	-0.052	0.007	-0.001	-0.062*	-0.04	0.005	0.033
Educational attainment																
B: 1 = have some college or higher degree	0.011	0.011	0.017	0.022	0.041	0.035	0.048	0.049	0.1	0.103	-0.019	-0.014	-0.107***	-0.098***	0.058	0.038
Immigration status: B: 1 = if Immigrant	-0.015	-0.015	-0.03	-0.031	0.027	0.025	0.01	0.024	0.012	0.017	-0.008	-0.009	0.028	0.025	-0.004	-0.028
Hispanic status: B: 1 if Hispanic or Latino	0.022	0.021	0.056	0.053	-0.065	-0.064*	-0.02	-0.003	-0.015	-0.008	-0.025	-0.016	-0.023	-0.039	0.036	-0.006
Ethnicity: B: 1 = if Caucasian	-0.028	-0.029	0.036	0.034	0.024	0.027	0.004	0.014	0.022	0.028	-0.063*	-0.080**	0.014	0.001	-0.055	-0.062
Flexibility in job arrival time																

	Model 3: complex tour with work-based sub-tour vs. complex work tour															
	Fraction of total household work hours		Fraction of total household maintenance hours		Fraction of total household discretionary hours		Monthly frequency of ride-hailing app. usage		Monthly frequency of online purchase		Fraction of trips made with household members		Fraction of trips made with non-household members		Fraction of trips made by private vehicle	
	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
B: 1 if have flexibility	-0.059**	-0.061**	-0.01	-0.006	-0.001	-0.001	-0.011	-0.007	0.022	0.026	0.048	0.060*	0.085**	0.085**	-0.02	-0.008
Employment type: B: 1 = if have full-time job	-0.001	-0.001	0.024	0.027	0.012	0.007	0.026	0.025	0.053	0.049	-0.001	0.012	0.051	0.059*	0.064*	0.055
Built Environment Characteristics																
Midpoint of population density in census block group of home location (persons per sq. mile)	-0.005	-0.003	0.022	-0.006	-0.045	-0.02	0.138***	0.149***	0.056*	0.056*	0.049	-0.021	-0.015	-0.073**	-0.249***	-0.249***
Distance from home to workplace (miles) (in log)	0.019	0.019	0.007	0.019	-0.033	-0.042	-0.094**	-0.101***	-0.044	-0.044	-0.047	-0.016	-0.034	-0.018	0.100***	0.100***
Proximity to transit station																
Average travel time to access the station (min.) (in log)	0.01	0.01	0.004	0.004	-0.015	-0.016	0.012	0.011	-0.032	-0.032	-0.059**	-0.052	0.022	0.026	0.024	0.024
Average travel time to destination from station (min.) (in log)	-0.001	0	-0.031	-0.047	0.044	0.058	0.018	0.025	-0.029	-0.03	0.031	-0.015	-0.008	-0.029	-0.144***	-0.144***
Activity-travel Characteristics																
Fraction of total household work hours			-0.080**	-0.080**	0.074	0.075*		-0.001			-0.166***	-0.168***	0.029	0.045		
Fraction of total household maintenance hours					-0.006	-0.006		-0.007*			-0.103***	-0.102	-0.090***	-0.091		
Fraction of total household discretionary hours				0				0.003			-0.133***	-0.133***	0.119***	0.119***		
Monthly frequency of ride-hailing app. usage			-0.052*	-0.052*		0						0.005		0.005		
Monthly frequency of online purchase			0.03	0.03		0		0				-0.003		-0.003		
Fraction of trips made with household members				-0.001		0	0.019	0.019						0		
Fraction of trips made with non-household members				-0.003		0	0.050***	0.050***				0				
Fraction of trips made by private vehicle	-0.009	-0.009	0.090***	0.092***	-0.099*	-0.101***	-0.060***	-0.044***	0.002	0.002	0.298***	0.304***	0.223***	0.203***		

Notes: 'B' stands for binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

effect is obtained in connection to high income. It implies that there might be other workers in the household who share both the work and maintenance activities in household.

Technology usage of a traveler is also affected by his/her socio-demographic and built environment characteristics. As anticipated, millennials are more tech-savvy and hence, more preferred to use ride-hailing services and to do internet shopping than non-millennials. Higher income is significantly associated with ride-hailing usage and internet shopping. Travelers living in higher density areas increases the likelihood to use ride-hailing services due to the availability of frequent services. A traveler being a millennial increases the chance of making higher fraction of trips with household or non-household members. As anticipated, presence of child and other adults in the household increases the chance of making higher fraction of trips with household members. Travelers with high income is more likely to make higher fraction of trips with household members compared to trips with non-household members. Again, presence of child and higher vehicle-driver ratio increases the chance of using private vehicle in the work tour.

3.6 Conclusions

This study characterizes the transit commuters based on the complexity of trip chaining they make within a work tour and assesses the impact of various factors on the likelihood of a commuter to choose a particular type of work tour. The impact of various factors on work tour choice is analyzed by conceptualizing a causal structure among a set of socio-demographic characteristics, built environment variables, activity participation, and a particular tour choice by using SEM for *path* model. Based on the 2017 NHTS data, results suggest that millennial male commuters with high vehicle ownership who have spouse, other adult members but no children at their households tend to make simple work tours. On the other hand, non-Caucasian non-millennial female commuters having children at home are more likely to make complex work tours. And, Caucasian higher income millennials who have a full-time job and who have higher flexibility in job arrival time are prone to make complex tours with work-based sub-tours. The findings of this study can provide better insights on identifying the transit commuters with a particular type of work tour and the factors that govern the tour choice, which can eventually help to predict the number of stops within a tour for each individual and then to schedule a tour in an activity-based model.

3.7 References

Acock, A. C. (2013). Discovering structural equation modeling using Stata. *Stata Press books*.

Bernardin Jr, V. L., Swenson, A., Jiang, Z., & Grovak, M. (2011). Income effects and other new findings on complexity of transit tours. *Transportation Research Record*, *2217*(1), 38-45.

Bhat, C. (1999). An analysis of evening commute stop-making behavior using repeated choice observations from a multi-day survey. *Transportation Research Part B: Methodological*, *33*(7), 495-510.

Bianco, M., & Lawson, C. (1996). Trip chaining, childcare and personal safety: critical issues in women's travel behavior. *In Proceedings from the second national conference on women's travel issues*. Washington DC

Cheng, L., Chen, X., Yang, S., Wu, J., & Yang, M. (2019). Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. *Transportation Letters*, *11*(6), 341-349.

Federal Highway Administration (2002). Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance. http://www.fhwa.dot.gov/policy/ 2002cpr/pdf/execsummary_book.pdf. Accessed Dec 24, 2018.

Fujii, S., & Kitamura, R. (2000). Evaluation of trip-inducing effects of new freeways using a structural equations model system of commuters' time use and travel. *Transportation Research Part B: Methodological*, *34*(5), 339-354.

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological*, *37*(1), 1-25.

Golob, T. F., and McNally, M. G. (1997). A model of activity participation and travel interactions between household heads. *Transportation Research Part B: Methodological*, *31*(3), 177-194.

Goulias, K. G., & Kitamura, R. (1991). Recursive model system for trip generation and trip chaining. *Transportation Research Record*, 1236, 59-66.

Hadiuzzaman, M., Farazi, N. P., Hossain, S., Barua, S., & Rahman, F. (2019). Structural equation approach to investigate trip-chaining and mode choice relationships in the context of developing countries. *Transportation Planning and Technology*, *42*(4), 391-415.

Hensher, D. A., and Reyes, A. J. (2000). Trip chaining as a barrier to the propensity to use public transport. *Transportation*, *27*(4), 341-361.

Ho, C. Q., & Mulley, C. (2013). Multiple purposes at single destination: A key to a better understanding of the relationship between tour complexity and mode choice. *Transportation Research Part A: Policy and Practice*, 49, 206-219.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

Islam, M. T., & Habib, K. M. N. (2012). Unraveling the relationship between trip chaining and mode choice: evidence from a multi-week travel diary. *Transportation Planning and Technology*, *35*(4), 409-426.

Kaplan, D. (2008). *Structural equation modeling: Foundations and extensions* (Vol. 10). Sage Publications.

Kline, R. B. (2016). *Principles and practice of structural equation modeling*. Guilford publications, New York, USA.

Krygsman, S., Arentze, T., & Timmermans, H. (2007). Capturing tour mode and activity choice interdependencies: A co-evolutionary logit modelling approach. *Transportation Research Part A: Policy and Practice*, *41*(10), 913-933.

Kuppam, A. R., & Pendyala, R. M. (2001). A structural equations analysis of commuters' activity and travel patterns. *Transportation*, *28*(1), 33-54.

Lee, M. S., & McNally, M. G. (2003). On the structure of weekly activity/travel patterns. *Transportation Research Part A: Policy and Practice*, 37(10), 823-839.

Levinson, D., & Kumar, A. (1995). Activity, travel, and the allocation of time. *Journal of the American Planning Association*, 61(4), 458-470.

Lu, X., & Pas, E. I. (1999). Socio-demographics, activity participation and travel behavior. *Transportation Research part A: policy and practice*, *33*(1), 1-18.

Kuppam, A. R., & Pendyala, R. M. (2001). A structural equations analysis of commuters' activity and travel patterns. *Transportation*, *28*(1), 33-54.

McGuckin, N., & Murakami, E. (1999). Examining trip-chaining behavior: Comparison of travel by men and women. *Transportation Research Record: Journal of the Transportation Research Board*, (1693), 79-85.

McGuckin, N., Zmud, J., & Nakamoto, Y. (2005). Trip-chaining trends in the United States: understanding travel behavior for policy making. *Transportation Research Record*, 1917(1), 199-204.

Mitra, S. K., & Saphores, J. D. M. (2017). Carless in California: Green choice or misery?. *Journal of transport geography*, *65*, 1-12.

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

Muthen, B. and Kaplan, D. (1992). A comparison of some methodologies for the factor analysis of non-normal Likert variables: A note on the size of the model. *British Journal of Mathematical and Statistical Psychology*, *45*(1), 19-30.

Noland, R.B., Schmocker, J.D. and Bell, M.G.H. (2008). Trip chaining behaviour of older people: Effects of medical conditions and urban form. *Presented at 87th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Primerano, F., Taylor, M. A., Pitaksringkarn, L., & Tisato, P. (2008). Defining and understanding trip chaining behaviour. *Transportation*, 35(1), 55-72.

Rafiq R. and McNally, M. G. (2019). Changes in Activity-Travel Behavior of Workers Before and After the 2009 Recession. *Presented at 98th Annual Meeting of the Transportation Research Board*, Washington, D.C.

R Documentation. LavOptions.www.rdocumentation.org/packages/lavaan/versions/0.6-1.1240/topics/lavOptions. Accessed July 22, 2018.

Strathman, J. G., Dueker, K. J., & Davis, J. S. (1994) Effects of household structure and selected travel characteristics on trip chaining. *Transportation*, 21(1), 23-45.

Strathman, J., Dueker, K. (1995). Understanding trip chaining. *Special Reports on Trip and Vehicle Attributes*, 1990 NPTS Report Series, US Department of Transportation and Federal Highway Administration.

Van Acker, V., & Witlox, F. (2010). Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. *Journal of Transport Geography*, *18*(1), 65-74.

Van Acker, V., & Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use?. *Transportation*, *38*(3), 465-486.

Wallace, B., Barnes, J., & Rutherford, G. (2000). Evaluating the effects of traveler and trip characteristics on trip chaining, with implications for transportation demand management strategies. *Transportation Research Record: Journal of the Transportation Research Board*, (1718), 97-106.

Wang, R. (2015). The stops made by commuters: evidence from the 2009 US National Household Travel Survey. *Journal of Transport Geography*, *47*, 109-118.

Yang, M., Wang, W., Ren, G., Fan, R., Qi, B., & Chen, X. (2010). Structural equation model to analyze sociodemographics, activity participation, and trip chaining between household heads: survey of Shangyu, China. *Transportation Research Record*, *2157*(1), 38-45.

CHAPTER 4: Tour Formation of Ride-hailing Users

4.1 Introduction

The emergence of technology-enabled on-demand ride services (e.g., Uber or Lyft), also known as *ride-hailing*, creates new opportunities for transportation and arguably has impacted daily activity-travel behavior in recent years. Since the advent of ride-hailing (circa 2009), services have experienced significant growth in demand. Recent studies in American cities show that about 21 percent of adults now personally use ride-hailing services and an additional 9 percent use it with friends (Clewlow and Mishra, 2017). Ride-hailing services expand the set of travel alternatives and substantially increase the flexibility in activity scheduling and travel choices, thus affecting travel behavior in several ways, including increasing travel options, reducing travel uncertainty, and potentially replacing the use of other travel modes (Alemi et al., 2018a). These services can offer superior user experiences through a set of benefits that other transport choices can hardly provide, such as real-time information about wait time, the identification of both drivers and passengers prior to making a trip, and a simple payment method.

Despite of the rising demand of ride-hailing services, the lack of available data from its major companies limits comprehensive examination of travel behavior of ride-hailing users. Prior studies considered ride-hailing in terms of its emergence (Taylor et al., 2015), user demographics and activity demands (Young and Farber, 2019), use across socio-demographic classes (Alemi et al., 2018b), use among older adults (Leistner and Steiner, 2017), regulations and legal issues (Beer et al., 2017; Flores and Rayle, 2017), differences with taxi service (Rayle et al., 2016), as well as impacts on transit and taxi (Hall et al., 2018; Contreras and Paz, 2018), VMT and parking (Henao and Marshall, 2018, 2019).

However, previous studies have focused on independent ride-hailing trips and thus, have not considered the complete sequence of activities and trips (*pattern*) made by a ride-hailing user over a full day and consequently are unable to address key interrelationships regarding the choice of time, destination, and mode usage for other trips in connection with the ride-hailing trip(s). In this study, these interrelations are analyzed in a holistic manner via an activity-based approach that uses full activity-travel *patterns* or *tours* as a basic unit of analysis, with a tour being defined as a sequence of trips and activities that begin and end at the same location. This approach is applied to explore the complex travel behavior of ride-hailing users. The particular research questions in this context are: how do people use ride-hailing in their daily life? Do heterogeneous groups of ride-hailing users with representative activity-travel pattern exist among the user population?

4.2 Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS), a source of information about travel by US residents in all 50 states and the District of Columbia. This survey sponsored by Federal Highway Administration includes data on trips made by all modes of travel (private vehicle, public transportation, pedestrian, biking, etc.) and for all purposes (travel to work, school, recreation, personal/family trips, etc.). The dataset contains the following four data tables:

- Households (socio-economic and location characteristics of surveyed households)
- Persons (information about the demographic characteristics of all individuals living in those households)

- Trips (trips made within a 24-hour period by all household members aged 5 or older and trip-related attributes)
- Vehicles (vehicles used by the responding households)

The dataset contains 264,234 persons from 129,696 households who took a total of 923,572 trips. For the analysis, *ride-hailing users* are identified as those individuals who make at least one trip on the survey day by using ride-hailing. Since ride-hailing was identified in NHTS as using taxi, limo, or Uber/Lyft, services provided by Transportation Network Companies cannot be separated from convention taxi services. The final sample was 1,677 individuals making 2,813 ride-hailing trips.

4.3 Analysis of Ride-hailing Trips

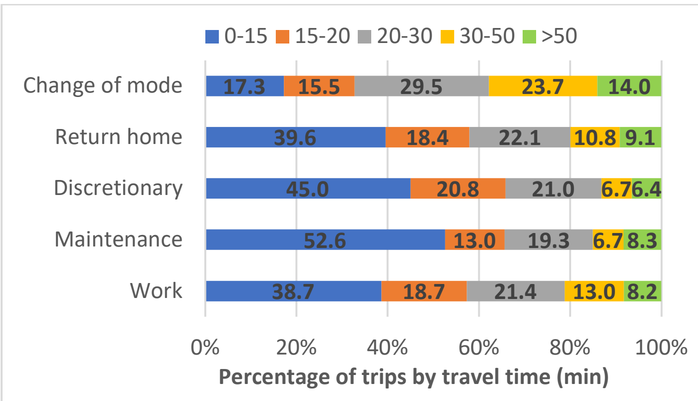
I categorize activity purposes for which ride-hailing trips are made into five groups: work (work- and work-related trips), maintenance (school/daycare/religious activity, medical/dental services, buying goods (groceries, cloths, appliances, gas), buying services (dry cleaners, banking, service a car, pet care), other general errands (post office, library), and drop off/pick up someone), discretionary (buying meals (go out for a meal, snack, carry-out), recreational activities (visit parks, movies, bars, museums), and visiting friends or relatives), change of mode (trip made to transfer from mode to another, say using Uber to catch a flight), and return home. A considerable fraction of ride hailing trips was reported to access discretionary activity locations (24 percent), whereas 9 percent trips were used for mode of change. The use of ride-hailing for returning home was reportedly quite high (about 37 percent). Returning home is indeed a very common use of ride-hailing (Young and Farber, 2019).

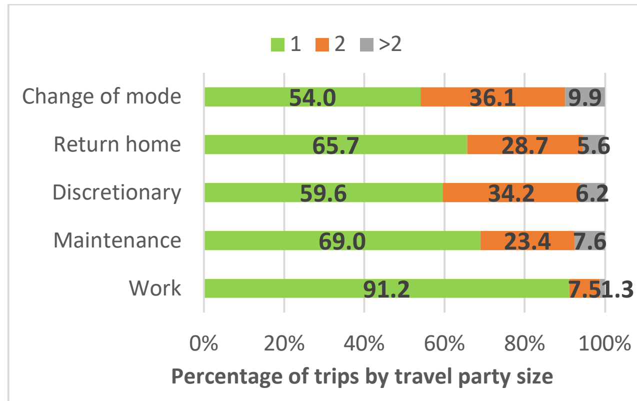
Table 4.1 Ride-hailing trips per day by ride-hailing users

No. of ride-hailing trips	Total % of travelers	Three dominant trip purposes	% of travelers
1	51.8	Return home	**39.9**
		Change of mode	18.1
		Discretionary	16.3
2	36.7	Return home and Discretionary	**35.3**
		Return home and maintenance	23.4
		Return home and work	6.2
> 2	11.5	Return home and two discretionary activities	**11.9**
		Return home and two maintenance activities	10.9
		Three discretionary activities	4.7

Table 4.1 shows the daily frequency of ride-hailing trips. It is observed that more than half of ride hailing users (51.8 percent) make only one ride-hailing trip, 36.7 percent make two ride-hailing trips, and the remainder make more than two trips per day. In all cases, returning home is the dominant activity purpose, followed by discretionary activities. Change of mode is also a common trip purpose for ride-hailing, especially when travelers make only one ride-hailing trip.

Figure 4.1(a) and 1(b) show the distribution of travel times (in minutes) and travel party size for various activities on ride-hailing trips. Since an estimated travel time from mapping services or ride-hailing apps infers better understanding on spatial distance between two locations than the actual distance, I here examine the distribution of travel time for various activities rather than travel distance. Maintenance trips are typically shorter than other trip purposes, while change of mode trips are longer than other purposes. More specifically, higher fraction of maintenance trips (53 percent) are less than 15 minutes, whereas the same fraction of change of mode trips (53 percent) reflect travel times between 20 to 50 minutes (Figure 4.1(a)). Regarding travel party size, ride-hailing users mostly travel alone (cf. Figure 4.1(b)) for any out-of-home activities (over 50 percent for all activities). In particular, about 91 percent ride-hailing trips for *work* are lone trips whereas trips for other purposes tend to be shared by multiple persons (the fraction of trips with two travelers is 34 percent for *discretionary* and 36 percent for *change of mode* purpose).





(a) (b)

Figure 4.1 Distribution of (a) travel time and (b) travel party size by activity type

Next, I investigate how the demand of ride-hailing trips varies over time-of-day. Figure 4.2 shows that for all conventionally defined periods of travel time periods, the majority of ride-hailing trips (about one-third) occur during evening period (7pm-6am) (Young and Farber, 2019), with only 10 percent of ride-hailing trips being made during the AM peak period (6am-9am). The demand of ride-hailing also varies between weekdays and weekends. The share of trips during weekdays is higher than weekends in most time periods (except evening when the trend is reversed). Figure 4.2 also shows that the majority of weekend ride-hailing trips are made during evening period.

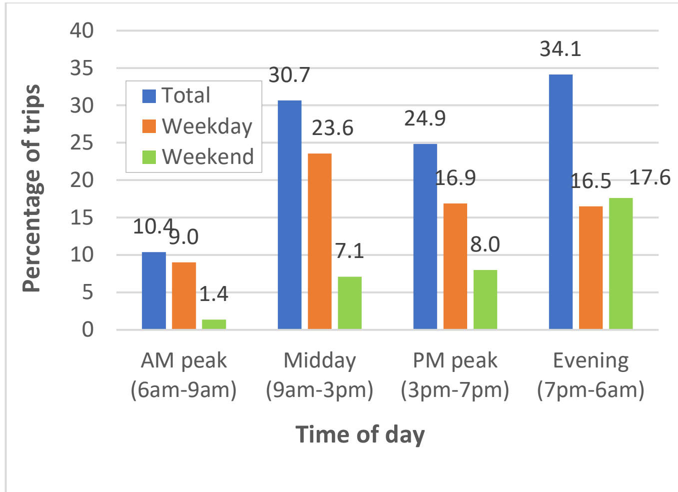
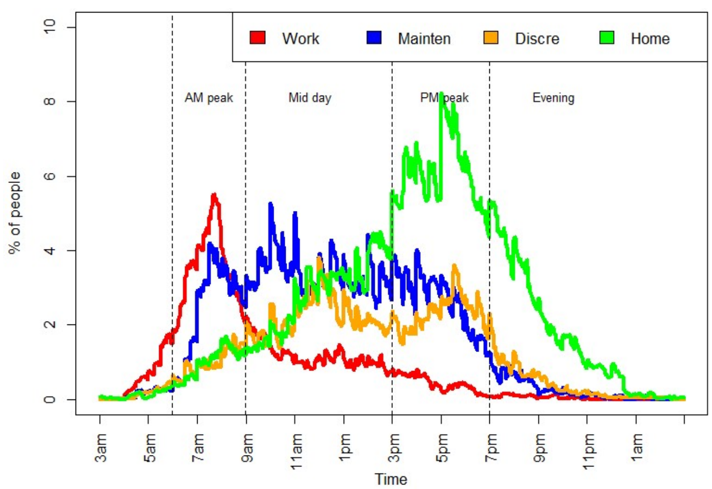
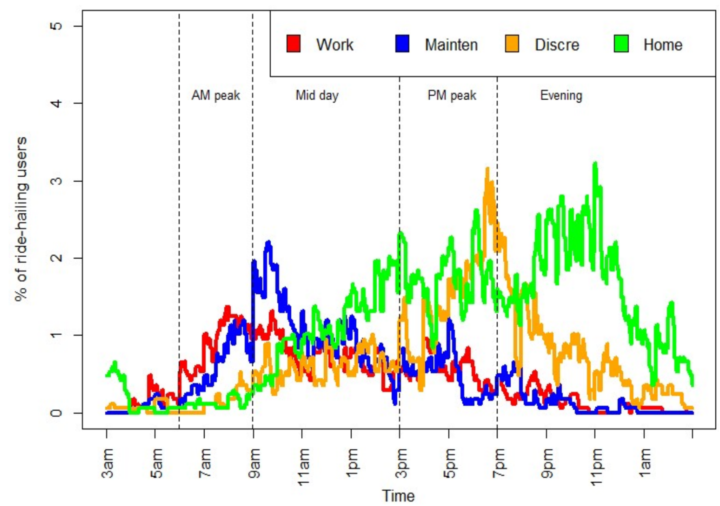


Figure 4.2 Temporal distribution of ride-hailing trips

The fraction of people travelling for different activity purposes (work, maintenance, discretionary, and return home) can be displayed in a *time in motion plot* as shown in Figure 4.3.



(a) Traveler by *all modes*



(b) Traveler by *ride-hailing*

Figure 4.3 Time in motion plot by activity purposes

The figure compares travelers making trips by (a) *all modes* versus (b) *ride-hailing only*. Note that the *range* of vertical axis of these two figures is different. It is observed that while travelers generally return home during the PM peak period (high peak of people participation in "return to home" during PM in Figure 4.3(a)), they tend to use ride-hailing later for the same purpose (during evening). Regarding discretionary trips, it is observed that there are two peaks occurring during the midday and PM peak periods. When travelers do use ride-hailing for discretionary purposes they make the higher portion of those trips during the PM peak period.

4.4 Analysis of Ride-hailing Tours and Patterns

The attention is now returned to analyzing the travel behavior of ride-hailing users that cannot be done with the single trip-based analysis presented earlier. This part of analysis is rather *complex* in nature as they involve analyzing trips in terms of *tours* and *patterns*. A *tour* is defined by a sequence of trips and activities that starts and ends at the same location, whereas *pattern* suggests a full sequence of activities and trips made in a day by an individual (this might include more than one tour).

In this study, all tours considered are home based tours (both start and end at home). A simple tour starts and ends at home and includes a single non-home activity. If the activity performed is work, then it is a *simple work* tour; for any other activity type, it is *simple non-work* tour. On the other hand, a tour containing more than one non-home activity location is defined as a *complex* tour. If all non-home activities are work, then the tour is a *complex work* tour; if all the non-home activities are non-work, then the tour is a *complex non-work* tour. Complex tours can also combine work and non-work activities in the same tour, in which case they are *work-nonwork mixed* tours (Rafiq and McNally, 2019).

Home-based ride-hailing tours are generated by linking person trip sequences that start and end at home and contain at least one trip by ride-hailing. The result was a total of 1,198 home-based tours. Note that while constructing “tours”, *change of mode* is not considered as an activity purpose. Because it is part of the whole trip to access a particular activity site and the inclusion of this type as a separate non-work activity may artificially increases the complex nature of tours (Noland *et al.*, 2008; Ho and Mulley, 2013). Among all ride-hailing tours, 45 percent of tours have exactly one ride-hailing trip and the same fraction of tours (45 percent) have two ride-hailing trips. A detailed analysis of the tours and patterns of ride-hailing users follows.

4.4.1 Analysis of Tours based on Activity-Travel Sequence

The tour characteristics of ride-hailing users are analyzed based on the sequence of activities and trips that form the tours. I first extract tour information from data, identify all home-based ride-hailing tours, and categorize them into *tour categories*. A small number of frequent tour categories are identified and the activity-travel characteristics of those tours, as well as socio-economic and demographic characteristics of individuals who made those tours, are analyzed.

4.4.1.1 Extracting tours from data

Tours are constructed in the form of *sequence of activities*. To do so, at first I extract trips for each person from the "trip" data table and code them as W (work), N (non-work), or H (home) based on where the trip's "to" purpose (for the first trip of the tour I also record the trip's "from" purpose. The trips are ordered by start times. Consecutive trips are separated by a time gap assumed equal to the duration of the activity performed. This represents each tour as a sequence of trips denoted by a string of three symbols (H, W, N), deemed a *tour string*. An example of a tour string is HNNWNNH, which indicates that the individual left home and performed two non-work activities prior to work and then two more non-work activities before returning home. In addition to the sequence of activities captured in the tour strings, the activity type of each non-work activity (maintenance, discretionary, etc.), the time spent at each activity, the mode of transportation, and the duration of each trip are also recorded by tour.

4.4.1.2 Dominant categories of tours

After constructing all tours, I identify the five most dominant strings, which are: HNH, HNNH, HNNNH, HWH and HWNH (their distribution is shown in Figure 4.4). These strings represent about 76 percent of the total tours while the remaining 24 percent of tours demonstrate a total of 67 diverse and more complicated tour strings. Based on our definition of tours, these five tour strings can be placed under four broad tour categories: simple non-work, complex non-work, simple work, and work-nonwork mixed (cf. Figure 4.4). Note that HNNH and HNNNH belong to the same category 2 (simple non-work tours) so they are marked as 2a and 2b respectively. In the following, I identify the individuals who made these tours and produce summary statistic of their socio-demographic and travel characteristics.

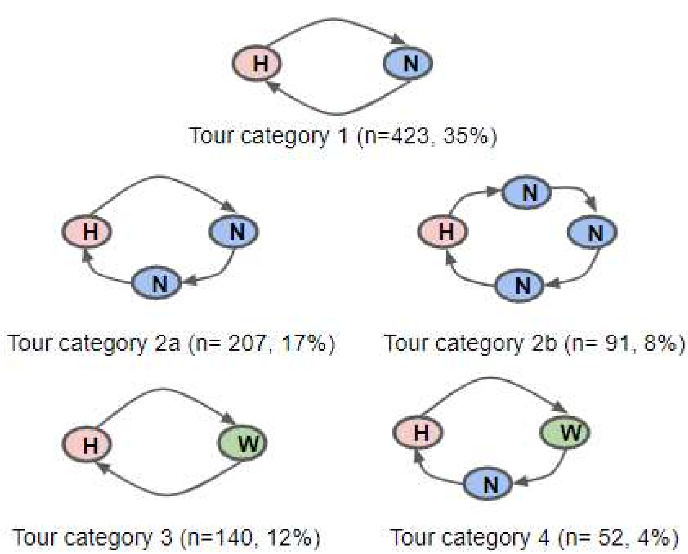


Figure 4.4 Dominant categories of ride-hailing tours: (1) simple non-work tour, (2a, 2b) complex non-work tour, (3) simple work tour, and (4) work-nonwork mixed tour

4.4.1.3 Socio-demographic characteristics

The distribution of socio-demographic characteristics of ride-hailing users by tour category is shown in Figure 4.5. A difference between the characteristics of people who use ride-hailing for work tours and those who use it for non-work tours is observed. The prevailing socio-demographic characteristics of non-work tour makers (categories 1 and 2, shown as solid lines in Figure 4.5) are non-millennials (age > 38 years) and married females. They typically belong to households that have at least two members and have more than one vehicle. A majority of them belong to high income group. In contrast, travelers who make work tours by ride-hailing are typically millennials (age 18-38) and married with high income (categories 3 and 4, shown as dashed lines in Figure 4.5). Again, simple work tour makers are male dominated group whereas work-nonwork mixed tour makers are dominated by female group. Most of the simple work tour makers (65 percent) are not considered as the primary driver in their households.

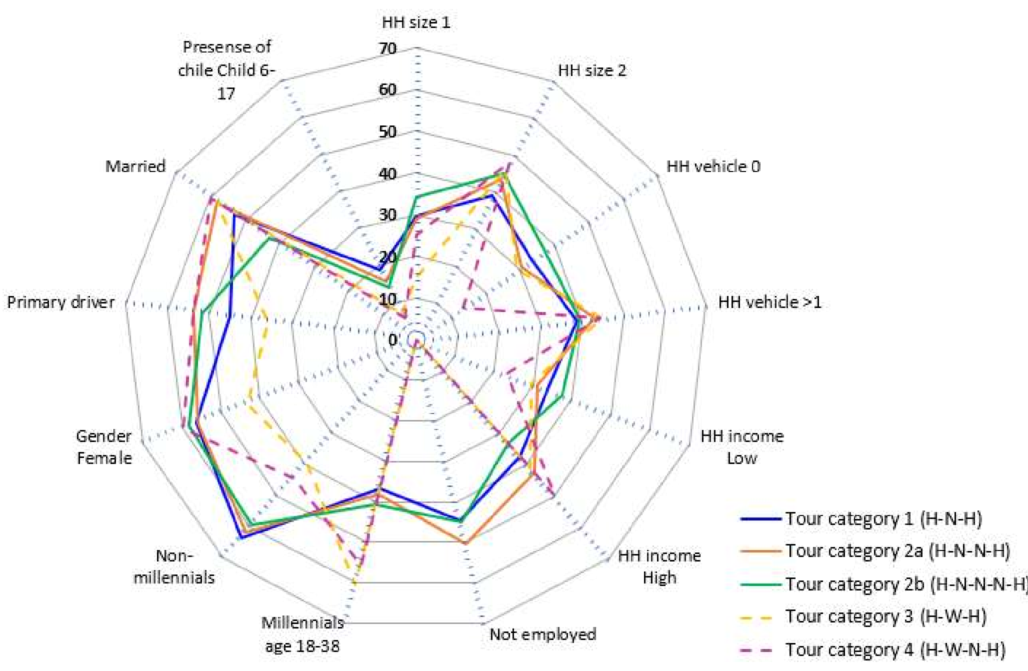


Figure 4.5 Socio-demographic characteristics of travelers for identified tour categories

4.4.1.4 Activity-travel characteristics

Next, the mode for each trip of a tour as well as the purposes for each non-work activities within the tour for each identified tour category are examined (cf. Table 4.2).

Table 4.2 Percentage of tours for trip modes and non-work activities

Trip Mode	Simple non-work (%)		Complex non-work (%)							Simple work (%)		Work-nonwork mixed (%)		
	Tour category 1		Tour category 2a			Tour category 2b				Tour category 3		Tour category 4		
	H-N-H		H-N-N-H			H-N-N-N-H				H-W-H		H-W-N-H		
	n = 423		n = 207			n = 91				n = 140		n = 52		
	H-N	N-H	H-N	N-N	N-H	H-N	N-N	N-N	N-H	H-W	W-H	H-W	W-N	N-H
Public Transit	7.1	2.4	13.5	6.3	3.9	20.9	5.5	6.6	5.5	12.9	5.7	25	17.3	1.9
Walk	5	5.4	14	**31.4**	13.5	20.9	**45.1**	**42.9**	14.3	2.9	3.6	3.8	15.4	7.7
Private vehicles	10.2	9.2	19.3	14	11.6	17.6	15.4	14.3	19.8	16.4	16.4	21.2	**28.8**	**42.3**
Ride hailing	79.4	83.7	57.5	51.7	75.8	41.8	31.9	37.4	62.6	71.4	77.9	53.8	46.2	51.9
Other	4	4.7	4.8	4.8	3.4	8.8	3.3	1.1	2.2	12.1	11.4	3.8	0	3.8
Nonwork activity purpose														
School/Daycare/Religious	10.6		9.2	1.4		6.6	5.5	4.4					1.9	
Medical/Dental	16.1		11.6	4.3		6.6	1.1	2.2					3.8	
Shopping/Errands	18.9		16.4	25.6		28.6	**29.7**	27.5					**32.7**	
Social/Recreational	**33.3**		**33.3**	**39.1**		**30.8**	20.9	**44**					**30.8**	
Pick up/Drop off	2.1		3.9	1		8.8	2.2	2.2					1.9	
Buying meals	17		22.2	26.6		15.4	**35.2**	16.5					25	
Others	1.9		3.4	1.9		3.3	5.5	3.3					3.8	

The table shows variations in the distribution of modes across different trip types. For non-work activities, it shows how non-work activity purposes differ across the different tour categories. The table reveals that ride-hailing is predominantly used in both legs in most of the *simple* tours (in about 80 percent of tours for non-work and 75 percent for work). Similarly, in *complex* tours, ride-hailing is mostly used for the first and last trips within a tour. However, for in-between trips, a large fraction of travelers is observed to walk while going from one non-work activity location to another and to use private vehicle to connect workplace with a non-work activity location.

For non-work activity purposes, Table 4 shows that discretionary activities (e.g. socializing with friends or relatives, recreational activities, buying meals) are the most frequent activities performed in non-work tours. On the other hand, when non-work activity is performed within a work tour, both maintenance (e.g. buying goods, services or other general errands) and discretionary activities are reported in a larger fraction of tours.

4.4.2 Analysis of Patterns by Clustering Ride-hailing Users

It is postulated that despite the complexity of individual's activity-travel patterns, the overall ride-hailing user population might fall into a small number of distinct sub-groups each of which might have representative activity-travel patterns, particularly in terms of ride-hailing usage. The identification of these distinct groups of people is done by cluster analysis, more specifically by using Latent Class Analysis (LCA). LCA is commonly used in a range of travel behavior research, including to classify immigrants based on their travel behavior (Beckman and Goulias, 2008), individuals based on their residential location preferences (Liao et al., 2015), ride-hailing users based on individual lifestyles (Alemi et al., 2018a), and millennials based on their mode usage (Molin et al., 2016; Ralph, 2017; Lee et al., 2019). The LCA is applied to *probabilistically* assign individual ride-hailing user to a set of classes where each class represents homogeneity of activity-travel patterns related to ride-hailing usages (in timing of trips and their purposes) within classes and heterogeneity of patterns across classes.

4.4.2.1 Latent Class Analysis for clustering ride-hailing users

LCA is a mixture model that hypothesizes that there is an underlying *unobserved* categorical variable that divides a population into mutually exclusive and exhaustive latent classes (Lanza and Rhoades, 2013). Due to Linzer and Lewis (2011), I have the following formal construct for the model. Suppose each member of the population (indexed by i) contains J "indicators" variables (indexed by j), each of which can take a value from a set of K_j possible outcomes (all indicators variables are categorical). Let $Y_{ijk} = 1$ if respondent i takes k-th outcome for its j-th categorical variable, and $Y_{ijk} = 0$ otherwise (Y_i denotes the corresponding vector). For a given number of classes, say R, LCA attempts to simultaneously compute: (a) the probability that a respondent falls into a certain class, denoted by p_r, for $r = 1, 2, \ldots R,$ and (b) the class-conditional probability, denoted by π_{jrk}, that an observation in class r produces the k-th outcome on the j-th variable. The likelihood of observing a certain respondent is therefore given by:

$$f(Y_i|\pi, p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}}$$

The parameters that the LCA model estimates are p_r and π_{jrk}, which are found via maximum log-likelihood estimation (MLE). In a more generalized LCA model, the class probabilities, p_r's, are regressed (by using a logit link function) from a set of observed variables, called "covariates". Hence, the estimation technique finds a set of per class co-efficient vector, β_r (instead of p_r), along with π_{jrk} (refer to Linzer and Lewis (2011) for details).

As stated, LCA requires a set of indicator variables that defines the characteristics of each latent class and a set of covariates that help to predict the probability an individual belonging to a latent class. The indicator variables I chose include the timing and purposes of ride-hailing trips, vehicle ownership and employment status of the traveler, frequency of ride-hailing usage (in last month), and the day of travel (weekend or weekday). The covariates are to understand the class membership profiles that consist of various socio-demographic characteristics, such as gender, age, household income and household size, and population density (persons per sq. mile) in the census block group at the home location.

I used poLCA (Polytomous variable Latent Class Analysis) in the statistical software package R to run LCA. R provides model parameters and goodness of fit measures, (chi square with degrees of freedom and information criteria AIC (Akaike Information Criteria) or BIC (Bayesian Information Criteria)). AIC or BIC are usually used to compare relative fit of models with different numbers of latent classes, where a lower value suggests a better model fit. In this case, I varied class sizes from 3 to 8 and observed the associated fit measures and also empirically assessed the extent that the resulting classes could be described and interpreted. I accepted the model with class size four.

Each of the identified four latent classes corresponds to an underlying group of individuals who are characterized by particular pattern of social-demographics features and ride-hailing usage. The resultant four classes are outlined in Table 4.3. Moreover, class-conditional membership probabilities for the indicator variables and covariates by each class are shown in Table 4.4 and the effects of covariates on class membership are presented in Table 4.5. What follows next are the detail description of (a)who belong to which class and their ride-hailing characteristics, (b)class membership profiles (which factor influenced an individual belonging to a certain class), (c)detailed activity-travel patterns of the four classes of ride-hailing users.

Table 4.3 Summary of ride-hailing users by four latent classes

Class	**Ride-hailing user class**	**Class size**	**Class share**	**Class properties**
1	*Work trip users*	292	17.0%	Young, all employed who use ride-hailing for work purpose and they are frequent ride-hailing users.
2	*Midday maintenance trip users*	332	19.8%	Older adults, living alone, a low-income group who use ride-hailing during midday for maintenance and return home purpose and infrequent ride-hailing users.
3	*Evening discretionary trip users*	611	36.1%	Young, employed, live with spouse/partner, use ride-hailing solely during night time for discretionary and return home purposes.
4	*Mode change trip users*	442	27.1%	Young, affluent who use ride-hailing during midday and PM-peak periods as access and egress mode

4.4.2.2 The four identified ride-hailing user classes

The first class (also the smallest one with 17 percent users) is the *work trip users* who, as the name suggests, use ride-hailing trips to go to work (100 percent) and make ride-hailing trips on weekdays (85.7 percent). This group appears to be regular ride-hailing users as 43.5 percent say they use ride-hailing apps more than 5 times in the last 30 days. The group constitutes millennials (aged between 18 to 38) males who are mostly employed (98.3 percent), have a high income (58 percent with annual income higher than $100K), and have at least one car in their household (85.1 percent). In addition to going to work, a considerable fraction of them (30.8 percent) uses ride-hailing to return home but only infrequently to perform other activity types. Their ride-hailing trips uniformly span the day, which can be attributed to their using ride-hailing to go work, perhaps during AM peak (6am – 9am) and Midday (9am – 3pm), and then again avail ride-hailing to return home in the late afternoon and in the evening.

The second ride-hailing user group is called *midday maintenance trip users* (19.8 percent of total users) who make ride-hailing trips during mid-day and most of them make ride-hailing trips for doing maintenance activities and for returning home (69.2 percent and 80.4 percent respectively). As per sociodemographic characteristics, these individuals are mostly single (43.5 percent live in households with only one member) older women who are not employed and have low income (75.9 percent earn below $35K per year). Importantly, this group of people do not have a personal vehicle (66.2 percent), in contrast to other classes with over 80 percent of members having at least one vehicle. This class only uses ride-hailing occasionally (78 percent did not use a ride-hailing app during the last 30 days). Leistner and Steiner (2017) found a similar class of ride-hailing users among seniors.

The third class is the largest ride-hailing user group identified (36.1 percent of 1677 users) and is deemed *evening discretionary trip users*. Members of this class use ride-hailing mostly for discretionary purposes, such as socialization and recreation, in the evening (59 percent have at last one discretionary trip while 83.5 percent have ride-hailing trips made during the evening (7pm – 6am)). Members of this class are mostly millennials, equal split between men and women, mostly employed (80 percent), higher income group (51.5 percent earn more than $100K per year) from car owning households (82.9 percent have at least one car) with two or more members. Unlike other classes, this class makes more ride-hailing trips on weekends than weekdays (59.4 percent vs 40.6 percent). Class members use ride-hailing for evening discretionary trips despite owning household vehicles, perhaps to avoid parking or legal constraints as reported in some studies (Clewlow and Mishra, 2017).

Finally, the last class (class 4) of ride-hailing users use ride-hailing for a very specific purpose, that is, to change of mode of transport. This change of mode corresponds to users going to a train/bus station or airport where they access another transport mode. This class is, therefore, called *mode change trip users* and constitutes a fairly large fraction of ride-hailing users (27.1 percent). While only a few individuals (5 percent or less) report using ride-hailing to change modes in other classes, 50 percent in this class made ride-hailing trips to do so, mostly during midday on weekdays. This group is fairly uniform over gender and age groups. They belong to higher income households having at least one vehicle with nearly 85 percent having two or more household members and they live in medium density areas.

Table 4.4 Class-conditional membership probabilities by each class

	Work trip users (%)	Midday maintenance trip users (%)	Evening discretionary trip users (%)	Mode change trip users (%)
Class size[a]	292	332	611	442
Class share	**17.0**	**19.8**	**36.1**	**27.1**
Indicator variables				
Purpose of ride-hailing trip				
Work	**100.0**	6.4	2.4	0.7
Maintenance	3.5	**69.2**	8.1	15.0
Discretionary	10.6	12.0	**59.0**	28.4
Return home	30.8	**80.4**	**81.5**	29.5
Change of mode	5.8	0.0	0.9	**49.7**
Timing of ride-hailing trip				
AM peak (6am - 9am)	33.2	24.0	0.2	20.4
Midday (9am - 3pm)	**48.1**	**71.5**	13.5	**46.1**
PM peak (3pm - 7pm)	40.5	26.9	41.0	35.8
Evening (7pm - 6am)	35.0	15.9	**83.5**	20.8
Day of travel				
Weekend	14.3	17.5	**59.4**	25.8
Weekday	**85.7**	**82.5**	40.6	**74.2**
Frequency of rideshare app usage (in last 30 days)				
None	30.5	**78.3**	18.7	35.2
1-5 times	25.7	9.6	38.3	**38.6**
more than 5 times	**43.8**	12.1	**43.0**	26.2
Household vehicle ownership				
Own at least one vehicle	**85.1**	33.8	**82.9**	**98.1**
Does not own vehicle	14.9	**66.2**	17.1	1.9
Employment status				
Employed	**98.3**	20.9	**80.2**	**66.4**
Not employed	1.7	**79.1**	19.8	33.6
Covariates				
Gender of the traveler				
Male	**54.6**	34.8	48.9	48.8
Female	45.4	**65.2**	**51.1**	**51.2**
Age of the traveler				
Millennials (18-38 years)	**44.5**	19.6	**55.7**	**29.2**
Generation X (38-58 years)	37.5	28.1	24.6	**29.5**
Older (more than 58 years)	15.4	**45.6**	14.6	**32.8**
Household income				
Low income (less than $35K)	16.1	**75.9**	11.0	6.0
Middle income ($35K - $100K)	24.5	16.7	36.4	25.4
High income (more than $100K)	**58.0**	2.6	**51.5**	**67.1**
Household size				
One person	20.8	**43.5**	27.4	13.9
Two persons	**40.1**	30.1	**48.3**	**51.9**
more than two persons	**39.1**	26.4	24.2	34.2
Population density (persons per sq. mile) in census block group				
Low density (0 - 2,000)	25.8	31.0	17.4	32.5
Medium density (2,000 - 10,000)	**49.1**	**48.3**	37.5	**43.9**
High density (more than 10,000)	25.1	20.7	**45.0**	23.6

[a] Class of each sample is determined by modal assignment (so the percentage may not match)

4.4.2.3 Prediction of latent class membership

Table 4.5 shows covariate coefficients for three classes relative to the first class (i.e., work trip users). Females are more likely to belong to class 2 (midday maintenance) and class 4 (mode change) than to class 1 (due to negative sign of the associated co-efficients). Generation X and older ride-hailing users more likely belong to midday users (class 2) and less likely to be evening users (class 3). Moreover, this group of people are more likely to use ride-hailing for change of mode of transport (class 4).

Table 4.5 Prediction of latent class membership (N = 1,677)

Covariates	Midday maintenance trip users vs work trip users	Evening discretionary trip users vs work trip users	Mode change trip users vs work trip users
Gender of traveler: Male	-0.460**	-0.163	-0.333*
Age of traveler (baseline: Millennials, 18-38 yrs.)			
Generation X (38-58 years)	0.915***	-0.645***	-0.088
Older (more than 58 years)	2.163***	-0.450*	0.875***
Household income (baseline: low income, < $35K)			
Middle income ($35K - $100K)	-2.089***	0.778***	0.790**
High income (>$100K)	-4.751***	0.412*	0.963***
Household size (baseline: single person)			
Two persons	-0.179	-0.008	0.457*
more than two persons	0.331	-0.639***	0.299
Population density (persons per sq. mile) in census block group (baseline: low density, 0-2,000)			
Medium density (2,000 - 10,000)	0.004	0.053	-0.286
High density (more than 10,000)	0.102	0.738***	-0.222

*, **, and *** indicate statistical significance respectively at 10%, 5%, and 1%.

Household income does affect the class membership: people with middle and higher income belong to class 3 and class 4 whereas lower income people belong to class 2. The effect of household size is rather limited: persons from single person households, especially elderly women, tend to belong to class 2, whereas persons from larger households are less likely to belong class 3. Interestingly, I find an association of location variable with class membership, particularly people living in high density areas are more likely to belong to class 3.

4.4.2.4 Activity-travel patterns of identified user classes

I now analyze activity-travel patterns of the identified four ride-hailing users. A graphical representation is utilized for each class that shows the sequence of *all* activities and travel reported in a travel diary day for a *randomly* selected 50 individuals from a given class. Figure 4.6 shows such drawings for each class (x-axis denotes the time of day and y-axis denotes each individual with their activities and trips). The sequence of activities and travel is shown as segments based on the activity and travel duration, color coded based on activity purposes and mode use.

<u>Class 1. Work trip users</u>

The number of work segments (shown in red in the Figure 4.6(a)) best illustrates the work focus in this class. The blue segments show ride-hailing use, predominantly preceding the red segments indicating ride-hailing as a commute mode from home. The presence of a good number of ride-hailing trips made in the late afternoon or evening suggests the use of ride-hailing after hours to return home. The majority of this class uses either private vehicle (42 percent) or ride-hailing (32 percent) as their regular work mode choice. It is found that on the diary day 50 percent of travelers use ride-hailing to work whereas 25 percent use this service to return home, while 20 percent use it both ways.

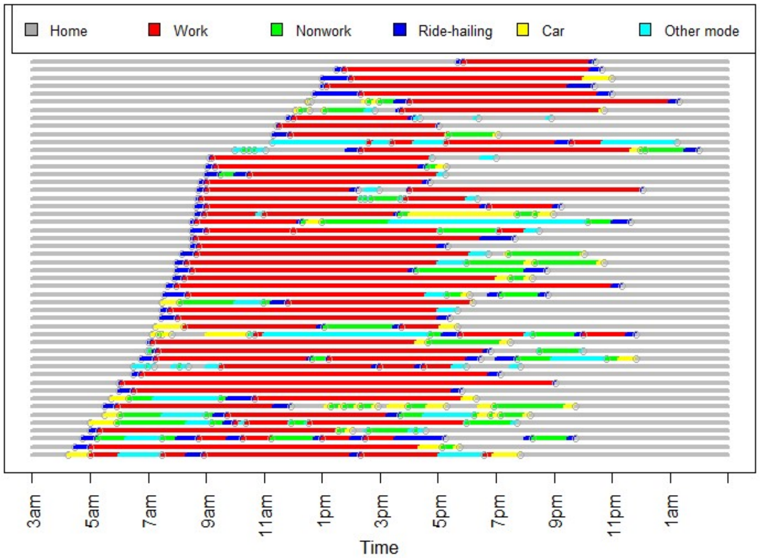
Green segments visible in the figure during the late PM peak or evening period show non-work activity either within the work tour or on separate non-work tours. While a majority of the class (37 percent) make work only tours, a large fraction mix non-work activities within work tours (26 percent) and a smaller fraction make separate non-work tours (15 percent). About 59 percent use ride-hailing as their travel mode while traveling between two non-home locations (e.g., work to work, work to non-work, or non-work to non-work). Interestingly, about 36 percent of this class did not make a complete tour during the day. Analysis reveals that most of these people did not start from their home on the travel day, starting instead from a non-home location with a ride-hailing trip to work.

Members of class 1 average 4.4 trips per day, with ride-hailing accounting for 50 percent of the trips (with private vehicle use at 21 percent and walk at 14 percent). This class has longer commute times to work than other classes (26 minutes versus 18 minutes for 'evening users' and 13 minutes for 'mode change trip users').

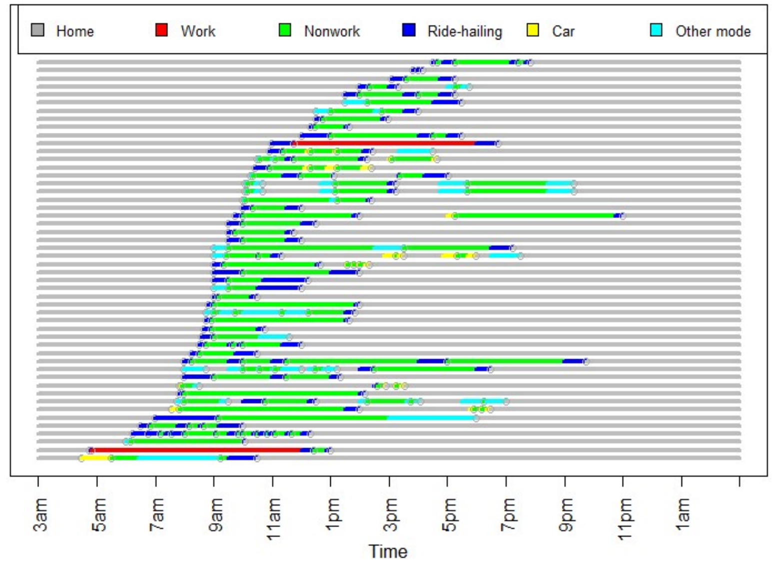
Class 2. Midday maintenance trip users

Figure 4.6(b) shows that class 2 demonstratively performs more non-work activities (green segments) and make most of their ride-hailing trips during midday (blue segments spanning 8am to 3pm). Ride-hailing is used to perform non-work activities (blue segments juxtaposed with green segments) and also to return home. Interestingly, these return to home ride-hailing trips happen during midday, which do mostly occur during the evening in other classes. About 60 percent use ride-hailing to access a non-work location from home, 77 percent use ride-hailing to return home, and 50 percent use it to do both.

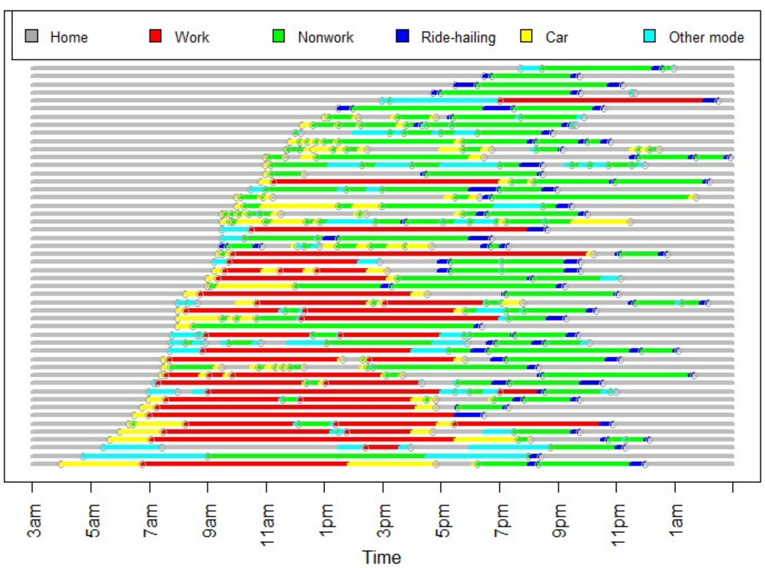
Most members of this class complete non-work tours (53 percent simple and 41 percent complex) for activities such as grocery shopping and medical visits. This class is dominated by



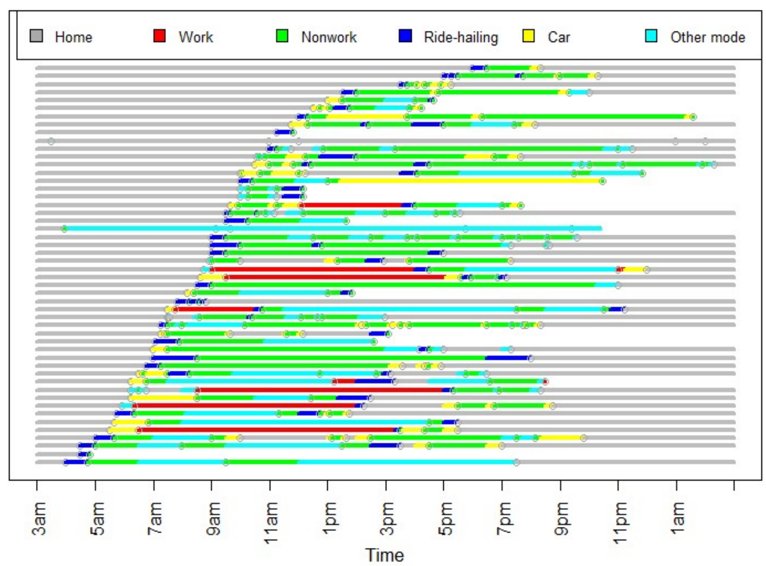
(a) Work trip users
(50 random samples out of 292)



(b) Midday maintenance trip users
(50 random samples out of 332)



(c) Evening discretionary trip users
(50 random samples out of 611)



(d) Mode change trip users
(50 random samples out of 442)

Figure 4.6 Sampled activity-travel patterns by ride-hailing class

low income, older, single living individuals who tend to not own a car. A large fraction of users (63 percent) in this group gave up driving due to medical conditions. Members of class 2 average 3.9 trips per day, with ride-hailing accounting for the majority the trips (60 percent, a higher share than in other classes). Other shares of travel modes correspond to walk (16 percent) and private vehicle (11 percent). The blue segments representing ride-hailing trips of midday users are longer than for evening users (Figure 4.6(c)), with class 2 having longer average travel times by ride-hailing (32 minutes compared to 24 minutes for evening users).

Class 3. Evening discretionary trip users

Members of class 3 make their ride-hailing trips in the evening (after 5pm) illustrated by a high concentration of blue segments on the right side of Figure 4.6(c). These ride-hailing trips are preceded and followed by non-work activities (green segments), which are predominantly discretionary activities (e.g. visiting recreational centers, restaurants, friends). About two-thirds of this class make at least one non-work tour (42 percent simple and 41 percent complex). Regarding mode usage, 35 percent use ride-hailing to go from home to non-work locations and 32 percent use it to travel between non-work locations. A high percentage of travelers use ride-hailing to return home from a non-work place (74 percent).

Some members do work (red segments) during midday but then access discretionary activities from work or via separate non-work tours after hours. While ride-hailing (blue) is associated with non-work (green) evening activities, other modes are associated with work (red) activities. This suggests that this class uses ride-hailing for non-work trips, but use either private vehicles or other modes on their AM-peak work commute (55 and 26 percent report private vehicle and public transit, respectively, as regular work mode). Members of class 3 average the greatest average trip rates compared to other user classes (5.6 compared to 4.4, 3.9, 4.8 for class 1, class 2, and class 3, respectively).

Class 4. Mode change trip users

The activity-travel pattern of class 4 are displayed in Figure 4.6(d) and show distinctly different travel patterns with members making trips using *other* travel modes (cyan segments). A number of travelers do not return home after their trips as marked by the absence of gray segments (indicative of being at home) at the end of the day. This class features long distance travelers (cyan colors with longer travel times) who do not return home within the same day. It is found that about 40 percent of members do not make any complete home-based tour.

Travel by other modes is preceded by or followed by ride-hailing (blue) which indicates that this class use ride-hailing to access airports, train stations, and other mode change locations or to reach to the final destination (typically home) from these transportation hubs.

4.5 Conclusion

Ride-hailing has become the pre-dominant shared-mobility service. The emergence of this technology-enabled (app based) on-demand ride services expands the set of travel alternatives and substantially increase flexibility in activity scheduling and travel choices, thus affecting travel behavior in several ways. This study analyzed the travel behavior of ride-hailing users from an activity-based approach that uses full activity-travel *patterns* or *tours* as a basic unit of analysis. Tours are analyzed based on the dominant sequence of activities and trips. Whereas patterns are analyzed by clustering ride-hailing users based on travel behavior indicators and by using Latent Class Analysis (LCA) technique. The empirical results using data from the 2017 NHTS show that 76 percent ride-hailing tours can be represented by five most dominant sequence of tours where non-work tours are the most frequent tours. A variation is also observed in the socio-demographic characteristics of ride-hailing users between work and non-work tours.

The Latent Class model suggests that the ride-hailing user population can be divided into four distinct classes where each class has a representative activity-travel pattern defining ride-hailing usage. This implies that people utilize ride-hailing in distinctly different ways (although any user could actually have behaviors exhibited in any of the four identified classes). Class 1 is composed of young and employed users who use ride-hailing for work. Single and older individuals comprise Class 2 and use ride-hailing for maintenance activities during midday. Ride-hailing Class 3 are younger, employed individuals who use it during evenings for discretionary purposes. Last, Class 4 members use it for mode change purpose. Since each identified class has different activity-travel patterns, they will show different responses to policy directives. This can help ride-hailing operators to address user travel needs as users respond to different policy constraints.

5.6 References

Alemi, F., Circella, G., Handy, S., & Mokhtarian, P. (2018a). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society*, 13, pp. 88-104.

Alemi, F., Circella, G., Mokhtarian, P., & Handy, S. (2018b). Exploring the latent constructs behind the use of ridehailing in California. *Journal of choice modelling*, Vol. 29, pp. 47-62.

Beckman, J. D., & Goulias, K. G. (2008). Immigration, residential location, car ownership, and commuting behavior: a multivariate latent class analysis from California. Transportation, 35(5), pp. 655-671.

Beer, R., Brakewood, C., Rahman, S., & Viscardi, J. (2017). Qualitative analysis of ride-hailing regulations in major American cities. *Transportation Research Record*, Vol. 2650(1), pp. 84-91.

Clewlow, R. R., & Mishra, G. S. (2017). Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States. Institute of Transportation Studies, University of California, Davis. Report UCD-ITS-RR-17-07, pp. 1-38.

Contreras, S. D., & Paz, A.(2018). The effects of ride-hailing companies on the taxicab industry in Las Vegas, Nevada. *Transportation Research Part A: Policy and Practice*, Vol. 115, pp. 63-70.

Flores, O., & Rayle, L.(2017) How cities use regulation for innovation: the case of Uber, Lyft and Sidecar in San Francisco. *Transportation research procedia*, Vol. 25, pp. 3756-3768.

Hall, J. D., Palsson, C., & Price, J. (2018). Is Uber a substitute or complement for public transit?. *Journal of Urban Economics*, Vol. 108, pp. 36-50.

Henao, A., & Marshall, W. E. (2018). The impact of ride-hailing on vehicle miles traveled. *Transportation*, pp. 1-22.

Henao, A., & Marshall, W. E. (2019). The impact of ride hailing on parking (and vice versa). *Journal of Transport and Land Use*, 12(NREL/JA-5400-73889).

Ho, C. Q., and Mulley, C. (2013). Multiple purposes at single destination: A key to a better understanding of the relationship between tour complexity and mode choice. *Transportation Research Part A: Policy and Practice*, Vol. 49, pp. 206-219.

Lanza, S. T., & Rhoades, B. L. (2013). Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. *Prevention Science*, Vol. 14(2), pp. 157-168.

Lee, Y., Circella, G., Mokhtarian, P. L., & Guhathakurta, S. (2019). Are millennials more multimodal? A latent class cluster analysis with attitudes and preferences among millennial and generation X commuters in California. *Transportation*, pp. 1-24.

Liao, F. H., Farber, S., & Ewing, R. (2015). Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis. *Urban Studies*, 52(2), pp. 314-337.

Leistner, D. L., & Steiner, R. L. (2017). Uber for Seniors?: Exploring Transportation Options for the Future. *Transportation Research Record*, Vol. 2660(1), pp. 22-29.

Linzer, D. A., & Lewis, J. B. (2011). poLCA: An R package for polytomous variable latent class analysis. *Journal of statistical software*, 42(10), pp. 1-29.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice*, 83, pp. 14-29.

Ralph, K. M. (2017). Multimodal millennials? The four traveler types of young people in the United States in 2009. *Journal of Planning Education and Research*, 37(2), pp. 150-163.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy*, Vol. 45, pp. 168-178.

Rafiq R. and McNally, M. G. (2019). Changes in Activity-Travel Behavior of Workers Before and After the 2009 Recession. *Presented at 98th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Taylor, Brian D., Chin, Ryan, Melanie, Crotty, Dill, Jennifer, Hoel, Lester A., Manville, Michael, Steve, Polzin, et al. (2015). Between Public and Private Mobility: Examining the

Rise of Technology-enabled Transportation Services. Special Report 319. Transportation Research Board: Committee for Review of Innovative Urban Mobility Services.

Young, M., & Farber, S. (2019). The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. *Transportation Research Part A: Policy and Practice*, Vol. 119, pp. 383-392.

CHAPTER 5: Tour Formation of Workers During Recession 2007-2009

5.1 Introduction

The technology, climate, economic, and demographic changes currently evident portend future change in travel behavior. Despite prior stability of automobile ownership and use patterns, these changes likely will have direct impacts on activity-travel patterns. To analyze such change essentially requires before or after data, something that is difficult to obtain when the drivers of change are not within our control. The 2009 recession provides a relatively short tenure economic change, and the American Time Use Survey (ATUS) provides data before, during and after that recession.

Prior studies consider recession impacts using ATUS data (Aguiar *et al*., 2013; Berik and Kongar, 2013) but these reflect only time allocation behavior and not travel behavior. Studies on changes in travel behavior due to recessions are limited. These works focused on various changes during recessions, such as automotive travel behavior (Thomas *et al*., 2015; Blumenberg *et al*., 2016), travel expenditures (Thakuriah and Mallon-Keita, 2014; Keita and Tilahun, 2017), traffic fatalities (Noland and Zhou, 2017), and millennials' activity-travel behavior (Garikapati *et al*., 2016). However, these studies did not consider changes in travel behavior from an activity-based approach.

Activity-based approach is widely used to analyze complex travel behavior. The fundamental tenet of this approach is that travel decisions are driven by a collection of activities that form an agenda for participation and, therefore, travel cannot be properly analyzed on individual trip basis. The process of assembling a travel-activity pattern and the choice attributes of each component can only be understood within the context of the entire agenda (McNally and

Rindt, 2008). In this work, time use data is utilized to analyze changes in travel behavior during a recession compared to that before and after in a holistic manner via an activity-based approach. This approach uses *tours* as a basic unit of analysis, with a tour being defined as a sequence of trips and activities that begin and end at the same location, in this case at home.

While ATUS time use data provides rich before and after data, it is limited in that it is a cross sectional survey of only a single household member. To narrow the focus, I examine the changes in travel behavior during a recession on only employed persons. Granted, individuals that maintain employment throughout an economic recession is less impacted, but this choice allows us to examine the relationships between changes in travel behavior and the changes in employment type (for example, fulltime, part time, or multiple jobs). My second interest narrows travel behavior to tour formation. The particular research questions are: how is time allocated to different activity demands at different times of a day and how are these activity demands allocated to out-of-home travel tours? How does the imposition of an external change affect how people organize their daily activity-travel patterns, here in the form of tours?

The next section describes relevant studies regarding recessions. Then I define the representation of complex travel behavior in the form of tour types. The time use data and the sample are then described followed by an overview of methodology, here, multiple group structural equation models (SEM). An extensive summary is then presented of model results and the implications for changes in travel behavior in the face of an external change, that is, the 2009 recession. Last, conclusions and potential implications for policy are provided.

5.2 Literature Review

This section provides an overview of previous research studies relevant to this work with a particular focus on time-use and travel behavior related studies considering recession.

5.2.1 The 2007-09 Recession and Its Notable Impacts

The most recent recession began in December 2007 and continued for the next two years (National Bureau of Economic Research, 2018). A recession is in general characterized by a slowdown in the national economy, a downturn in the business cycle, and a decrease in the amount of production and sales of goods and services (Bureau of Labor Statistics, 2012). The recent 2007-09 recession had also some notable changes. One of the remarkable features of the recession was higher unemployment rates. According to the Bureau of Labor Statistics (2012), the national unemployment rate was 5 percent at the end of the year 2007 but this was doubled over the next two years (to 10 percent in October 2009). Recession caused a reduction in not only employment status but also to workers' hours. It was reported that the aggregate work hours (product of total number of employees and average weekly hours) dropped by 7.7 percent between December 2007 to December 2010 (Kroll, 2011). Moreover, during the recession, the number of individuals who are employed part-time for economic reasons (also known as involuntary part-time workers) increased drastically (Borbely, 2009). The result was that workers often started to find and work in more than one job (Hipple, 2010).

In addition to employment, notable changes occurred in consumers' purchasing behavior during the recession, for example, in the housing sector. Homeownership rates dropped in conjunction with the depreciation in housing prices and increase in home foreclosures. Winkler (2013) reported that from 2007 to 2010, housing prices fell about 13 percent in the US whereas the home foreclosure rate increased from 0.87 percent to 3.26 percent. Another change in consumer purchasing behavior was observed in the auto sector, which can be characterized by lower car ownerships, delayed purchase of additional vehicles (new or used) when selling, increased number of zero-car households and therefore reduced transportation expenditures during the recession (Thakuriah and Mallon-Keita, 2014).

5.2.2 Changes in Time Use and Travel Behavior During the Recession

During the recession, changes occurred in time allocation behavior. By using the 2003-2010 ATUS data, Aguiar *et al*. (2013) identified that household production and leisure activities mostly absorb the reduced work hours during recession. According to their findings, 30 percent of the foregone work hours is substituted by core household production activities, such as cooking and cleaning and 50 percent is substituted by sleeping and watching television. A significant difference in time allocation behavior between men and women is also observed. For example, the reduced work hours are allocated more to core household activities for women whereas TV watching and education for men.

Again, using the same dataset, Berik and Kongar (2013) examined that the gender gap is narrowed in both paid and unpaid work hours during recession between married mothers and fathers as mothers substituted paid work for unpaid work and fathers' paid work hours were reduced. In addition to time allocation behavior, Krueger and Mueller (2012) investigated the relationship between unemployment and well-being issues. They found that although unemployed people spent more time in leisure activities than employed people during recession, they enjoyed those activities to a lesser degree by reporting higher level of sadness than their employed counterparts. Thus, the effects of recession are predominantly considered from the perspective of time allocation behavior in social science literature. But these studies do not address the recession effects from travel behavior perspective.

Several studies in transportation planning field observed recession effects on travel behavior. McCahill (2017) examined that total domestic vehicle miles traveled (VMT) peaked in 2007, dropping significantly until 2014. Per capita VMT decreased by about 7 percent in this period despite a general recovery in the economy. Furthermore, public transit ridership in many metropolitan areas in the US dropped significantly, a trend that unlike VMT did not return to pre-recession levels (per capita transit use dropped about 9.7 percent since 2014) (The Transport Politic, 2018). Other studies also consider recession impacts on public transit but mostly in the context of European countries (Efthymiou *et al*., 2018; Ulfarsson et al., 2015; Cascajo et al., 2018).

Again, studies report about the reduced travel expenditure during recession (Thakuriah and Mallon-Keita, 2014; Pauline, 2012). Since income has effect on travel behavior, the decline in household income due to the economic downturn leads to reduction in travel spending, which results in reduced mobility and activity participation particularly in female-headed and low-income households (Keita and Tilahun, 2017; Thomas *et al*., 2015). The decline in household income, on the other hand, causes reduction in making trips and consequently reduction in traffic fatalities (Noland and Zhou, 2017; Maheshri and Winston, 2016).

The 2007-09 recession has impacts on travel behavior of millennials. Garikapati *et al*. (2016) observed a lag among millennials in adopting the activity-travel pattern of their predecessor generation, which is partially due to the lingering effects of the great recession. Blumenberg *et al*. (2012) examined changes in travel behavior of youth and adults during the recession. They found that unemployment was considerably higher among youth than adults, which results in a higher decline in work-related travel as well as travel for other purposes among the youth population. Since it was difficult for them to own and operate automobiles due to the economic crisis, they rely more on alternative modes, such as public transit and walking for travel.

5.2.3 This Study in the Context of Previous Studies

Previous literature in social science mostly focuses on the changes in time allocation behavior during the recession, but provide little consideration on travel for various activities. Research that focuses on changes in travel behavior due to the economic crisis, explore changes in travel in the context of vehicle miles traveled, travel expenditure, transit usage, and traffic fatalities. However, in these studies, findings are mostly drawn based on univariate statistical analysis. Again, these studies do not consider changes in activity-travel behavior from an activity-based perspective. In particular, they do not take into account whether people change their sequence of activities and trips (tour) during a recession to gain efficiency in activity participation, for example, performing multiple out-of-home activities within a single tour instead of going to multiple places back and forth from home or mixing non-work activities with work instead of making separate non-work tours.

This study, on the other hand, explores such changes in tour patterns for employed people by using a multivariate statistical technique. In this study, a multiple group structural equation modeling (SEM) is developed that enables the investigation of invariance in causal structures among the pre, during, and post-recession years. More specifically, it helps to examine whether the choice of tours (work and non-work) varies during the recession due to the changes in socio-economic characteristics (e.g. nature of jobs) and time spent in activity participation. Multiple group SEM is widely used in travel behavior research to find out differences across various transport user groups (detailed discussion in model specification section). However, little is known about the use of this technique to explore the temporal differences in the conceptualized causal structure.

To develop this model, American Time Use Survey (ATUS) data is used. ATUS is the most reliable national-level time-use data that is widely used in social science literature to analyze time-use behavior of individuals (e.g. Robinson and Martin, 2010; Mastracci, 2013; Anand and Ben-Shalom, 2014). This data is also used in travel behavior studies to examine activity-travel behavior of particular groups (Bernardo et al., 2015; Fan, 2017; Garikapati et al., 2016; Gimenez-Nadal et al., 2018) or to connect activity-travel time use with well-being issues (Archer et al., 2013; Stone and Schneider, 2016; Morris, 2015). In addition, from activity-based perspective, researchers use this data to model various activity choice, time-use, joint-activity participation, and activity scheduling issues (Ferdous et al., 2010; Srinivasan and Bhat, 2008; Langerudi *et al*., 2016). However, to the best of my knowledge, this study is the first to use ATUS data to provide a tour-based representation of activity-based approach that enables to analyze how the employed people organize their daily activity-travel pattern (i.e. tours) at different times of a day relative to work activity.

5.3 Tour Formation of Employed People

This study considers home based tours: those that both start and end at home. A simple tour starts and ends at home and includes a *single* non-home activity. If the activity performed is work, then it is a *simple work* tour; for any other activity type, it is *simple non-work* tour. On the other hand, a tour containing more than one non-home activity location is defined as a *complex* tour. If all non-home activities are work, then the tour is a *complex work* tour; if all the non-home activities are non-work, then the tour is a *complex non-work* tour. Complex tours can also combine work and non-work activities in the same tour, in which case they are *work-nonwork mixed* tours. Since the number of complex work tours are found to be very small in the dataset (less than 2% of all tours), simple and complex work tours are combined into a single category as *work-only* tours, which effectively gives us four types of tours: work-only, simple non-work, complex non-work, and work-nonwork mixed (similar to Golob's classification (Golob, 2000)).

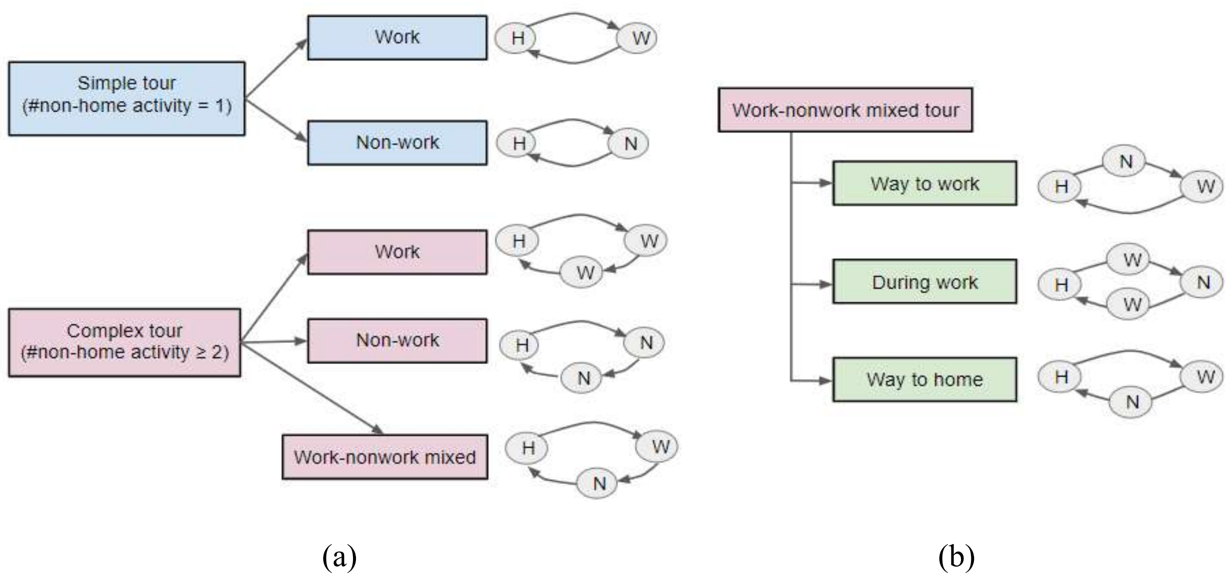


Figure 5.1 Definition and classification of tours

Since work activities are less flexible, employed people with a non-home work activity typically make at least one work tour (either work-only or work-nonwork mixed) and then align their non-work activities with respect to that tour. Non-work activities can be performed as separate non-work tours or as a part of a work-nonwork mixed tour, in any of five ways:

1. "before work:" non-work performed before starting the first work tour of the day by making a non-work (simple or complex) tour,

2. "way to work:" when an individual has started his work tour but did not yet reach the workplace and performed non-work activities on the way,
3. "during work:" non-work activities that are performed outside workplace but the person returned to workplace after completing them,
4. "way to home:" non-work activities that are performed as the person is on his way to home from the workplace but has not reached home yet,
5. "after work:" non-work activities that are performed by making separate non-work tours after returning home from work.

The partition of non-work activities into five timeslots also appears in prior studies (Damm, 1982; Bhat and Singh, 2000). For people who work only at home and do not make any work tour, I took the longest duration of work as a reference point and distribute ‘before’ and ‘after’ out-of-home non-work activities accordingly.

5.4 Data and Sample

5.4.1 The American Time Use Survey Data and Sample

The American Time Use Survey (ATUS) from 2006, 2009, and 2012 for pre-, during, and post-recession years, respectively are used in this study. Defined in economic terms, the recession started in December 2007 and continued till June 2009 (National Bureau of Economic Research, 2018). There are several reasons that I consider the full year of 2009 as the peak recession year. First, although the economic downturn ended in the middle of the 2009, associated transportation impacts typically change more slowly and last longer, and thus were expected to extend beyond the year 2009. Second, this selection enables to explore the seasonal effects on tour choice in a whole year in the model. Finally, the choice is consistent with prior studies (Aguiar *et al*., 2013;

Berik and Kongar, 2013). The before and after recession years were chosen so that they are not too far removed from the recession year so as to be affected by other trends.

ATUS surveys are conducted every year facilitating the pooling of data for the pre-, during, and post-recession years, each three years apart. ATUS surveys time use information for detailed activity categories (e.g., work, socializing, traveling) performed by individuals for one complete day (from 4am to 4am the next day). ATUS data also contain socio-demographic information for the household respondent and location information defining the geographical area in which the respondent resides (obtained by interfacing with Current Population Survey data). The target group is defined as employed adults who on the survey day worked, made at least one home-based tour, made not more than 10 trips, and did not use transit for any trips (due to low sample size). After removing the missing observations from data, the result was a total of 8,251 respondents, with 2712, 2723, and 2816 for the years 2006, 2009, and 2012, respectively.

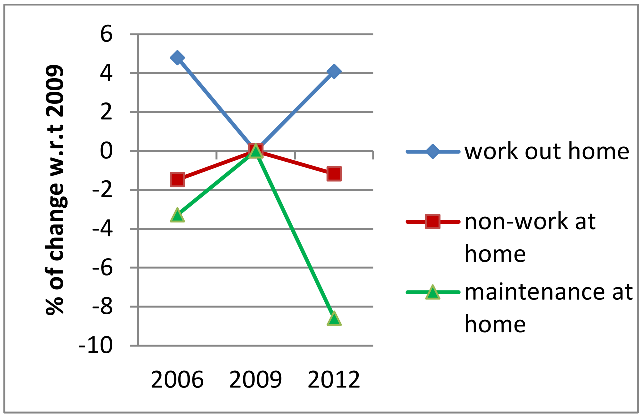
5.4.2 Data Processing and Tour Construction

In order to construct tours, at first, I extract activities of each person of the study group (from "atusact" data table) and code each of the activity with four symbols based on their types: W to indicate work, N for non-work, T for travel and H for staying at home (i.e., activities performed at home). In the dataset, each activity of an individual on the survey day is recorded with the activity type/purpose (coded with a three-level hierarchy), start time, end time, duration, location and other relevant information. The activities are arranged in ascending order of their start times one after another starting from 4:00am up until 4:00am in the following day. With this coding, the activity sequence of an individual can be expressed as sequence of four symbols (H, T, W, N), which is called *activity string*. For example, HTNNTWTHTNTH is an activity string of an individuals that reads as follows. The individual was at home at the beginning of the day and made a trip to a place to do two non-work activities back to back and then went to work by making a travel. After that, he/she returns home by making another travel. This individual again heads out from home to perform a non-work activity and then returns home. Apparently, the individual made two tours in a day: the first one being a complex tour (work-nonwork mixed) and the second one being a simple non-work tour. Note that each activity string maintains details of all activities performed within that string (duration, purpose codes, location, start time, end time, etc.) stored in separate data structures. For a given activity string, I split the entire string into segments each of which starts and ends with H (each segment effectively corresponds to a tour). Then, I determine which of the four tour types the segment represents.

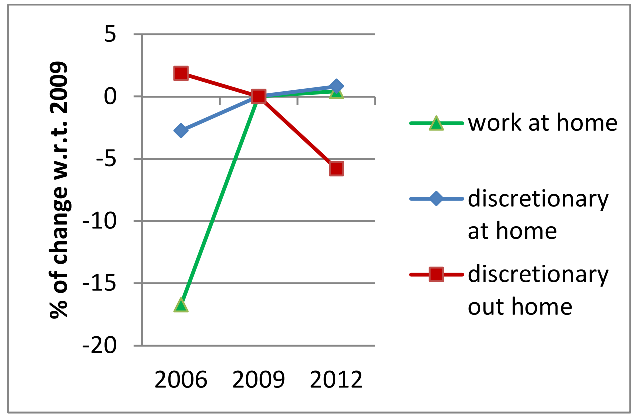
5.4.3 Activity-Travel Time Use During the Recession

I attempted to determine in which types of activity and travel people allocated time differently in the recession year than the pre- and post-recession years. To do so, *Kruskal-Wallis* non-parametric test (with *p-value* <0.1) were conducted. Four distinct categories of significant changes in activity-travel durations were identified after the difference test: (1) 2006 durations that changed in 2009 but returned to the 'old duration' in 2012 (2) 2006 durations that changed in 2009 and changes were maintained in 2012 as a 'new duration' (3) 2006 durations that did not change in 2009 but changes occurred after 2009, and (4) 2006 durations that changed in 2009 and changes were continued in 2012.

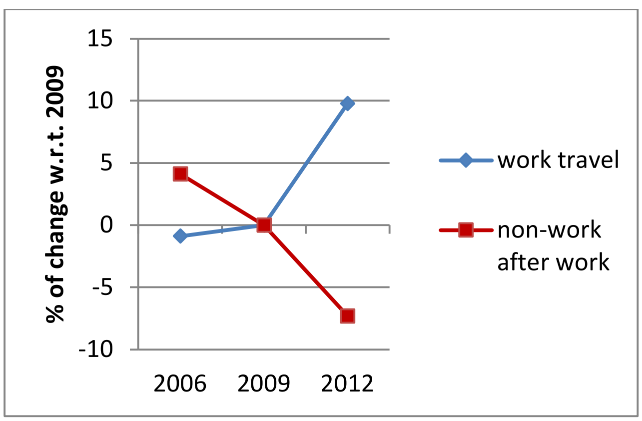
Figure 5.2 shows these four categories of change in mean activity durations. The horizontal axis represents the three years and the vertical axis represents the change in mean activity durations in 2006 and 2012 with respect to the 2009 mean duration. Note that in this figure maintenance activities include household activities, childcare, personal services, consumer purchases, and religious activities whereas taking meals, socializing, relaxing, leisure, sports, exercise, recreation, and phone calls are considered as discretionary activities.



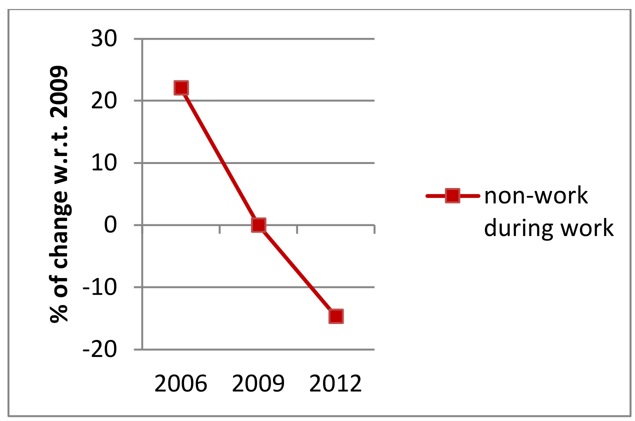
(a) Durations were changed in 2009 but returned to the 'old one' in 2012



(b) Durations were changed in 2009 and maintained as 'new one' in 2012



(c) Durations were not changed in 2009 but changes occurred in 2012



(d) Duration were changed in 2009 and changes continued in 2012

Figure 5.2 Changes in mean activity durations in 2006 and 2012 with respect to 2009

In Figure 5.2(a), it can be observed that the average duration of work outside home decreased significantly by around 5 percent in the recession year and again increased by 4 percent in the post-recession year. As discussed earlier, previous studies also found that 2007-09 recession caused a decline in work hours (Kroll, 2011; Goodman and Mance, 2011). In contrast to the reduction in work hours, it is found that the average duration of total non-work activities, particularly the duration of maintenance activities inside home increased significantly during recession, which again dropped after the recession (Krueger and Mueller, 2012).

Figure 5.2(b) denotes that in the recession year, people on average spent more time at home for work than in the pre-recession year. Similarly, in the same year, people spent more time doing discretionary activities at home. Aguiar *et al*., (2013) reported that during the recession (defined from 2008 to 2010 in their study) people spent more time in leisure at home in the form of watching TV and sleeping. It is also observed that the tendency of spending more time at home for doing work and discretionary activities remained unchanged in the post-recession year. On the other hand, some activity durations did not change during the recession, but changes happened only after the recession. For example, average work travel time increased in 2012 (see Figure 5.2(c)).

Again, Figure 5.2(d) denotes that there was a decrease in the average duration of non-work activities performed during work hour over the three data points. From the data it is found that as a non-work activity during work hour, people mostly take meals (lunch) outside workplace. Since there were more part-time workers during the recession (Borbely, 2009), they might participate less in any non-work activities during work hour, for example taking meals outside the workplace (49 percent of people did so during the recession compared to 57 percent in the pre-recession year). Less participation in non-work activities during work hours in the recession year (cf. Table 5.1) might reduce the average duration of these activities in that year than the pre-recession year. Interestingly, even in the post-recession year, a lower percentage of people did non-work activities during work hour than the pre- and during recession years and this reduced participation might cause average duration to reduce even more.

5.5 Model Specification

To find out the nature of changes in tour choice during recession, I conceptualize a causal structure between activity-travel participation and choice of tours. This structure also captures the effects of socio-demographic and economic factors on activity-travel as well as tour choice indicators. More specifically, multiple group structural equation modeling (SEM) is used to investigate invariance in causal structure across the pre (2006), during (2009) and post (2012) recession years.

Structural equation modeling (SEM) is a comprehensive methodological framework that can simultaneously estimate the causal relationships among a set of observed variables based on a specified model (Kaplan, 2008). The strength of a SEM is that in addition to find out the direct effect of one variable to another one, it can capture the indirect effect as well through other mediating variables. The summation of direct and indirect effects represents the total effect that provides valuable insights on the interrelationships between variables. The conceptual structure of a SEM can be graphically depicted by path diagrams. An arrow in a diagram indicates the direct effect from one variable to other. The rectangular boxes represent exogenous and endogenous variables. A variable is exogenous if it is not determined by the model (an arrow is directed from it) and it is endogenous if it is determined by the model (an arrow is directed to and/or from it).

Structural equation modeling (SEM) is widely used in travel behavior research, including trip chain generation (Golob, 2000), spatial features and car availability (Van Acker *et al*., 2014), and commuter activity-travel patterns (Kuppam and Pendyala, 2001). Multiple group SEM is also used in previous studies to identify the difference across gender in terms of internet use (Ren and Kwan, 2009), activity-travel participation (Susilo *et al.*, 2019), and public transit usage (Fu and Juan, 2017), difference in attitude toward public transit between car and non-car owners (Thøgersen, 2006), difference in commuting behavior between work only and more complex tours (Van Acker and Witlox, 2011), comparing mode-specific preference groups (Fu and Juan, 2016), sectors of the trucking industry (Golob and Regan, 2001), and two working women groups (Rafiq and McNally, 2018). However, little is known about the use of multiple group SEM to explore the temporal differences in the conceptualized causal structure. The model specifications and conceptualized causal structure are described next.

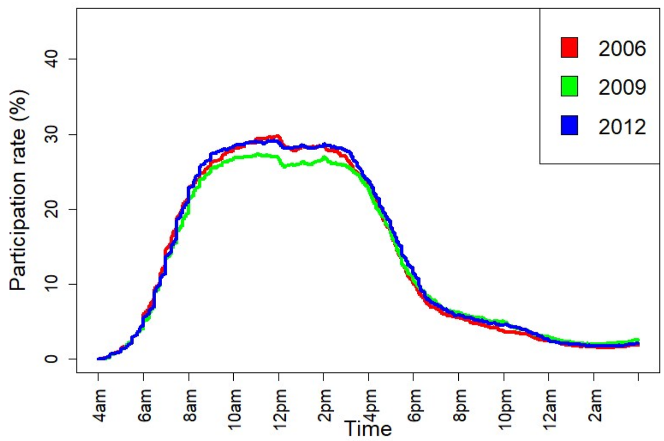
5.5.1 The Exogenous and Endogenous Variables

The model's endogenous and exogenous variables and their summary statistics are shown in Table 5.1 and 2.2, respectively. The endogenous variables are of three broad types: activity duration, travel duration, and choice of tours. There is a total of seven activity duration variables and six travel durations: one variable is for in-home work activity and the rest six are for out-of-home activity (one work and five non-work), each with a corresponding travel duration. Finally, this study considers four tour choice binary variables indicating whether an individual made at least one tour of a given type. In Table 5.1, for a given year the first column represents the percentage of respondents that performs a particular tour or activity, and the second and third columns show the average time spent on a particular tour or activity for the participating respondents and the associated standard deviation respectively. All the durations are provided in minutes.

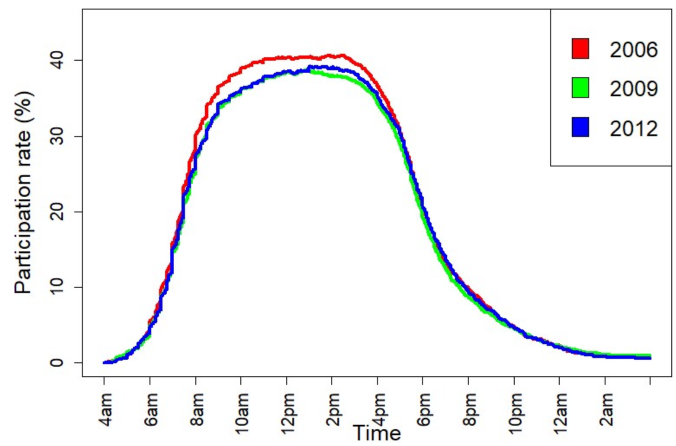
Table 5.1 Summary statistics of endogenous variables

Variables	2006			2009			2012		
	% cases > 0	For cases > 0		% cases > 0	For cases > 0		% cases > 0	For cases > 0	
		Mean	SD		Mean	SD		Mean	SD
Tour choice (1= yes, 0=no)									
Work-only tour	40.2	457.9	180	40.7	451.7	185.4	41.7	470.7	180.6
Work-nonwork mixed tour	49.4	559.8	190.3	45.6	566.1	183.4	46.8	566.8	182.9
Simple non-work tour	39.3	108.1	94.5	38.1	110.7	105.6	37.8	110.7	97.2
Complex non-work tour	21.1	218.1	138.9	21.3	220.3	146.1	18.8	210.5	149.7
Activity duration (minutes)									
Work at home	25.8	141.7	159.9	29.5	149.0	171.7	28.7	153.7	168.6
Work out-of-home	86.1	444.0	154.9	83.2	438.6	159.1	85.2	445.9	153.2
Non-work way to work	22.1	44.5	83.8	20.9	48.2	91.6	20.3	39.1	66.3
Non-work during work	14.7	39.0	45.0	12.7	37.0	44.7	11.0	36.4	36.1
Non-work way to home	31.8	75.2	95.3	30.6	71.2	94.5	32.6	73.1	89.8
Non-work before work	20.6	135.4	133.7	21.6	133.3	128.4	19.9	126.4	125.1
Non-work after work	37.8	130.3	109.8	36.1	130.7	111.6	34.1	128.4	116.3
Travel duration (minutes)									
Work travel	86.1	49.4	42.1	83.2	51.7	43.6	85.2	55.4	51.0
Non-work travel way to work	22.1	16.2	37.6	20.9	17.0	37.9	20.3	12.1	13.2
Non-work travel during work	14.7	22.7	23.4	12.7	26.6	36.7	11.0	28.4	36.9
Non-work travel way to home	31.8	22.1	24.6	30.6	21.4	35.4	32.6	23.3	34.0
Non-work travel before work	20.6	50.2	46.6	21.6	50.4	53.4	19.9	50.7	58.0
Non-work travel after work	37.8	44.7	46.0	36.1	49.5	60.1	34.1	52.3	75.5

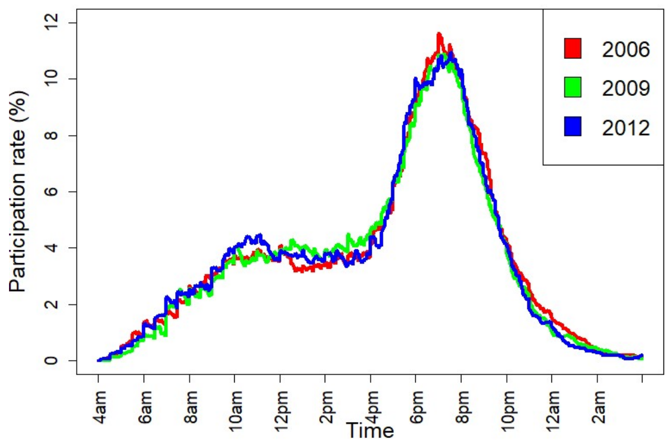
Figure 5.3 shows the fraction of people making certain types of tours at a particular time in a day in three different years. It is observed that participation of people in work-only tours slightly reduced during recession. On the other hand, the mid-day participation of people in non-work activities by making complex non-work tours increased notably in 2009 compared to 2006 and 2012. However, no significant changes are observed for other two types of tours.



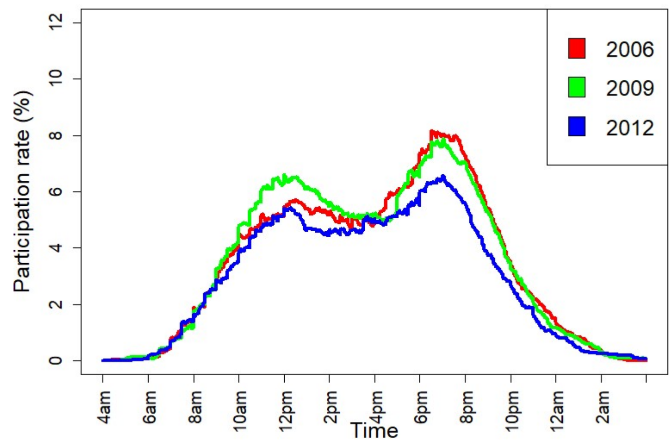
(a) Work-only tour



(b) Work-nonwork mixed tour



(c) Simple non-work tour



(d) Complex non-work tour

Figure 5.3 Participation rates by tour type and time of day

The exogenous variables shown in Table 5.2 include household and personal socio-demographic characteristics, residential location variables, and seasonal effects. Summary statistics in Table 5.2 reveal some changes in employment characteristics during the recession. For example, the percentage of full-time workers slightly reduced during recession from pre-recession (81 percent in 2006 and 80 percent in 2009) whereas the percentage of multiple job holders increased (12 percent in 2006 and 14 percent in 2009).

Table 5.2 Summary statistics of exogenous variables

Variables	2006		2009		2012	
	Mean	SD	Mean	SD	Mean	SD
Total respondents	2,712		2,723		2,816	
Household characteristics						
Household size	2.98	1.49	2.93	1.48	2.94	1.52
Household ownership						
Binary: 1= Owned, 0 = Rented with or w/o cash	0.78	0.42	0.76	0.43	0.72	0.45
No. of children						
No. of children aged between 0-5	0.24	0.53	0.24	0.55	0.25	0.57
No. of children aged between 6-10	0.26	0.56	0.26	0.57	0.26	0.57
No. of children aged between 11-18	0.36	0.71	0.33	0.67	0.33	0.67
Monthly household income (USD)						
Binary: 1= Low income (less than $20K)	0.10	0.30	0.09	0.29	0.11	0.31
Binary: 1= Middle income ($20K to $60K) (baseline)	0.41	0.49	0.39	0.49	0.38	0.48
Binary: 1= High income ($60K or more)	0.49	0.50	0.52	0.50	0.52	0.50
Personal characteristics						
Type of employment						
Binary: 1= Full time, 0 = Part time	0.81	0.39	0.80	0.40	0.80	0.40
Ethnicity status						
Binary: 1= Hispanic, 0 = Others	0.12	0.33	0.14	0.35	0.13	0.34
Multiple job status						
Binary: 1= Yes, 0 = No	0.12	0.33	0.14	0.34	0.11	0.31
Gender						
Binary: 1= Male, 0 = Female	0.49	0.50	0.49	0.50	0.50	0.50
Age	41.31	12.97	42.52	13.07	43.57	13.23
Marital status						
Binary: 1= Married and spouse employed	0.44	0.50	0.41	0.49	0.40	0.49
Binary: 1= Married and spouse unemployed	0.12	0.33	0.14	0.35	0.14	0.35
Binary: 1= Single (baseline)	0.44	0.50	0.45	0.50	0.45	0.50
Metropolitan status of residential location						
Binary: 1= Principal city (baseline)	0.29	0.45	0.29	0.46	0.31	0.46
Binary: 1= Suburb	0.52	0.50	0.51	0.50	0.50	0.50
Binary: 1= Non-metropolitan area	0.19	0.39	0.20	0.40	0.18	0.39
Seasonal effect						
Binary: 1= Winter, 0 = Others	0.26	0.44	0.26	0.44	0.26	0.44

5.5.2 The Structural Equation Modeling for Path Model

Let us denote measured exogenous variables as **X** and measured endogenous variables as **Y**. The equation for the endogenous variables is given by (Kline, 2016):

$$\mathbf{Y} = \mathbf{\Gamma X} + \mathbf{BY} + \boldsymbol{\zeta} \tag{1}$$

where **Y** is an ($m \times 1$) column vector of endogenous variable and **X** is an ($n \times 1$) column vector of measured exogenous variables.

The structural parameters are the elements of the matrices are (Golob and McNally, 1997):

$\boldsymbol{\Gamma}$ ($m \times n$) matrix of direct causal (regression) effects from the (n) exogenous variables to the (m) endogenous variables;

B ($m \times m$) matrix of causal links between the m endogenous variables; and

$\boldsymbol{\zeta}$ ($m \times 1$) matrix of m error terms

Equation (1) can be expressed in matrix form as (Kline, 2016):

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \cdots & \cdots & \cdots \\ \gamma_{m1} & \cdots & \gamma_{mn} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_n \end{bmatrix} + \begin{bmatrix} 0 & \cdots & \beta_{1m} \\ \cdots & \cdots & \cdots \\ \beta_{m1} & \cdots & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \cdots \\ \zeta_m \end{bmatrix} \quad (2)$$

Other parameter matrices include the covariance matrix of the measured exogenous variables $\boldsymbol{\Phi}$ and the covariance matrix of the error terms $\boldsymbol{\Psi}$, shown in Eq. (3).

$$\boldsymbol{\Phi} = \begin{bmatrix} \phi_{11} & & & \\ \phi_{21} & \phi_{22} & & \\ \vdots & \vdots & \ddots & \\ \phi_{n1} & \phi_{n2} & \cdots & \phi_{nn} \end{bmatrix} \boldsymbol{\Psi} = \begin{bmatrix} \psi_{11} & & & \\ \psi_{21} & \psi_{22} & & \\ \vdots & \vdots & \ddots & \\ \psi_{m1} & \psi_{m2} & \cdots & \psi_{mm} \end{bmatrix} \quad (3)$$

For identification of system (1), **B** must be chosen such that (**I-B**) remains non-singular, where **I** is an identity matrix of dimension m. For an identified system, the model implied total effects of the endogenous variables on each other are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{yy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1} - \boldsymbol{I} \quad (4)$$

The total effects of the exogenous variables on the endogenous variables implied by the system are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{xy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1}\boldsymbol{\Gamma} \tag{5}$$

The model parameters of the system in the Eq. (1) are estimated using variance analysis methods, also known as *methods of moments*. The theory is that the population covariance matrix of the observed variables (Σ) can be expressed as a function of a set of parameters θ, shown in Eq. (6) (Lu and Pas, 1999).

$$\boldsymbol{\Sigma} = \boldsymbol{\Sigma}\,(\boldsymbol{\theta}) \tag{6}$$

Here, θ represents the model parameters of **Γ, B, Φ,** and **Ψ.** These unknown parameters are estimated such that the difference between the sample covariance matrix *S* and the model implied covariance matrix Σ (θ) is minimized. This is achieved by minimizing a fitting function, which is a function of *S* and Σ (θ). Several estimation methods are available to identity a best fitting model. The maximum likelihood (ML) method works well when the endogenous variables have multivariate normal distribution. On the contrary, weighted least square mean and variance adjusted (WLSMV) estimator accounts for non-normally distributed data (Muthen and Kaplan, 1992).

5.5.3 The Initial Conceptual Model

The conceptual tour choice model has the following features: (1) the model captures non-work activity-travel demand and its associated tour choice for workers at different times aligned with the work tour; (2) it distinguishes the degree of variation in non-work activity demand and associated time use with respect to work, and consequently how this variation impacts non-work tour choices between people who work at home and who work out of home; (3) the model explicitly factors in the effect of travel time in addition to activity duration on tour choices. The last feature stands out as a contrast to earlier models (e.g., Golob, 2000), where tour generation was shown to be dependent on activity duration and travel times are hypothesized as the outcome of tour choice. Although activity demand (work or non-work) necessitates the occurrence of a tour, the type of tour undertaken should depends on *both* activity and travel duration. The impact of travel time can be very explicit, as when people use mapping services to find an estimated travel time for a certain activity, and this travel time influences the decision to chain other activities along the way or not.

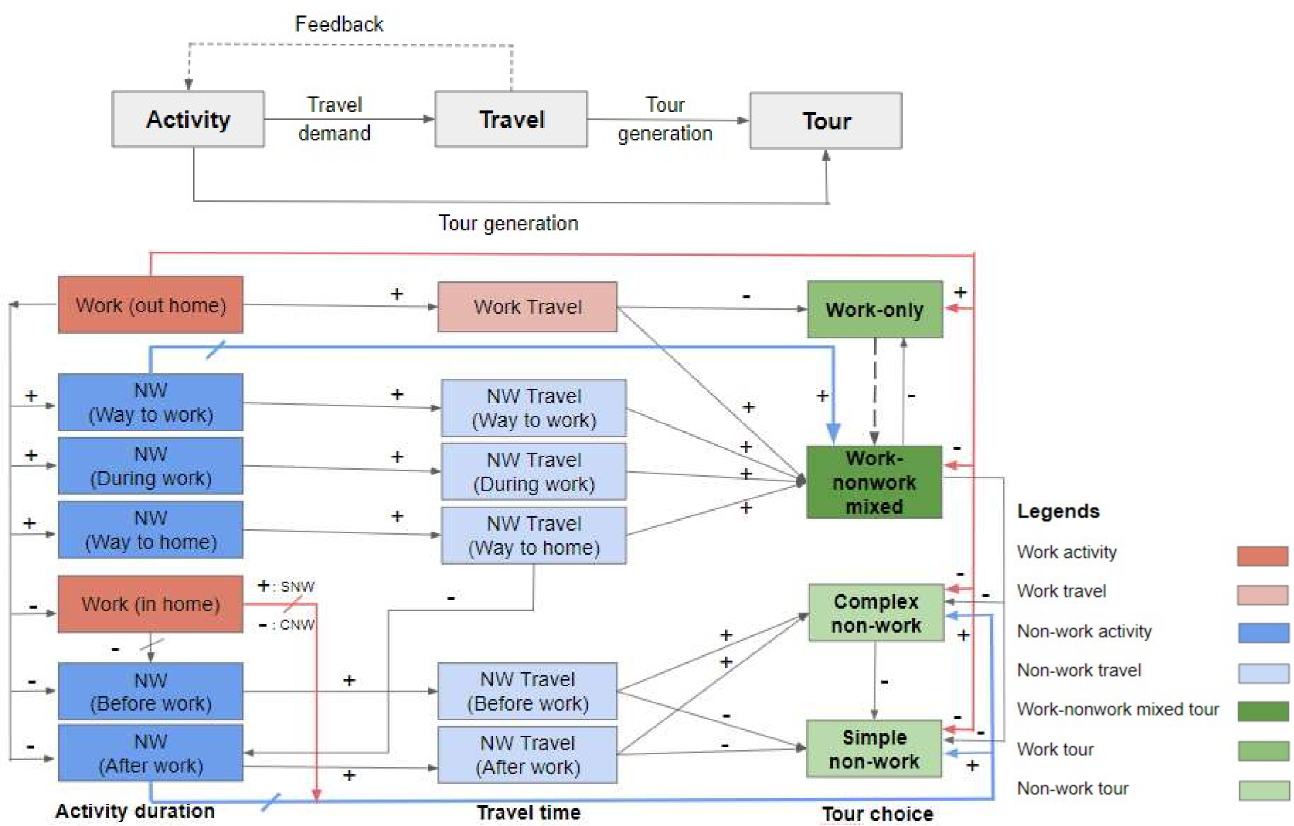


Figure 5.4 Structural equation model

The initial conceptual structure of the proposed model is shown in *solid lines* and additional link to improve the model is shown in *dashed line* in Figure 2.4. The upper figure shows the higher level of the conceptual model, where the demand for activity creates the demand for associated travel and both the activity and travel influence on tour generation. The rectangular boxes in the lower figure represent the endogenous variables and the arrows represent postulated non-zero direct effects and their expected sign. In the following the expected interactions between three layers of endogenous variables: activity durations, travel time, and tour choice are discussed.

5.5.3.1 Work and non-work activity interactions

Work is a mandatory activity and usually the least flexible because it is most often pursued at a fixed location on a fixed schedule. Other non-work activities need to be aligned with the work time (Golob and McNally, 1997; Rafiq and McNally, 2018). Therefore, out-of-home work duration has the following postulated effects: (1) *negative* effects on in-home work duration, (2) *positive* on within work tour non-work activities, and (3) *negative* on before and after work non-work.

The *negative* effects on after work non-work imply that employed persons spending more time working out-of-home might not be interested in going out again after returning from work. They may also have less time to accommodate out-of-home non-work activities before going to work because of less flexibility of start time of their works. They may instead prefer do the same on the way to work that would save them return trips to home. Similar effects can be observed with respect to choosing whether to finish some of the non-work activities on the way to home while returning from work (as part of work tours) or to make a separate "after work" non-work tour. The effects from out-of-home work to 'within work' non-work activities are postulated *positive* because they are part of work tours and are performed when the out-of-home work activities are made.

Similar to out-of-home work, in-home work duration is expected to have negative effects on both "before work" and "after work" non-work. As discussed earlier, since work is a mandatory task, spending more time in work activity naturally reduces the time for other activities since the total duration of a day (24 hours) is fixed (Golob and McNally, 1997).

5.5.3.2 Activity and travel interactions

In the model, a direct connection from each of the out-of-home activity to their associated travel is assigned. These direct connections represent travel as a derived demand meaning that the demand for travel is created to participate in out-of-home activity (McNally and Rindt, 2008). Each of the coefficients is assumed to be *positive*. We have added one feedback effect from 'way to home travel time to 'after work' nonwork activity time and expecte a *negative* effect.

5.5.3.3 Activity-travel interactions with tours

In terms of activity and tour choice interactions, activity durations have generally *positive* effect on associated tour choices because activity demand creates the necessities of tours. One exception is out-of-home work duration negatively affecting work-nonwork mixed tour and non-work tours assuming that one spending more time in work may not have enough time left for mixing non-work activities within work tour or making separate non-work tours (simple or complex) before or after the work. Unlike work out-of-home, a positive effect is postulated from work in-home to simple non-work tour anticipating that working at home is more flexible than working out-of-home (Alexander *et al*., 2010), which will provide more opportunities to make simple non-work tours before or after work.

Causal connections from work travel time to both the work-only and work-nonwork mixed tour choices are provided where I posit the first connection as *negative* and the second one as *positive* assuming that if a person travels a longer distance (longer travel time) for work, it will provide him an exposure to a greater range of non-work activity locations, which might increase the likelihood of doing non-work activities during the journey to or from work (Kondo and Kitamura, 1987; Nishii *et al*., 1988; Bhat, 1999). All non-work travel within work tours are expected to have *positive* coefficients to work-nonwork mixed tours anticipating that the tendency to combine non-work with work increases with the increase of distance between home and non-work activity locations (Kondo and Kitamura, 1987). Moreover, two direct connections from each of the non-work travel times (before and after work) are assigned to simple and complex non-work tours. The anticipated connections with simple non-work tour are *negative* and with complex non-work tour as *positive*. It is assumed that if a person has to travel longer distance (longer travel time) to avail a non-work activity before or after work activity, he might be more interested to chain other non-work activity demands within that tour by making a complex tour. In contrast, if the travel distance to avail a non-work activity is short, that person might be more interested to make frequent simple non-work tours.

5.5.3.4 Interactions between tours

It is postulated that chaining more than one activity within a tour reduces *de facto* the demand for single purpose simple tours (Golob, 2000). Thus, direct links are provided from work-nonwork mixed tour to work-only tour and complex non-work tour to simple non-work tour assuming each coefficient to be *negative*. Moreover, work-nonwork mixed tour is anticipated to affect the choice of non-work tours *negatively*.

5.5.3.5 Effects of exogenous variables and error-term covariance

For each of the specified endogenous variables, a subset of exogenous variables is selected that may potentially affect the endogenous variable. In the model, some error-term covariance between two similar set of variables are added, for example work only and work-nonwork mixed tours, simple and complex non-work tours, and non-work before work and after work. In addition, I added two error-term covariances: between work travel to way to work and way to home non-work activity. This is because these non-work activities are part of a work tour of an individual when the individual is traveling to or from work and the unaccounted factors affecting the work travel may be correlated with the duration of those non-work activities performed on the way.

5.5.4 Degree of Causal Invariance due to Recession

Given the postulated conceptual model, I investigate how this causal structure varies in terms of size, sign, and significance of the model parameters across pre (2006), during (2009) and post (2012) recession. It is anticipated that the model parameters will vary significantly across the three years.

5.5.5 Estimation of the Model

Based on the conceptual structure of endogenous variables and the best possible combination of exogenous variables, two *multiple group structural models* (constrained and unconstrained) are estimated using `lavaan` in R. I took logarithms of all activity and travel durations to reduce skewness (however, some skewness in travel durations still remained). The weighted least square mean and variance adjusted (WLSMV) estimator is used that works with categorical endogenous variables (four binary variables for tour choices, which are regressed by a probit function in `laavan` (R documentation, 2018)) and that accounts for non-normally distributed data (Muthen and Kaplan, 1992).

I specified one model by constraining all the corresponding parameters to be equal for 2006, 2009, and 2012 and another model without having such constraints. The main model fit statistic is χ^2 statistic that tests whether the observed covariance matrix and the model implied covariance matrix are equal. Smaller χ^2 value with high *p-value* (*p-value* > 0.05) indicates better model fit. However, χ^2 value tends to increase with sample size so models with larger sample sizes might show larger χ^2 value and subsequently may lead to rejection of an otherwise good model (Van Acker and Witlox, 2011). Other model fit indices, such as Root Mean Square Error Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker Lewis Index (TLI) are also reported.

The conceptual structure resulted in large χ^2 value with a lower *p-value* for both constrained and unconstrained models, which indicates a poor fit. To improve the model, I introduced a direct effect from work only tours to work-nonwork mixed tours and found that this additional direct connection (shown in *dashed line* in Figure 2.4) improved the model significantly: χ^2 (751) = 1187 (*p-value* = 0.000) for the constrained model and χ^2 (393) = 742 (*p-value* = 0.000) for the unconstrained model. This indicates that these two tour choices demonstrate feedback effects. In other words, the choice of work-only tour affects the choice of work-nonwork mixed tour and vice versa. Other model fit indices indicate satisfactory fit (constrained: χ^2 /df = 1.58, RMSEA= 0.015, CFI=0.993, TLI=0.996; unconstrained: χ^2 /df = 1.88, RMSEA= 0.018, CFI= 0.995, TLI= 0.994) (Van Acker *et al*., 2014). I subsequently performed a χ^2 difference test between the constrained and unconstrained models (χ^2 = 445, df =

358, $p = 0.001<0.05$), which confirms that model parameters are *not* equal across pre-, during, and post-recession years. Therefore, the unconstrained version is chosen as the final model.

5.6 Model Results and Discussion

Here I discuss unstandardized coefficients of *direct* effects (Table 5.3) and *total* effects (Table 5.4) that are statistically significant. If not otherwise stated, all the mentioned effects below represent direct effects. Note again, exogenous variables are not influenced by any other variable, whereas endogenous variables are both influenced (either directly or indirectly) and can influence other variables. In both the above-mentioned tables, the set of exogenous and endogenous variables are provided in rows and the list of endogenous variables are again placed in columns so that for a pair of variables corresponding effects (direct or total) can be interpreted in the direction from rows to columns. Again, each cell represents three coefficients for a pair of variables in 2006, 2009, and 2012 respectively. Three dashes indicate that the particular variable is a part of the model, but not significant whereas blank cells indicate that the particular variable is not a part of the model.

5.6.1 Effects between Endogenous Variables

5.6.1.1 Work and non-work activity interactions

Work out-of-home positively affects non-work activities performed within work tours and negatively affects "before work" and "after work" non-work activities. Non-work activities performed on the way to home have higher effect than during work and way to work. This indicates that if people need to perform non-work activities as a part of their work tours, they tend to prefer performing them more on the way to home than the other two ways. A rationale for this behavior may be that the post-work, way-to-home period puts fewer constraints on performing non-work activities, whereas way-to-work and during work timeslots are more constrained by the fixed nature and importance of the work activity. Similar findings are reported in previous works (Strathman et al., 1994, Castro et al., 2011). Moreover, way to home non-work has negative total effects (cf. Table 5.4) on "after work" out-of-home non-work activities, which suggests that when people meet their non-work activity demand on their way to home, they may be reluctant to make another tour after returning home (similar results appear in Bhat and Singh (2000)). As anticipated, both out-of-home work and in-home work affects before and after work non-work activities negatively.

5.6.1.2 Activity-travel interactions

All estimated activity-travel coefficients are found positive and statistically significant. One feedback effect from way-to-home travel time to "after work" non-work activities (negative) is found. This implies that people who spend more time travelling on their way to home have less time available for out-of-home, non-work activities after returning home (also reported in Golob, 2000; Kitamura *et al*., 1996).

5.6.1.3 Activity-travel interactions with tours

The model results based on *total* effects reveal that out-of-home work *positively* affects both the choice of work tours, higher on work-nonwork mixed tours than work-only tours. This result contradicts with the assumption and the study results reported in Bhat (1999). However, result from the direct effect shows expected *negative* correlation between out-of-home work duration and the choice of work-nonwork mixed tour. Secondly, work time *negatively* affects the choice of non-work tours (as postulated). Moreover, the choice of work tour type depends on work travel time. For instance, I found that work-only tours are preferred when work travel time is longer. But it differs with the postulation of association between these two variables. However, this positive correlation can be rationalized by the time constraints and stress people may face to perform additional non-work activities within work tour while travelling longer distance (time) for work.

Both "before work" and "after work" non-work activities have positive effects, as expected, on choosing simple non-work tours, with "after work" having the higher influence (coefficients are 0.284 and 0.316 respectively in 2006, Table 5.4). Effects on complex non-work tours are also positive albeit smaller sizes and they are obtained only from total effects. This observation matches with summary statistics shown in Table 5.2, where I see that, in 2006, 38.8% people are reported to make simple non-work tours compared to 21.3% people making complex ones and around 21% people make non-work tours before work versus around 38% after work. Furthermore, both before work and after work non-work travel time affects non-work tour choice as postulated but not all effects are obtained with significance in all years (cf. Table 5.4).

5.6.1.4 Interactions between tours

Results from the model show that, as expected, work-nonwork mixed tours reduce the demand for work-only tours. Moreover, making work-nonwork mixed tours negatively affects the choice of both simple and complex non-work tours.

5.6.2 Effects of Exogenous Variables

Women tend to perform more out-of-home non-work activities (specifically "way-to-work" and "way-to-home" non-work) and consequently make more work-nonwork mixed tours than men (cf. Table 5.4). Similar observations are found in some prior works (Strathman *et al*., 1994; Bhat, 1999; Kuppam and Pendyala, 2001). Men usually travel farther to work as they have longer work travel time and make less complex non-work tours than women. Older people apparently do more in-home work, less out-of-home work and less "after work" non-work compared to younger people (Bhat and Singh, 2000; Rajagopalan *et al*., 2009). They usually do not prefer mixing work with non-work thus prefer to make fewer complex tours (total effects) (Kuppam and Pendyala, 2001).

Generally, single persons tend to do more non-work activities than their married counterparts, in part because they might enjoy more flexible time management. Married persons with unemployed spouse spend less time in non-work activities than those with an employed spouse (while all effects are negatives, the effects for the former group have mostly smaller absolute values). This indicates that unemployed spouses might take care of some household tasks while their partners are at work and let them do less non-work. Persons with children usually perform more mixed tour and less work-only tours (total effects). Persons having children aged below 5 do less "after work" non-work activities, whereas persons with children aged 6-18 do more "after work" (mostly perhaps via simple non-work tours) as these children may perform more non-home activities (Bhat and Singh, 2000).

Full time workers spend less time in non-work activities (and consequently fewer non-work tours) than part-time workers, except for during work when they spend more possibly go out of their workplace to have lunch during midday (Castro *et al*., 2011). People with multiple jobs tend to spend less time working out-of-home than people with a single job. They prefer to do non-work before their work and when they combine their non-work with their work, they do so particularly on their way to home (cf. Table 5.3 and Table 5.4) (Castro *et al*., 2011). One notable observation is that people with multiple jobs tend to choose work only tours differently in the pre- and during recession years (negative total effect in 2006, but positive in 2009, detailed discussion is provided in the later section).

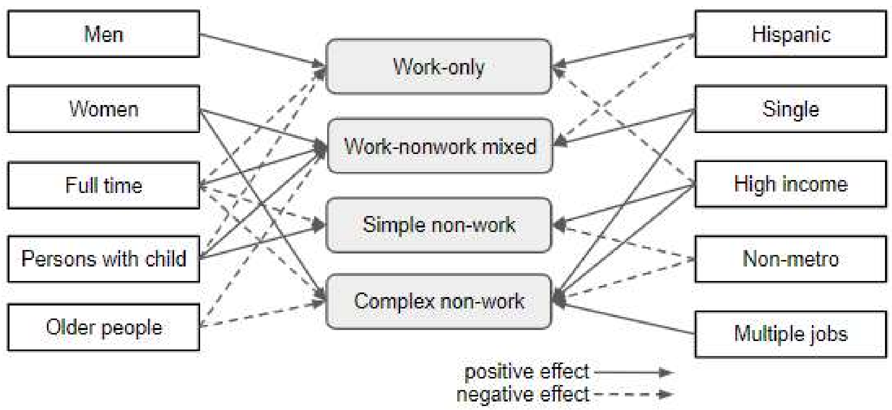


Figure 5.5 Significant effects of socio-demographic variables on tour choices

High income people make more non-work tours and fewer work-only tours (Strathman *et al*., 1994; Kuppam and Pendyala, 2001). People living in suburb and non-metropolitan areas do more out-of-home work and less non-work of any type than those living in principal cities. Figure 5.5 summarizes how the tour choices vary for a set of ten socio-demographic characteristics.

5.6.3 Differences in Causal Effects in Pre-, During, and Post- recession Years

The significant causal effects (i.e., model coefficients) identified for the recession are now compared to these effects for the pre- and post-recession years. To measure statistical difference between two coefficients observed at two different years (which are assumed to be independent since ATUS does not represent panel data), a Z-test is applied; in particular, for two coefficients, say β_1 and β_2 with standard errors, se_1 and se_2, the test statistic is: $Z = (\beta_1 - \beta_2)/\sqrt{se_1^2 + se_2^2}$, which is supposed to follow standard normal distribution under the null hypothesis that both coefficients are equal (Kühne *et al*., 2018).

In regard to highlighting the differences in causal effects, I identify three categories of effects (direct and total) that are discussed below. Since the list of variables under each category is broad, I limit discussion mostly to those variables that affect tour choices.

(a) Effects that are significant in 2009 but neither in 2006 nor in 2012 (unique recession effects)

It is observed that during recession the tendency of choosing complex non-work tours is low for full-time workers and aged people. Interestingly, winter season played a significant role during recession in choosing simple tours. More specifically, people preferred less to make work-only tours or simple non-work tours in winter compared to other seasons, say fall or summer.

(b) Effects that are significant in 2009 and in either 2006 or 2012, with 2009's effects significantly differ from the other year's effects (whichever exists)

People having multiple jobs showed a sheer variation in their work tour choices. For instance, work-only tours are less preferable during pre-recession (negative total effect), whereas the contrary is true during recession (positive total effect). In the pre- and post-recession years, people perhaps preferred to make work-nonwork mixed tours more than work-only tours. On the other hand, in the recession year, they perhaps preferred to make work-only tours more either by making one long work-only tour (went from one work to another without returning home) or making more work-only tours (returned home before going to another job).

I have checked this categorically in our dataset and noted that the fraction of people with multiple jobs making work-only tours in recession year was indeed higher than the pre- and post-recession years (44% compared to 36% and 38% respectively). Moreover, during recession higher fraction of people doing multiple jobs performed *work-only tours* in combination of work-nonwork mixed tours or other non-work tours than pre- and post-recession years (8% people combined work-nonwork mixed tours compared to 4% and 5% respectively whereas 25% people combined any non-work tours compared to 18% and 17% respectively). One possible reason for such behavior may be less out-of-home work during recession (average out-of-home work duration in 2009 was around 366 minutes which differ significantly from 383 and 378 minutes in 2006 and 2012 respectively with p-values < 0.05) led to make other work or non-work tours with work-only tours.

(c) Effects that are significant in all the three years and represent one of the following four sub-trend groups:

<u>Group 1</u>: Norms that did not change in pre-, during and post-recession years

In this study, the multiple group SEM is constructed to study the invariance in causal structures among the three target years. Arguably, there can be a considerable portion of causal effects that happen to demonstrate no changes across the three years. These are the effects that remained unchanged and constitute the time invariant travel behavior of the target population. In this study, around 47 percent effects are those effects that did not change in the pre-, during, and post-recession years. For example, the structural relationships of out-of-home work activity with different non-work activities and the choice of tours did not change in the three target years. That means, the process of balancing less mandatory tasks (non-work) and choosing associated work or non-work tours based on the mandatory task (work) remained unchanged over time.

<u>Group 2</u>: 2006 norms that changed during the 2009 recession but returned to the 'old norm' in 2012

It is observed that, part-time workers are more likely to make simple non-work tours than full-time workers since they have to spend less time at work and thus, get more chances to make non-work activities by making separate non-work tours. This effect significantly became lower in the recession year than the pre- and post-recession years. One possible explanation may be during recession, part-time workers might have replaced some of their out-of-home non-work demands with an equivalent in-home counterpart, say shopping online from home instead of going to marketplaces or doing recreational activities at home instead of visiting outside. Data show that average in-home non-work activity duration is indeed increased significantly during recession compared to pre- and post-recession (836 minutes compared to 824 and 826 minutes respectively). Also, lower fraction of part-time workers preferred to make simple non-work tours in 2009 than 2006 and 2012 (39% compared to 45% and 43% respectively).

As anticipated, work-nonwork mixed tour reduced the demand of making complex non-work tours in all the three years. This negative effect was higher in the recession year than the pre- and post-recession years. This indicates that during recession, workers who made non-work stops within their work tours, may preferred to meet all the non-work activity demands within that tour to avoid extra home-based trips by making separate complex non-work tours.

Group 3: 2006 norms that changed during the 2009 recession and were maintained in 2012 as 'new norm'

A positive association between "before work" non-work activity time and the choice of simple non-work tour in all the three years is found. The positive association between these two variables indicate that since typically there are time constraints before starting an individual's work activity, he/she may prefer to meet the demand of a non-work activity that arises at that time—for example, dropping children at school or doing grocery or taking breakfast outside—by making a simple non-work tour instead of a complex one.

It is also observed that the recession year has got the larger effect than the pre-recession year and this larger effect also continued during the post-recession year. The larger effect might be due to the higher percentage of people participating in non-work activity before starting their work in 2009 than 2006 (22% people did so in 2009 compared to 21% in 2006, cf. Table 5.1). This higher participation of people perhaps increased the chances of making a simple non-work tour in the recession year. During recession as individuals spent significantly more time working at home (mean around 37 and 44 minutes for 2006 and 2009 respectively with *p-value* = 0.005), it perhaps gave them some flexibility in terms of when to start and finish the work and thus, led them to participate in non-work activities before starting the work (Alexander et al., 2010) more than the pre-recession year. Interestingly, this recession effect did not change in the post-recession year. Data reveals that during recession a higher fraction of people out of those who made non-work before starting their work, worked only from home than the post-recession year (45% did so during the recession compared to 43% in the post-recession year). It also shows that the new trend of performing single or multiple jobs both at home and workplace remained unchanged (8% people in 2006 compared to 10% in both 2009 and 2012) and the average time spent on work at home did not significantly differ between 2009 and 2012. These facts may rationalize of having some degree of flexibility in the post-recession year to make non-work activities before starting work by making simple non-work tours.

Group 4: 2006 norms that did not change during the 2009 recession but changed after the recession

Two notable effects under this sub-trend are while making work tours, men are more likely to make work-only tours and less likely to work-nonwork mixed tours and the size of these effects are larger in post-recession year compared to the recession year. Since women are reported to spend less time in out-of-home work than men (430 minutes versus 447 minutes in 2009 where the difference is significant with *p-value* = 0.000) and they happen to take care of their children and household chores most of the times (Rosenbloom, 2006), they manage to do more non-work activities within work tours, for example, drop off children at school or daycare on the way to work or consumer purchase for household, on the way to home from work than men. This tendency is higher in post-recession year because the work out-of-home time gap between women and men is also higher in that year (429 versus 459 minutes with *p-value* = 0.000).

5.7 Conclusions

This study explored how employed individuals change their activity-travel patterns during a recession by using a tour-based representation of the activity-based approach. Unlike previous studies, this study captured the nature of changes in travel behavior during the recession by using a rigorous methodological framework. A multiple group structural equation modeling (SEM) is used by conceptualizing a causal structure between activity-travel participation and choice of tours. This structure also captured the effects of socio-demographic and economic factors on activity-travel as well as tour choice indicators. The multiple group SEM enabled assessment of the invariance in causal structure across the pre (2006), during (2009) and post (2012) recession years. Although multiple group SEM is widely used in travel behavior research to identify differences across various transport user groups, little is known about the use of this technique to explore the temporal differences in the conceptualized causal structure. To develop this model, the American Time Use Survey (ATUS) data is used, which is the most reliable national-level cross-sectional survey data providing an individual's time usage in various activities on a single day.

Results show that activity-travel relationships and their role in tour choice differed significantly in the recession year (2009) compared to pre- and post-recession years. While analyzing the temporal changes in causal effects, I identify four sub-trend groups. Group 1 had norms that did not change in pre-, during and post-recession years. For example, the process of balancing less mandatory tasks (non-work) and choosing associated work or non-work tours based on the mandatory task (work) remained unchanged over time. The 2006 norms for Group 2 changed during 2009 recession but returned to the 'old norm' in 2012. While part-time workers are more likely to make simple non-work tours than full-time workers, the effect significantly became lower in the recession year than the pre- and post-recession years. Moreover, during the recession workers more preferred to meet non-work activity demands within the work tour instead of making separate complex non-work tours. For Group 3, 2006 norms that changed during 2009 recession were maintained in 2012 as a 'new norm.' For example, the tendency of making simple non-work activities before work increased during the recession and this tendency is continued in the post-recession year. Last, for Group 4, 2006 had norms that did not change during the 2009 recession but did change after the recession. For example, men were more likely to make work-only tours and less likely to work-nonwork mixed tours and the size of these effects were larger in the post-recession year compared to the pre- and during recession years.

A recession can bring a wide spectrum of potential responses to newly imposed constraints. I have limited the range of impacts by focusing only on employed individuals, although the nature of their employment may change. For example, the average number of jobs held varies, possibly reflecting additional part-time work, as has become common in the *gig economy*, and more work in home. Results from this study suggest how the changes in the nature of jobs affect the tour choices of an individual. For instance, prior to the recession, people having multiple jobs made fewer work-only tours; during the recession, the contrary was true. Our findings on changes in tour choice pattern during the recession provide valuable insights on possible changes in worker's travel demand during an economic downturn, which would contribute to building better pattern choice sets in tour-based models. Moreover, the terms that I introduce to analyze the recession effects such as old norms and new norms can have broader applications to other studies related to trend analysis.

Since the purpose of developing the multiple group SEM structure was to identify the temporal variation in the causal structure among socio-economic characteristics, activity-travel participation, and choice of tours, it cannot be immediately used for long term travel demand forecasting purpose. Nonetheless, the conceptual SEM structure and the model results will provide valuable insights on how workers allocate time to various out-of-home activity demands at different times of a day aligned with work activity, how these activity demands are allocated to different tours, and what kind of tours are preferred by an individual with given socio-economic characteristics, and consequently contribute to better development of a tour choice prediction model.

5.8 References

Aguiar, M., Hurst, E., & Karabarbounis, L. (2013). Time use during the great recession. American Economic Review, 103(5): 1664-96.

Alexander, B., Dijst, M., & Ettema, D. (2010). Working from 9 to 6? An analysis of in-home and out-of-home working schedules. *Transportation*, 37(3): 505-523.

Anand, P., & Ben-Shalom, Y. (2014). How do working-age people with disabilities spend their time? New evidence from the American Time Use Survey. *Demography*, *51*(6), 1977-1998.

Archer, M., Paleti, R., Konduri, K. C., Pendyala, R. M., & Bhat, C. R. (2013). Modeling the connection between activity-travel patterns and subjective well-being. *Transportation Research Record*, *2382*(1), 102-111.

Berik, G., & Kongar, E. (2013). Time allocation of married mothers and fathers in hard times: The 2007–09 US recession. Feminist Economics, 19(3): 208-237.

Bernardo, C., Paleti, R., Hoklas, M., & Bhat, C. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A: Policy and Practice*, *76*, 71-91.

Bhat, C. (1999). An analysis of evening commute stop-making behavior using repeated choice observations from a multi-day survey. *Transportation Research Part B: Methodological*, 33(7): 495-510.

Bhat, C. R., & Singh, S. K. (2000). A comprehensive daily activity-travel generation model system for workers. *Transportation Research Part A: Policy and Practice*, 34(1): 1-22.

Blumenberg, E., Ralph, K., Smart, M., & Taylor, B. D. (2016). Who knows about kids these days? Analyzing the determinants of youth and adult mobility in the US between 1990 and 2009. *Transportation Research Part A: Policy and Practice*, 93: 39-54.

Blumenberg, E., Taylor, B. D., Smart, M., Ralph, K., Wander, M., & Brumbagh, S. (2012). What's youth got to do with it? Exploring the travel behavior of teens and young adults.

ITS, UCLA. http://www.escholarship.org/uc/item/9c14p6d5. Accessed September 15, 2019.

Borbely, J. M. (2009). US labor market in 2008: Economy in recession. *Monthly Labor Review.*, Bureau of Labor Statistics, *132*, 3-19. https://www.bls.gov/opub/mlr/2009/03/art1full.pdf. Accessed March 14, 2019.

Bureau of Labor Statistics. (2012). BLS spotlight on statistics: The recession of 2007–2009. *Unemployment demographics*.

Cascajo, R., Olvera, L. D., Monzon, A., Plat, D., & Ray, J. B. (2018). Impacts of the economic crisis on household transport expenditure and public transport policy: Evidence from the Spanish case. *Transport policy*, *65*, 40-50.

Castro, M., Eluru, N., Bhat, C., & Pendyala, R. (2011). Joint model of participation in nonwork activities and time-of-day choice set formation for workers. *Transportation Research Record: Journal of the Transportation Research Board*, 2254: 140-150.

Damm, D. (1982). Parameters of activity behavior for use in travel analysis. *Transportation Research Part A: General*,16(2): 135-148.

Efthymiou, D., Antoniou, C., Tyrinopoulos, Y., & Skaltsogianni, E. (2018). Factors affecting bus users' satisfaction in times of economic crisis. *Transportation Research Part A: Policy and Practice*, *114*, 3-12.

Fan, Y. (2017). Household structure and gender differences in travel time: spouse/partner presence, parenthood, and breadwinner status. *Transportation*, *44*(2), 271-291.

Ferdous, N., Eluru, N., Bhat, C. R., & Meloni, I. (2010). A multivariate ordered-response model system for adults' weekday activity episode generation by activity purpose and social context. *Transportation research part B: methodological*, *44*(8-9), 922-943.

Fu, X., & Juan, Z. (2016). Empirical analysis and comparisons about time-allocation patterns across segments based on mode-specific preferences. *Transportation*, *43*(1), 37-51.

Fu, X., & Juan, Z. (2017). Exploring the psychosocial factors associated with public transportation usage and examining the "gendered" difference. *Transportation research part A: policy and practice*, *103*, 70-82.

Garikapati, V. M., Pendyala, R. M., Morris, E. A., Mokhtarian, P. L., & McDonald, N. (2016). Activity patterns, time use, and travel of millennials: a generation in transition?. *Transport Reviews*, 36(5): 558-584.

Gimenez-Nadal, J. I., Molina, J. A., & Velilla, J. (2018). The commuting behavior of workers in the United States: differences between the employed and the self-employed. *Journal of transport geography*, *66*, 19-29.

Golob, T. F. (2000). A simultaneous model of household activity participation and trip chain generation. *Transportation Research Part B: Methodological*, 34(5): 355-376.

Golob, T. F., and McNally, M. G. (1997). A model of activity participation and travel interactions between household heads. *Transportation Research Part B: Methodological*, 31(3): 177-194.

Golob, T. F., & Regan, A. C. (2001). Impacts of highway congestion on freight operations: perceptions of trucking industry managers. *Transportation Research Part A: Policy and Practice*, *35*(7), 577-599.

Goodman, C. J., and Mance, S. M. (2011). Employment loss and the 2007–09 recession: an overview. *Monthly Labor Review*, Bureau of Labor Statistics, 134(4), 3-12. https://www.bls.gov/opub/mlr/2011/04/art1full.pdf. Accessed March 14, 2019.

Hipple, S. F. (2010). Multiple jobholding during the 2000s. *Monthly Labor Review*, Bureau of Labor Statistics, *133*(7), 21-32. http://www.uvm.edu/~fmagdoff/employment%20Jan.12.11/Multiple%20jobholding%20during%20the%202000s.pdf. Accessed March 21, 2019.

Kaplan, D. (2008) Structural equation modeling: Foundations and extensions. Sage Publications.

Keita, Y. M., & Tilahun, N. (2017). Impact of the great recession on transportation spending distribution of poor and middle income households: A gender analysis. Presented at 96th Annual Meeting of the Transportation Research Board, Washington, D.C.

Kitamura, R., Yamamoto, T., Fujii, S., & Sampath, S. (1996). A discrete-continuous analysis of time allocation to two types of discretionary activities which accounts for unobserved heterogeneity. Transportation and traffic theory, 26: 431-453.

Kline, R. B. (2016). *Principles and practice of structural equation modeling*. Guilford publications, New York, USA.

Kondo, K., & Kitamura, R. (1987). Time-space constraints and the formation of trip chains. *Regional Science and Urban Economics*, 17(1): 49-65.

Kroll, S. (2011). The decline in work hours during the 2007-09 recession. *Monthly Labor Review*, Bureau of Labor Statistics, *134*(4), 53-59. https://www.bls.gov/opub/mlr/2011/04/art10full.pdf. Accessed March 13, 2019.

Krueger, A. B., & Mueller, A. I. (2012). Time use, emotional well-being, and unemployment: Evidence from longitudinal data. *American Economic Review*, *102*(3), 594-99.

Kühne, K., Mitra, S. K., & Saphores, J. D. M. (2018). Without a ride in car country a comparison of carless households in Germany and California. *Transportation research part A: policy and practice*, 109: 24-40.

Kuppam, A. R., & Pendyala, R. M. (2001). A structural equations analysis of commuters' activity and travel patterns. Transportation, 28(1): 33-54.

Langerudi, M. F., Anbarani, R. S., Javanmardi, M., & Mohammadian, A. (2016). Resolution of Activity Scheduling Conflicts: Reverse Pairwise Comparison of In-Home and Out-of-Home Activities. *Transportation Research Record*, *2566*(1), 41-54.

Maheshri, V., & Winston, C. (2016). Did the Great Recession keep bad drivers off the road?. *Journal of Risk and Uncertainty*, *52*(3), 255-280.

Mastracci, S. H. (2013). Time use on caregiving activities: Comparing Federal Government and private sector workers. *Review of Public Personnel Administration*, *33*(1), 3-27.

McCahill, C. (2017). VMT growth continued, slowed in 2016. State Smart Transportation Initiative. https://www.ssti.us/2017/05/vmt-growth-continued-slowed-in-2016/. Accessed April 26, 2019.

McNally, M. G., and Rindt, C. (2008). The activity-based approach. In *Handbook of Transport Modeling* (D. A. Hensher and K. J. Button, ed.), 2nd ed., pp.55-73.

Morris, E. A. (2015). Should we all just stay home? Travel, out-of-home activities, and life satisfaction. *Transportation Research Part A: Policy and Practice*, *78*, 519-536.

Muthen, B., & Kaplan, D. (1992). A comparison of some methodologies for the factor analysis of non-normal Likert variables: A note on the size of the model. *British Journal of Mathematical and Statistical Psychology*, 45(1): 19-30.

National Bureau of Economic Research. (2010). US Business Cycle Expansions and Contractions. http://www.nber.org/cycles.html. Accessed July 30, 2018.

Nishii, K., Kondo, K., & Kitamura, R. (1988). Empirical analysis of trip chaining behavior. *Transportation Research Record: Journal of the Transportation Research Board*, 1203: 48-59.

Noland, R. B., & Zhou, Y. (2017). Has the great recession and its aftermath reduced traffic fatalities?. *Accident Analysis & Prevention*, *98*, 130-138.

Paulin, G. (2012). Travel expenditures, 2005-2011: spending slows during recent recession. Washington, DC: Bureau of Labor Statistics. Beyond the Numbers, 1(20).

Rafiq, R., and McNally, M. G. (2018). Modeling the structural relationships of activity-travel participation of working women. *Transportation Research Record*, 0361198118784135.

Rajagopalan, B., Pinjari, A., & Bhat, C. (2009). Comprehensive model of worker nonwork-activity time use and timing behavior. Transportation Research Record: Journal of the Transportation Research Board, 2134: 51-62.

Ren, F., & Kwan, M. P. (2009). The impact of the Internet on human activity–travel patterns: analysis of gender differences using multi-group structural equation models. *Journal of Transport Geography*, *17*(6), 440-450.

R Documentation. LavOptions.www.rdocumentation.org/packages/lavaan/versions/0.6-1.1240/topics/lavOptions. Accessed July 22, 2018.

Robinson, J. P., & Martin, S. (2010). IT use and declining social capital? More cold water from the General Social Survey (GSS) and the American Time-Use Survey (ATUS). *Social Science Computer Review*, *28*(1), 45-63.

Rosenbloom, S. (2006). Understanding Women's and Men's Travel Patterns: The Research Challenge. In Conference Proceedings 35: Research on Women's Issues in Transportation: Report of a Conference; Volume 1: Conference Overview and Plenary Papers, Transportation Research Board of the National Academies, Washington, DC, pp. 7-28.

Srinivasan, S., & Bhat, C. R. (2008). An exploratory analysis of joint-activity participation characteristics using the American time use survey. *Transportation*, *35*(3), 301-327.

Stone, A. A., & Schneider, S. (2016). Commuting episodes in the United States: Their correlates with experiential wellbeing from the American Time Use Survey. *Transportation research part F: traffic psychology and behaviour*, *42*, 117-124.

Strathman, J. G., Dueker, K. J., & Davis, J. S. (1994). Effects of household structure and selected travel characteristics on trip chaining. *Transportation*, *21*(1), 23-45.

Susilo, Y. O., Liu, C., & Börjesson, M. (2019). The changes of activity-travel participation across gender, life-cycle, and generations in Sweden over 30 years. *Transportation*, *46*(3), 793-818.

Thakuriah, P., & Mallon-Keita, Y. (2014). An analysis of household transportation spending during the 2007-2009 US economic recession. Presented at 93th Annual Meeting of the Transportation Research Board, Washington, D.C.

The Transport Politic (2018). U.S. Transit Ridership. www.thetransportpolitic.com/databook/u-s-transit-ridership/. Accessed April 26, 2019.

Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. *Transportation Research Part A: Policy and Practice*, *40*(8), 621-638.

Thomas, T., Blumenberg, E., & Salon, D. (2015). Travel Adaptations and the Great Recession: Evidence from Los Angeles County. Presented at 94th Annual Meeting of the Transportation Research Board, Washington, D.C.

Ulfarsson, G. F., Steinbrenner, A., Valsson, T., & Kim, S. (2015). Urban household travel behavior in a time of economic crisis: Changes in trip making and transit importance. *Journal of Transport Geography*, *49*, 68-75.

Van Acker, V., & Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use?. *Transportation*, 38(3): 465-486.

Van Acker, V., Mokhtarian, P. L., & Witlox, F. (2014). Car availability explained by the structural relationships between lifestyles, residential location, and underlying residential and travel attitudes. *Transport Policy*, 35: 88-99.

Winkler, A. E. (2013). The relationship between the housing and labor market crises and doubling up: an MSA-level analysis, 2005-2011. *Monthly Labor Rev.*, Bureau of Labor Statistics, *136*, 1. https://www.bls.gov/opub/mlr/2013/article/the-relationship-between-the-housing-and-labor-market-crises-and-doubling-up.htm. Accessed March 21, 2019.

Table 5.3 Direct effects of exogenous and endogenous variables (see footnotes for explanation)

From	To																
Variables	Work-only tour	Simple non-work tour	Work-nonwork mix tour	Complex non-work tour	Work in home	Work out of home	NW way to work	NW during work	NW way to home	NW before work	NW after work	Work travel	NW travel way to work	NW travel during work	NW travel way to home	NW travel before work	NW travel after work
HH size	---	-0.029**	-0.094*	---	---		---		-0.132*	---	---						
	---	---	-0.100*	---	-0.103*		---		-0.065**	---	-0.120*						
	---	---	-0.076*	---	-0.110*		-0.050**		-0.118*	---	-0.129*						
HH ownership		---	---	---	---		---	---	-0.208*	---	---	---	---	---	---	---	---
		---	---	---	---		---	---	---	---	---	---	---	---	---	---	---
		-0.141**	---	---	---		-0.126*	---	---	0.179**	---	---	---	---	---	---	---
No. of child aged 0-5	---	---	---	---	---	-0.169**	0.191*	---	0.246*	0.114**	-0.189**	---	0.061*	---	---	---	---
	---	---	---	---	0.155*	---	---	---	0.171*	---	---	---	---	---	0.053**	---	---
	---	0.112*	---	---	0.128**	-0.176**	0.194*	0.083**	0.172*	---	---	---	0.088*	---	0.074*	---	---
No. of child aged 6-10	---	---	---	---	0.094**	---	---	---	0.279*	---	---	---	---	0.051**	---	---	---
	---	---	---	---	---	-0.171*	---	---	0.117**	---	0.286*	---	0.082*	---	0.048**	---	-0.057**
	0.046**	---	---	0.109*	---	-0.274*	0.105*	---	0.201*	---	---	---	---	---	---	---	---
No. of child aged 11-18	---	0.110*	0.097**	---	---	---	---	---	0.111**	---	0.176*	---	0.038**	---	---	---	---
	---	0.078**	0.093**	---	0.100**	---	---	---	0.207*	---	0.210*	---	0.046**	---	---	---	---
	---	0.154*	---	---	---	---	0.131*	---	---	---	0.206*	0.070*	---	---	---	---	0.045**
Low income (<$20K)	---	---	---	---	---	0.319**		---	-0.250**	-0.315**	---	---		---	---	---	---
	---	---	---	---	---	---		---	-0.236**	---	-0.424*	---		---	---	---	---
	---	---	---	---	---	---		---	---	---	---	---		---	---	---	---
High income (>=$60K)	---	---	---	---	0.301*	-0.452*		0.210*	0.234*	---	0.217*	---		---	---	-0.050**	---
	---	---	0.173*	0.106*	0.339*	-0.443*		0.127*	0.144**	---	0.348*	0.076**		---	---	---	---
	---	---	---	0.097**	0.348*	-0.389*		0.204*	0.162*	---	---	---		---	---	---	---
Employment type	-0.151*	---	0.156**	---	---	0.708*	-0.257*	---	-0.254*	---	---	-0.153*	---	---	0.070**	0.070*	---
	-0.145*	---	0.226*	-0.116*	0.159*	0.624*	---	0.169*	-0.173*	---	---	---	---	---	0.093*	---	---
	-0.177*	---	0.218*	---	0.280*	0.643*	-0.139*	---	---	-0.166*	---	---	---	---	---	---	---
Ethnicity	---	---	-0.444*	-0.169*	-0.385*					---	---						
	0.174*	---	-0.267*	-0.174*	-0.448*					-0.356*	---						
	0.159*	---	-0.439*	---	-0.457*					-0.188**	---						
Multiple jobs status	0.094*	---	---	---	0.531*	-0.463*	---	---	0.264*	---	---	---	---	---	---	---	---
	0.190*	---	-0.296*	---	0.421*	-0.232**	0.150*	---	0.265*	---	---	0.117*	---	---	-0.072**	---	---
	0.128*	---	-0.331*	---	0.423*	-0.492*	0.203*	0.140*	0.221*	---	---	0.203*	---	0.103*	---	---	---
Gender			---	-0.088**	0.100**	---	---	0.149*	-0.278*	---	---	0.115*	-0.078*	---	---	---	---
			---	-0.124*	0.168*	---	-0.135*	---	-0.180*	---	---	---	---	---	-0.081*	---	---

From	To																
Variables	Work-only tour	Simple non-work tour	Work-nonwork mix tour	Complex non-work tour	Work in home	Work out of home	NW way to work	NW during work	NW way to home	NW before work	NW after work	Work travel	NW travel way to work	NW travel during work	NW travel way to home	NW travel before work	NW travel after work
			---	-0.085**	---	---	-0.236*	---	-0.357*	---	---	0.086*	-0.064*	---	---	---	---
Age	---	---		---	0.011*	-0.010*	---	---	---	---	-0.011*					---	---
	---	---		-0.003**	0.009*	-0.007**	---	---	---	---	-0.013*					---	---
	---	---		---	0.010*	-0.008*	---	---	---	---	-0.011*					---	---
Married & spouse employed	---	---	---	---	0.183*	---	---	---	---	---	---					---	---
	---	---	---	---	---	-0.262*	---	---	-0.201*	-0.268*	---					---	0.095*
	---	---	0.128**	---	---	-0.261*	---	-0.107**	---	---	---					---	---
Married & spouse unemployed	---	---	---	---	0.348*	---	-0.241*	---	---	-0.236**	---					---	---
	---	---	---	---	---	---	-0.156**	---	-0.433*	-0.352*	---					---	0.089**
	---	---	---	-0.142**	---	-0.377*	---	---	---	---	---					---	---
Suburb	---	---	---	---	---	0.225*	---	---	---	---	---	---	---	---	---	---	0.064**
	-0.055*	---	---	---	---	---	---	---	---	-0.154*	---	---	---	---	---	---	---
	---	---	---	---	---	---	-0.118*	---	-0.187*	---	---	---	---	-0.055**	---	---	---
Non-metropolitan area	---	-0.155*	---	---	---	0.270*	---	-0.165*	---	-0.177**	---	-0.163*	---	---	---	-0.062**	---
	0.073**	---	---	---	-0.159**	0.350*	---	---	---	---	---	-0.227*	---	---	---	---	---
	0.083**	---	---	---	-0.253*	0.473*	---	---	---	---	---	-0.179*	---	---	---	---	---
Winter	---	---	---	---		---				---	---						
	-0.059*	---	---	---		---				---	---						
	---	---	0.199*	---		---				0.120**	---						
Work-only tour			1.059*														
			0.943*														
			0.914*														
Simple non-work tour																	
Work-nonwork mix tour	-1.062*	-0.110*		-0.113*													
	-1.091*	---		-0.163*													
	-1.073*	---		-0.103*													
Complex non-work tour		---															

Work in home		---		-0.024**						-0.101*	---						
		0.043*		-0.022**						-0.086*	-0.050*						
		0.044*		-0.031*						-0.069*	---						
Work out of home	0.363*	---	-0.297*	-0.058*	-0.605*		0.114*	0.135*	0.271*	-0.537*	-0.267*	0.630*					
	0.285*	0.116*	-0.130**	-0.050*	-0.622*		0.124*	0.107*	0.247*	-0.519*	-0.317*	0.632*					

From	To																
Variables	**Work-only tour**	**Simple non-work tour**	**Work-nonwork mix tour**	**Complex non-work tour**	**Work in home**	**Work out of home**	**NW way to work**	**NW during work**	**NW way to home**	**NW before work**	**NW after work**	**Work travel**	**NW travel way to work**	**NW travel during work**	**NW travel way to home**	**NW travel before work**	**NW travel after work**
	0.308*	0.109*	-0.187*	-0.054*	-0.587*		0.104*	0.093*	0.283*	-0.469*	-0.288*	0.630*					
NW way to work			0.615* 0.552* 0.707*										0.601* 0.608* 0.554*				
NW during work			0.959* 0.758* 0.597*											0.720* 0.756* 0.705*			
NW way to home			0.603* 0.640* 0.583*												0.579* 0.584* 0.598*		
NW before work		0.576* 0.429** 0.922*		0.151** 0.188* ---												0.770* 0.757* 0.779*	
NW after work		0.673* --- 0.719*		--- --- 0.131**													0.762* 0.795* 0.783*
Work travel	0.174* 0.309* 0.271*		--- -0.251* ---														
NW travel way to work			0.488* 0.325* 0.213**														
NW travel during work			--- 0.364* 0.396*														
NW travel way to home			--- --- 0.251*								-0.157* -0.122* -0.120*						
NW travel before work		--- --- -0.775**		--- --- 0.368*													
NW travel after work		--- --- -0.513**		0.236* --- ---													

Only significant values are shown in the table for clarity of presentation. Each cell represents three coefficients for a pair of variables in 2006, 2009, and 2012 respectively.

* : 5% level of significance, **: 10% level of significance; Three dashes (---) indicates variable is a part of the model, but not significant; Blank cell indicates variable is not a part of the model

Table 5.4 Total effects of exogenous and endogenous variables (see footnotes for explanation)

From	To																
Variables	Work-only tour	Simple non-work tour	Work-nonwork mix tour	Complex non-work tour	Work in home	Work out of home	NW way to work	NW during work	NW way to home	NW before work	NW after work	Work travel	NW travel way to work	NW travel during work	NW travel way to home	NW travel before work	NW travel after work
	0.203*	---	-0.190*	---	---		---		-0.132*	---	---		---		-0.077*	---	---
HH size	0.183*	---	-0.106**	---	-0.103*		---		-0.065**	---	-0.110*		---		-0.038**	---	-0.088*
	0.244*	-0.047**	-0.181*	---	-0.110*		-0.050**		-0.118*	---	-0.119*		-0.028**		-0.071*	---	-0.093*
	---	---	---	---	---		---	---	-0.208*	---	---	---	---	---	-0.154*	---	---
HH ownership	---	---	---	---	---		---	---	---	---	---	---	---	---	---	---	---
	---	---	---	---	---		-0.126*	---	---	0.169**	---	---	---	---	---	---	---
	-0.554*	---	0.462*	---	0.198*	-0.169**	0.172*	---	0.200*	0.185*	---	---	0.164*	---	---	0.139*	---
No. of child aged 0-5	-0.367*	---	0.176**	---	0.235*	---	---	---	0.139**	---	---	---	0.074**	---	0.134*	---	---
	-0.447*	0.091**	0.283*	---	0.231*	-0.176**	0.176*	---	---	---	---	---	0.185*	---	0.147*	---	---
	-0.408*	---	0.424*	---	---	---	---	---	0.273*	---	---	---	0.082*	0.073**	0.150*	---	---
No. of child aged 6-10	-0.361*	0.158*	0.170**	---	0.198*	-0.171*	---	---	---	---	0.319*	---	0.113*	---	0.092**	---	0.197*
	-0.418*	---	0.238*	0.154*	0.185*	-0.274*	---	---	0.124**	---	0.182*	-0.161*	0.078*	---	---	---	0.142*
	-0.217*	0.125*	0.302*	---	---	---	---	---	0.120**	---	0.156*	---	---	0.062**	0.071**	---	0.132*
No. of child aged 11-18	-0.320*	0.137*	0.296*	---	---	---	---	---	0.199*	---	0.200*	---	---	---	0.123*	---	0.165*
	-0.239*	0.141*	0.231*	---	---	---	0.124*	---	---	---	0.212*	---	0.098*	---	0.089**	---	0.211*
	---	---	---	---	-0.321**	0.319**	---	---	---	-0.454*	---	---	---	---	-0.159**	-0.311*	---
Low income (<$20K)	---	---	---	---	---	---	---	---	-0.226**	---	-0.412*	---	---	---	---	---	-0.262**
	0.282**	---	-0.286**	---	---	---	---	---	---	---	---	---	---	---	---	---	---
	-0.581*	0.102**	---	0.210*	0.574*	-0.452*	-0.051*	0.149*	---	0.231*	0.308*	-0.233*	-0.031*	0.123*	---	0.127*	0.286*
High income (>=$60K)	-0.601*	0.215*	---	0.214*	0.615*	-0.443*	-0.055*	---	---	0.144**	0.452*	-0.204*	-0.034*	---	---	---	0.326*
	-0.394*	0.192*	---	0.200*	0.576*	-0.389*	-0.040*	0.168*	---	0.206*	0.239*	-0.243*	-0.022*	0.136*	---	0.143*	0.197*
	0.235**	-0.306*	---	---	-0.316*	0.708*	-0.177*	0.168*	---	-0.472*	-0.205**	0.293*	---	0.146*	---	-0.294*	-0.182*
Employment type	---	-0.132*	0.431*	-0.338*	-0.229*	0.624*	---	0.236*	---	-0.343*	-0.288*	0.368*	---	0.178*	---	-0.276*	-0.192*
	---	-0.315*	0.238**	-0.281*	---	0.643*	---	0.127*	---	-0.461*	-0.359*	0.347*	---	---	---	-0.314*	-0.249*
	0.551*	---	-0.360*	---	-0.385*					---	---					---	---
Ethnicity	0.465*	---	---	-0.193*	-0.448*					-0.318*	---					-0.241*	---
	0.630*	---	-0.293*	---	-0.457*					---	---					---	---
	-0.315**	---	---	0.181*	0.811*	-0.463*	---	---	---	0.259*	---	-0.279*	---	---	---	0.246*	---
Multiple jobs status	0.281**	---	---	0.157**	0.566*	-0.232**	0.121**	-0.120**	0.207*	0.221*	---	---	0.083**	---	---	0.140**	---
	---	---	---	---	0.712*	-0.492*	0.152*	---	---	0.238*	---	---	---	0.170*	---	0.238*	---
	0.189**	---	-0.242*	---	0.167*	---	---	0.134*	-0.307*	---	---	---	-0.122*	0.075**	-0.222*	---	---
Gender	0.295*	---	-0.237*	---	0.164*	---	-0.134*	---	-0.178*	---	---	---	-0.095*	---	-0.185*	---	---
	0.560*	---	-0.493*	---	---	---	-0.237*	---	-0.361*	---	---	---	-0.195*	---	-0.252*	---	---
Age	---	---	---	---	0.018*	-0.010*	---	---	---	---	-0.009*	-0.007*	---	---	---	---	---

From	To																
Variables	Work-only tour	Simple non-work tour	Work-nonwork mix tour	Complex non-work tour	Work in home	Work out of home	NW way to work	NW during work	NW way to home	NW before work	NW after work	Work travel	NW travel way to work	NW travel during work	NW travel way to home	NW travel before work	NW travel after work
	---	---	-0.010*	---	0.013*	-0.007**	---	---	-0.006*	---	-0.011*	-0.004**	---	---	-0.004*	---	-0.009*
	---	---	---	-0.005**	0.015*	-0.008*	---	---	---	---	-0.008*	-0.005*	---	---	---	---	-0.006*
Married & spouse employed	---	---	-0.244**	---	0.273*	---	---	---	---	---	---	---	---	---	---	---	---
	---	---	-0.405*	---	0.206**	-0.262*	---	---	-0.266*	---	---	-0.166*	---	---	-0.155*	---	---
	---	0.148*	---	---	0.228*	-0.261*	---	-0.132*	-0.169**	---	0.200**	-0.164*	---	-0.093*	-0.101**	---	---
Married & spouse unemployed	---	---	-0.452*	---	0.443*	---	-0.259*	---	---	---	---	---	-0.156*	---	---	---	---
	0.550*	---	-0.751*	---	0.251**	---	-0.179**	---	-0.479*	-0.278*	---	---	-0.109**	---	-0.280*	-0.205**	---
	---	---	-0.305**	---	0.262**	-0.377*	---	---	-0.230**	---	---	-0.238*	---	---	-0.138**	---	---
Suburb	---	---	---	---	-0.167**	0.225*	---	---	---	-0.163*	---	0.158*	0.087**	---	---	-0.145*	---
	---	---	---	---	---	---	---	---	---	-0.166**	---	---	---	---	---	-0.128*	---
	0.234*	---	---	---	---	---	-0.108**	---	-0.159*	---	---	---	-0.075*	---	---	---	---
Non-metropolitan area	0.265**	-0.250*	---	-0.240*	-0.243*	0.270*	---	-0.129**	---	-0.298*	-0.272*	---	---	---	---	-0.292*	-0.193**
	---	---	---	---	-0.377*	0.350*	---	---	---	-0.267*	---	---	---	---	---	-0.249*	---
	0.303*	-0.130**	---	-0.240*	-0.531*	0.473*	---	---	---	-0.204**	-0.291*	---	---	---	---	-0.176*	---
Winter	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
	---	-0.114*	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---
	-0.212**	---	0.209**	---	---	---	---	---	---	---	---	---	---	---	---	---	---
Work-only tour		-0.041*	1.059*	-0.119*													
		-0.051*	0.943*	-0.154*													
		-0.045*	0.914*	-0.095*													
Simple non-work tour																	
Work-nonwork mix tour	-1.062*	-0.039*		-0.113*													
	-1.091*	-0.054*		-0.163*													
	-1.073*	-0.050*		-0.103*													
Complex non-work tour		---															

Work in home		---		-0.056*						-0.101*	---					-0.078*	---
		---		-0.052*						-0.086*	-0.050*					-0.065*	-0.039*
		---		-0.050*						-0.069*	---					-0.054*	---
Work out of home	0.401*	-0.208*	0.568*	-0.276*	-0.605*		0.114*	0.135*	0.271*	-0.477*	-0.267*	0.630*	0.068*	0.097*	0.157*	-0.367*	-0.203*
	0.381*	-0.199*	0.544*	-0.294*	-0.622*		0.124*	0.107*	0.247*	-0.465*	-0.304*	0.632*	0.076*	0.081*	0.144*	-0.352*	-0.241*
	0.391*	-0.215*	0.520*	-0.263*	-0.587*		0.104*	0.093*	0.283*	-0.429*	-0.303*	0.630*	0.057*	0.065*	0.169*	-0.334*	-0.237*
NW way to work	-0.965*	-0.035*	0.909*	-0.102*									0.601*				

From	To																
Variables	Work-only tour	Simple non-work tour	Work-nonwork mix tour	Complex non-work tour	Work in home	Work out of home	NW way to work	NW during work	NW way to home	NW before work	NW after work	Work travel	NW travel way to work	NW travel during work	NW travel way to home	NW travel before work	NW travel after work
	-0.818* -0.885*	-0.040* -0.041*	0.750* 0.825*	-0.122* -0.085*									0.608* 0.554*				
NW during work	-1.152* -1.127* -0.940*	-0.042* -0.056* -0.043*	1.085* 1.033* 0.876*	-0.122* -0.169* -0.091*										0.720* 0.756* 0.705*			
NW way to home	-0.759* -0.775* -0.786*	-0.057* -0.063* -0.062*	0.715* 0.711* 0.732*	-0.101* -0.132* -0.092*							-0.091* -0.071* -0.072*				0.579* 0.584* 0.598*		-0.069* -0.057* -0.056*
NW before work		0.284* 0.342* 0.364*		0.230* 0.215* 0.241*												0.770* 0.757* 0.779*	
NW after work		0.316* 0.344* 0.362*		0.221* 0.226* 0.231*													0.762* 0.795* 0.783*
Work travel	--- 0.582* 0.449*	--- --- ---	--- --- ---	--- --- ---													
NW travel way to work	-0.518* -0.355* -0.229**	-0.019* -0.018* ---	0.488* 0.326* 0.213**	-0.055* -0.053* ---													
NW travel during work	--- -0.397* -0.425*	--- -0.020* -0.020*	--- 0.364* 0.396*	--- -0.059* -0.041*													
NW travel way to home	--- --- -0.269*	-0.057* -0.049* -0.056*	--- --- 0.250*	-0.057* -0.047* -0.054*							-0.157* -0.122* -0.120*						-0.120* -0.097* -0.094*
NW travel before work		--- --- -0.705*		--- --- 0.368*													
NW travel after work		--- --- -0.488**		0.236* --- ---													

Only significant values are shown in the table for clarity of presentation. Each cell represents three coefficients for a pair of variables in 2006, 2009, and 2012 respectively.
* : 5% level of significance, **: 10% level of significance; Three dashes (---) indicates variable is a part of the model, but not significant; Blank cell indicates variable is not a part of the model

CHAPTER 6: Summary and Conclusions

In this dissertation, I apply a tour-based approach to analyze the complex travel behavior of people from *three* relevant perspectives, namely sustainability, technology, and economics. First, I examine the complex travel behavior of workers who utilize a *sustainable* transport option, namely public transit. I identify the dominant patterns of work tours made by transit commuters by using 2017 National Household Travel Survey (NHTS) and analyze the attributes of these tours using a set of activity-travel analytics (Chapter 2). Major insights of this study are: about 80 percent of work tours consist of 7 unique dominant patterns whereas the remaining 20 percent of tours demonstrate a total of 106 diverse and more complicated patterns, transit work tours are pretty complex, transit complex tours are multimodal, and transit is utilized many ways within a work tour beyond the traditional home to work commute with a diverse set of choices at various stages of activity scheduling.

Next, I characterize the transit commuters based on their work tour choice and analyze the factors that determine the choice of work tours by using Structural Equation Modeling (SEM) (Chapter 3). Results suggest that millennial male commuters with high vehicle ownership who have spouses, other adult members but no children at their households tend to make simple work tours. On the other hand, non-Caucasian non-millennial female commuters having children at home are more likely to make complex work tours. And, Caucasian higher-income millennials who have a full-time job and who have higher flexibility in job arrival time are prone to make complex tours with work-based sub-tours. The results of this study can provide better insights on identifying the transit commuters who have complex travel needs and how they meet their needs while utilizing transit in their work tours. Also, this study can help the transit authorities to find out the potential target market who have complex travel needs and to formulate better land use and transit operating policies to foster higher usage of this sustainable transportation option.

Since location data is not provided in the NHTS data, it was not possible to analyze how the land use distribution near home, work or transit stations might influence activity choices as well as tour formation of transit commuters. Also, the travel activity scheduling of a transit commuter may be greatly influenced by the travel choices made by other individuals in the same household. The connections between tours, rather than within tours, as well as identifying the difference in complex travel behavior between bus and rail commuters, is the subject of on-going research. It would be interesting to compare the dominant patterns of work tours between transit and non-transit commuters.

Second, from the *technology* perspective, I analyze the complex travel behavior of people who use the recent technology-enabled ride-hailing services, such as Uber and Lyft (Chapter 4). The empirical results using data from the 2017 NHTS show that 76 percent of ride-hailing tours can be represented by five dominant tour types. The Latent Class Analysis (LCA) model suggests that the ride-hailing user population can be divided into four distinct classes where each class has a representative activity-travel pattern defining ride-hailing usage. Class 1 is composed of young and employed users who use ride-hailing for work. Single and older individuals comprise Class 2 and use ride-hailing for maintenance activities during midday. Ride-hailing Class 3 are younger, employed individuals who use it during evenings for discretionary purposes. Class 4 members use it for mode change purposes. The results of this study can help ride-hailing operators to find out and address the travel needs of various heterogeneous groups of potential market users who will show different responses to policy directives. The limitation of this study is that services provided by Transportation Network Companies (e.g., Uber/Lyft) cannot be separated from convention taxi services because all ride-hailing options such as taxi, limo, or Uber/Lyft are identified under a single code in the NHTS dataset. To make a comparison between the taxi services and the recent on-demand ride-hailing services (Uber/Lyft), this study reserves the analysis of the tour formation of taxi-only users (when the Uber/Lyft services were not introduced) and a comparison between the tour formation of taxi-only and taxi with Uber/Lyft users to future work.

Lastly, I explore the travel behavior of people, again in terms of tours, when they are exposed to an *economic* downturn, i.e. 2007-2009 recession (Chapter 5). In particular, I investigate whether workers changed their tour choice during a recession based on the American Time Use Survey (ATUS). I apply multi-group SEM to analyze changes in tour choice during the recession (2009) compared to pre- and post-recession years (2006 and 2012 respectively). Results show that activity-travel relationships and their role in tour choice differed significantly in the recession year particularly due to the changes in the nature of jobs. To analyze temporal changes in causal structure, four sub-trend groups are identified: (1) norms that did not change in pre-, during and post-recession years, (2) norms that changed during the recession but returned to the old norm, (3) norms that changed during the recession and were maintained as a new norm, and finally (4) 2006 norms that did not change during the 2009 recession but changed after the recession. The results of this study provide valuable insights on possible changes in worker's travel demand during an economic downturn, which would contribute to building better pattern choice sets in tour-based models.

The common thread throughout this dissertation is the development of a comprehensive framework for analyzing complex travel behavior under disruptive changes due to environment, technology, and economics forces.

As mentioned, to analyze the complex travel behavior (i.e. tour formation) of the travelers, I used two different national-level datasets: the American Time Use Survey (ATUS) and the National Household Travel Survey (NHTS). The former represents the activity-based or time-use oriented survey whereas the later one denotes the trip-based survey. The NHTS collects nationally representative data for *all* the members from the selected households on both long-distance and daily trips. For each respondent, trips made by all modes of travel (private vehicle, public transport, pedestrian, biking, etc.) and for all purposes (work, school, shopping, recreation, etc.) are recorded for a randomly assigned day (24 hours). On the other hand, ATUS collects nationally representative data for only *one* member (aged 15 and older) from the selected households on time use information for detailed activity categories (e.g., work, socializing, traveling) for a 24-hour period.

Both of the datasets have some advantages and *limitations*. For example, the activity-based survey provides a greater number of trips than the trip-based survey. In other words, the trip-based survey may result in underreporting of trips. Because the activity-based survey is more intuitive and guides the respondent to better recall the short and infrequent trips (Pendyala, 2003). But in the trip-based survey, the respondents are required to record the travel "out of context" of the activities performed (Harvey, 2003). Again, while ATUS provides detailed information on both in-home and out-of-home activities, the substitution effects between these two activity locations can be captured by using this data. In contrast, such substitution effects cannot be captured by NHTS data as it provides information on in-home activities at a very limited scope. Moreover, ATUS data is collected every year and thus, short term changes in travel behavior can be better captured by this data compared to NHTS that collects data every ten years. One of the biggest limitations of ATUS is that it provides data on only one member from each household. Thus, travel interactions among household members cannot be analyzed with this dataset. On the contrary, NHTS supports such analysis as it collects data on all the members from each household. Furthermore, ATUS does not provide household vehicle ownership data, which is considered as one of the most important travel behavior indicators. Finally, since both the ATUS and the NHTS do not provide location information, the influence of land use distribution and spatial characteristics surrounding home, workplace, and other activity locations on complex travel behavior cannot be captured in this dissertation.

Finally, the tour-based travel behavior analysis of this study can lead to a better understanding of the complex travel behavior of the three groups of travelers: who are exposed to changes in the economy, who use sustainable transport option under environmental concerns of extensive car usage, and who use the recent technology-enabled on-demand ride-hailing services, which can improve the knowledge of linkages between activity and mobility. Identification of tour-based information is very crucial and at the same time challenging for the understanding and the development of the tour- or activity-based demand models (Wang, 2015) as TRB (2007) indicated that the analytical complexity and prohibitive data demands of the tour- or activity-based models enable only a small number of US transportation agencies to apply them. Note that while I analyze the travel behavior of these groups of travelers by applying the tour-based approach, it does not directly represent an activity-based (or tour-based) *forecasting* model. However, the insights of this study can be utilized to develop better tour-based models.

References:

Harvey, A. S. (2003). Time-Space Diaries: Merging Tradition, In Transport Survey Quality and Innovation, (Pergamon 2003) Elsevier Science Ltd, Oxford, UK.

Pendyala, R. (2003) Quality and Innovation in Time Use and Activity Surveys. In P.R. Stopher and P. Jones (eds) Transport Survey Quality and Innovation. Elsevier Science Ltd, Oxford, UK, pp. 181-190.

TRB. (2007). *Metropolitan Travel Forecasting: Current Practice and Future Direction--Special Report 288* (No. 288). Transportation Research Board.

Wang, R. (2015). The stops made by commuters: evidence from the 2009 US National Household Travel Survey. *Journal of Transport Geography*, *47*, 109-118.