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Development and Application of Advanced Econometric Models for Exploring Activity-Travel Behavior

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Historically, transportation planning relied on aggregate, trip-based procedures, namely, four-step modeling, for modeling travel demand. The aggregate approaches served well when the capacity oriented policies were of primary interest. However, in the last few decades, with the growing demand for travel and the increasing externalities (e.g. congestion, energy implications, pollution), there is a widespread acknowledgement that capacity oriented approach to transportation planning is unsustainable. Instead, the focus of the transportation planners has shifted towards sustainable demand management strategies wherein the idea is to alter existing behaviors and promote new behaviors such that demand for travel can be met while also reducing the externalities of travel choices. This swing in policy necessitated a shift to disaggregate, activity-based approaches for analyzing travel behavior. One of the fundamental differences between the trip- and activity-based travel behavior analyses lies in the treatment of time. In the trip-based approach, time is merely treated as a cost of accessing activity opportunities separated in space. On the other hand, activity-based approach, dwells on the understanding of time expenditure behavior of individual including how, where, and with whom individuals spend their time. Subsequently, trips are organically derived from activity engagement behavior.

As can be seen, a robust understanding of time engagement decision of individuals forms the backbone of current day transportation planning process. Individuals' allocation of time has intrigued researchers not only from the field of transportation, but also from various other disciplines such as economics, philosophy, psychology, and sociology.

The overarching objective of this dissertation is to advance the time engagement research with the goal of enriching the state-of-the-art activity-based travel analysis techniques. To this end, the contributions of the research are twofold. First, on the substantive side, the dissertation utilizes a

multidisciplinary approach by incorporating theories from various disciplines such as economics, and psychology to further our understanding of the time engagement decisions of individuals. Second, on the methodological side, the dissertation develops, and applies advanced econometric methodologies to characterize the time engagement behavior of the individuals. The substantive and methodological findings allowed for an enriched formulation of time engagement in activity-based travel behavior models.

Development and Application of Advanced Econometric Models for

Exploring Activity-Travel Behavior

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Development and Application of Advanced Econometric Models for

Exploring Activity-Travel Behavior

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DEDICATION

To my parents, Nilufar Banu and Ali Ahmed Enamul Haque

&

To my mentors

Who believed in me and nurtured me to the person I am today

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CHAPTER 1

INTRODUCTION

1.1 Background

Transportation infrastructure and its system performance intricately determines the economy of a country as well as the quality of life of its citizens. The goal of transportation planning is to analyze the existing demand of the users as well as to predict the future demands so that a transportation system can be developed that not only addresses the current issues but also accommodates future demand. Traditional approach to transportation planning consists of predicting the number of trips produced by the system users and to provide the necessary infrastructure to accommodate the ever increasing demand of the users. However, with the increased concerns about the scarce resources, it was realized that this capacity oriented approach is unstainable and that providing infinite supply to meet the ever increasing need for transportation infrastructure is not a viable option. Consequently more emphasis has been placed on demand management strategies that attempt to alter existing behaviors and promote new behaviors such that demands of the system's users can be met in an efficient manner while also ensuring sustainability. The need to manage transportation demand resulted in demand responsive transportation policies such as promotion of high occupancy vehicle lanes (HOV lanes), congestion pricing, high occupancy toll lanes (HOT lanes), variable parking pricing, promotion of ridesharing and teleworking, incentivize transit and flexible work hours among others (Kalra et al. 2012). This change in policy focus has also resulted in a paradigm shift in the approach to transportation planning. While aggregate approaches have dominated travel demand modeling in the past, there has been a growing use of disaggregate approaches in the recent decades. In the aggregate approaches trips are the focus. On the other hand, in the disaggregate approaches also referred to as activity-based approaches, the activity engagement choices are the focus with trips being recognized as being derived by engaging in activities separated in space i.e. it is the need to access the opportunities that are distributed in space and time that results in trips. The activity-based approaches also allow for explicit recognition of different types of constraints and interactions that individuals experience when making activity-travel choices, thus, resulting in more realistic

representations of travel behaviors. Also, the need to promote effective demand management strategies has nudged transportation planners to delve deeper into disaggregate approaches that are better able to capture the individual behaviors and decision-making processes.

In the last four decades, transportation planning has been steadily shifting towards the more disaggregate analysis of travel behavior from its trip based counterpart. Below we summarize the state of time use research followed by methodological challenges, research objective and thesis organization.

1.2 Time Use Research

The traditional aggregate approach to travel demand does not acknowledge the derived nature of travel, and thus disregards the underlying association between the activity engagement propensities and the travel choices. On the other hand, in the activity-based approach individual activity engagement tendency is of prime concern – travel choices are organically derived from the need to access activity opportunities that are not collocated in space. One of the fundamental differences between the trip and activity based travel analysis lies in the treatment of time. In the trip based travel analysis time is merely regarded as a cost or disutility associated with pursuing travel from one location to another. In the trip-based analysis of transportation planning, value of time saving played an important role for project appraisal. In contrast, in the activity-based approach, time engagement choices are the focus i.e. people make decisions about how to spend time (i.e. in pursuit of what), where to spend time (i.e. location choice), and with whom to spend time (i.e. accompaniment choice). It is the time engagement choices that result in travel when they engage in activities that are separated in space. Consequently, transportation researchers and planners have emphasized the importance of understanding the time engagement behaviors of individuals including identifying the factors that influence time engagement decisions, understanding the role of time as a constraint, and, representing time as a continuous entity among others.

1.2.1 Inter-disciplinary approach to time use research

Benjamin Franklin identifies time to be the 'stuff' of life as quoted by Barlett (1968): "*Dost thou love life? Then do not squander Time; for that's the stuff life is made of*". Understanding the time engagement behaviors has intrigued researchers for centuries across different disciplines including economics,

philosophy, sociology, and psychology. The time engagement research evolved rather independently in these various disciplines. Lack of interaction among disciplines meant diversity in viewpoints and variety of approaches to study time engagement behaviors. Additionally, the overall motivations and objectives for the study of time engagement behaviors have also varied significantly across different disciplines. For example, economists have pondered to understand the work, leisure, and subsistence time allocation behaviors with the goal of predicting market- and domestic-labor supply. The work conducted by the researchers such as Becker (1965), DeSerpa (1971), Evans (1972) resulted in the quantification of time value of work as well as time value of leisure. Psychologists such as Maslow (1943), Tonn (1984) emphasized the socio-psychological motivation for individuals' time allocation behavior. The transportation researchers such as Gershuny (2003), Kitamura (1984), Bhat and Koppleman (1999), and Bhat et al. (2013) have been concerned about the understanding the time allocation behavior of individuals with the aim to forecast the activity pursuits of the individuals in time and space. The ultimate goal of the time use research conducted in the transportation field is to predict the travel that results from activity engagement choices of individuals. Traditionally, transportation researchers have focused on the socio-economic differences of the individuals such as the differences in their age, gender, income, employment status, education status, family structure to infer and consequently predict the differences in the time engagement decision. However, the acknowledgement of the socio-psychological factors elucidated by psychologists and sociologists like Maslow (1943) and Allardt (1993) in determining the differences in individuals' time allocation behavior have been very limited in the transportation literature. The dissertation proposes methodological advancements to incorporate the theories and findings from the fields of social psychology with the goal of enriching the representation of time engagement choices in the state of the art models of travel behavior.

1.2.2 Methodological challenges to time use research

As noted above, transportation researchers are not only interested in predicting the time engagement behavior but they are also interested in enumerating the factors important for time engagement choices while quantifying the influence of those factors. To this end, statistical modeling techniques are

employed. Additionally, models are developed with an aim to make future predictions under different policy scenarios to assess impacts. The factors affecting the time engagement choices has often been limited to exogenous entities such as socio-economic, demographic, built and natural environment characteristics. The dominant methodological approach to model transportation choices dwells on random utility theory (RUM) (Manski 1977). According to the theory, individuals are assumed to be rational decision makers with perfect knowledge and ability to evaluate their choice environment. According to the RUM framework, the individuals make choices through an exhaustive search of their choice environment, so that the utility (pleasure) gained from the choice outcome is maximized. On the other hand, theories from the field of psychology allude to the importance of socio-psychological factors to analyze behaviors. Understanding the association between different socio-psychological factors such as individual's needs, perceptions, emotions, and attitudes on time allocation behaviors of individual is still in its infancy. This is mainly due to the challenges associated with incorporating such factors in the state of the art choice models based on random utility theory. It can be noted that, in the RUM framework, decision makers are treated solely as cognitive entities while any influence of affective and emotional states of the decision makers as well as their limited information processing capabilities are ignored. Additionally, the treatment of the socio-psychological variables have been challenging owing to their accurate measurement and consequent incorporation into the choice models. First, reporting of the psychological variables such as attitude, emotion, perception and need is often saddled with the measurement errors due to individual biases. Second, the computational method for incorporating such variables in the models of choice become intractable very quickly due to the methods' dependency on numerical simulation. Because of this, understanding the influence of such factors in predicting the time allocation behavior of individual have been scarce.

1.2.3 Representation of time engagement choices in transportation modeling

Activity-based modeling approach started with the aim to represent individuals' activity pursuit on a continuous time scale which can predict the transportation network at fine resolution of time. However, in most activity-based modeling systems to date time is represented as a discrete entity. It has been proved to

be challenging to represent time as a continuous entity and ensure the interrelationship between different activity pursuits over the span of continuous time. This has forced the researchers to make simplifying assumptions about the actual human behavior – these assumptions include discretizing time into mutually exclusive bins, neglecting interdependencies across activities conducted over a period of time, and neglecting the role of time as a constraint among others. Most often, the state of the art activity based models do not explicitly account for the temporal constraints that encompasses the activity-travel engagement choices of individuals. Rather, the decision makers are treated as myopic entities making decisions about the activity engagement choices as they arise in a sequential manner. This often results in unreasonable predictions of the time engagement behavior which then require heuristics to resolve. The dissertation strives to enrich the behavioral representation of the time engagement choices in the state of the art activity-based modeling framework.

1.3 Research Objectives

The overarching goal of the dissertation research is to contribute to the time use research with the aim of advancing the activity-based analysis of transportation planning. To this end, the contribution of the dissertation is twofold. First, on the substantive side, the dissertation undertakes a multidisciplinary approach that incorporate theories from various disciplines including philosophy, sociology, and psychology to better narrate the time allocation behavior. Second, the research proposes novel model formulations and develops computationally efficient estimation techniques to enable feasible testing of various narrations of time allocation behavior. The primary motivation of the dissertation is to enrich the behavioral representation of the time allocation choices of the individual while ensuring computational tractability, so that the improved models of time engagement behavior can be incorporated in the existing frameworks of activity-based model systems. The specific objectives of the dissertation research are provided below:

(1) The <u>first</u> objective of the dissertation research is to understand the time allocation behavior from the perspective of individual needs satisfaction as it relates to the domain of life, health, finance, job, and marriage. Drawing from socio-psychology and need-based theories, this study sheds light on the

association between individual time allocation behavior and their perceived well-being at any cross-section of time, where well-being is measured via reported satisfaction of needs.

(2) The second objective of the dissertation is to develop an integrated framework to incorporate psychological factors in random utility models where the choice component assumes the form of a multiple discrete continuous choice scenario. The dissertation develops a weighted composite marginal likelihood based estimation technique that enables consistent and efficient recovery of the true parameter estimates underlying the data generation process. The proposed estimation technique is then used to study the association between day-level moods and discretionary time allocation behavior of individual.

(3) The third objective of the dissertation is to develop a bi-level framework to represent the time allocation behavior into tours and stops. The proposed framework overcomes a number of limitations of the existing tour-based frameworks – in the proposed framework time is treated as a continuous entity, temporal constraints to participate in tours and stops are explicitly acknowledged; also the interrelationship between tours as well as between stops within tours are explicitly accounted for.

(4) The fourth objective of the dissertation research is to explore the trend in the time allocation behavior of individual. For this study the dissertation investigates the role of age-, period- and cohort-effects in deciphering the trend in time allocation behavior of the twentieth century American generations.

1.4 Thesis Organization

The rest of the dissertation is organized in additional six chapters as follows.

The second chapter of the dissertation provides a review of the existing literature with the specific aim of identifying the gaps in the literature that this dissertation aims to address. The literature review chapter starts with an illustration of the time use research from multiple disciplines including economics, sociology, psychology, and transportation. In these subsections, special attention is paid to the evolution of the empirical explorations of time allocation behavior. The subsequent section highlights the emergence of random utility theory upon which the transportation researchers have relied heavily to explain the activity/travel choices of the people including their time engagement choices. This section

concludes with the criticisms of the random utility theory from various disciplines including behavioral economics, sociology, and psychology. The next section presents the methodological developments and challenges associated with extending the random utility theory. Finally the chapter concludes with a depiction of the treatment of time allocation behavior in the existing activity-based systems of travel demand models.

The third chapter addresses the first objective of the dissertation research which is to investigate the time allocation behavior of the elderly Americans from the perspective of their physical and mental well-beings in addition to the commonly used socio-economic variables such as age, gender, income among others. The mental well-being of the individual is measured via their reported satisfaction of needs with different domains in life including health, job, finance, marriage and cognition. This study is motivated by the research conducted by the psychologists and need based theorists who postulates that, people allocate their time differently depending on their satisfaction of needs at a certain cross-section in time. For this study data is drawn from disabilities and use of time survey (DUST) conducted in 2009 which provides information about two activity diaries of elderly individuals. The study employs a panel multiple discrete continuous extreme value (MDCEV) framework to narrate the time allocation decision of the elderly people as a function of their varied level of needs satisfaction. The study highlights considerable heterogeneity in the time allocation behavior of the elderly American as a function of different socio-economic variables as well as different levels of needs satisfaction. The study also highlights the importance of incorporating social, psychological, constitutional and situational constraints in depicting the time allocation behavior of the elderly people of the society.

The fourth chapter proposes an integrated choice and latent variable modeling framework with multiple discrete continuous choice kernel. The purpose of this chapter was to propose a general framework that would allow the study of association between different psychological and attitudinal factors and individual choices where the choice dimension takes the form of multiple discrete continuous choice kernel. This chapter proposes a numerical simulation free weighted composite marginal likelihood (CML) based estimation technique for recovering the true parameters of the underlying data generation

process. The performance of the proposed estimation routine was investigated using synthetically generated dataset. Simulation results of parameter estimates point to the validity and usability of the estimation technique in terms of recovering the consistent and efficient estimates of the true parameters. The proposed routine was applied to explore the association between day level moods and discretionary activity engagement decisions of individual using data from American Time Use Survey (ATUS) conducted in 2013. The empirical study identifies interesting association between day level moods and discretionary activity participation decisions. Studying such associations allow to unravel unobserved heterogeneity in the activity participation and time allocation behavior due to moods. Moreover, the endogenous treatment of moods also allow to capture non-linear influence of different exogenous variables on the choice i.e. their direct influence on the choice outcome and their indirect influence through their correlations with the moods variables. The empirical study was followed by a validation study with hold out sample to demonstrate the forecasting ability of the ICLV framework with MDC kernel. The estimation routine based on weighted CML proposed in this chapter for estimating hybrid multiple discrete continuous (HMDC) choice models can be applied to a various number of choice scenarios from the field of energy consumption, food consumption, and, vehicle usage among others.

The fifth chapter contributes towards the third objective of the dissertation research which is to propose a temporally constrained hierarchical framework for representing bi-level decision making process in the presence of multiple discrete continuous choice scenario. The primary objective of this chapter is to address three major limitations associated with the representation of time in the existing activity-based modeling frameworks where tour is used as a unit of analysis. In the proposed framework, time is represented on a continuous scale as opposed to on a discrete scale, the temporal constraints operating at the two levels of the multiple discrete continuous choices are explicitly accounted for, and the framework allows the interrelationship between the choice alternatives at both levels. The proposed framework imitates a bi-level structure where the participation (whether to pursue?) and time allocation (how much time?) decisions to daily tours are modeled at the upper level. Within each participated tour, participation and time allocation decisions for different stops are modeled at the lower level. The model

formulation for the bi-level structure builds on the utility theoretic multiple discrete continuous probit (MDCP) modeling approach. To demonstrate the feasibility of the proposed framework, the dissertation uses data from National Household Travel Survey (NHTS) from 2008 to model tour and stop time allocation decision of individual. The proposed framework contributes towards the day pattern generation dimension of the activity-based frameworks. This framework presents a behaviorally consistent representation of tour and stop generation process and can readily be incorporated into the existing activity-based modeling frameworks. The proposed framework would replace the need for estimating a large number of independent models of tour and stop generation and time allocation behavior.

The sixth chapter contributes towards the fourth and final objective of the dissertation research. This chapter portrays the evolution in the time allocation behavior of the American generations including the GI Generation (birth year: 1901-1924), the Silent generation (birth year: 1925 – 1943), the Baby Boomers (birth year: 1944 – 1964), the Generation X (birth year: 1965 – 1981) and the Millennials (birth year: 1982 -2000). . In particular, the study aims at isolating the structural changes in the society from the inherent behavioral changes of different cohorts by explicitly accounting for the age-, period- and cohort-effects in addition to different socio-economic and demographic variables. The data for the current study has been drawn from fours waves (1965, 1985, 2005 and 2012) of the American Heritage and Time Use Study (AHTUS). The analysis reveals that, the Millennials have delayed the major changes in their life courses compared to the recent previous generations in terms of delayed marriage, delayed work force entry and prolonged student status. Even after controlling for the student and employed population, the millennial generation shows lower participation into work and higher participation into discretionary activities compared to the previous generations of the same age groups. On the other hand, Baby Boomers clearly exhibit a spike in travel compared to the previous generations at different stages of life.

The seventh chapter concludes the dissertation research. The purpose of this chapter is to document the contribution of the research, discuss policy implications, highlight the limitations of the presented studies, and propose directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The last four decades have seen a proliferation in the time use research in the field of travel behavior owing to the rise in the tour- and activity based modeling approaches of transportation planning. However, the inception of time allocation research can be dated back to as early as nineteenth century when philosophers and researchers started to investigate the motivation for human activity engagement. This chapter provides a brief overview of the historical perspective of time use research starting with the motivational theories of human activity engagement and time allocation behavior, followed by the review of the microeconomic theories of time allocation, and the overview of the time allocation research in transportation planning arena. Next, the chapter takes a brief digression to present the state of the art random utility based consumer choice theory which serves as the working horse for time engagement research in the transportation planning arena. This is followed by an overview of methodological advances as well as challenges associated with extending random utility theory for developing unifying models of time engagement behavior of individual. This chapter concludes with a narration of the representation of time in the state-of-the-art tour- and activity- based models of travel behavior.

2.2 Time Use Research: Motivational Theories

According to Aristotle, we become what we repeatedly do. Philosophers have been interested in understanding the time allocation behavior of individual as a way to comprehend human nature and explaining what separates human from the rest of the species. Early philosophers such as Aristotle and Plato differentiated human species on the basis of the possession of "free will" – according to them the mechanism of free will led human being manage their activities differently from the rest of the species. Rene Descartes entertained this dualistic theory of human and animal behavior. However, such dualistic theory was vehemently opposed by Darwin (1856) according to whom it is the need for survival that govern the activity behavior of all species including human. His theory was supported by the twentieth century psychologist Freud (1915) who also identifies the instinct for survival as the major determinant of

the activity time allocation of the human species. Later, such animalistic theories of time allocation was replaced with more humanistic theories of motivation. Rogers (1959) identifies personal growth and creation of positive self-image as the major motivations for the activity participation of human being. Maslow (1943) in his hierarchical needs theory tries to unify the diverging view of these two schools. According to him, human needs follow a certain hierarchy where the needs motivated by the pleasure seeking, animal instincts need to be satisfied first in order for the self-actualization needs to surface. According to him, human being exhibit different tendencies in their activity engagement behavior depending on their level of satisfaction with different needs pertaining to physiological, safety, love, esteem and self-actualization. Later Sociologist Allardt (1993) emphasized more on the non-materialistic aspect of human need. According to him, human needs can be categorized into three categories namely "to have" needs that refer to the materialistic needs in life related to education, work, and money, "to love" needs that refer to the social needs such as being with other human beings, and "to be" needs that refers to the self-actualization needs.

Fried et al. (1977) theorizes that the dynamics in the activity participation and time allocation behavior and long term choices such as residential location and work status are manifestations of the reconciliation of the current and anticipated needs given the surrounding opportunities. Tonn (1984) identifies physiological, sexual-sensual and group-belonging as the motivating needs for human time allocation. In addition to identifying motivations for human time allocation, he also postulated different decision strategies that people employ while allocating times between various activities. He identifies these strategies as perfection, balance, and hierarchy. Tonn (1984) emphasizes the role of various constraints in synthesizing human time allocation behavior including pure constraints, social condition, personal situation, personality and uncertainty.

2.3 Time Use Research: Microeconomic Theories

In the field of microeconomics, time use research evolved to explain the market and domestic labor supply behavior. Some microeconomic models of time allocation treat individuals as the decision making units while others use households as the decision makers. In terms of activity categorization, some

synthesis use only two categories where anything other than work is grouped with leisure. In some other categorizations, time allocation to tertiary, travel and sleep activities are treated separately.

Becker (1965) can be credited for formulating the first microeconomic theory of time allocation between work and leisure activity. He did not consider the contribution of time in the (dis)utility derived by the individual while allocating time between work and leisure. In other words, the role of time was only incorporated in the constraints while maximizing the utility derived from goods consumption. Johnson (1966) was the first to incorporate time in the utility. According to him, the utility derived by the households is a function of the goods consumption as well as time allocation. DeSerpa (1971) introduced technical constraints in the time allocation theory that relate the goods consumption with time allocation. Technical constraints acknowledges the minimum goods consumption (time allocation) requirement of time allocation (goods consumption). Finally, Evans (1972) proposed an utility equation that was solely based on the allocated time. Amount of goods consumption was determined from the technical relationship between goods consumption and time allocation.

In the last decade Jara-Diaz (2007) operationalizes a microeconomic model of time allocation using exogenous values for minimum time for goods consumption and minimum goods for time allocation. He uses a Cobb-Douglas form of the utility function to derive the time value of work and leisure. The Cobb-Douglas form of the utility makes the sign of the marginal utility of time to be fixed among the population. Also the formulation does not allow zero allocation of time to any of the activity types considered for analysis.

2.4 Time Use Research: Transportation Planning

In the transportation research arena, historically emphasis has been paid towards quantifying the value of time savings to aid in the process of evaluation and selection of alternative transportation projects. Train and McFadden (1978) developed a random utility based mode choice model to quantify the value of travel time saving. They investigated the influence of wage rate on the coefficient of travel time and travel cost across different formulations of goods and leisure time indifference curves. Kitamura (1984) in his seminal work developed a random utility based framework for quantifying discrete activity participation

and continuous time allocation for non-work discretionary activities. This research conceptualizes time allocation as a resource allocation problem. Following this good number of research has been conducted to study the after work activity participation and duration problems. Hamed and Mannaring (1993) develops a series of discrete models of activity participation, and continuous (regression and hazard based) models of travel time and activity duration for understanding after work activity participation and time engagement decision of workers. These models are statistically stitched together to account for the dependency across different decision variables of post work activity participation and time allocation. Kitamura et al. (1996) develops a random utility based doubly censored Tobit model to analyze weekly discretionary time allocation using panel dataset. Similarly, Bhat and Mishra (1999) presents another study of weekly discretionary time allocation using Panel data from Netherlands. Timmermans et al. (2001) presents a conceptual model of anticipated time pressure on activity agenda of individual. The above description reveals that, the early formulation of activity participation and time allocation behavior uses discrete models of activity participation and continuous models of activity duration for a single activity type. These formulations have been followed by simultaneous equation systems for simultaneously allocating time across multiple activities. It can be noted that, the simultaneous equation system does not allow corner solution meaning a non-zero amount of time needs to be allocated to all the activity types considered in the problem.

Kim et al. (2002) proposes a translated additive utility formulation that can accommodate corner solution as well as multiple-discreteness (i.e. consumption of one or more goods but not all) in the selection of goods. Bhat (2005, 2008) in his seminal work, replaces Kim et al.'s (2002) utility formulation with an elegant form of utility to model multiple discreteness in goods consumption. The formulation popularly known as multiple discrete continuous (MDC) choice models has been widely applied to model activity participation and time allocation decision of individual. For example, Sener and Bhat (2007) studies the social context of children's time allocation behavior. Spissu et al. (2009) studies the weekly discretionary time allocation behavior using a panel MDCEV formulation. Another appealing aspect of the MDCEV formulation is that, it collapses to a multinomial logit (MNL) formulation in case of a single

discrete scenario. It can be noted that, the basic MDCEV formulation however, does not incorporate any monetary constraint in the model. As a result, this formulation does not yield time value of money. The basic MDCEV formulation has been extended in different ways to allow flexible error structures (Bhat and Pinjari 2010) and to accommodate multiple constraints (Castro et al. 2012) among others.

The complex dependency between the household members while allocating daily/weekly times between activity types have intrigued travel behavior researchers to investigate joint time allocation of household members (Golob 2000, Simma and Axhausen 2001). Fujii et al. (1999) develops a structural Tobit model to analyze joint time allocation decision of individual. MDCEV formulation has also been used to analyze joint and independent discretionary activity participation of individual (Srinivasan and Bhat 2006). Zhang and Fujiwara (2006) captures interaction between elderly couples' time allocation decision using social welfare based utility function. In the recent times, the role of information and communication technology (ICT) has been studied on the time allocation behavior of individual and household (Graaff and Rietveld 2007). Though most of the time allocation models conceptualizes time allocation as a static phenomenon limited research has been conducted to understand the dynamics in the time allocation behavior of the individual. For example Meloni et al. (2007) studies the dynamics of discretionary time allocation behavior. Arentze et al. 2010 demonstrate the dynamics in the day to day variation in time allocation behavior using a synthetic dataset that captures budget constraints over a longer time horizon.

A review of the time allocation literature from the transportation field reveals that the time allocation research has been evolved to empirically investigate and predict the time allocated into different activities. Different individual level variables such as the age, gender and employment status of the individual as well as household variables such as household size, presence of kid, household income have been identified to be important determinants of time allocation behavior. Increasingly more attention has been paid to account for the temporal and monetary constraints as well as the interaction between multiple members of the household to better represent the time allocation mechanism. However, it can be noted that, while developing the empirical models of time allocation behavior, transportation researchers

have fairly distanced themselves from the motivational theories of individual time engagement. As a result the empirical models are not sensitive to the changes in the human cognitive and affective states and are not capable of capturing the variation of time allocation behavior as a function of human needs, perceptions and emotions among other.

2.5 Consumer Choice Theory

Travel behavior research has heavily relied on the consumer theory for explaining activity travel behavior of individual, time allocation behavior is not an exception either. The random utility theory of consumer behavior considers individuals as rational decision makers. According to the random utility theory, induvial associates a certain utility with different choice alternatives or alternative bundles and selects the bundle that provides the maximum amount of utility subjected to certain constraints. This section briefly narrates the evolution of consumer choice theory and critically reviews its potential and drawbacks for operationalizing individual activity and travel behavior.

2.5.1 Evolution of random utility theory

According to Mandler (1999), the history of modern economics can be divided into three eras namely: (i) classical era, (ii) early neoclassical era and (iii) post war neoclassical era. During the classical and early neoclassical era, economists were inspired by the field of psychology to understand human behaviors and human decision making. During this period, economists were fairly comfortable dealing with the unobserved entities such as the "cognitive" (refers to the mental process of acquiring and processing information) and "affective" (refers to the influence by or result of emotions) states of individuals to understand their consumer behavior. Early neoclassical economics was inspired by the pleasure/pain view of human nature (Bentham 1996). This approach to the study of individual behaviors was primarily built on hedonic psychology. According to Bentham (1996) and other pioneering early neoclassical economists (such as Jevons [1871] 1965), the basic motivation of human action is to maximize pleasure and minimize pain. According to researchers in this era, utility of any human action is identical to and is derived from the happiness accrued via participation in that action. However, the post war neoclassical economists consciously distanced themselves from hedonic and for that matter any kind of psychological

underpinnings of human behavior and referred to utility as an indicator of human preference. It is important to mention that the postwar neoclassical economists did not argue that utility of human action can be mediated via pleasure/pain or other mental states. However, they were skeptical about the human motivation and preference formation and argued that understanding the cognitive and affective underpinnings of human behavior is outside the scope of economics. They held the view that the ultimate test of an economic theory lies in its predictive ability and that a sound theoretical foundation is not essential for an economic theory to be applicable (Colin and George 2004, Anger and Loewenstein 2007). According to Mandler (1999), by relinquishing the ties with psychology, the postwar economists lost the theoretical foundation and the ability to describe preference formation and most importantly the ability to explain aspects of human behavior (e.g. irrationality).

Following the neoclassical economists, travel behavior researchers adopted the concept of commensurability of alternatives i.e. to express the attractiveness of different alternative as a scalar quantity (utility) which in turn can be expressed as a function of a number of measureable attributes. Further, utility based decision rules which assume individuals as rational decision makers were imposed in an effort to explain choice behaviors. Rationality in decision making is a strong notion which assumes that individuals exhibit consistent (if an individual is faced with similar choice situations in separate occasions they would end up repeating their choice decisions) and transitive (if an individual prefers choice alternative x to y and y to z then he must also prefer x to z) preferences when faced with choice alternatives. This approach to explaining individual choices was also referred to as deterministic choice theory because it assumes that the utility can be fully specified and that choice process employed by individuals doesn't vary. However, experiments since have shown that individual decision making is not consistent and often violates the notion of transitivity (Ben-Akiva and Lerman 1985). In order to account for the deviations from rational decision making, Manski (1977) proposed the notion of random utility theory (RUM) which hypothesizes that inconsistencies in human choice behavior (i.e. the deviation from "perfect rationality") arise mainly due to the analysts viewpoint who only has access to limited information about the factors underlying the choice process. Instead of suggesting that everything about

individual behaviors is known to the analyst, RUM assumes that the analyst only observes some of the many factors that influence individual decision making and other factors are assumed unknown. Further, unlike the deterministic choice theory RUM proposes that the analyst can only explain individual choice process with a degree of certainty (or probability) that a particular choice is made from a set of alternatives (McFadden 1976). This RUM approach retains the elegance of the utility maximization framework employed by the deterministic choice theory but overcomes some of its limitations through the specification of utility as being comprised of observed and unobserved components. In the travel behavior research arena, RUM framework has been widely used to explain various aspects of individual activity and travel behavior dimensions to date. While RUM framework has been extensively applied to model individual behaviors, it is not without its fair share of limitations. It can be seen that, the RUM still makes a simplification (commensurability of alternatives) of the decision making process that a person employs prior to arriving at their choice when faced with alternatives. Additionally, the framework does not make any reference to the cognitive or affective factors of individuals which also in part define the utility function. Rather they use the utility as a black box to predict the final choice outcome.

2.5.2 Emergence of behavioral economics

During the heyday of neoclassical economics, a number of economists (sometimes independent of one another) continued to argue that the economic theories make compromising assumptions in describing human behavior and restoring ties with psychology was essential. The deliberate attempt of the neoclassical economists at large to abandon psychological foundations of human behavior led to the development of a new sub discipline of economics, known as behavioral economics. Behavioral economists argued that human psychology is the primary driver of one’s economic behavior and understanding psychological underpinnings of human behavior was essential for not only better understanding the decision process but also for helping build better predictive models of decision outcomes.

Herbert Simon (Simon 1987 (a), 1987 (b)) was one of the early pioneers in the field of behavioral economics. He first coined the term “bounded rationality” that relaxed the notion of rationality assumed

by earlier economic theorists to explain individual behaviors. Bounded rationality recognizes human beings limitations as problem solvers and the ability to process complex information about alternatives. Further, it also recognizes an individual's access to only partial information about the alternatives when making decisions. These assumptions of bounded rationality are in contrast to the concept of an all-knowing individual who has access to full information about all the alternatives and has the problem solving abilities to consume complex information about the alternatives to make the perfectly rational choice. According to Simon, behavioral economics does not base itself on any particular theoretical framework. Rather it empirically tests the assumptions made by neoclassical economic theories and attempts to modify the theories based on empirical test results. Another pioneer in the field of behavioral economics was George Katona (Katona 1975). Katona's primary criticism of neoclassical economic theories was the lack of psychological variables such as human motives, and attitudes in explaining human behavior. He also argued that the focus of neoclassical economists was not on explaining human behavior but only on predicting human behavior.

With the theoretical developments in the field of cognitive psychology, scholars and researchers in the behavioral economics field started acknowledging human brain as the hub for processing information. Early developments in behavioral economics can be described as understanding human decisions at the cognitive level (Gardner [1985] 1987). Exploring human behavior at the cognitive level gave rise to the alternate decision theories such as prospect theory, time discounting, risk aversion (Taversky and Kahneman 1992), regret minimization. These decision theories overcome fundamental criticisms of the deterministic and random utility theories that assume human beings to be rational decision makers who attempt to maximize their utilities when making choices. For example, the theory based on risk aversion assumes that human beings seek to avoid risk rather than maximize gains when faced with a choice situation. Similarly, unlike RUM that does not acknowledge the existence of a reference point when faced with choices, prospect theory claims moving to an inferior choice alternative from the reference point provides more disutility than moving to a superior alternative from the reference point. Or in other words individuals weigh losses more heavily than they value gains.

More recently, developments in the field of behavioral economics have diverged from the sole reliance on cognitive processing of information for explaining the differences in individual choice outcomes. In the recent years, behavioral economists have postulated (and have verified using experiments) that individual affect plays an important role in the cognitive information processing capability of human being. This in turn influences their decision making process as well as the final choice outcomes. For example, Lowenstein and Lerner (2003) and Rick and Lowenstein (2007) provide a comprehensive review of recent developments exploring the influence of affect/emotion on human judgement and economic decision making.

2.5.3 Influence of behavioral economics on activity-travel behavior research

Following the development in the field of behavioral economics, researchers in the field of transportation shared some of the same concerns about the applicability and limitations of the widely used random utility modeling (RUM) framework. Earliest research in incorporating psychological variables (such as attitudes, beliefs, and perceptions among others, also referred to as psychometric indicators) in explaining travel behavior decisions can be traced back to the work of Golob et al. (1977) and McFadden (1986). McFadden (1986) identified perceptions or belief, attitudes or values and behavioral intentions as the “critical constructs” for better understanding cognitive processes that underlie individual choice behavior.

Despite this recognition nearly three decades ago, the study of psychological factors that underlie individual activity and travel behaviors has been slow. This can be attributed primarily to the challenges associated with the measurement and quantification of different psychological factors and subsequently the difficulty associated with incorporating such factors in the models of choice in a statistically rigorous manner. One of the primary objectives of the proposed research is to contribute to this line of inquiry of investigating the role of psychological factors on activity and travel behaviors that is less understood. The current research will further the understanding of activity and travel decision making process by incorporating psychological factors such as attitudes, perceptions and beliefs into the random utility modeling (RUM) framework. Incorporating psychological variables will help better understand the cognitive and affective processes that contribute to the decision outcome. Further, this will help build

predictive models that have enhanced explanatory power. In the next section, the state of the art methods for incorporating psychometric variables in the models of activity and travel choice dimensions and the associated challenges are briefly reviewed.

2.6 Extending Random Utility Theory

2.6.1 Measuring psychometric variables

The psychometric variables attitudes, perceptions, and beliefs are not readily observable therefore they cannot be measured directly. They are instead measured indirectly using indicators. For generating indicators, individuals are asked to report their level of agreement or disagreement with various statements describing different aspects of the underlying psychological factor (namely attitudes, perceptions, and beliefs) of interest on a Likert scale. Often more than one indicator variable is used to measure the underlying latent psychological construct. Once measured through indicators, the underlying latent construct can then be included as an explanatory variable in models of choice and used to understand the influence of the psychological construct.

There are a number of approaches to incorporating latent psychological factors into models of choice each with varying degrees of assumptions which in turn have implications for the inferences that are drawn. The treatment of psychological factors in models of travel behavior has evolved over the years with increasingly sophisticated models being used in practice today.

2.6.2 Treatment of psychometric variables: methodological challenges

One of the earliest techniques to study the influence of psychological factors was to include the indicator variables directly into the utility function of the choice alternatives (Koppelman and Hasuer 1978, and Harris and Keane 1998). For example Koppelman and Hasuer (1978) studied the influence of attractiveness (in terms of variety, quality, satisfaction, value and parking) of shopping destination on the frequency of visit to a destination. Similarly, Harris and Keane (1998) used user ratings of different unobserved attributes to understand the choice of health care plans. However the problem with this approach is that it assumes each indicator represents a complete psychological construct. This is problematic especially when multiple indicators for the same psychological factor are included together.

Often the multiple indicators are attempting to measure different aspects of the same underlying psychological construct. Further, the multiple indicators designed to measure a given psychological factor may share high degree of correlation potentially causing issues related to multicollinearity (Ashok et al. 2002). Another issue with this approach is that the indicator variables cannot be predicted directly thus limiting its potential for use in scenario analyses.

Another widely used method is to perform a factor analysis on the indicator variables to construct the latent psychological variables of interest. The predicted factor scores are then used in the model of choice as measures of the psychological variables. This approach to model estimation is also referred to as the two stage sequential estimation technique. A number of researchers have adopted this technique to incorporate psychological variables into the models of choice. Prashker 1979 and Madanat et al. (1995) provide a review of earliest applications of the two stage sequential estimation technique. While this method overcomes some limitations of the previous approach related to multicollinearity, this method also has its fair share of criticisms. Coefficients estimated using the two stage estimation technique are inconsistent and inefficient when the choice model probabilities are not integrated over the distribution of the latent psychological factors. Thus, the inference drawn using the choice models based on this approach may be misleading.

More recently, a simultaneous estimation approach called the integrated choice and latent variable model (ICLV) was proposed by Ben-Akiva et al. (2002) that addresses the limitations of the two stage estimation technique. In this technique, the latent variable model for measuring the psychological factors (Bollen 1989) and the choice model that includes latent psychological factors as explanatory variables (Ben-Akiva and Lerman 1985) are estimated simultaneously using the simulated maximum likelihood estimation (SMLE) technique. This technique overcomes the statistical issues of the sequential approach namely inconsistency and inefficiency of parameter estimates. Further, this approach can also be used for prediction as the latent psychological factors themselves are specified using observed explanatory variables. In the recent years, there has been a growing use of the SMLE technique to incorporate psychometric constructs into the models of choice (Bolduc et al. 2005, Johansson et al 2006,

and Daly et al. 2012). For example Johansson et al. (2006) explored the influence of different personality traits such as environment friendliness on the choice of mode between car and train. Daly et al. (2012) is another study that employed the ICLV framework to study the impact of privacy, security and liberty concerns on the rail travel decision.

While the ICLV provides a valid framework for incorporating latent psychological constructs into models of choice in a methodologically rigorous way, the SMLE technique for model estimation limits the use of the framework. The ICLV approach requires the choice probabilities to be integrated over the distribution of the latent variables. This means that when there are multiple latent psychological factors of interest, the dimension of the integrals increases proportionally and the subsequent SMLE becomes unwieldy. More recently, to overcome this estimation issue for dealing with multiple psychological constructs Bhat and Dubey (2014) proposed a new estimation technique using composite likelihood (CL) estimation method. The approach referred to as maximum approximate composite marginal likelihood (MACML) reduces the dimensionality of the integral using pseudo likelihoods and analytical approximations for evaluating higher dimensional integrals. In this research, the approaches described above have been applied to further our understanding about the influence of psychological factors on different activity and travel behavior choices – a topic that is less understood. Additionally, the proposed research furthers recent methodological developments for incorporating multiple psychological factors in models of choice.

2.7 Representation of Time in Activity-based Modeling Framework

Activity-/tour-based modeling frameworks have been evolved to capture the dynamics in activity travel behavior through better representation of time of day decisions of activity travel participation. This section provides a brief overview of the evolution of activity-/tour-based framework with a critical assessment of the representation of time in the respective frameworks.

2.7.1 Rule based micro-simulation frameworks

Clarke (1986) developed a computer simulation model, CARLA for activity scheduling given a fixed set of activity set observed from activity diary. The simulation program is created to re-organize the activity

schedule in terms of the sequence, time and location of the activity and the travel arrangements to move from one location to another.

Root and Recker (1981) proposes a model of individual activity scheduling and trip chaining called STARCHILD as a stochastic multiobjective dynamic problem. According to their framework, individual activity agenda includes a set of activity types and corresponding duration that are executed subjected to a number of temporal and spatial constraints such as the opening hours of business as well as the spatial distribution of the activity opportunities. In the proposed dynamic programming approach, the individual reevaluates and updates the activity agenda at the end of each activity execution. Their formulation proposes presence of a fixed travel time and travel budget constraints based on the empirical research. While the duration of the activity is expected to vary depending on the activity type as well as the site of the activity. Additionally, time spent away from home is considered to cause disutility according to their formulation.

Garling (1989), Garling et al. (1994) proposes another theoretical framework, SCHEDULER for individual activity scheduling over a given time period based on cognitive theories of individual decision making process (Hayes-Roth and Hayes Roth 1979). According to the theoretical framework individual maintains a cognitive representation of the environment around them in terms of opening hours of the business and the travel speed between locations among others. More activity specific information are also assumed to be contained in a long term memory which include available locations for different activity types as well as the minimum time required to perform the activity. Several simplifying assumptions are made while implementing the theoretical framework for scheduling household activities. The operational model is implemented as a computational process model that identifies the activity type, location and start time dimensions of each activity episode on an incremental basis from a pre-specified set of activities. The activity duration is not modeled explicitly, but is considered to be available as an input to the process model. The utility associated with different activities are assumed to vary by the time of day. Also the routine activities are assumed to take priority over the unplanned activities.

Kitamura et al. (1996) in his seminal work developed a microsimulation based integrated land use and transportation model, SAMS at the heart of which exists an activity-mobility simulator called AMOS. The activity mobility simulator is created based on adaptation approach of decision making, where the householders are assumed to adapt to their travel environment by making changes to their base level trip frequency, departure time, mode choice or route choice decisions. The activity duration in AMOS arises from the arrival time decision to different activities, thus the duration of different activities are neither explicitly modeled nor exogenously available like SCHEDULER. While responding to the changes in the travel environment, householders evaluate a number of feasible response alternatives. The time use utility of activity participation is used as a criterion to select from competing adaptation options.

SMASH (Ettema et al. 1996) builds on SCHEDULER and STARCHILD. SMASH schedules activities through the steps of adding, deleting, and substituting from a pre-specified agenda. Activity scheduling only involves determination of activity type and the location – fixed activity duration is assumed given, non-fixed activity durations are assumed to evolve from the end time of the previous and successive activities. SMASH is a microsimulation framework that uses heuristics for activity scheduling that incorporates the limited information processing capability of individual instead of an optimal search strategy.

Miller and Roorda (2003) presents yet another microsimulation framework, TASHA for activity schedule generation for greater Toronto area. They adopt a bottom up approach for activity scheduling where the activity episodes are selected to accomplish an overall project. In their framework, the frequency of different activity types namely work, school, shopping and other, the start time and the duration are randomly selected from the marginal distribution of these variables generated from the observed the data. They use different ad-hoc rules to resolve the conflicts that arise while trying to stitch the activity episodes on the 24-hour period of the day. In this process the high priority activity episodes (such as work) are scheduled first followed by the activity types assuming to have a lower priority (such as shopping).

Arentze and Timmermans (2004) uses a computational process model, ALBATROSS to schedule daily activity of two adult household members from a given list of activity agenda. In terms of temporal decisions, the fixed activities such as work and school are assumed to be conducted at a fixed location, for a given duration, at a fixed time of the day. Consequently, the scheduling decision involve determining the choices such as type, location, time of day, duration and accompaniment type for the flexible activities on the agenda. If the non-fixed activities are linked with fixed activities at both the start and end of the time scale, then the duration and start time are automatically determined; otherwise there exists some flexibility for both the time of day and duration choice. The duration of the non-fixed activities are determined qualitatively from the options of short, average and long episodes. A supervised learning algorithm, decision rules are used for determining the choice on the various dimensions of the activity schedule including mode choice, activity type, accompaniment type, activity duration, time of day and location.

Auld and Mohammadian (2009, 2012) proposes a microsimulation framework, ADAPTS for activity planning and scheduling. The primary departure of their formulation from the previous similar microsimulation framework is in the incorporation of the planning horizon in the activity scheduling process. According to the formulation, different activity attributes such as location, accompaniment, time of day and duration are conceptualized to be planned at different discrete time points thus incorporating the heterogeneity in the planning process while generating activity schedule. In terms of the generation of different attributes of an activity, such as time of day, accompaniment and duration, ADAPTS currently rely on the marginal distributions generated from the observed data. Conflicts arising from the activity scheduling phase, due to non-synchronization of various activity attributes get resolved at the conflict resolution stage just before the execution of the activity.

2.7.2 Econometric frameworks

Bowman and Ben-Akiva (2001) presents a comprehensive tour-based formulation for daily activity scheduling. According to the framework, a person's daily pattern is composed of a sequence of primary and secondary home based tours. The framework is operationalized as a sequence of interlinked decisions

of participation, mode, destination and time of day choice, where the decisions at the bottom level are constrained by the top level decisions and the top level decisions get informed about the bottom level decision through an accessibility (also known as a logsum) parameter. The duration of any particular activity is roughly determined from the time of day choice, where, the time of day is modeled as a combination of start and end time pair. It can be noted that, the time of day choice model does not involve any explicit temporal constraint, however, the choice set itself is constrained based on the previous choice decisions. For example the choice set for any secondary tour is created by excluding the time window used by the primary tour of the day. The proposed formulation with various extensions and updates from the original framework have been applied in different regions of the USA including in Portland, Oregon, Denver, Colorado and Sacramento, California among others. In the SacSim (2010) implementation (in Sacramento, CA), the time of day choice model uses a time resolution of half an hour.

Bhat et. al. (2004) puts forward another microsimulation framework for activity generation and activity scheduling with independent econometric models as building blocks. The activity generation step determines the activity agenda for the day including the duration of the mandatory activities, while the activity scheduling stage actually schedule the activities during the 24 hour period of the day. The home stay durations between tours as well as the activity durations for different stops on the tours are modeled on a continuous scale using independent regression models. However, while determining the stop/activity and home stay durations the temporal constraints are not explicitly accounted for. The advantage of the CEMDAP system over the Bowman & Ben-Akiva (2001) framework is however in acknowledging the intra-household dependencies (Pinjari et al. 2006).

FAMOS (Pendyala 2004) is an implementation of the activity mobility simulator. In FAMOS, fixed activity (work and school) start and end times are determined from the observed data. Latest possible arrival time and earliest possible departure time from mandatory activities determine the open time blocks. For each open time block, independent econometric models are estimated to determine the activity type, duration, destination and mode choice. Therefore, similar to CEMDAP, FAMOS employs continuous time duration models for activity scheduling. Compared to the use of regression models for

the determination of home stay duration FAMOS employs a more behaviorally intuitive way of generating open time blocks for flexible activity participation. However, the activity type and duration for each open block are determined independently using truncated distribution for activity duration.

More recently Habib (2011, 2015) proposes a random utility based dynamic activity scheduling framework, where activity scheduling entails the choice of the activity type, the time allocation as well the location choice for out of home activities. At each scheduling step (which is considered to be equal to the number of activity episodes in the training dataset), the activity duration is determined by solving an optimization problem of resource allocation between the current activity and a composite good. This way the time budget is updated at each scheduling step based on the available time to conduct the rest of the day's activities.

In can be noted that, in the rule based microsimulation frameworks, the duration of activities (especially of fixed activities) are assumed to be given or are drawn from a distribution observed in the survey data. Often non-fixed activity durations are elicited from the fixed activity durations or are determined qualitatively as large, medium of short episodes of activities (Arentze and Timmermans 2004). Inconsistencies in the activity durations are often mitigated heuristically using ad-hoc rules. Sometimes generated out-of-home activity episodes are abandoned if the conflicts cannot be resolved with a reasonable number of trials **-** resulting in underrepresentation of trips and out-of-home activity episodes (Auld and Mohammadian 2009).

The econometric frameworks either models the duration on a continuous scale (Bhat 2004, Pendyala 2004) or the duration is indirectly determined from the activity arrival and departure time decisions; where the activity arrival and departure time decisions are modeled on a discrete time scale. The econometric models more often determines the duration of different activity episodes independently that does not account for the overall temporal constraints or the interdependencies across the durations of various activity types.

In the last decade much research has been conducted to improve the time of day/activity duration choice representation in the microsimulation frameworks of activity travel behaviors. However, there

exists avenue for improving the state-of the art approach by accounting for the constraints as well as the interdependencies between different activities types while modeling time of day, duration choices. This will help make the microsimulation frameworks more sensitive to the changes in the individuals travel environment and will consequently help yield better predictions.

CHAPTER 3

RELATIONSHIP BETWEEN WELL-BEING AND ACTIVITY TIME ENGAGEMENT

3.1 Introduction and Motivation

In the travel behavior arena, the study of the special population groups including elderly, children, individuals with disabilities, people from lower income groups, and immigrants among others is considered important owing to the additional challenges faced by these groups for their activity and travel needs (Mohammadian and Bekhor 2008). Among the different special population groups, the study of elderly is gaining interest because of increase in the number of people belonging to this group due to improved life expectancy (Arentze et al. 2008, Nordbakke and Schwanen 2014). In the US, the focus on the mobility needs of the elderly is also increasing due to the unprecedented shift in population demographics expected in the next few decades due to the aging baby-boom generation. According to the US Census Bureau, 13 percent of the population was above 65 years old in the year 2010. However, this number is expected to increase by about 104 percent by 2030 (Mohammadian et al. 2013). Additionally, despite the physical and medical barriers faced by the elderly, they are more mobile today than they were in the years past with very active lifestyles (Rosenbloom 2001). The increase in the elderly population combined with the increased mobility needs is expected to exert demands on the built environments including transportation infrastructures in never before seen ways. As a result, the study of the elderly population has been of emerging interest in the transportation arena and many recent studies on the topic are a testament to this interest (Rosenbloom 2004a, Cao et al. 2010).

Among different generations of elderly population, "baby boomers" – those who were born post World War II between 1946 and 1965 have received considerable attention. A number of studies have attempted to compare the activity travel pattern of the baby boomer generation with other generations (Goulias et al. 2007, Miranda-Moreno and Lee-Gosselin 2008). Studies have shown that baby boomers tend to maintain a more active lifestyle, prefer late retirement, and tend to work full-time or part-time even after retirement compared to similar aged individuals from earlier generations (Srinivasan et al.

2006, Goulias et al. 2007). Similar trends have also been observed in European contexts. Klein-Hitpaß and Lenz (2011) found that the number of elderly people who do not make a single trip in a day has decreased over the years in Germany and during the same period the trip lengths have increased. In another study, using data from 2002 to 2005 in Quebec City, Canada, it was found that participation into out-of-home activities increased during the three years among baby boomers (Miranda-Moreno and Lee-Gosselin 2008). Alsnih and Hensher (2003) have arrived at similar conclusion while studying elderly activity-travel behaviors in the context of developing economies. Siren and Haustein (2013) also echo a number of findings from earlier studies about elderly activity-travel behaviors. However, they also note that there is considerable heterogeneity in the travel behaviors of the baby boomer generation which needs to be recognized when formulating policy. The primary objective of this study is to add to the literature on exploring the factors that contribute to heterogeneity in mobility choices of the elderly (studied through the lens of activity participation and time allocation behaviors). Next subsections presents the existing literature on elderly time use. It can be noted that there has been a plethora of literature on time use; an exhaustive review of the time use literature is outside the scope of the current effort; readers interested in general time use literature can refer to Jara-Diaz and Rosales-Salas (2017) and Liu et al. (2017).

3.1.1 Factors contributing to elderly mobility

This section identifies the factors identified by the existing literature to be important contributor of elderly mobility. Previous studies have identified car ownership and possession of driving license as the two most important contributors to the continued mobility at the old age (Alsnih and Hensher 2003, Cao et al. 2010, Klein-Hitpaß and Lenz 2011). Rosenbloom (2004) have highlighted the gender difference of the mobility needs of elderly people by arguing that women are more dependent on the family members to meet their mobility requirements compared to the men. In addition to car ownership and possession of driving license; education status, worker status, income and household structure have been identified to be important contributors to the mobility at the old age (Miranda-Moreno and Lee-Gosselin 2008). Nordbakke and Schwanen (2015) attempt to identify the factors associated with the unmet mobility needs

of elderly. According to them, in addition to the individual resources such as (driving license and car availability), social support and network, general outlook on life as well as transportation infrastructure (such as availability of public transportation) are associated with unmet mobility needs.

One additional factor that has emerged to have close association with mobility at the old age is the quality of life. In the last decade, travel behavior researchers in general have strived to investigate the relationship between individual's perceived quality of life - often referred to as subjective well-being (SWB) and mobility as implied by activity-travel participation (Duarte et al. 2010, Ettema et al. 2010, De Vos et al. 2013, Schwanen and Wang 2014).

In addition to subjective well-being, physical well-being is believed to be closely linked to the activity-travel engagement behavior of the elderly. Recent literature has identified disability as an important consideration for mobility at the old age (Alsnih and Hensher 2003, Cao et al. 2009, Freedman et al. 2012). In the current study, the association between different types of disability (physical and perceived) and the activity-travel engagement behavior of the elderly individual are explored.

3.1.2 Elderly mobility and subjective well-being

In understanding the association between mobility and SWB different researchers have approached it from different perspectives. For example, according to Abou-Zeid and Ben-Akiva (2012) activity-travel engagement of individual is influenced by one's desire to maintain or enhance their well-being. Archer et al. (2013) and Ravulaparthy et al. (2013) argue that location of activity participation (in-home versus out-of-home), activity duration as well as activity type are correlated with individual well-being. A few studies have also tried to understand the association between well-being (both stated happiness with life and the stated happiness with regard to the transportation system) and the choice of travel mode (Duarte et al. 2010). A number of studies have attempted to understand the association between mobility at old age and perceived quality of life (SWB). Banister and Bowling (2004) attempt to deconstruct the elements that contribute to the quality of life of elderly. In their study, the authors found that living in a neighborhood with good transport services contributed positively to the quality of life by facilitating participation into social activities. In another study, Spinney et al. (2009) found that increased transport

mobility is correlated with increased life satisfaction for elderly Canadians. More recently, Nordbakke and Schwanen (2014) provide a comprehensive review of literature exploring the relationship between mobility and well-being of the elderly people from the fields of gerontology, health and transportation. From the review, the authors note that the nexus of elderly mobility and well-being research has been pursued along two lines of inquiries. One stream of research has been focused on various aspects of elderly driving cessation including coping with driving cessation and subsequent implications for travel behavior (Coughling 2001, Bauer et al. 2003, and Davey 2007). The second line of research has been focused on identifying aspects of elderly life (including mobility choices) that improve well-being of the elderly (Siren and Hakamies-Bolmqvist 2009, Musselwhite and Haddad 2010, Ziegler and Schwanen 2011). In this line of research, access to good transportation that enables people to participate in activities of their choice was found to be an important factor for maintaining quality of life.

In the second line of research that explores the relationship between well-being and activity-travel engagement choices of elderly, mobility has often been quantified in terms of out-of-home trip frequency. Very few studies have considered the full range of time use choices of elderly (e.g. activity participation, and time allocation decisions of all types of activities that elderly pursue). Additionally, very few studies accurately account for different types of constraints and interactions they experience (e.g. physical abilities and temporal constraints as formulated by Hagerstrand 1970). It has been well established that travel is derived from individual needs to engage in activities. By understanding the time use choices one can more accurately characterize and analyze association between well-being and mobility. Spinney et al. (2009) is one of the few studies that attempted to generate contextually derived time budgets for psychological, exercise and community times. Further, they attempted to understand how they vary across different levels of life satisfaction. Nordbakke and Schwanen (2015) is another such study that attempts to explore the association between the quality of life (measured via satisfaction with life) and the unmet mobility needs of the elderly. Next section presents the subject well-being perspective adopted in the current research followed by the motivation to investigate the association between elderly time use choices and subjective well-being.

3.1.3 Well-being perspectives

Subjective well-being is a broad psychological construct proposed by Kahneman et al. (1999) that represents individuals' cognitive and affective evaluation of his/her life. However, research from different disciplines such as economics, psychology, sociology, public health, geography and gerontology conceptualize well-being differently. Below different perspectives adopted by researchers while studying well-being is presented followed by a discussion of the existing conceptualization of the linkage between well-being and time allocation behavior. While some researchers have defined well-being as a subjective phenomenon arising from an individual's overall evaluation of his/her life (Veenhoven 2002), others have formulated well-being based on objective circumstances that an individual experiences (Phillips 2006). Similar to the definition of well-being, the approaches to study well-being also vary considerably across disciplines. The utility approach within economics defines well-being as the maximization of preference satisfaction. According to the basic needs approach, well-being is derived from the satisfaction of the basic needs. The works adopting this approach draws on Maslow's need hierarchy (1943). According to Maslow, basic needs such as physiological needs, safety needs, love needs, esteem needs and needs for self-actualization follow a certain hierarchy. A need down in the hierarchy surfaces only when the preceding needs are satisfied to a certain extent. Similar to the basic needs approach, in the integral needs approach, well-being is derived from the satisfaction of needs. However, compared to the basic needs approach, integral needs approach also emphasize the non-material aspects of life for need fulfillment. For example according to Finnish Sociologist Eirk Allardt (1993), people considers needs satisfaction from three aspects: to have (refers to the material needs in life such as education, work, and money), to love (refers to the social needs such as being with other human beings), and to be (refers to the self-actualization needs). Additionally, in gerontology, health is most often considered to be the prime determinant of well-being.

In the presented study well-being is defined from the perspective of needs satisfaction. According to the adopted definition, well-being is perceived as a subjective phenomenon and is derived from the individual's own evaluation of needs. Further, well-being is characterized not using a single measure but

with a variety of measures offering their perceived satisfaction in different domains of life. The particular domains considered in the current study are the satisfaction with life, job, finance and marriage. Job and financial satisfaction are closely related to the "to have" needs highlighted by Allardt (1993). Similarly, satisfaction with marriage would relate to the "to be" and "love needs" identified by Allardt (1993) and Maslow (1943) respectively. Finally, the overall satisfaction with life would be related to the "to be" need or the self-actualization need identified by Allardt (1993) and Maslow (1943) respectively. In addition to satisfaction with life, job, finance and marriage the research also considers health related satisfaction for deriving well-being of the elderly.

3.1.4 Well-being and time use

Tonn in his 1984 paper talked about the socio-psychological aspect of time use. He proposed that mathematical models of individual time use behaviors should be grounded in psychological motivations and must also consider the temporal constraints that exist. According to the author, three types of needs, namely, will to live, sexual-sensual desire and need for social interaction, guide the time use behaviors of individuals. Tonn also postulated that, while allocating time to satisfy different types of needs, individuals strive to maintain a certain balance in terms of needs satisfaction rather than trying to exhaust a need before moving onto the next one. Borrowing from Tonn's hypothesis, in the current study, time use decisions of elderly are assumed to vary depending on the level of needs satisfaction (measured via the satisfaction with life and different domains of it). As identified in the last section, we adopt the definition of well-being where well-being is derived from needs satisfaction.

Arentze and Timmermans (2009) and Nijland et al. (2010) have also studied the association between needs and activity agenda formation. The authors explored the dynamic evolution of needs and it's interrelationship with activity agenda formation. However, the current study is different from these explorations. While they focus on the short-term dynamics of need formation and activity generation process, the current study focuses on the association between needs satisfaction and overall activity participation and time allocation at a particular cross-section in time (e.g. an average day in a person's life). The motivation of the current study closely resembles Dekker et al. (2014). Dekker et al. studied the

influence of perceived needs satisfaction potential of different leisure activities on the choice of the leisure activity. They found that needs satisfaction potential accounts for substantial heterogeneity in the selection of leisure activity type. Despite the similarity in motivations, there are considerable differences between the current research and Dekker et al. The empirical study presented in Dekker et al. uses stated preference data. On the other hand, revealed data about time use choices is used in the current research thus offering more realistic insights into the time use behaviors. While Dekker et al. only considers the participation choice into leisure activities, in the current research, not only both participation and time allocation decisions are considered but also these decisions are considered for all types of activities that elderly individuals pursue. Additionally, while Dekker et al. studies the interrelationship between perceived needs satisfaction potential and the time use decision, the current study explores the association between expressed needs satisfaction (measured via satisfaction with life and various aspects of it) and the full range of time use choices.

While considering the needs satisfaction helps understand the socio-psychological motivations for time use decisions, one must also consider the situational constraints that individuals experience to accurately characterize time use behaviors (Hagerstrand 1970, Tonn 1984). Among the different types of constraints identified by the researchers such as time, physical, economic, personal, scheduling and institutional constraints (Tonn 1984), time constraint is perhaps the most important and the easiest to characterize/consider in studies of time use behaviors. In particular, every individual has 24 hours at their disposal to pursue their various activities. Therefore, the 24 hour duration serves as a natural constraint for the time allocated by individuals. Unlike most of the previous studies (e.g. Miranda-Moreno and Lee-Gosselin 2008, and Spinney et al. 2009) which ignore the temporal constraints when studying time use choices of elderly, the current study explicitly accounts for the temporal constraints in the empirical analysis.

3.1.5 Study overview

The review of the literature on elderly activity-travel suggests that, empirical research to date have mostly focused on the elderly mobility outcomes in terms their trip length, trip rate and mode choice (Banister

and Bowling 2004, Klein-Hitpaß and Lenz 2011). Few studies have considered the participation into different out-of-home activities while also considering the tradeoff between out-of-home and in-home activity participation (whether to participate in an activity?) (Miranda-Morebo and Lee-Gosselin 2008). Also, to the best of the authors' knowledge, time allocation (how much time to spend in a chosen activity?) behavior of the elderly has not been extensively studied. It should be noted that, one of the fundamental aspects of the study of time allocation behavior is the explicit consideration of the temporal constraints (Becker 1965, Johnson 1966, Evans 1972). Study of different types of activities in isolation fail to capture the tradeoffs that people make in order to participate in and allocate time into different activities within limited time constraint. The current study adds to this line of inquiry that is less understood by exploring the daily participation and time allocation of elderly into different in-home and out-of-activities while explicitly accounting for the temporal constraint. It can be noted that the formulation adopted in the research for the study of time allocation behavior of the elderly allows variable satiation effect associated with different activity types which essentially allude to the differing capability of different activity types in satisfying different types of needs. In particular, the focus of the study is in understanding the heterogeneity in elderly activity engagement behaviors with particular attention to their physical and subjective well-being.

In this empirical study, the variation in time use choices (including participation and time allocation decisions) across different levels of well-being perceived by the elderly (measured via satisfaction with life and different domains of it such as satisfaction with job, finance and health) is explored. To the best of the authors' knowledge, the empirical study presented in the current paper is one of the very first explorations that attempts to explore heterogeneity in time use behaviors of elderly as a function of the well-being in addition to the individual and household characteristics. Also, unlike previous studies, where the time allocation in different activities have been explored in isolation, the current study explores the time use decisions into different activities simultaneously using an econometric framework that can accurately capture the temporal constraints within which a person operates.

It should be noted that, while investigating the association between long term well-being and activity-travel engagement choices of the elderly, the current study does not postulate a causal structure; rather these indicators of quality of life are used to unravel the heterogeneity in the mobility choices of the elderly individuals. Also, it is acknowledged that the perceived overall satisfaction of life (and with different domains of life) and mobility evolve with time and with changing stages of life. Therefore, a simultaneous investigation of the association between well-being and mobility engagement using longitudinal data would provide more insights into the interplay between mobility and quality of life. Nonetheless, the focus of the study is on exploring the relationship between well-being and activity engagement choices at a particular snapshot in time.

In this study, data from the Disabilities and Use of Time (DUST) supplement of Panel Studies of Income Dynamics (PSID) conducted in 2009 was used. The DUST dataset contains information about activity participation and time use choices for each elderly respondent for both weekdays and weekends. The Multiple Discrete Continuous Extreme Value (MDCEV) framework proposed by Bhat (2005, 2008) was used to model the activity participation and time use decision. The MDCEV framework is particularly suited for this study because the utility-theoretic formulation can simultaneously accommodate the participation and time use decisions of activity engagement while accounting for the time constraints that individuals experience when making these choices. The MDCEV framework has been applied in multiple studies to explore different aspects of activity-travel engagement decisions for different population segments (Copperman and Bhat 2007, Kapur and Bhat 2007, Sener and Bhat 2007, Sener et al. 2008). More recently, extensions of the MDCEV have been proposed to support the empirical exploration of interest at hand (Pinjari and Bhat 2010, Sobhani et al. 2013, Sobhani et al. 2014). The current study employs a panel version (Spissu et al. 2009) of the MDCEV framework to appropriately handle multiday observations (a weekday and a weekend) of the survey participants.

The rest of the chapter is organized as follows. The next section introduces the DUST data set along with a description of the sample composition. An overview of the panel MDCEV model formulation is presented in the third section. This section also elaborates on the model specification while

also presenting the specific hypothesis that informed the model development. Findings from the empirical study is presented in the fourth section. Final section presents a summary of findings along with a discussion of the policy implications of the empirical findings. This section also presents ideas for future research regarding elderly mobility.

3.2 Data Composition

Data from the 2009 Disabilities and Use of Time (DUST) supplement of Panel Study of Income Dynamics (PSID) was used in the study (PSID 2014). PSID is a longitudinal household survey which began collecting information regarding employment, income, wealth, expenditures, health, marriage, childbearing, child development, and education from a nationally representative sample of individuals in the US since 1968. DUST contains information about elderly couples where both spouses were at least 50 years old by December 31, 2008 and at least one spouse was over the age of 60 at the time of the data collection. The elderly couples were interviewed on a randomly selected weekday and weekend day using time diaries. The time diary included information about all activities performed by the individual including start time, duration, location, travel mode, accompaniment type, and for whom they carried out the activities among others. Respondents were also asked to report physical well-being in a yes/no format. Additionally, respondents provided information regarding their subjective well-being by rating different aspects of life on a scale of 1 to 7 where 1 means very unsatisfied and 7 means very satisfied. The diary also included more specific well-being questions related to three randomly selected activities reported by the survey respondents. The focus of this study was on exploring the role of the physical and subjective well-being on activity engagement decisions. In addition to the above, socioeconomic information regarding individuals' employment status, education status, household type, household composition, and vehicle ownership were available from the PSID survey.

The initial survey sample comprised of 755 individuals. After eliminating individuals with missing information, the subsample used in the analysis consisted of 728 individuals with valid responses. Out of 728, 724 individuals reported data for both weekday and weekend and 4 individuals provided data only on a weekend. In terms of gender distribution, there is nearly an equal percentage of male and female

with 357 of the 728 individuals being male (49 percent) and the rest being female. 47 percent (339 individuals) of the respondents in the subsample are less than or equal to 65 years old, 42 percent (309) of the respondents belong to the 65 to 80 years' age group, and the remaining 11 percent (80) respondents are over 80 years old. A significant percentage of the elderly population is also employed; 261 of the 728 individuals (36 percent) reported that they were employed either full-time or part-time.

Activities were classified into very detailed categories in the DUST. However, in the current study the detailed categories were consolidated based on two criteria. (1) The study only focused on the discretionary activity types where the participants can exercise choice while deciding whether to participate in the activity and how much time to spend in the activity. This criterion resulted in excluding three types of activities such as sleep and relax, personal maintenance, and work for pay, (2) For the remaining activity types considered in the analysis (including meal, study and volunteer, shopping, household chores, social recreation, and leisure), the activity types were disaggregated into in-home and out-of-home activities based on location of the activity. Initial analysis indicated that some of these disaggregate activities were predominantly conducted at one location (either in-home or out-of-home). For example, shopping was mostly performed out-of-home whereas household chores and leisure were performed mostly in-home. As a result, the disaggregate categories based on location with very limited observations were combined into a single activity category that was location indifferent. The above criteria led to following eight non-fixed activity types including in-home meal (IH meal), out-of-home meal (OH meal), in-home social recreation (IH social), out-of-home social recreation (OH social), study and volunteer, shopping, household chores (chores) and leisure.

Table 3.1 Activity Description, Participation and Mean Duration

Activity Category	Location	Description	Participation (%)		Mean Duration[c] (Min.)	
			Weekday[a]	Weekend[b]	Weekday	Weekend
In-home (IH) Meal	In-home	Having meal/snack/drinks at home	638 (88%)	632 (87%)	59.00	62.00
In-home (IH) Social	In-home	Socializing, caring for others, time for family, religious and spiritual activities and organizational activities conducted at in-home location	460 (64%)	443 (61%)	90.00	93.00
Chores	In-home	Food and drink preparation, laundry, clothing preparation, financial management related to household and household planning	653 (90%)	636 (87%)	172.00	159.00
Leisure	In-home	Watching television, movies, activities related to arts and entertainment such as attending to hobbies, reading, listening to music, playing video games, attending and watching sports, doing physical activities, traveling for recreating, smoking, having alcohol and so on	710 (98%)	708 (97%)	353.00	392.00
Out-of-home (OH) Meal	Out-of-home	Having meal/snack/drinks outside home	220 (30%)	234 (32%)	88.00	99.00
Out-of-Home (OH) Social	Out-of-home	Same activity types as In-home Social but conducted at out-of-home location	268 (37%)	350 (48%)	121.00	185.00
Shopping	Out-of-home	Shopping for grocery, foods as well as other durable and non-durable goods	337 (47%)	317 (44%)	89.00	106.00
Study and Volunteer	Both In-home and Out-of-home	Studying and volunteering	58 (8%)	37 (5%)	193.00	233.00

Notes:
[a] Weekday percentages are calculated across 724 individuals
[b] Weekend percentages are calculated across 728 individuals
[c] Mean taken only across the individuals who have reported to participate in at least one episode of the activity

Table 3.1 provides a brief description of the final activity categories considered in the analysis. The table also lists the primary activity location, participation rates as well as the mean duration of participation by weekday and weekend. In calculating the mean duration, only individuals participating in at least one episode of the particular activity type were considered. The participation rates indicate that there is a slightly higher tendency to participate in out-of-home (OH) meal and OH social activities during weekend. It is interesting to note that the activities conducted at OH location have a higher mean duration compared to activities conducted at in-home (IH) location. This is partly owing to the fact that duration for OH activities includes both the activity and the travel to engage in the activities. Leisure has the highest mean duration followed by study and volunteer. The next section presents a brief overview of the panel MDCEV model structure followed by a description of the model specification.

3.3 Econometric Methodology

The MDCEV model formulation is presented in this section. Following Bhat (2008) and Spissu et al. (2009), the functional form for the total utility derived by an individual n on a certain day t by engaging in activities K_{nt} can be given as shown in Equation 1.

$$U_{nt}(x) = \sum_{k=1}^{K_{nt}} \gamma_{nkt} \exp(\beta' Z_{ntk} + \varepsilon_{ntk} + \eta_{nk}) ln\left(\frac{x_{ntk}}{\gamma_{ntk}} + 1\right) \quad (3.1)$$

In the above equation, x is the vector of the time allocated to different activities $(x_{nt1}, x_{nt2}, \dots, x_{ntk})$. Z_{ntk} is a vector of exogenous variables (including a constant) corresponding to an alternative k and β represents the corresponding vector of unknown coefficients, ε_{ntk} and η_{nk} are the associated random error components. The term $\exp(\beta' Z_{ntk} + \varepsilon_{ntk} + \eta_{nk})$ represents the marginal random utility[1] for allocating a unit of time to alternative k at the point of zero-time allocation and controls an individual's participation in alternative k. The term γ_{ntk} is a translation parameter which serves to allow corner

[1] Also referred to as baseline utility preference.

solutions (representing zero allocation of time to alternative k). The parameter also serves to account for satiation effects when allocating time to different activities. Values of γ_{ntk} closer to zero imply higher satiation (or lower allocation of time) for a given level of baseline preference and vice-versa. Furthermore, the study parameterizes γ_{ntk} as $exp(\lambda'\omega_{ntk})$, where ω_{ntk} is a vector of individual specific characteristics and λ is the associated vector of unknown parameters to be estimated.

In equation (3.1), the first error component ε_{ntk} is assumed to be independently and identically type I extreme value distributed across alternatives, individuals and days with a scale parameter σ. The second random error component η_{nk} is assumed[2] to be normally distributed with a mean of zero and a variance-covariance matrix of Ω; Ω is a diagonal matrix with diagonal elements ω^2. A statistically significant value of ω indicates the presence of error correlations across days for the same individual (i.e. this provides evidence in support of a significant individual effect).

The MDCEV framework proceeds to model activity engagement by maximizing the utility $U_{nt}(x)$ subject to the time constraint $\sum_k^{K_{nt}} x_{ntk} = T_{nt}$ where T_{nt} is the total time available to participate in K_{nt} different activities. Given the assumptions about the error terms as preliminaries, the conditional probability (conditional on the error component η_{nk}) of an individual n allocating time to the first M_{nt} of the K_{nt} alternatives on a certain day t is shown in equation (3.2) below.

$$l_{nt} = P(x^*_{nt1}, x^*_{nt2}, \dots, x^*_{ntM}, 0, 0, \dots, 0|\eta) =$$

$$\frac{1}{\sigma^{M_{nt}-1}}\left[\prod_{i=1}^{M_{nt}} f_{nti}\right]\left[\sum_{i=1}^{M_{nt}} \frac{1}{f_{nti}}\right]\left[\frac{\prod_{i=1}^{M_{nt}} e^{(V_{nti}+\eta_{ni})/\sigma}}{\left(\sum_{k=1}^{K_{nt}} e^{(V_{ntk}+\eta_{nk})/\sigma}\right)^{M_{nt}}}\right](M_{nt}-1)! \qquad (3.2)$$

[2] Note that the second error component η_{nk} is assumed to be independently and identically distributed across alternatives and individuals but is held constant across observations from the same individual.

In the above equation, V_{ntk} is the utility of alternative *k* defined as $V_{ntk} = \beta' Z_{ntk} - \ln\left(\frac{x^*_{ntk}}{\gamma_{ntk}} + 1\right)$ where $f_{nti} = \frac{1}{x^*_{nti} + \gamma_{nti}}$. The likelihood function for the sample can finally be written as in Equation (3.3).

$$L = \prod_{n=1}^{N} \int_{\eta_n} \prod_{t=1}^{T_n} l_{nt} \, dF(\eta_n) \tag{3.3}$$

where *F* is a multivariate cumulative normal distribution function, T_n is the total number of choice situations for individual *n* (i.e. number of days), and *N* represents the total number of individuals in the sample. The likelihood function in equation (3.3) involves a multidimensional integral which can be evaluated using maximum simulated likelihood approach (Train 2009). In approximating the integral shown in Equation (3.3), scrambled Halton draws were used (Bhat 2003). After monitoring stability in the parameter estimates with increasing number of draws, 200 scrambled Halton draws were employed for the final model estimation. The panel MDCEV code developed for this study builds on the Mixed MDCEV GAUSS code distributed for public use by Bhat (2008).

3.3.1 Model specification

This section introduces the specification of the model while also highlighting the hypothesis that guided the model development. The primary purpose of the study was to capture the heterogeneity in the elderly activity participation and time allocation decisions while also accounting for the physical and subjective well-being experienced by this group. The different individual and household level characteristics along with the physical and subjective well-being variables that were used to specify the model are introduced next. It must be noted that these variables were used to explore the variability in both activity participation and time allocation decisions (i.e. they constitute the vector Z and ω introduced in the previous section).

3.3.1.1 Individual characteristics

The different individual level characteristics used to parameterize the baseline marginal utility and the satiation parameter are gender, age, education status, worker status, living status and race. Drawing from previous literature (Alsnih and Hensher 2003, Banister and Bowling 2004), elderly individuals in the dataset were further separated into three age categories: the "young" group (those who are less than 65

years old), the "middle" group (those who are between 65 and 80 years old) and "old" group (those who are above 80 years old). It was assumed that, elderly individuals who are still working for pay would have different life styles compared to those who do not. The work status indicator was introduced to account for this effect. It was hypothesized that, the people with special living arrangements would have different mobility needs (especially in terms of social and recreational activities) compared to those individuals who stay with family. This was captured using the living status indicator. Very limited literature has considered the influence of race while examining the mobility needs of the elderly (Rosenbloom 2004b). Assuming that there are inherent differences in the way individual pursue their daily life based on their ethnic background, the present study explores differences in activity engagement using ethnicity indictors.

3.3.1.2 Household characteristics

In the literature, the composition of the households has been identified as an important source of heterogeneity in activity participation and time allocation decisions (Kapur and Bhat 2007, Copperman and Bhat 2007). The current study assumes that presence of adults (in addition to the spouse) and kids in the household would potentially alter the way elderly individual participate in different in-home and out-of-home activities. Drawing from the previous studies on this topic (Rosenbloom 2004b), it was assumed that presence of adults in the household would allow elderly individuals to pursue different out-of-activities where they may require some assistance which might not be possible if there were no adults to assist them. Building on the previous literature, the current study also explores heterogeneity due to household income (Banister and Bowling 2004) and the vehicle availability (Klein-Hitpaß and Lenz 2011).

3.3.1.3 Physical and subjective well-being

Existing literature has considered influence of disabilities on mobility at old age (Freedman et al. 2012). The current study expands the source of disability to include both walking disability and disabilities related to cognitive functioning. Physical well-being information was collected on a dichotomous scale

(in a yes/no format); consequently, indicator variables were constructed to indicate the presence of disability.

As highlighted previously, the study also attempts to identify the association between perceived level of satisfaction in different domains of life and the activity participation and time allocation. To this end, indicators of satisfaction with life and different domains of it including health, job and finance were explored. These variables are used to explain the heterogeneity both in the participation as well as in the time allocation decision (through their specification in vectors Z and ω respectively). The satisfaction information with life (and different domains of it) were collected on a scale ranging in values from 1 to 7. Consequently, three indicator variables were created to denote low (less than 3), medium (between 3 and 5) and high level of satisfaction (6 and 7). The next section presents the model estimation results. Additionally, where appropriate, findings from the empirical analysis are compared and contrasted with those from previous studies on the topic of elderly mobility.

3.4 Model Estimation Results

A panel MDCEV model was estimated to understand the heterogeneity in in-home and out-of-home activity engagement decisions (including participation and time allocation) of the elderly individuals while accounting for different types of constraints that guide the time allocation behavior. The activity types considered for the current exploration include four in-home (IH) activities: IH meal, IH social, chores, and leisure, three out-of-home (OH) activities: OH meal, OH social, shopping, plus the study and volunteer activity. The amount of time available (T_{nt}) for activity engagement is equal to 1440 minutes minus the duration of all fixed activities (including sleep and relax, personal maintenance, and work for pay) that individuals pursue over the course of a day.

As noted in the previous section in addition to the household-level demographic variables physical and subjective well-being attributes were used to explore the non-fixed activity participation and time use decisions of the elderly. It must be noted that, constants were retained in the model specification even if they were not statistically significant because all the error components were assumed to have a zero mean. Model estimation results for the baseline utility (explaining the activity participation decision)

are presented in Tables 3.2 and 3.3 and the estimation results for the satiation parameter (explaining the time allocation decision) are presented in Table 3.4. The results are discussed in further detail in the following subsections beginning with summary of model goodness of fit and findings from the panel structure exploration. In the second subsection, the estimation results for the baseline utility are presented followed by a discussion of the satiation parameter in the third subsection. It should be noted that, while presenting the observations from the empirical analysis, the study does not imply causality between the explanatory variables (including the individual characteristics, household attributes, and subjective and physical well-being measures) and the activity engagement choices. Rather, the study attempts to highlight the substantial variability that exists in the elderly in-home and out-of-home activity participation and time allocation choices as a function of different explanatory variables.

3.4.1 Estimation summary

Most of the model coefficients were statistically significant at the 95 percent level of confidence. The log-likelihood of the final model at convergence (-35020.9) was higher than the log-likelihood for the constants only model (-35316.7) indicating that the final model with the explanatory variables helps explain the choices better than a model with just the constants. Further, the log-likelihood ratio test confirmed this observation at a 95 percent level of confidence ($\chi^2 = 297.8$, critical value of $\chi^2 = 124.342$ with 99 degrees of freedom). A comparison of the log-likelihood values of the panel model (with a final log-likelihood of -35020.9) and cross-sectional model (with a final log-likelihood of -35041.3) indicates that, accounting for the individual specific error correlation (individual effect) is warranted. This is also confirmed by the log-likelihood ratio test ($\chi^2 = 40.7$, critical value of $\chi^2 = 3.841$ with 1 degrees of freedom). Further, the model estimation results show a significant ω parameter in the mixing distribution (with a value of 0.3874 and corresponding t-statistic of 11.21) of the baseline utility. The presence of individual specific error correlation was tested in the satiation parameter but was found to be insignificant.

Table 3.2 Model Estimation Results for the Baseline Utility: Demographic Explanatory Variables

	IH Social	Chores	Leisure	OH Meal	OH Social	Shopping	Study and Volunteer
Constants	-1.0244 *(-5.4)*	0.1160 *(0.3)*	1.8577 *(6.9)*	-3.5445 *(-13.9)*	-2.4229 *(-9.2)*	-1.8416 *(-3.5)*	-5.6361 *(-7.8)*
Personal-level Demographics							
Female indicator	0.4659 *(4.6)*	0.8431 *(6.3)*			0.1116 *(1.1)*		-0.4743 *(-2.1)*
Age <= 65 indicator		0.3316 *(2.3)*			0.4781 *(2.6)*	0.4608 *(2.6)*	0.9345 *(2.2)*
Age > 65 and <= 80 indicator		0.2565 *(1.9)*			0.3911 *(2.2)*	0.3453 *(2.0)*	0.5556 *(1.3)*
Education more than high school indicator							0.4191 *(1.8)*
Worker indicator					0.1210 *(1.0)*	-0.5282 *(-1.5)*	
Living in elderly home indicator	-0.1981 *(-1.1)*	-0.4763 *(-2.8)*	0.2116 *(1.3)*	0.3845 *(1.8)*	0.2383 *(1.2)*		
Race is Black or African American indicator	0.3756 *(2.6)*		0.3500 *(2.8)*	-0.9030 *(-3.3)*	0.3618 *(2.2)*	0.3471 *(2.2)*	
Race is Asian indicator			-0.3956 *(-1.2)*	-1.0219 *(-1.9)*	-0.6749 *(-1.4)*	-0.4414 *(-1.1)*	
Household-level Demographics							
Family income > \$25K and <=\$50K indicator			-0.8356 *(-4.0)*	0.2851 *(1.2)*			
Family income > \$50K and <=\$100K indicator				0.6336 *(2.8)*			
Family income > \$100K indicator				0.6478 *(2.7)*			
Number of adults > 2 indicator	0.3947 *(3.5)*		0.2442 *(2.4)*			0.2472 *(2.0)*	
Number of children		0.2567 *(2.1)*	0.1661 *(1.4)*		0.2151 *(1.4)*		
Number of vehicle >= 2 indicator				0.6742 *(4.3)*	0.2944 *(2.4)*	0.2140 *(1.8)*	
Weekend indicator		-0.0961 *(-1.4)*	-0.2890 *(-1.4)*		0.3783 *(4.0)*		

Notes:
(1) Values in the row next to a variable name represent the coefficient estimates and values in parentheses represent the corresponding t-statistics

Table 3.3 Model Estimation Results for the Baseline Utility: Physical and Subjective Well-being Explanatory Variables

	IH Social	**Chores**	**Leisure**	**OH Meal**	**OH Social**	**Shopping**	**Study and Volunteer**
Physical Well-Being							
Cognitive issue indicator		0.0779 *(2.4)*			-0.0890 *(-2.3)*		0.2089 *(1.6)*
Walking issue indicator			0.1688 *(1.9)*				
Need assistance for daily errands indicator	-0.3496 *(-2.3)*	-0.5474 *(-3.7)*			-0.2938 *(-1.5)*	-0.4933 *(-2.5)*	
Subjective Well-Being							
Life satisfaction >=3 and <= 5 indicator		-0.8914 *(-2.2)*			-0.2116 *(-1.8)*	-0.5937 *(-1.2)*	
Life satisfaction >=6 indicator		-1.0149 *(-2.6)*				-0.5980 *(-1.2)*	
Health satisfaction >=3 and <= 5 indicator			-0.6473 *(-3.3)*				
Health satisfaction >=6 indicator			-0.7344 *(-3.7)*				
Financial satisfaction >=3 and <= 5 indicator	-0.5017 *(-2.7)*						
Financial satisfaction >=6 indicator	-0.4435 *(-2.5)*						
Job satisfaction >=3 and <= 5 indicator		0.3750 *(2.4)*		0.5833 *(3.4)*	0.3970 *(2.4)*	0.8918 *(2.6)*	0.4492 *(1.5)*
Job satisfaction >=6 indicator		0.2678 *(2.0)*		0.6187 *(4.8)*		0.8452 *(2.3)*	

Notes:
(1) Values in the row next to a variable name represent the coefficient estimates and values in parentheses represent the corresponding t-statistics

Table 3.4 Model Estimation Result for the Satiation (Translation) Parameter

	IH Meal	IH Social	Chores	Leisure	OH Meal	OH Social	Shopping	Study and Volunteer
Constants	3.043 *(13.1)*	3.4824 *(29.0)*	3.7952 *(14.3)*	3.0799 *(15.4)*	4.2307 *(21.6)*	4.4636 *(17.0)*	3.6842 *(30.4)*	2.8641 *(2.8)*
Person-level Demographics								
Female indicator	-0.1974 *(-2.1)*	0.1736 *(1.4)*	-0.5218 *(-3.6)*	-0.3214 *(-3.5)*				
Worker indicator			-0.3678 *(-2.6)*					
Household-level Demographics								
Family income > $25K and <=$50K indicator				0.8793 *(3.8)*		-0.3961 *(-1.4)*		
Family income > $50K and <=$100K indicator		-0.1475 *(-1.3)*	-0.1477 *(-1.4)*			-0.4625 *(-1.8)*		
Family income > $100K indicator			-0.1790 *(-1.4)*			-0.7648 *(-2.8)*		
Weekend indicator				0.463 *(2.1)*	0.1599 *(1.1)*	0.6138 *(4.2)*	0.2026 *(1.6)*	
Physical and Subjective Well-being Variables								
Life satisfaction >=6 indicator					-0.2264 *(-1.2)*			0.6377 *(1.3)*
Health satisfaction >= 3 and <= 5 indicator	-0.5559 *(-2.4)*		-0.2680 *(-1.0)*					
Health satisfaction >= 6 indicator	-0.6582 *(-2.8)*	-0.2417 *(-2.2)*	-0.2969 *(-1.1)*					
Memory satisfaction >= 3 and <= 5 indicator								2.2622 *(2.0)*
Memory satisfaction >= 6 indicator								1.6301 *(1.5)*
Financial satisfaction >=6 indicator						0.2338 *(1.6)*	0.2152 *(1.6)*	
Job satisfaction >= 3 and <= 5 indicator		-0.1794 *(-1.0)*						

Notes:
(1) Values in the row next to a variable name represent the coefficient estimates and values in parentheses represent the corresponding t-statistics

3.4.2 Baseline utility parameters (β): explaining the heterogeneity in activity participation

The baseline utility represents preferences of the elderly to participate in different non-fixed activity types in a day. IH meal was used as the baseline for the choice of activity type. It can be seen from the estimates of constants that all other things assumed equal, elderly prefer to participate in leisurely activities the most followed by chores compared to IH meal activity. All other activity types including IH social, shopping, OH social, OH meal, and study and volunteer were less preferred than the IH meal. A discussion of the influence of the different explanatory variables is presented below.

3.4.2.1 Influence of person- and household-level explanatory variables

Table 3.2 presents model estimation results for the household- and person-level demographic variables. It was found that elderly females have a higher tendency to participate in chores, IH social, and OH social compared to their male counterparts and prefer less to participate in study and volunteer activities. These findings provide evidence in favor of traditional gender roles wherein women assume responsibilities for housework (part of chores), and care giving activities (part of IH and OH social).

An exploration of the relationship between age and activity participation showed that elderly who are less than 80 years old have a higher preference for participating in OH activities including OH social, shopping, and study and volunteer. Elderly in this age group were also found to be involved in more household chores than elderly who are greater than 80 years. This is reasonable considering the additional barriers one faces with such age. The notion of increased barriers with aging is also evident by observing the relative magnitude of the coefficients for elderly who are less than 65 and elderly who are between 65 and 80. It can be seen that the former group has a higher preference to participate in different activities than the latter group. This observation is also in line with the previous research by Banister and Bowling (2004). The authors conducted a bi-variate analysis to identify relationship between age and out-of-home activity participation. They also found that frequency of out-of-home activity participation decreases with the increase of age even within the elderly cohort.

Education status of elderly marginally affects activity participation. It was found that elderly with at least high school education prefer to engage in study and volunteer type of activities. The influence of

working status was found to be only marginally significant. It was found that elderly workers tend to engage more in OH social and less in shopping. The tendency to participate more in OH social may be reflective of additional socializing opportunities with colleagues at work. The negative relationship with shopping may be reflective of the constraints imposed by the work activity schedules of workers.

Living arrangement of elderly is one of the factors that did not receive adequate attention in the existing literature. This factor revealed interesting observations regarding elderly mobility. It was found that individuals who live in an elderly home engage less in IH social and chores and more in leisure, OH meal, and OH social. The tendency to participate less in chores is reflective of the nature of the elderly homes where care givers may be taking on the chores requiring elderly to engage less in these activities. Further, the additional time afforded by decreased participation in chores may be affording elderly to pursue OH activities.

Race of elderly was also found to be significantly correlated with activity participation. Elderly Black or African American individuals were more active i.e. tend to participate more into out-of-home activities compared to the rest of the elderly cohort, while elderly Asian individuals were relatively less mobile. This finding however contradicts the observation presented by Rosenbloom (2004b) based on the bi-variate analysis of trip rates by ethnicity using data from 1995. The author found that mobility of Asians is comparable, especially among male population, to the White population. The author also observed that Black population generally suffered higher losses in mobility with aging.

In addition to the different person-level explanatory variables, a host of household-level explanatory variables were found to be correlated with elderly activity participation including family income, household composition, and auto ownership. It is interesting to note that as family income increases elderly participate more in OH meal activities. This may be attributed to the additional disposable income available to higher income families compared to families with lower levels of income. This observation is also in line Miranda-Moreno and Lee-Gosselin (2008) who found that elderly individuals belonging to high income households tend to participate less in habitual (routinely performed at a fixed place and time) activities. It was also found that in the presence of household adults (in addition

to the significant other), elderly individuals participate more indifferent out-of-home activities such as shopping and out-of-home meal compared to when they live only with their significant other. This observation is reasonable since the presence of other household members provide elderly individuals additional opportunities to pursue out-of-home activities. It is also plausible that the presence of additional adult members affords them additional opportunities for assistance, thus, allowing them to pursue more activities. This finding is in line with Rosenbloom (2004b) who found that this age cohort is generally dependent on the family members for performing out-of-home activities. It is interesting to note that vehicle ownership is positively correlated to participation in OH activities. This shows that elderly individuals without vehicle availability constraints (as reflected by the presence of more than 2 vehicles) are more active and favor participation in OH activities (OH meal, OH social and shopping). This observation is supported by the findings from a number of previous studies regarding this age cohort's dependency on car for performing out-of-home activities (Alsnih and Hensher 2003, Klein-Hitpaß and Lenz 2011). Lastly, the differences in elderly activity participation patterns between weekdays and weekends were evident from lower participation into chores and leisure and higher participation into OH social activities on weekends.

3.4.2.2 Influence of physical and subjective well-being explanatory variables

Table 3.3 presents model estimation results for the physical and subjective well-being variables. It was found that there exists significant variability in elderly activity participation choices across different levels of physical and subjective well-being. Individuals who reported having difficulties with concentration, remembering and/or decision making were found to engage more in chores and less in OH social. The decreased participation may be due to their discomfort and uneasiness when being around people. This observation is in line with the finding reported by Freedman et al. (2012). In the study, the authors note that presence of disability results in less socialization. It is however interesting to note that these same individuals tend to engage more in study and volunteer activities compared to others.

It was also found that, elderly individuals who reported having difficulties with walking tend to engage more in leisure activities compared to others. This may be reasonable because this category

involves activities performed at home entailing little physical exertion such as watching television, and movies, engaging in arts and entertainment among others. Further, it was found that elderly who reported needing assistance to run their daily errands tend to be less active in general with reduced participation in both IH (social, chores) and OH (social, shopping) activities due to their limitation.

In the DUST survey, other subjective well-being measures were collected by asking the participants to report their perceived satisfaction with life, health, financial stability, memory, job and marriage. Among these measures, satisfaction related to life, health, financial condition and job were found to impact the elderly activity participation. It can be noted that, among the above types of satisfactions, satisfaction with life can be related to the self-actualization need (Maslow 1943) or the "to be" need pointed out by Allardt (1993). Whereas, the satisfaction with finance and job can be related to the "to have" needs (Allardt 1993). It was found that elderly individuals with both high (value of 6 or more) and moderate levels of life satisfaction (value of 3 through 5) tend to participate less in chores and shopping activities. However, it is interesting to note that the tendency to participate is lesser for the elderly who are more satisfied. It was observed that elderly with higher levels of health satisfaction engage less in leisure activities. This is plausible since leisure includes discretionary activities performed at home with little physical exertion such as watching television, reading book and so on. Elderly who are financially satisfied tend to engage less in IH social activities compared to others. Lastly, it was found that elderly with higher levels of job satisfaction participate more in different activity types compared to those who reported lower job satisfaction. It is interesting to note that the influence of job satisfaction on activity participation is increasing with increasing levels of satisfaction across different activity types. Elderly who are highly satisfied with their job tend to engage more in OH meal activities, and less in chores and shopping compared to those who are moderately satisfied with their job.

3.4.3 Satiation parameter (λ): explaining the heterogeneity in time allocation

In the current study, the satiation (translation) parameter γ_{ntk} was parameterized using a range of explanatory variables including demographics, physical and subjective well-being to capture the influence of these different factors on the time use decisions of the elderly. Estimation results are presented in Table

3.4. It must be noted that a negative (positive) coefficient of a variable indicates higher (lower) satiation i.e. lower (higher) amount of time spent in an activity type. All else being equal, it can be seen that elderly tend to invest higher time in OH activities including OH social, OH meal, and shopping activities compared to IH activities such as IH meal, IH social, and leisure.

3.4.3.1 Influence of person- and household-level explanatory variables

A range of person- and household level explanatory variables including gender, worker status, income, and day of the week were found to influence the time use decisions. Elderly female individuals were found to invest more time in IH social than their male counterparts. It was also found that they tend to spend less time in IH meal, chores, and leisure activities compared to males. It is interesting to note that elderly females tend to participate more in IH social activities (see Table 3.2) and also engage in such activities for longer duration (see Table 3.4). On the other hand, even though they participate more than elderly males, the amount of time spent in chores is less than males.

Elderly workers were found to engage less in chores compared to non-workers which is reasonable considering the additional constraints experienced by workers due to their work activity schedule. In terms of family income, it was found that with increasing income elderly individuals spend lesser time on OH social activities. Elderly individuals with income more than $50,000 were found to spend less time on chores. Individuals with family income in between $25,000 and $50,000 were found to spend more time on leisure activities. Consistent with expectation, it was observed that elderly individuals spend more time in OH (meal, social and shopping) and leisurely activities during the weekend than on weekdays.

3.4.3.2 Influence of physical and subjective well-being explanatory variables

Subjective well-being measures (measured via satisfaction with life and different domains of it such as health, job and finance) were found to be correlated with the time allocation decisions of elderly. It was observed that elderly individuals who were highly satisfied with their life spend less time on OH meal and more time on study and volunteer activities. It was also found that elderly who were satisfied with their

health tend to spend less time on at home activities including IH meal, IH social, and chores. Elderly with higher levels of cognitive satisfaction (related to concentration, memory and decision making) tend to spend more time on study and volunteer. Elderly who were financially satisfied were found to spend more time on OH social, and shopping. Finally, it was observed that elderly who are satisfied with their job tend to spend less time on IH social activities.

In the next section a summary of the findings is presented along with some concluding thoughts about the policy implications of the research presented in this chapter.

3.5 Summary and Conclusions

The study of activity engagement choices of elderly Americans is of interest because of the unprecedented growth in the elderly population that is anticipated due to aging baby-boomers and increased life expectancy among others. While there is a rich body of literature related to elderly mobility, most studies to date have mainly focused on the mobility outcomes of this population segment. Much less attention has been paid to the generator of travel namely activity engagement choices (including activity participation in various in-home versus out-of-home activities and time allocation). The studies that have considered the activity engagement choices have done so in a disjointed manner by considering one activity at a time without accounting potential tradeoffs that exist across various activity types. The studies have also not accounted for the time constraints within which activity engagement choices are made. *The objective of the conducted study is to explore the heterogeneity in in-home and out-of-home activity participation and time allocation decisions of the elderly population with explicit consideration to the time constraint within which the elderly individual operates.* In addition to explicit consideration to the temporal constraints, the study also explored other types of constraints (such as physical constraint, economic constraint, personal energy constraint, and constitutional constraint) for explaining heterogeneity in time allocation behavior of the elderly. An additional novelty of the current research endeavor was in exploring the association between subjective well-being (derived from perceived need satisfaction of the elderly) and the time use choices of the elderly. Borrowing from the studies conducted in the field of sociology and psychology regarding human motivation for time allocation (Maslow 1943,

and Tonn 1984), the current study postulates that the heterogeneity in the activity engagement behavior of the elderly can be further captured via the difference in the level of perceived need satisfaction of the elderly. In the current research, a panel version of the (MDCEV) model was estimated using data from the Disabilities and Use of Time (DUST) survey of Panel Study of Income Dynamics (PSID) to simultaneously study the participation and time allocation behavior while accounting for the temporal constraints. Unlike previous research on elderly mobility, the use of the MDCEV model formulation allows to study the tradeoffs across activity types by considering the various activity types simultaneously. The current study presents a more holistic picture of the daily activity engagement choices of elderly. The findings from the study provide interesting insights with implications for policy aimed at addressing the elderly activity and travel needs.

The analysis results indicate that elderly Americans are in general active. It was also found that elderly with constitutional constraints are relatively less mobile (as indicated by lower participation into out-of-home activities) due to their physical limitations. While less mobile, elderly with special needs (except for those who depend on others for assistance) were found to compensate for the limited OH activity engagement with more IH activity participation. This might be a trade-off that these older populations with disabilities are forced to make, due to the lack of arrangements for pursuing out-of-home activities. Affordable transportation options may address the mobility needs of people with disabilities. It can be noted that, American Disabilities Act (ADA) requires public transport operators to provide demand-responsive services to people with serious disabilities. However, the high cost associated with these services as well as the stringent definition of disabilities used by this act limit their use and ability to serve those in most need of these services. Elderly people with non-life threatening disabilities are most often precluded from availing these services on a day-to-day basis (Rosenbloom 2009). Additionally, limitations exist on the coverage of these services in terms of spatial extents and hours of operation.

The study highlights the importance of considering different types of constraints for capturing the heterogeneity in the time allocation behavior of the elderly. One of the constraints that emerged to have significant influence on the time allocation behavior of the elderly are vehicular constraint which might

be related to the physical constraint for time use behavior identified by (Hagerstrand 1973). According to the empirical results, older people who do not have vehicular constraints perform more out-of-home activities compared to others. This points to the dependency of the older people on personal vehicles for performing out-of-home activities. It is important to acknowledge that this dependency on automobile for performing out-of-home activities may adversely impact the elderly cohort at a later stage of life when their driving abilities have deteriorated or they can no longer afford driving. Demand responsive paratransit services and customized services from transportation network companies (e.g. Uber) might be an appealing substitute to private vehicle for these group of elderly individuals due to the better flexibility afforded by these services compared to fixed route and schedule based public transportation services.

Another interesting observation was noted related to the living arrangement of the elderly individual. It was found that, people living in an elderly home appear to participate less in in-home activities such as in-home social and chores. It also appears like the additional time afforded is utilized by higher participation in out-of-home meal and out-of-home social activities. An increase in the population proportions of the elderly living in elderly homes could create additional demands on the transportation infrastructure compared to increase in the population proportions of the elderly living in their own homes. Community based shared ride services might address the mobility needs of the elderly living in elderly communities. However, before employing policies based on this finding, it is also important to study the differences in perceived quality of life between these two living arrangements so that appropriate policies that not only meet the mobility objectives but also social well-being objectives can be implemented.

It was found that elderly who are actively working seek more OH opportunities to socialize compared to those who are not currently working. Additionally, a significant positive correlation was observed between job satisfaction of workers and the participation in OH opportunities (such as OH meal, OH social, shopping, and study and volunteer). Further research is needed to identify whether the elderly individual after retirement suffer from mobility losses due to shrinking social networks and lesser disposable incomes.

In terms of household composition, it was interesting to note that activity participation decision of the elderly varies considerably depending on household composition. Elderly who live with other family/non-family members in addition to their spouses were found to engage more in in-home activities such as IH social and leisure; as well as out-of-home activities such as shopping. It indicates a two-fold impact of the presence of other household adults in the activity participation decisions of the elderly individual. Presence of household adults not only enable the elderly people to pursue additional out-of-home activities but also provide additional opportunities of recreation at home through IH social activities. Furthermore, the significant higher participation into shopping, chores, and out-of-home social activities in the presence of other family members and kids lend evidence in support of the notion that this group of elderly cohort namely the baby boomer generation are the sandwich generation i.e. they not only take care of their parents but they also take care of their kids/grand kids. A comparative study of such influences for other generational cohorts will allow one to confirm the findings of the baby boomers being a sandwich generation.

In terms of constitutional constraints, it was noted that, individual reporting cognitive difficulties participate less into OH social activities and more into chores. Less participation in OH social activities for the people with constitutional constraint might indicate less opportunities for socialization for this group of people.

The empirical study also finds considerable heterogeneity in the participation and time allocation behavior based on the level of satisfaction with life (relates to the “self-actualization needs”, according to Maslow (1943) or “to-be need” according to Allardt (1993), job and financial satisfaction (relates to the “to-have” need (Allardt 1993)) and health satisfaction (relates to the basic need (Maslow 1943)). In terms of “self- actualization” or “to-be” need it was observed that, people reporting high level of satisfaction participate less into shopping and OH social activities. The observation of less participation for shopping might be attributed to the “gratification shoppers” as identified by Arnolds and Reynolds (2003). In their study of hedonic motivation for shopping, the authors identified “stress relief” as one of the motivations for participating into shopping activities (the authors identify this group of people as “gratification

shoppers") – people reporting higher satisfaction with life might not be inclined to pursue shopping as a means to stress relief, which in reflected by their lower participation in the shopping activity in the current empirical study. It was also interesting to note that people reporting high level of satisfaction with job (related "to-have" needs) participate more into different types of "active" leisure types of activities such as OH meal, OH social and shopping. Higher satisfaction with finance (another indicator of "to-have" need satisfaction) also found to be associated with higher time allocation into "active" leisure activities such as OH social and shopping. It can be noted that, satisfaction with marriage (relates to the "to love" need) was not found to be significantly associated with the time allocation behavior of the elderly. It might be due to the marginal variability in the marriage satisfaction in the data among this age group.

Additional research is needed to understand the causal relationships between activity engagement choices and well-being of the elderly individual. Since these two dimensions may actually be evolving with time by constantly influencing each other. The study of the evolution of these dimensions using an appropriate longitudinal dataset constitutes an interesting future research endeavor. Also, it can be noted that, in the current research different measures of subjective well-being were used directly in the model without accounting for the possibility that the different measures are indicators of some underlying latent construct of well-being. Statistical rigor of the presented exploration can be improved by considering well-being as a latent construct measured via indicators using integrated choice and latent variable model formulation (Ben-Akiva et al. 2002, Enam et al. 2016). Lastly, elderly was in general found to be active; however, research conducting comparison of the participation and time allocation decisions across generations of the elderly population is needed to better inform the planner and policy makers regarding temporal stability in trends of elderly mobility.

CHAPTER 4

AN INTEGRATED CHOICE AND LATENT VARIABLE MODEL FOR MULTIPLE DISCRETE CONTINUOUS CHOICE KERNEL: HYBRID MULTIPLE DISCRETE CONTINUOUS (HMDC) CHOICE MODEL

4.1 Introduction and Motivation

There is a growing interest in the field of travel behavior research to incorporate psychological factors including attitudes, perceptions, beliefs, knowledge, emotions and learning for explaining the activity and travel behaviors exhibited by individuals (McFadden 1986, Gärling 1998, Hess 2012). This interest is in part motivated by theoretical and methodological advances in behavioral economics that support the notion that heterogeneity in behavior is not just attributable to the socio-economic and demographic differences but is also due to the differences in the underlying psychological factors.

Earliest efforts aimed at incorporating psychological factors for explaining individual behaviors in the transportation field can be traced back to the work by Golob et al. (1977). More recently with growing concerns of non-renewable energy consumption and greenhouse gas emissions, researchers have attempted to study the role of attitudes such as “pro environmental”, “addiction to car” on different dimensions of travel behaviors namely mode choice and vehicle type choice (Bolduc et al. 2005, Anable 2005, Daly et al. 2012, Glerum and Bierlaire 2012, Alvarez-Daziano and Bolduc 2013, Atasoy et al. 2013, Kamargianni and Polydoropoulou 2013, Hess and Spitz 2016).

In most studies, the random utility maximization framework proposed by McFadden (1986) is used. Psychological factors are constructed (“measured”) from associated indicators using either summary measures (e.g., mean of all indicators) (Koppelman and Hauser 1978, Harris and Keane 1998) or data reduction techniques (e.g., factor analysis) (Madanat et al. 1995). The constructed factors are then included as explanatory variables in the RUM based model to study the relationship between the factors and the choice variables. It can be noted that, the indicators do not capture all aspects of the underlying psychological factors and are often associated with measurement errors. Consequently, inconsistent and

inefficient parameter estimates are obtained if the measurement errors in the indicator variables are not explicitly accounted for in the model formulation (Ashok et al. 2002). In an effort to address the measurement error issue (and other limitations of the RUM framework), the Hybrid Choice Modeling (HCM) framework was developed (Ben-Akiva et al. 2002, and Walker and Ben-Akiva 2002). In this paper, the specific variant of the HCM framework (also referred to as Integrated Choice and Latent Variable (ICLV) model in the literature) that combines the Multiple Indicator Multiple Cause (MIMIC) model for constructing psychological factors with RUM based model for representing the choice variables is of interest.

Over the years, a number of implementations of ICLV models have been developed and applied to study the role of psychological factors on different dimensions of activity and travel choices (see Kim et al. 2014 for a review of recent progress in HCM). In most ICLV implementations, the choice component has been limited to a "single discrete" choice dimension (wherein individual makes a choice of a single alternative from available alternative set). However, numerous activity-travel choice situations (and more generally in other consumer behavior research arenas) are characterized by "multiple discreteness"; i.e., individuals potentially choose more than one alternative from the available choice set of alternatives. Additionally, for the selected alternatives, they also make the choice of how much of the alternative to "consume" subject to resource constraint(s) (Bhat 2005). Such choice dimensions are characterized as multiple discrete-continuous (MDC). In the literature, activity-travel behaviors are increasingly being characterized and modeled as MDC variables to accurately account for the underlying decision-making process (e.g. choice of goods under presence of budget constraints, and satiation effect among others). Examples of MDC choices include study of vehicle fleet composition and usage (Bhat et al. 2009, Jäggi et al. 2012, Pinjari et al. 2016), activity participation and time allocation choices (Sener et al. 2008, Bhat et al. 2010), vacation types and time spent (LaMondia et al. 2008, Lingling et al. 2011), vacation destination choices (Von Haefen et al. 2004, Van Nostrand et al. 2013), and land use choices (Pinjari et al. 2009, Kaza et al. 2011) among others. The study of individual behaviors as MDC choices is also widespread in other fields such as marketing and economics. For example, Shin et al. (2016) study

commodity bundling in Korean telecommunications market as MDC choices. Richards et al. (2012) use MDC models for a study of shopping behaviors. Jeong et al. (2011) and Biying et al. (2012) study energy consumption behaviors as MDC choices. Despite the growing popularity of study of consumer choices as MDC variables, there is lack of ICLV implementation in the literature that is able to accommodate a MDC choice kernel. *In this research, a new Hybrid Multiple Discrete Continuous (HMDC) choice model formulation and associated estimation routine are presented that allows the study of the influence of psychological constructs on MDC choice dimensions*.

The Maximum simulated likelihood estimation (MSLE) technique has served as the workhorse for evaluating integrals involved in the ICLV model implementations (Kim et al. 2014). The computational intensity of the MSLE approach has limited empirical researchers from exploring the full breadth of ICLV model specification, such as the number of latent variables to explore, interactions between latent variables and sociodemographic variables, and correlations among latent variables and among choice alternatives. To overcome the limitations of MSLE, alternative estimation approaches such as composite marginal likelihood approach (Bhat and Dubey 2014) and Bayesian approach (Daziano 2015) have been proposed in the recent years. The current exploration proposes a CML based estimation approach with analytical approximation for normal cumulative density function (known as MACML in the literature, due to Bhat 2011) similar to Bhat et al. (2016). Unlike Bhat et al. (2016), however, the current research employs a *weighted* CML approximation for estimating ICLV models with MDC kernel. *The current paper is perhaps the first to highlight and demonstrate the importance of weights in the composite marginal likelihood (CML) estimation routine for ICLV models*. Based on the literature on CML approach for clustered data (Varin et al. 2011), the dissertation proposes a set of values to weigh the decomposed lower dimensional probabilities while decomposing using the CML technique. The presented research highlights the feasibility of the proposed set of weights and also demonstrates the substantial gain in the parameter consistency offered by the weighted CML routine over the unweighted CML routine. Further discussion on the choice of weight and the comparison of results between

parameter estimates of the HMDC model using a weighted and unweighted CML estimation technique are provided in section 4.3.

It should be noted that, though ICLV framework has been a mainstay for analyzing the influence of psychological factors on different choice dimensions, it has received its fair share of scrutiny. Chorus and Kroesen (2014) note that cross-sectional data only offer evidence of inter-person variabilities, as opposed to changes in individual-level behavior. Consequently, policy interventions aiming at altering the level of latent variables for changing the choice outcomes are not supported by cross-sectional data driven ICLV implementations. Despite the criticism, researchers have continued to highlight the importance of the ICLV framework in terms of its ability to better reflect on consumer behavior (Bolduc and Daziano 2010). More recently, Vij and Walker (2016) conducted a systematic analysis based on multiple synthetic datasets to highlight the contribution of the ICLV framework over the traditional RUM based choice models that leave the source of heterogeneity to unobserved error components. The authors reemphasize the importance of the ICLV framework for lending structure to the underlying heterogeneity and for decomposing the influence of observed variables into constituent components, each of which might be attributable to different latent constructs. Given the statistical rigor and potential appeal in disentangling the structure in the unobserved heterogeneity, the current research attempts to add to the body of ICLV modeling and estimation approaches.

In addition to the aforementioned methodological contribution, this paper demonstrates the applicability of the proposed HMDC model using the 2013 American Time Use Survey dataset to explore the association between individuals' experienced moods (such as happiness, sadness, pain, stress and tiredness) and their discretionary activity engagement and time allocation in a day.

The rest of the chapter is organized as follows. Section 4.2 presents the HMDC model formulation along with the proposed approach to parameter estimation and inference. Section 4.3 presents a simulation study to demonstrate the ability of the proposed estimation approach to recover consistent and efficient estimates of the parameters. Section 4.4 presents an empirical application of the HMDC model to explore association between individuals' moods and their time-use. The estimated HMDC

model is also validated using a holdout sample in this section. Section 5 concludes the chapter with a summary of contributions, findings, and avenues for future research.

4.2 Econometric Methodology

The HMDC formulation extends the existing ICLV model implementations by replacing the single discrete choice kernel with a MDC choice kernel. The choice kernel in the HMDC assumes the multiple discrete continuous probit (MDCP) structure proposed by Bhat et al. (2013). The estimation of the HMDC model proceeds by combining the pairwise composite marginal likelihood (CML) (Varin 2008) with the maximum approximated composite marginal likelihood (MACML) (Bhat 2011). *However, unlike Bhat et al. (2016), parameter estimation for HMDC employs a weighted version of the pairwise CML approximation*. Below, the model formulation is presented followed by a discussion of the approach for estimating model parameters.

4.2.1 Model formulation

Similar to the ICLV framework, HMDC model formulation consists of three main components: 1) structural equation model of the latent variables, 2) measurement equation model of the latent variables and 3) MDC choice model. Figure 4.1 presents an overview of the proposed HMDC model formulation. In the traditional ICLV model, the utility in the choice model component is measured via one choice indicator whereas in the HMDC model, the utility of the choice model is measured via consumption quantities of multiple alternatives as indicators. In the remaining subsections (in 4.2.1.1, 4.2.1.2 and 4.2.1.3), the formulation of each of the three components of the HMDC model is presented in detail.

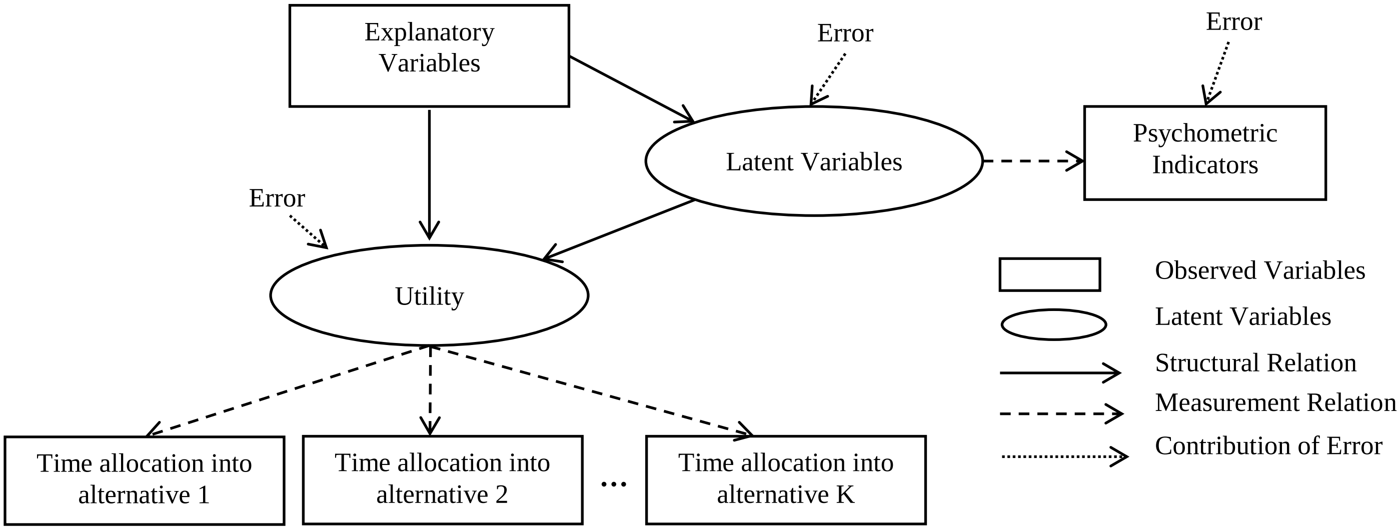

Figure 4.1 Hybrid multiple discrete continuous (HMDC) model framework

4.2.1.1 Structural equation model of latent variables

Equation 4.1 shows the structural equation of the latent variables in matrix form[3].

$$z^* = \omega\rho + \eta \tag{4.1}$$

where z^* is a $(L \times 1)$ vector of latent psychological factors, ω is a $(L \times D)$ matrix of observed covariates for explaining the variability in the psychological factors, ρ is a $(D \times 1)$ vector of coefficients associated with the observed covariates and η is a $(L \times 1)$ vector of random error terms associated with the latent factors. η is assumed to be multivariate normally distributed: $\eta \sim N[0_L, \Gamma]$ with Γ representing the correlation matrix[4].

[3] In presenting the model formulation, the subscript for the individual is suppressed for the sake of brevity.
[4] The identification conditions are similar to those of a MIMIC model; please see Bollen (1989) for a detailed discussion about the identification conditions for the MIMIC model.

4.2.1.2 Measurement equation model of latent variables

In the proposed HMDC formulation, latent factors can be constructed from both continuous and ordinal indicator variables. The measurement equation for the continuous indicators used to construct the latent variables (in matrix form) is shown in Equation 4.2.

$$y_c = \delta + dz^* + \xi \tag{4.2}$$

where y_c is a $(H \times 1)$ vector of continuous indicators, δ is a $(H \times 1)$ vector of constant terms, d is a $(H \times L)$ matrix of latent variable loadings onto the continuous indicators (commonly referred to as factor loadings), and ξ is a $(H \times 1)$ vector of error terms. ξ is also assumed to be multivariate normally distributed: $\xi \sim N[0_H, \Sigma_{y_c}]$ with Σ_{y_c} representing the covariance matrix. For identification purposes Σ_{y_c} is assumed to be a diagonal matrix[4].

Equation 4.3 shows the measurement equation for the ordinal indicators used to construct the latent variable.

$$y_o^* = \tilde{\delta} + \tilde{d}z^* + \tilde{\xi} \text{ and } y_o = j \text{ if } \tau_{low} < y_o^* < \tau_{up} \tag{4.3}$$

where y_o is a $(G \times 1)$ vector of ordinal indicators and y_o^* is the $(G \times 1)$ vector of the continuous latent propensity variables underlying the ordinal indicators, $\tilde{\delta}$ is a $(G \times 1)$ vector of constant terms, $\tilde{d}$ is a $(G \times L)$ matrix of latent variable loadings onto the ordinal indicators, τ_{low} and τ_{up} are both $(G \times 1)$ vectors obtained by stacking the lower and the upper thresholds of the ordinal indicators respectively. j represents the ordinal indicator category and $j = \{1,2, \dots, J\}$. $\tilde{\xi}$ is a $(G \times 1)$ vector of error terms associated with the underlying propensity of the ordinal indicators and is assumed to be multivariate normally distributed: $\tilde{\xi} \sim N[0_G, \Sigma_{y_o^*}]$ with $\Sigma_{y_o^*}$ representing the covariance matrix. For identification purposes $\Sigma_{y_o^*}$ is assumed to be an identity matrix[4].

By stacking the vector of the continuous indicators and the vector of the ordinal indicators and replacing the latent variable z^* with the structural equation shown in Equation 4.1, the reduced form expression for the measurement equation can be obtained as in Equation 4.4:

$$\breve{y} = \breve{\delta} + \breve{d}(\omega\rho) + \breve{d}(\eta) + \breve{\xi} \tag{4.4}$$

where $\breve{y} = (y_c', [y_o^*]')'$, $\breve{\delta} = (\delta', \tilde{\delta}')'$, $\breve{d} = (d', \tilde{d}')'$ and $\breve{\xi} = (\xi', \tilde{\xi}')'$

4.2.1.3 Multiple discrete continuous (MDC) choice model

Following Bhat (2008), the MDC choices can be formulated as an allocation problem wherein an individual consumes $x = \{x_1, x_2, \ldots, x_K\}$ amounts of K goods to maximize his/her utility (U) subject to a budget constraint (E) as shown below:

$$\max U(x) = \sum_{k=1}^{K} \gamma_k \Psi_k \ln\left(\frac{x_k}{\gamma_k} + 1\right) \tag{4.5a}$$

$$\text{subject to } \sum_{k=1}^{K} x_k = E \tag{4.5b}$$

where x is a (K×1) vector of the quantity of goods consumed, γ_k (> 0) is the translation (also satiation) parameter and $\Psi_k(> 0)$ is the baseline marginal utility. Ψ_k represents the marginal random utility at the point of zero consumption for good k. γ_k parameter serves to account for satiation effects associated with consuming goods. It should be noted that, to meet the budget constraint, every individual must consume at least one good (referred to with index m[5] from this point forward) from the available set of K goods. Both the baseline marginal utility and the translation parameter are parametrized in terms of exogenous explanatory variables. Further, the proposed HMDC framework parameterizes the baseline marginal utility (Ψ_k) in terms of latent psychological factors. Equation 4.6 shows the parameterized baseline marginal utility in the HMDC:

$$\Psi = \exp(\nu\beta + \lambda z^* + \varepsilon) \tag{4.6}$$

where Ψ is a ($K \times 1$) vector of baseline marginal utilities associated with the different goods, ν is a ($K \times D$) matrix of observed explanatory variables, β is a ($D \times 1$) vector of coefficients associated with the ν, λ is a ($K \times L$) matrix of coefficients associated with the psychological factors and ε is a ($K \times 1$) vector of stochastic error terms which are assumed to be multivariate normally distributed: $\varepsilon \sim N[0_K, \Lambda]$ with Λ

[5] For individuals who consume multiple goods, *m* can be assumed to be the good with the lowest index of *k* without any loss of generality.

representing the covariance matrix. The optimization problem defined in Equation 4.5 can be solved by forming the Lagrangian and applying the Karush-Kuhn Tucker (KKT) conditions. From KKT first order conditions it follows that:

$$\mu_{km}^{*} = 0, if\ x_k{}^{*} > 0, k = 1,2, \ldots, K, k \neq m \tag{4.7a}$$

$$\mu_{km}^{*} < 0\ if\ x_k{}^{*} = 0, k = 1,2, \ldots, K, k \neq m \tag{4.7b}$$

where $\mu_{km}^{*} = \mu_k - \mu_m$ and $\mu_k = \beta' \nu_k - ln\left(\frac{x_k}{\gamma_k} + 1\right) + \lambda_k' z^{*} + \varepsilon_k$. By replacing the latent variable z^{*} with the corresponding structural equation (as shown in Equation 4.1), the $(K-1)$ sized vector μ^{*} can be expressed in the matrix notation as shown in Equation 4.8 below:

$$\mu^{*} = \overleftrightarrow{\nu}\beta + \overleftrightarrow{\lambda}(\omega\rho) - \ln(\overleftrightarrow{q}) + \overleftrightarrow{\lambda}(\eta) + \overleftrightarrow{\varepsilon} \tag{4.8}$$

where $\overleftrightarrow{\nu}$ is a $((K-1) \times D)$ sized matrix created by stacking $(1 \times D)$ sized vectors $\nu_k - \nu_m$, $\overleftrightarrow{\lambda}$ is a $((K-1) \times L)$ sized matrix created by stacking $(1 \times L)$ sized vectors $\lambda_k - \lambda_m$, $\overleftrightarrow{\varepsilon}$ is a $(K-1)$ sized vector created by stacking $\varepsilon_k - \varepsilon_m$ and $\overleftrightarrow{q}$ is a $(K-1)$ sized vector created by stacking $\frac{\frac{x_k}{\gamma_k}+1}{\frac{x_m}{\gamma_m}+1}$ for $k = 1,2, \ldots, K, k \neq m$.

Finally it is assumed that the correlation between the measurement equation of the latent variables and the utility equations of the choice model arise only due to the common influence of the latent variables. As a result, $\check{\xi}$ (the error component in the measurement equation of the latent variables) and ε (the error component in the MDC choice model) are independent.

4.2.2 Model estimation

The estimation of the HMDC model entails finding estimates for the following sets of parameter vectors: avec(ρ), avec(Γ), avec($\check{\delta}$), avec($\check{d}$), avec($\check{\Sigma}$), avec(τ_{low}), avec(τ_{up}), avec(β), avec(λ), avec(Λ) and avec(γ) where avec is used to represent the vector of the parameter inside the parentheses. The estimates can be obtained by applying the maximum likelihood estimation technique. The likelihood function of the HMDC model can be expressed as the joint probability of observing the vector of continuous indicator $(y_c = i)$, the vector of ordinal indicators $(y_o = j)$ and the vector of consumption quantities for the K

goods (x). Furthermore, the probability of observing vector of ordinal indicator vectors (y_o) and the goods consumption (x) can be expressed in terms of the underlying propensity variables (y_o^*) and utility differences (μ^*) respectively. Denoting the vector of all parameters to be estimated as Θ, the likelihood function for the HMDC model formulation can be expressed as shown in Equation 4.9.

$$L(\Theta) = Pr(i, j, x|\Theta) = Pr\left(y_c = i, \tau_{low} < y_o^* < \tau_{up},\ \mu_{cm}^* = 0, \mu_{nm}^* < 0|\Theta\right) \quad (4.9)$$

where μ_{cm}^* and μ_{nm}^* represents $(M-1)$ and $(K-M)$ sized partitions of the vector μ^* respectively with $c = \{1,2, \dots, M-1\}$ and $n = \{(M+1), (M+2), \dots, K\}$ and M being the total number of alternatives that are consumed.

The joint probability in Equation 4.9 can be broken down into a marginal probability density function (PDF) and a conditional cumulative density function (CDF) as shown in Equation 4.10.

$$L(\Theta) = Pr\left(y_c = i, \mu_{cm}^* = 0|\Theta\right) \times Pr(\tau_{low} < y_o^* < \tau_{up}, \mu_{nm}^* < 0|y_c = i, \mu_{cm}^* = 0, \Theta\right) \quad (4.10)$$

The dimension of the joint CDF in Equation (4.10) can vary from G (representing the case where all available goods are consumed i.e. $M = K$) to $(G + K - 1)$ (representing the case where only one good is consumed i.e. $M = 1$). This high dimensionality of integral in the likelihood function above is evaluated by adopting the composite likelihood estimation (Varin 2008) along with an analytical approximation for the multivariate CDF called maximum approximated composite marginal likelihood (MACML) proposed by Bhat (2011).

4.2.2.1 Composite likelihood estimation

The multivariate CDF component in Equation 4.10 is evaluated by applying the pairwise CML approach[6]. In the HMDC, decomposing the integral using pairwise CML entails treating the non-chosen alternatives

[6] Under regularity condition CML estimators are consistent and asymptotically normally distributed; for a formal proof see Xu and Reid (2011).

as a single event (i.e. as a bundle). This process results in a total of ${}^{G}C_2$ (read as G choose 2 combinations and is evaluated as $\frac{G*(G-1)}{2}$) marginals of observing any two ordinal indicators and G marginals of observing an ordinal indicator along with the vector of non-chosen alternatives. Equation 4.11 presents the pairwise CML approximation of the likelihood function presented in Equation 4.10.

$$L_{PCML}(\Theta) = Pr(y_c = i, \mu_{cm}^* = 0|\Theta)$$
$$\times \left(\prod_{g=1}^{G-1}\prod_{g'=g+1}^{G} Pr\left(\tau_{low,g} < y_{o,g}^* < \tau_{up,g}; \tau_{low,g'} < y_{o,g'}^* < \tau_{up,g'}|y_c = i, \mu_{cm}^* = 0, \Theta\right)^{W}\right)$$
$$\times \left(\prod_{g=1}^{G} Pr\left(\tau_{low,g} < y_{o,g}^* < \tau_{up,g}; \mu_{nm}^* < 0|y_c = i, \mu_{cm}^* = 0, \Theta\right)^{W}\right) \tag{4.11}$$

The third probability component in the Equation 4.11 above is transformed so that the evaluation of orthant probability (i.e. bounded on both sides) is replaced with an evaluation of only cumulative probabilities (i.e. bounded on one side).

$$L_{PCML}(\Theta) = \Pr(y_c = i, \mu_{cm}^* = 0|\Theta)$$
$$\times \left(\prod_{g=1}^{G-1}\prod_{g'=g+1}^{G} Pr\left(\tau_{low,g} < y_{o,g}^* < \tau_{up,g}; \tau_{low,g'} < y_{o,g'}^* < \tau_{up,g'}|y_c = i, \mu_{cm}^* = 0, \Theta\right)^{W}\right)$$
$$\times \left(\prod_{g=1}^{G} \begin{pmatrix} Pr\left(y_{o,g}^* < \tau_{up,g}; \mu_{nm}^* < 0|y_c = i, \mu_{cm}^* = 0, \Theta\right) - \\ Pr\left(y_{o,g}^* < \tau_{low,g}; \mu_{nm}^* < 0|y_c = i, \mu_{cm}^* = 0, \Theta\right) \end{pmatrix}^{W}\right) \tag{4.12}$$

In Equations 4.11 and 4.12, W represents the weight. It can be seen that the second probability component of the pairwise likelihood expression in Equation 4.12 only involves the evaluation of bivariate normal CDF which is fairly easy to handle. However, the third probability expression still involves the evaluation of a multivariate normal CDF whose dimension can be as high as K. This multivariate normal CDF in the expression above is evaluated using the MACML analytical approximation.

4.2.2.2 Choice of weight

The dimension of the multivariate normal CDF to be approximated varies from one observation to another because of the presence of the MDC choice kernel wherein individuals choose a subset of the K goods. As a result, this requires that a weight other than unity be used to facilitate the recovery of the

population parameters (Joe and Lee 2009). Generally speaking, in the pairwise treatment of CML, each random variable (event) appears in $(m_i - 1)$ (where m_i is the size of the random vector for the i^{th} observation) number of probability calculations i.e. the number of pairs for each observation varies across observations and as a result the contribution of each observation to the overall likelihood of the sample also varies if unit weights are assumed. Weighting (i.e. $W \neq 1$) allows one to ensure that the contribution of each observation to the overall likelihood is proportional to the size of the random vector of that observation.

There are a number of studies on the selection of optimal weights that will improve efficiency of the parameter estimates. A review of the literature suggests that one of the main considerations for the choice of weights is the dependency structure (Joe and Lee 2009) among the multivariate random vectors. The most widely recommended and implemented weight for a moderate dependency structure is $\frac{1}{(m_i - 1)}$ (Kuk and Nott 2000, Zhao and Joe 2005). In estimating parameters of the HMDC, the following weights given by Equation (4.13) are proposed – this is analogous to $\frac{1}{(m_i - 1)}$ weight for clustered data.

$$W = \begin{cases} \frac{1}{G} & where, M < K \\ \frac{1}{(G-1)} & where, M = K \end{cases} \tag{4.13}$$

It can be noted that, in the HMDC formulation, the size of the integral (S) we are dealing with using CML approximation can be of the following two sizes – assuming the vector of the non-chosen alternatives, i.e. μ_{nm}^{*} to be a bundle or in other words of one dimension.

$$S = \begin{cases} G + 1 & where, M < K \\ G & where, M = K \end{cases} \tag{4.14}$$

Consequently, the CML approximation results in $\frac{(G+1)\times G}{2}$ and $\frac{G\times(G-1)}{2}$ number of pairwise marginal probabilities based on the relationship between M and K respectively. In order to make the contribution from each observation proportional to their respective size of the integrals (i.e. (G+1) and G), each of the resulting marginal probability pairs are weighted by $\frac{1}{G}$ and $\frac{1}{(G-1)}$ respectively.

4.2.2.3 Log-likelihood function

The log-likelihood function for the entire sample is shown in Equation 4.15.

$$LL(\Theta) = \sum_{n=1}^{N} \ln(L_{PCML,n}(\Theta)) \tag{4.15}$$

The above likelihood function and the associated gradients are implemented in matrix programming language GAUSS to obtain the parameter estimates $\hat{\Theta}_{PCML}$. Also, the variance-covariance matrix of the parameter estimates was obtained using the robust Gobambe sandwich estimator (Godambe 1960) shown in Equation 4.16 below.

$$V(\Theta) = (H[\Theta])^{-1}(J[\Theta])(H[\Theta])^{-1} \tag{4.16}$$

where, $H[\hat{\Theta}] = -\left(\sum_{n=1}^{N} \frac{\delta^2 lnL_{PCML,n}(\Theta)}{\delta\Theta\delta\Theta'}\right)_{\hat{\Theta}_{PCML}}$ and

$J[\hat{\Theta}] = \sum_{n=1}^{N}[(\frac{\ln(L_{PCML,n}(\Theta))}{\delta\Theta})(\frac{ln(L_{PCML,n}(\Theta))}{\delta\Theta'})]_{\hat{\Theta}_{PCML}}$. Section 4.3 presents a simulation study that demonstrates the ability of the proposed estimation technique for recovering consistent and efficient estimates of the model parameters.

4.3 Simulation Study

A simulation study was performed to assess the ability of the estimation technique to recover the parameters. The simulation study was aimed at mimicking the subsequent empirical application (see Section 4.4). However, simplifications were made with regard to the model and parameter specification for the different components of the HMDC model to enable rapid testing and ease of interpretation. In the simulation study, following assumptions were made with regard to the different components of the HMDC model specification:

i. With regard to the structural component of the latent variables, it was assumed that there are three latent variables (i.e. psychological factors) of interest. Further, each of the latent variables are assumed to be a function of two explanatory variables. All the 6 covariates of the structural equation of latent variable are generated from a $N[1,1]$ distribution.

ii. With regard to the measurement component of the latent variables, it was assumed that there are six indicators including two continuous and four ordinal indicators. Each latent variable is measured using a pair of indicator variables.

iii. With regard to the choice model component, it was assumed that there are five alternatives that the individual can consume. The baseline marginal utility equations for each of the five alternatives were assumed to be a function of a constant (normalized to zero for the first alternative), one observed explanatory variable and three latent variables. All the coefficients (including the coefficients of the latent variables) in the choice model are assumed to be alternative specific. The five covariates of the choice model utilities are generated from $N[0,1]$ distribution. Furthermore the budget for the MDC choice model was generated from $N[300,30]$ distribution.

The exogenous variables were generated only once and were kept fixed for the rest of the simulation study. The simulation study was conducted on simulated datasets of three different sizes namely: 1000, 2000 and 2500. For each sample size, 50 sets of observations were generated using different realizations of the error components η, $\breve{\xi}$, and ε. The variance covariance matrices assumed as well as the corresponding lower triangular Cholesky matrix for the error components η and ε are shown below. $\breve{\xi}$ is assumed to be an identity matrix and only the diagonal elements corresponding to the continuous indicators are estimated[7].

$$\Gamma = \begin{pmatrix} 1 & 0.5 & 0.5 \\ 0.5 & 1 & 0.683 \\ 0.5 & 0.683 & 1 \end{pmatrix} \qquad \equiv \qquad C_{\Gamma} = \begin{pmatrix} 1 & 0 & 0 \\ 0.5 & 0.866 & 0 \\ 0.5 & 0.5 & 0.707 \end{pmatrix}$$

[7] No correlation has been allowed between the errors of the measurement equation, which is not a restrictive assumption rather normalization similar to that suggested by Bollen (1989) and others. The behavioral interpretation for this normalization could be that the indicators are correlated because of their dependency on the common latent variables, and once we account for those common latent variables, no other correlation exists between the indicators.

$$\Lambda = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1.21 & 0.66 & 0 & 0 \\ 0 & 0.66 & 1.17 & 0 & 0 \\ 0 & 0 & 0 & 0.64 & 0.80 \\ 0 & 0 & 0 & 080 & 1.81 \end{pmatrix} \qquad \equiv \qquad C_\Lambda = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1.1 & 0 & 0 & 0 \\ 0 & 0.6 & 0.9 & 0 & 0 \\ 0 & 0 & 0 & 0.8 & 0 \\ 0 & 0 & 0 & 1 & 0.9 \end{pmatrix}$$

In the HMDC model estimation, for each of the three error components, the parameters of the variance-covariance matrices are not estimated directly instead the corresponding Cholesky factors are estimated. This was done to ensure that estimated parameter values result in positive definiteness of the variance-covariance matrices. Also, note that the first element in Λ was normalized to 1 for the purpose of identification (Train 2009). Lastly, as mentioned earlier in the formulation, all matrices associated with the error terms above represent variance-covariance matrix except Γ which represents a correlation matrix. One must ensure that the parameters that are retrieved for Γ correspond to a correlation matrix. This can be achieved by only estimating the off diagonal elements in the lower triangular portion of the corresponding Cholesky matrix (C_Γ) and then using the Equation 4.17 below to retrieve the i^{th} diagonal element.

$$c_{ii} = \sqrt{1 - \sum_{j=1}^{i-1} c_{ij}^2} \tag{4.17}$$

4.3.1 Simulation results

In order to assess the ability of the proposed estimation procedure in recovering the parameters, two measures namely Absolute Percentage Bias (APB) and Relative Asymptotic Efficiency (RAE) are used. APB is used to assess the bias in the parameter estimates and RAE is used to evaluate the asymptotic efficiency of the estimates. Equations for the measures are shown in Equation 4.18.

$$APB = \left|\frac{\text{True value} - \text{Estimate}}{\text{True value}}\right| \times 100\% \qquad \text{and} \qquad \text{RAE} = \frac{ASE}{\text{FSSE}} \tag{4.18}$$

where, ASE is the asymptotic standard error and is equal to the mean of the standard errors calculated using Godambe sandwich estimator given by Equation 4.16 across the fifty simulated datasets and $FSSE$ stands for the finite sample standard error and is equal to the standard deviation of the parameter estimates across the fifty sets of simulated data. Additionally, the confidence interval for the parameter estimates are also reported where the confidence interval is calculated using equation (4.19).

$$\text{Confidence Interval } (CI) = \text{ Estimated Value } \pm 1.96 * \text{Asymptotic Standard Error } (ASE) \qquad (4.19)$$

In general, the proposed estimation technique (and the estimators) appears to be promising with very good recovery of the parameter values both in terms of APB (indicating the degree of bias) and RAE (pointing to the asymptotic efficiency). Only the results obtained using the sample data set with size 2500 have been reported in Table 4.1[8,9].The average values of the APB and RAE across all the 59 parameters were found to be 0.636% (value close to zero indicating no bias) and 1.099 (value close to one indicating good asymptotic efficiency) respectively. The average values of APB and RAE were also checked separately for different group of parameters of the latent variable model and the MDC choice model and it was found that for all groups of parameters, the average value of APB was very close to 0 and the average RAE value varied in the acceptable range of 0.75 and 1.25 except for correlation parameters of the structural equation of latent variable. One plausible reason for this high RAE value of the correlation parameters might be owing to the fact that the Cholesky factors of these correlation parameters were further parameterized to ensure that we were estimating a correlation matrix instead of a variance covariance matrix. Also note that in the presented simulation study, the densest possible correlation matrix for the structural equation of the latent variable (i.e. allowed correlation between all the possible pairs of latent variables) was assumed. A less dense structure of the correlation matrix resulted in better RAE of the correlation parameters. We don't present results from this additional exploration for the sake of brevity. Additionally, the study of implications of error structures on the efficiency is an interesting

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[8] The average values (across all the parameters) of the APB and RAE for the 1000 sample data set are respectively 1.538% and 1.126; and the average values of the APB and RAE for the 2000 sample data set are respectively 1.112% and 1.131.

[9] The notation used to denote different set of parameters has been introduced in section 4.2, however we introduce suffix to differentiate between different parameters in Table 4.1. For example $\check{d}_{ij}$ represents the factor loading of the i^{th}indicator on the j^{th}latent variable, similarly λ_{ij} represents the coefficient of the j^{th} latent variable on the i^{th} choice alternative. Similarly the Cholesky factors of all the error components are denoted using c_{ij}, where i and j represents row and column indices respectively.

avenue for future research. Nonetheless, the simulation study provides substantial evidence towards good recovery of the parameter values and the performance of the proposed estimation technique (and the estimators) is very promising.

In the simulation study, to examine the importance of weights in setting up the CML function, parameters were also estimated by assuming a unit weight. The results (presented in Appendix[10]) highlight the differences in recovery of the parameters using weighted CML and unweighted CML in the presence of MDC choice kernel. As can be observed from the Table A.1 in the Appendix, large percentage bias values are observed (APB = 10.39%) when unit weight is assumed in CML approximation. Furthermore, the bias is much higher for most of the MDC choice kernel parameters (parameters with large bias percentages are highlighted in the Table). On the other hand, as reported in Table 4.1, weighted CML approximation reduces the bias percentages significantly. Use of weights brings the APB values of MDC choice kernel parameters to a range that is comparable with parameters of other components of the HMDC. It can be noted that, for simulation results with weight, the true parameter value always falls within the 95% confidence interval and the 95% confidence interval is quite tight around the true parameter value. However, for simulation results without weight, the true value falls outside the confidence interval for a good number of (13 out of 26) MDC parameters. This further highlights the importance of using weights in setting up the estimator using CML technique in the current scenario. These observations (which are in line with the work by Varin et al. 2011) point to the importance of using weights in the CML approximation to ensure good recovery of the parameters when the size of the vector (to be dealt with CML) varies across observations.

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[10] The results reported in Table A.1 are comparable with those reported in Table 4.1, because the same set of simulated data have been used for producing these two sets of results. Both the tables report the summary results obtained from 50 independent model runs.

Table 4.1 Simulation Results

Parameters	True Values	Estimated Values	Absolute Percentage Bias (APB)	Asymptotic Standard Error (ASE)	Finite Sample Standard Error (FSSE)	Relative Asymptotic Efficiency (RAE)	Confidence Interval	Contains True Value?
α_1	1.1	1.0981	0.1696	0.0300	0.0273	1.1007	(1.04) - (1.16)	Yes
α_2	1.7	1.7009	0.0516	0.0391	0.0379	1.0333	(1.62) - (1.78)	Yes
α_3	1.2	1.2114	0.9495	0.051	0.0654	0.7795	(1.11) - (1.31)	Yes
α_4	1.8	1.8023	0.1298	0.0693	0.0711	0.975	(1.67) - (1.94)	Yes
α_5	1.4	1.3985	0.1097	0.0899	0.0619	1.4539	(1.22) - (1.57)	Yes
α_6	1.6	1.5861	0.8698	0.1006	0.0683	1.4736	(1.39) - (1.78)	Yes
Γ_{21}	0.5	0.506	1.1954	0.0381	0.0281	1.3584	(0.43) - (0.58)	Yes
Γ_{31}	0.5	0.4999	0.0296	0.0452	0.0249	1.8157	(0.41) - (0.59)	Yes
Γ_{32}	0.5	0.5144	2.8809	0.0655	0.0425	1.5416	(0.39) - (0.64)	Yes
$\bar{\delta}_1$	-1.1	-1.1062	0.5652	0.0473	0.0427	1.1088	(-1.2) - (-1.01)	Yes
$\bar{\delta}_2$	-1.7	-1.7003	0.0156	0.0498	0.0498	1.0014	(-1.8) - (-1.6)	Yes
$\bar{\delta}_3$	-2.5	-2.4864	0.5441	0.1489	0.1588	0.9377	(-2.78) - (-2.19)	Yes
$\bar{\delta}_4$	-2	-1.9931	0.3432	0.1076	0.1184	0.9084	(-2.2) - (-1.78)	Yes
$\bar{\delta}_5$	-2	-1.9707	1.4635	0.1161	0.1005	1.1553	(-2.2) - (-1.74)	Yes
$\bar{\delta}_6$	-2.8	-2.7736	0.9433	0.1725	0.1636	1.0549	(-3.11) - (-2.44)	Yes
$\bar{d}_{11}$	1	1.0011	0.1087	0.0207	0.0202	1.0266	(0.96) - (1.04)	Yes
$\bar{d}_{21}$	1.1	1.1006	0.0589	0.0224	0.0212	1.0563	(1.06) - (1.14)	Yes
$\bar{d}_{32}$	1.2	1.2153	1.2737	0.0852	0.0876	0.9724	(1.05) - (1.38)	Yes
$\bar{d}_{42}$	1	1.0111	1.1134	0.061	0.0694	0.8788	(0.89) - (1.13)	Yes
$\bar{d}_{53}$	1.1	1.1201	1.8261	0.0928	0.0762	1.2179	(0.94) - (1.3)	Yes
$\bar{d}_{63}$	1.3	1.3206	1.5832	0.1224	0.0898	1.3635	(1.08) - (1.56)	Yes
Σ_{11}	1	0.9983	0.1675	0.0192	0.0169	1.1361	(0.96) - (1.04)	Yes
Σ_{22}	1	0.9954	0.4555	0.0209	0.0203	1.0301	(0.95) - (1.04)	Yes
β_1	-1	-1.0004	0.0355	0.1707	0.1499	1.1385	(-1.33) - (-0.67)	Yes
β_2	2	1.9907	0.4644	0.1693	0.1510	1.1206	(1.66) - (2.32)	Yes
β_3	-2	-1.9879	0.6059	0.1751	0.1578	1.1097	(-2.33) - (-1.64)	Yes
β_4	2.5	2.5106	0.4257	0.2129	0.1683	1.2653	(2.09) - (2.93)	Yes
β_5	-1	-0.9944	0.5576	0.0593	0.0678	0.8752	(-1.11) - (-0.88)	Yes
β_6	3	2.9991	0.0309	0.0604	0.0736	0.8215	(2.88) - (3.12)	Yes

Table 4.1 Simulation Results (Continued)

Parameters	True Values	Estimated Values	Absolute Percentage Bias (APB)	Asymptotic Standard Error (ASE)	Finite Sample Standard Error (FSSE)	Relative Asymptotic Efficiency (RAE)	Confidence Interval	Contains True Value?
β_7	-1	-0.9996	0.0353	0.0292	0.0329	0.8881	(-1.06) - (-0.94)	Yes
β_8	3.5	3.4924	0.2164	0.0801	0.0801	0.9999	(3.34) - (3.65)	Yes
β_9	-3.5	-3.5231	0.6599	0.1043	0.1075	0.9701	(-3.73) - (-3.32)	Yes
λ_{21}	-1.5	-1.4902	0.6544	0.0555	0.0556	0.9982	(-1.6) - (-1.38)	Yes
λ_{22}	1.2	1.2063	0.5278	0.0575	0.0556	1.0333	(1.09) - (1.32)	Yes
λ_{23}	1.1	1.1095	0.8666	0.0773	0.0506	1.528	(0.96) - (1.26)	Yes
λ_{31}	-1.6	-1.5896	0.6489	0.056	0.0583	0.9596	(-1.7) - (-1.48)	Yes
λ_{32}	1.1	1.1029	0.2631	0.0537	0.0476	1.1291	(1) - (1.21)	Yes
λ_{33}	1	1.0083	0.8293	0.0713	0.0455	1.5668	(0.87) - (1.15)	Yes
λ_{41}	-1.4	-1.3945	0.3919	0.0543	0.0591	0.9183	(-1.5) - (-1.29)	Yes
λ_{42}	1.3	1.3028	0.2174	0.0608	0.0540	1.1244	(1.18) - (1.42)	Yes
λ_{43}	1.1	1.1145	1.3181	0.0778	0.0500	1.5545	(0.96) - (1.27)	Yes
λ_{51}	-3	-2.9975	0.0831	0.0901	0.0930	0.9685	(-3.17) - (-2.82)	Yes
λ_{52}	1	1.0009	0.0915	0.0551	0.0482	1.1432	(0.89) - (1.11)	Yes
λ_{53}	1	1.0147	1.4705	0.0748	0.0625	1.1968	(0.87) - (1.16)	Yes
γ_1	1.5	1.4898	0.6774	0.1061	0.1091	0.9723	(1.28) - (1.7)	Yes
γ_2	1.8	1.7972	0.1528	0.0811	0.0883	0.9187	(1.64) - (1.96)	Yes
γ_3	2.2	2.2339	1.5411	0.0815	0.1035	0.7879	(2.07) - (2.39)	Yes
γ_4	2.5	2.4809	0.7639	0.089	0.0821	1.0835	(2.31) - (2.66)	Yes
γ_5	2.8	2.7999	0.0051	0.1141	0.0997	1.1443	(2.58) - (3.02)	Yes
Λ_{22}	1.1	1.1002	0.0144	0.0551	0.0653	0.8432	(0.99) - (1.21)	Yes
Λ_{32}	0.6	0.5927	1.2234	0.0674	0.0662	1.0181	(0.46) - (0.72)	Yes
Λ_{33}	0.9	0.8875	1.3842	0.0272	0.0258	1.0554	(0.83) - (0.94)	Yes
Λ_{44}	0.8	0.7901	1.2316	0.0681	0.0613	1.1111	(0.66) - (0.92)	Yes
Λ_{54}	1	1.0016	0.1595	0.1046	0.0785	1.3327	(0.8) - (1.21)	Yes
Λ_{55}	0.9	0.9027	0.3016	0.0768	0.0710	1.0825	(0.75) - (1.05)	Yes
$\tau_{up,1}$	1.5	1.5114	0.7603	0.0815	0.0853	0.9548	(1.35) - (1.67)	Yes
$\tau_{up,2}$	1.5	1.4975	0.1636	0.0676	0.0852	0.7938	(1.37) - (1.63)	Yes
$\tau_{up,3}$	1.5	1.5161	1.0741	0.0735	0.0725	1.0129	(1.37) - (1.66)	Yes
$\tau_{up,4}$	1.5	1.5121	0.8038	0.0876	0.0845	1.0361	(1.34) - (1.68)	Yes
Mean			**0.6356**			**1.0989**		

4.4 Empirical Study

The primary purpose of the empirical study was to demonstrate the feasibility and applicability of the proposed HMDC model implementation for exploring the association between psychological factors and MDC choice dimensions. To this end, the association between moods experienced by an individual and their daily activity engagement choices were explored to understand the heterogeneity in individual activity participation and time allocation behaviors. The choice of the empirical study was motivated also in part due to gaps in the empirical literature. While there is a rich body of literature exploring the role of psychological factors on the different dimensions of travel choices (Anable 2005, Glerum and Bierlaire 2012, Alvarez-Daziano and Bolduc 2013, Atasoy et al. 2013, Kamargianni and Polydoropoulou 2013, Hess and Spitz 2016), literature exploring the relationship between psychological factors and the activity engagement choices of individuals is limited (Ettema et al. 2010, Abou-Zeid and Ben-Akiva 2012, Ravulaparthy et al. 2013). The study of the daily activity engagement choices is important because it helps better understand the factors influencing travel and subsequently allows the design of effective policies aimed at managing travel demand (Kitamura 1988, Pendyala and Bhat 2004, Chen and Mokhtarian 2006).

In the following subsections, the study motivation, data composition, model setup, estimation results, and validation analysis are presented.

4.4.1 Study motivation

4.4.1.1 Moods and behaviors

While traditional decision theories postulate decision making as a cognitive process, behavioral decision theories have increasingly emphasized the role of emotions/moods on decision making process as well as on the choice outcomes (Loewenstein and Lerner 2003). Loewenstein and Lerner (2003) identify two ways in which behavior can be influenced by the affect or emotions. According to authors, on one hand, individual behavior can be shaped by the expected emotion that would arise from the decision outcome. On the other hand, there is the immediate influence of the mood experienced at the time of making a choice which might not only impact the decision making process but also the decision outcome. Clark

(2006) defines mood as a prevailing psychological state, feeling, or emotion which may be habitual or temporary. Decades of experimental work performed by behavioral psychologists show that positive and negative moods (emotions) have distinct effects on an individual's decision making process as well as on decision outcome (Fredrickson 2001, Isen 2001). For example, Fredrickson (2001) notes that a positive mood is associated with "broad, flexible cognitive organization and the ability to integrate diverse material" in the decision making process. On the other hand, a negative mood has been associated with narrowing individuals' attention while making decisions. Forgas (1989) studied the influence of both positive and negative moods in social decision making context. He notes that, sad people use comparatively direct search strategies at arriving decisions compared to happy people and also tend to prefer rewarding outcomes. In the current study, we explore the correlation between the moods that the individual experiences over the course of a day, and the activity participation and time allocation behaviors. This is in line with the exploration of influence of mood at the time of decision making postulated by Loewenstein and Lerner (2003).

4.4.1.2 Moods and activity-travel choices

There is research suggesting that cognitive and affective states of an individual contain both stable (Fredrick and Loewenstein 1999) and variable components (Oishi et al.1999). Also, researchers have shown that it is possible to identify the "stable" component of cognitive and affective states at the level of days or weeks (Gadermann and Zumbo 2007). Drawing on the work from the field of behavioral psychology and decision theory, current research aims to identify the association between "day level moods" and activity participation and time allocation decisions. Day level mood is defined as the "stable" state, feeling, or emotion that the individual experiences over the course of a day. It is the influence of this "stable" mood on activity engagement choices that is explored in this study. From this point forward, the "stable" component of the individual's mood will be referred to as merely moods.

In the context of activity-travel choices, there is recent research exploring how activity and travel choices impact the moods experienced. For example, Morris and Guerra (2015) explored the role of travel mode on the mood experienced. Mokhtarian et al. (2015) identify the influence of different trip attributes

such as trip length, distance, purpose, mode on the fatigue experienced during travel. Similarly, Legrain et al. (2015) investigate most stressful mode of commute using a university wide travel survey. The current research attempts to explore the alternative association wherein the moods that sustain over the course of a day influence the daily discretionary activity engagement choices. This is done while controlling for the impact of other exogenous variables that contribute to heterogeneity in activity engagement choices[11]. Considering moods allows us to account for unobserved heterogeneity in the decision making process due to the differences in moods experienced (in addition to other observed explanatory variables) which would have been attributed to random error components otherwise (Hess 2012). Additionally, adopting the ICLV framework to include mood in exploring activity participation and time allocation behavior allows us to disentangle the influence of the observed explanatory variables into constituent components: 1) their direct influence on the activity participation and time allocation choices and 2) their indirect influence through their correlation with the latent mood variables (Vij and Walker 2016).

4.4.1.3 Activity engagement choices

In the empirical exploration, discretionary activity engagement choices are of interest. Discretionary activities offer the most flexibility in terms of their planning and scheduling when compared with other activities (e.g. work, education and maintenance activities to some extent). As a result, they are also the most amenable to being influenced by the factors of interest (including moods). The use of HMDC for the empirical exploration is appropriate because discretionary activity engagement requires handling multiple choice dimensions simultaneously. First, there is the discrete choice of participating in an activity and there is the continuous choice of amount of time spent in the activity, and second, there are multiple

[11] Also, the authors recognize that the relationship between the moods and the activity engagement choices is not one directional. In particular, the "variable" component of the moods also affect activity engagement choices, and activity participation and time allocation choices in turn affect "variable" component of moods. The evolution of the "variable" component of the moods (and other cognitive and affective states) are not the focus of this paper.

instances of these participation and time use variables because an individual could participate in multiple discretionary activity types over the course of a day. Thus discretionary activity engagement results in a multiple discrete continuous (MDC) choice situation.

4.4.1.4 Study objectives

The purpose of the case study is to investigate the influence of moods on choice outcome such as discretionary activity engagement behavior. More specifically, the study attempts to examine if higher levels of positive moods is associated with less passive leisure and higher participation in other types of discretionary activities. Alternatively, also of interest is whether high levels of negative moods would have the opposite association (i.e. more passive leisure and less participation in other discretionary activity types). This hypothesis is partly derived from the research that suggests positive association between negative moods and narrowing of attention while selecting between alternatives. It is postulated that, a direct search (under the influence of negative moods) would more often lead the individual into the most obvious choice of discretionary activity which is passive leisure, whereas a proactive search (under the influence of positive moods) would lead them to consider various options for discretionary activity participation and time allocation behavior. It is acknowledged that activity participation in turn can affect the moods experienced (in particular the "variable" component of the moods) (Ettema et al. 2010). However, it is posited that there is a "stable" component of the moods (both positive and/or negative) that may sustain over the course of the given day in an individual's life. It is the association between these sustained moods and the discretionary activity engagement choices that are of interest in this research.

4.4.2 Data composition

The data used for the empirical study was drawn from the 2013 American Time Use Survey (ATUS). ATUS is cross-sectional survey collecting information about the activity engagement choices from a representative sample of individuals across the US since 2003. The survey follows an activity diary format asking a single individual (over the age of 15 years) from a household to report all the activities performed over a full 24 hour period. Individuals are also asked to provide a detailed account of the different activity characteristics including activity duration, location, and accompaniment type among

other information. More recently, ATUS started administering supplemental modules to collect additional information regarding various psychological factors of interest. In the well-being module (that is of interest in this study), people are asked to report their general health and life satisfaction. Additionally, people are asked to rate their feeling with respect to 5 moods: happiness, sadness, pain, stress and tiredness for three randomly chosen time intervals during the day on a scale of 0 to 6.

Respondents in the dataset for whom the total activity durations did not add up to 1440 minutes or those who had invalid responses for the questions regarding moods were excluded from the analysis. This data preparation process resulted in 4002 observations. A quarter of the sample was set aside to perform a holdout sample validation. The remaining sample available for model estimation and subsequent empirical exploration comprised of 3025 observations. As noted earlier, the discretionary activity engagement choices were of interest in this study; fixed activities and maintenance activities were not considered in the analysis. The discretionary activities were categorized into six types namely: 1) active leisure, 2) passive leisure, 3) physical activity, 4) shopping for non-maintenance, 5) attending sports and arts events, and 6) social activity.

A brief description of the six discretionary activity types along with the percentage of respondents who participated in each of the particular discretionary activity types and the average amount of time spent in the discretionary activity type are reported in Table 4.2. It should be noted that the mean activity duration is the average across all respondents who have reported participating in the activity type on the survey day. As can be seen from Table 4.2, almost 90 percent of the respondents participated in some form of passive leisure during weekends; this activity type also was used as the reference activity type in the HMDC model specification. A little less than half of the respondents reported participating in some form of active leisure and social activity. Passive leisure had the highest mean duration, followed by attending sports and arts events. Similar to the participation rates, the average duration for active leisure and social activity appear to be similar. Finally, shopping for non-maintenance has the lowest mean duration across all discretionary activity types.

Table 4.2 Weekend Discretionary Activity Participation and Time Allocation

Activity Category	Activity Description	Participation (%)	Mean Duration (Minutes)[1]
Active leisure	Playing games, using computer for leisure, pursuing hobbies (arts and crafts, collecting), leisure reading, leisure writing	45	153
Passive leisure	Relaxing, thinking, using tobacco and drug, watching television, listening to the radio, listening to or playing music	88	256
Physical activity	Participating in sports, exercise, recreation	18	122
Shopping for non-maintenance	Shopping except for food, groceries and gas	25	81
Attending sports and arts events	Attending performing arts, attending museums, movies, films, gambling, other arts and entertainment, attending sporting and recreational events	6	190
Social activity	Socializing and communicating, attending and hosting social events	47	147

Notes:
(1) Mean duration has been calculated on only across the individuals who have reported to participate into at least one episode of a particular type of activity

4.4.3 Exploratory analysis

A descriptive analysis was first conducted to test the stability of the five types of mood variables across the day. As mentioned earlier, in the AUTS respondents were asked to report the five moods at three random time points across the day on a scale of 0 to 6. Descriptive analysis revealed that the reported moods remained very stable across the day with minimal variation. For example for the negative moods such as pain and tiredness, about 80 to 90 percent people showed a variation of 1 unit or less across the day. For the rest of the moods, such as happiness, stress and tiredness the percentage of people showing a variation of less than or equal to 1 unit varied from about 70 to 80 percent. For all the five types of moods less than 5 percent of people showed a variation of more than or equal to 3 units across the day. These results provide credence to our assumption that the mood variables represent stable, day-level moods that are not influenced by activity participation; instead, they can potentially influence daily activity participation behavior.

Descriptive analysis was followed by exploratory factor analysis to explore the structure of the latent constructs of overall positive and negative moods that sustained throughout the day. There could be multiple constructs of positive and negative moods. The latent constructs were developed based on indicators regarding the levels of five moods: happiness, sadness, pain, stress and tiredness reported at three random time periods during the day. An exploratory factor analysis was performed using the fifteen indicator variables without specifying any prior structure for the factors. The process resulted in five latent constructs of moods with the indicators of the same mood at the different time periods loading onto the same latent construct. Therefore, the five latent constructs can be described as capturing the five moods of happiness, sadness, pain, stress and tiredness and also they seem to sustain throughout the day with little variability. This result was not surprising. The stability of moods throughout the day may partly be attributed to the data collection approach. In the survey, users were asked to provide information about the moods not during the act of participating in the activity but after the fact. It is reasonable to assume that in such a context, it is only the feelings that they experienced/sustained throughout the day that will be remembered and thus reported.

Following the exploratory factor analysis, the HMDC model was estimated with five latent variables identified using three indicators each. Further, the choice model consisted of a multiple discrete continuous kernel that models both the participation and time use decisions for the six discretionary activity types. Section 4.4.4 presents the HMDC model estimation results.

4.4.4 Model Estimation Results

Table 4.3 summarizes the parameter estimates for the structural equations of the latent variables. Results from the measurement equations of the latent variables are presented in Table 4.4. Finally, parameter estimates for the multiple discrete continuous choice model are reported in Table 4.5 and 4.6. The t-statistics for the coefficient estimates are reported in the parentheses. The total number of parameters estimated in the model is 210 and the mean value of the log-likelihood function at convergence is -34.6150. The model estimation results obtained were behaviorally plausible and consistent with expectations. A detailed discussion of the results is presented in the following subsections.

Table 4.3 Estimation Results for the Structural Equation Model of Latent Variables

	Happiness	Pain	Sadness	Stress	Tiredness
Indicators to exogenous variables					
Female indicator	0.1749 (3.971)	0.0832 (2.193)	0.0773 (1.873)	0.2595 (6.038)	0.3261 (7.876)
Middle Income ($25 - $50 K)[1]		-0.2311 (-3.951)	-0.2094 (-3.521)	-0.1228 (-2.081)	-0.0732 (-1.578)
High Income ($50 - $100 Thousand)[1]		-0.1801 (-3.241)	-0.1749 (-2.918)	-0.1409 (-2.522)	
Very High Income (>$100 Thousand)[1]		-0.2854 (-4.856)	-0.2047 (-3.142)	-0.1609 (-2.593)	
Age 35 to 54[2]		0.2744 (6.377)	0.1877 (4.238)		-0.0935 (-2.018)
Age 55 to 64[2]	0.1313 (2.219)	0.4186 (6.947)	0.2207 (3.409)	-0.286 (-5.079)	-0.2462 (-3.905)
Age 65 & above[2]	0.2225 (3.702)	0.3749 (6.59)	0.1723 (2.882)	-0.3957 (-7.326)	-0.4445 (-7.305)
High school graduate[3]				0.1268 (2.684)	
College graduate[3]	-0.2021 (-4.245)			0.2083 (3.938)	
Post graduate[3]	-0.4316 (-6.659)	-0.1129 (-2.457)		0.336 (5.125)	
Presence of spouse or partner	0.2122 (4.873)	-0.0614 (-1.657)	-0.1392 (-3.741)		
Unemployment					-0.1996 (-2.865)
Health condition very good[4]	0.681 (5.021)	-1.5286 (-9.793)	-1.0292 (-5.881)	-0.9066 (-5.553)	-1.0505 (-8.806)
Health condition good[4]	0.4808 (3.619)	-1.0949 (-7.035)	-0.7944 (-4.525)	-0.7053 (-4.385)	-0.8001 (-6.926)
Life condition poor[5]	-1.2488 (-9.043)	0.6225 (4.717)	1.2525 (6.984)	1.2329 (7.875)	0.9511 (8.637)
Life condition good[5]	-0.6474 (-11.788)	0.2598 (5.436)	0.4882 (9.177)	0.5321 (9.476)	0.3186 (6.491)
Lower triangular Cholesky factors of the correlation matrix					
Happiness	1				
Pain	-0.1422 (-5.676)	0.9898			
Sadness	-0.3948 (-11.663)	0.3001 (9.666)	0.8684		
Stress	-0.3866 (-11.627)	0.3542 (11.34)	0.5786 (13.889)	0.6248	
Tiredness	-0.2211 (-8.556)	0.3743 (14.488)	0.2006 (7.593)	0.3623 (10.454)	0.7997

Notes: (1) Values in the parentheses represent t-statistics.
(2) Base: Income below $25,00 K
(3) Base: Age below 35 years old
(4) Base: Less than high school education
(5) Base: Poor health condition
(6) Base: Very good life condition

Table 4.4 Estimation Results for the Measurement Equation Model of Latent Variables

	Constants	Standard Deviation	Loading on Happiness	Loading on Pain	Loading on Sadness	Loading on Stress	Loading on Tiredness
Indicator1	4.1239 (31.944)	1.1216 (37.093)	0.8981 (30.723)				
Indicator2	3.9851 (26.996)	1.0867 (32.521)	1.0445 (31.174)				
Indicator3	3.9767 (27.061)	1.0959 (37.702)	1.03 (31.87)				
Indicator4	2.2478 (11.826)	0.8649 (27.194)		1.2136 (40.646)			
Indicator5	2.2877 (11.344)	0.5876 (16.561)		1.3048 (43.426)			
Indicator6	2.2463 (11.741)	0.8391 (25.621)		1.2244 (40.613)			
Indicator7	1.2093 (7.629)	0.8942 (27.294)			0.8687 (25.302)		
Indicator8	1.1819 (7.511)	0.8017 (22.911)			0.881 (25.347)		
Indicator9	1.1502 (7.59)	0.8268 (25.181)			0.851 (25.525)		
Indicator10	1.7383 (9.529)	1.1459 (39.53)				1.0932 (21.778)	
Indicator11	1.6611 (8.692)	1.0158 (33.18)				1.153 (21.847)	
Indicator12	1.5193 (8.837)	1.0894 (38.23)				1.0357 (23.19)	
Indicator13	2.8038 (18.647)	1.3196 (47.503)					1.2022 (35.132)
Indicator14	3.0506 (17.109)	0.9496 (26.92)					1.4854 (34.745)
Indicator15	3.4224 (21.773)	1.4169 (53.65)					1.2972 (32.984)

Notes: (1) Values in the parentheses represent t-statistics.

4.4.4.1 Structural equation model of latent variables

The estimates of parameters in the structural equation (SE) provide valuable information regarding the variation of the latent construct with changes in observed explanatory variables. The choice of the explanatory variables used was based on a review of previous research from the field of happiness (or the lack of it) (Clark 2006 and Gerdtham and Johannesson 2001). The different variables used in the SE model include socio-economic characteristics such as gender, age, household income, education level, presence of spouse or partner as well as unemployment indicator. Additionally, it was hypothesized that the overall health and life satisfaction (which can be thought of as a proxy for the overall well-being of individual) will also have a strong influence on the daily moods experienced/exhibited by individuals.

Most of the coefficients are statistically significant and provide plausible behavioral interpretations. Females appear to have a higher level of both positive and negative moods. Individuals with higher income are generally found to be associated with lower negative moods. However, it was interesting to find that income didn’t have a significant impact on happiness itself. This observation is in line with earlier research from the field of happiness where it was also found that higher income does not necessarily make people happier despite general belief that it would (Kahneman et al. 2006). It was found that positive and negative moods seem to vary in differing ways across various age groups. For example, people above 55 years old seem to be happier as well as less stressed and less tired compared to others. On the other hand with regard to the negative moods of pain and sadness it appears like they are increasing with aging in general. Education attainment was found to significantly impact happiness and stress. Individuals who have high levels of educational attainment are found to be less happy – it may be likely that individuals who are highly educated may generally be more critical about their feeling of happiness. Also, there is a significant trend of increased stress with higher levels of education attainment.

Presence of spouse or partner in the household appears to have a positive impact on the happiness and negative impact on the feelings of pain and sadness. The effect of unemployment was found to be significant only for tiredness. It is plausible that people who are unemployed for long durations tend to get used to their circumstances and do not let their employment status influence their general moods.

There is also evidence to this end in the area of happiness (e.g. Clark 2006). Finally, both the conditions of health and life were found to have a very substantial influence (both in terms of statistical significance and magnitude of the coefficient estimates) on moods. As one would expect, good health was found to be negatively associated with all 4 negative moods and positively associated with feeling of happiness. Similar association was also observed for evaluation of overall life satisfaction on the different moods wherein poor life satisfaction was associated with higher levels of negative moods and also with lower level of happiness. It should be noted that, the significant contribution of health and life condition of individual on the latent constructs (i.e. mood) further lend evidence on the stability of these affective states of individual and supports the validity of the day level construction of mood in this particular empirical context.

One of the many desirable features of the HMDC formulation is its ability to accommodate correlations between error terms due to unobserved explanatory variables. A full correlation matrix across the five latent constructs was explored and the estimates of the lower triangular Cholesky matrix corresponding to the correlation matrix are reported in Table 4.3. It can be seen that all estimates of the lower triangular Cholesky values are very significant. The correlation matrix corresponding to the Cholesky values is reported below:

$$\Gamma = \begin{pmatrix} & \textbf{Happiness} & \textbf{Pain} & \textbf{Sadness} & \textbf{Stress} & \textbf{Tiredness} \\ \textbf{Happiness} & 1 & -0.1422 & -0.3948 & -0.3866 & -0.2211 \\ \textbf{Pain} & -0.1422 & 1 & 0.3532 & 0.4056 & 0.4019 \\ \textbf{Sadness} & -0.3948 & 0.3532 & 1 & 0.7614 & 0.3738 \\ \textbf{Stress} & -0.3866 & 0.4056 & 0.7614 & 1 & 0.5605 \\ \textbf{Tiredness} & -0.2211 & 0.4019 & 0.3738 & 0.5605 & 1 \end{pmatrix}$$

As expected, the feeling of happiness is negatively correlated with all the four negative moods while the four negative moods are positively correlated to each other. Also, among the five moods, stress seems to have the strongest correlation with the rest of the moods. The magnitude of correlation between stress and sadness is the highest.

4.4.4.2 Measurement equation model of latent variables

The purpose of the measurement equation is to help define the underlying latent constructs. In the empirical study the indicators are treated as continuous indicators. The measurement equation parameter estimates themselves do not provide any interesting behavioral insights. As noted earlier as part of the exploratory factor analysis, all the indicators load positively and significantly on each of the 5 latent moods further validating the construction/definition of the latent variables as moods that sustain over the course of a day.

4.4.4.3 Multiple discrete continuous (MDC) choice model

The parameter estimates for the MDC choice model are presented in this subsection. The influence of observed exogenous variables are presented first followed by a discussion of the association between moods and the weekend discretionary activity engagement behaviors.

The choice of the exogenous variables in the MDC model was motivated by previous research on the topic of activity engagement (Srinivasan and Bhat 2006, Pinjari and Bhat 2010, Garikapati et al. 2014 among others). The findings are in line with the earlier literature on the topic. Also it should be noted that, some of the exogenous variables explored in the MDC model were also included in the structural equation model of the latent variables. In other words there is a direct influence of the observed explanatory variables and there is also an indirect effect of these variables mediated through the latent variable. In this section, only the direct influence of the observed exogenous variables on the discretionary activity participation and time allocation decisions are discussed[12]. A number of household- and person-level exogenous variables were explored. Additionally, built environment variables and day of week for which

[12] An analysis of the total effect of different exogenous variables (calculated from the direct and indirect effect) did not reveal any change in the sign of the coefficient corresponding to different exogenous variables.

activities are reported are used to further explain the heterogeneity in the activity engagement behaviors. Lastly, the latent constructs are used to understand the role of moods.

Baseline marginal utility

Results for the baseline marginal utility (see Table 4.5) which provide insights into the participation choices (i.e. what activities to participate in) of the individuals are discussed in this subsection. Passive leisure was chosen as the reference alternative. The constants of the MDC choice model capture the influence of the average unexplained effect after accounting for different exogenous and endogenous variables. Both the signs and the magnitudes of the constants are consistent with expectations. All else being equal, passive leisure was found to be the most popular discretionary activity to participate in followed by social activity and active leisure; individuals appear to have the least propensity to participate in attending sports and arts events.

Table 4.5 Estimation Results for the Multiple Discrete Continuous Choice Model (Baseline Marginal Utility)

	Active leisure	Physical activity	Non maintenance shopping	Attending sports and arts events	Social activity
Coefficients to the exogenous variables					
Constants	-1.6013 (-19.15)	-2.2099 (-17.311)	-2.1471 (-18.364)	-3.1597 (-11.309)	-1.4192 (-17.035)
Individual level characteristics					
Female indicator	0.3787 (6.851)		0.2624 (4.314)	0.2044 (2.672)	0.4217 (7.613)
Young age indicator	0.1472 (2.292)	0.1266 (1.589)		0.2003 (2.311)	
Old Age indicator	0.2725 (4.474)	-0.1935 (-2.18)			
Student indicator		0.3107 (3.087)			
Employment indicator		0.1122 (1.679)	0.2744 (4.6)	0.2716 (3.432)	0.1515 (3.198)
Disability indicator	-0.1908 (-1.987)	-0.485 (-3.493)	-0.4889 (-4.055)	-0.3065 (-1.874)	-0.3554 (-3.941)
Household level characteristics					
HH income indicator ($25 to $50 K)				0.1188 (1.392)	
HH income indicator ($50 to $100 K)	0.1795 (2.871)	0.1827 (2.486)			
HH income indicator (More than $100 K)	0.429 (4.417)	0.5086 (4.81)	0.2304 (2.359)	0.3739 (3.21)	0.113 (1.321)
Spouse/partner indicator				0.1568 (2.097)	
Presence of kid indicator (Age 0-5)	0.2424 (4.019)		0.0931 (1.319)		
Presence of kid indicator (Age 6-12)				-0.2787 (-2.529)	
Presence of kid indicator (Age 13-17)			0.1575 (1.783)		0.1078 (1.511)
Built environment characteristic					
Metropolitan indicator			-0.1732 (-2.28)		
Day of week indicator					
Saturday indicator	0.0791 (1.622)	0.1265 (2.093)	0.2985 (5.224)	0.358 (4.397)	0.0659 (1.421)
Coefficients to the endogenous latent variable					
Happiness	-0.0533 (-1.656)	0.1375 (3.41)	0.0041 (0.109)	0.1391 (2.687)	0.1127 (3.572)
Pain	-0.0715 (-2.242)	-0.0923 (-2.339)	-0.0358 (-1.019)	-0.1382 (-2.451)	-0.0543 (-1.852)
Sadness	-0.0747 (-1.329)	0.0193 (0.248)	-0.2854 (-4.144)	-0.2322 (-2.509)	-0.1111 (-2.039)
Stress	0.1106 (1.679)	0.0463 (0.516)	0.3788 (4.955)	0.3546 (3.4)	0.2202 (3.53)
Tiredness	-0.0557 (-1.398)	0.0421 (0.822)	-0.1057 (-2.331)	-0.0084 (-0.135)	-0.0301 (-0.802)

Table 4.6 Estimation Results for the Multiple Discrete Continuous Choice Model (Satiation Parameter)

	Active leisure	Passive leisure	Physical activity	Non maintenance shopping	Attending sports and arts events	Social activity
Coefficients to the exogenous variables						
Constants	5.2008 (53.88)	5.1603(59.266)	5.4227 (39.278)	4.4034 (36.711)	7.5567 (13.302)	5.3042 (46.659)
Individual level characteristics						
Female indicator	-0.169 (-1.882)		-0.4885 (-4.002)	0.2183 (2.24)		-0.2001 (-2.101)
Young age indicator	0.2537 (2.429)			0.177 (1.717)		0.2833 (2.727)
Old Age indicator						-0.3797 (-3.635)
Household level characteristics						
HH income indicator ($25 to $50 K)		-0.2565 (-3.166)	0.2859 (1.858)			
HH income indicator ($50 to $100 K)	-0.1967 (-1.919)	-0.1913 (-2.243)				
HH income indicator (More than $100 K)	-0.3889 (-3.549)	-0.2818 (-2.186)		0.1606 (1.466)		

Notes: (1) Values in the parentheses represent t-statistics.

Female respondents appear to participate more in social activity, active leisure, non-maintenance shopping and sports and arts events compared to male respondents. Younger individuals (ages 15 to 34 years) appear to have a higher propensity to engage in active leisure compared to individuals belonging to middle age group (35 to 64 years). This propensity seems to be even higher for the elderly (above 65 years). As expected, those who are in the youngest age group appear more inclined to participate in physical activity compared to those in the middle age group. The opposite seems to hold true for the elderly. Younger individuals also appear to have a higher propensity for sports and arts events compared to other age groups. Students were found to exhibit a higher tendency to participate in more physical activity compared to those who are not enrolled. Individuals who are employed seem to have an inclination to participate more into almost all types of discretionary activities other than active leisure compared to passive leisure. This is not surprising because those who are employed may have additional disposable income thus allowing them to seek discretionary activities other than passive leisure.

The disability indicator was found to have significant influence on the weekend discretionary activity participation. The coefficient was found to be negative for all discretionary activity types and highly significant. This is reasonable because it is likely that these individuals may be suffering from mobility restrictions and as a result participating less in different types of discretionary activities compared to those who do not have any disabilities. Among the different household level characteristics, those with high income appear to have higher propensity to participate in different types of discretionary activities compared to passive leisure. Presence of children was found to have a differing effect based on the age of the children. This is reasonable because older children may not be dependent on their parents' as much as younger children possibly leading to different types of discretionary activity engagement. It was interesting to note that whether the respondents reported their time use on Saturday or Sunday had a significant influence. Saturday indicator had a positive effect on participation in all five discretionary activity types compared to passive leisure. This is plausible because most individuals use Sunday as a day to relax and prepare for a new work week.

The association between moods and weekend discretionary activity participation is discussed below. It can be seen that the coefficients of all five moods: happiness, sadness, pain, stress and tiredness on all the discretionary activity types are shown in the table even though some of the coefficients are insignificant. This was done because examining the association between moods and discretionary activity engagement choices was the primary focus of the empirical study so even the insignificant coefficients are reported for the sake of completeness. It must be noted that no inferences are drawn for the moods with insignificant coefficient values; all insignificant coefficients of moods are highlighted in the table. The coefficient estimates provide support to the a priori hypothesis that people with high levels of positive moods engage more in discretionary activities other than passive leisure. On the other hand, those individuals who suffer from negative moods were found to do the opposite by participating more in passive leisure; one exception to this was the relationship between those who experience higher levels of stress (a negative mood) on their discretionary activity participation choices.

In general it appears like people who are happy want to participate more in physical activity, sports and arts events and social activities compared to passive leisure. On the other hand those suffering from high levels of pain and sadness tend to participate less in discretionary activities other than passive leisure. Similar observations were also made for tiredness but it was found to significantly associate with participation in two activity categories namely active leisure and non-maintenance shopping. It is interesting to note that unlike other negative moods, higher levels of stress were not associated with lower levels of participation in discretionary activities when compared to passive leisure. One plausible explanation to this observation may be how people cope when faced with stress – individuals may seek out opportunities (including look for moral and social support) to deal with stress (Scheier et al. 1986). It is also interesting to note that even though stress and other negative moods were highly correlated, the association between these latent constructs and the activity participation choices are very different and quite the opposite.

It can be noted that some of the findings obtained from the current exploration can potentially be explained using an alternative direction of causality. For example, the positive association between

positive moods and higher participation in physical activity, sports and arts events can also plausibly be because these activities can make people happy. Similarly, the positive association between stress and shopping activity may be because shopping is considered as a stressful activity by some individuals.

However, it is worth noting that the current analysis focuses on the association between individuals' moods that are "stable" over the day and their activity engagement choices on that day. Since these moods do not vary across the day, we believe that the plausibility of the causality we are testing (that stable moods on a day influence activity engagement on that day) is greater than that for the reverse causality (that activity engagement on a day influences stable moods on that day). Of course, it is likely that activity engagement habits over a long period of time influence stable moods people experience on a given day. Exploration of such long-term relationships between moods and activity engagement is not a focus of this study; albeit certainly worthy of future research and so is the exploration of relationship between moods that vary across a day and activity engagement.

Correlation structure

Finally, different error structures were tested for the error components associated with the baseline marginal utilities of the different discretionary alternatives. More specifically, the presence of heteroscedasticity as well as correlation across different alternatives was explored. It must be noted that, theoretically it is possible to estimate all the $(\frac{n*(n-1)}{2} - 1)$ Cholesky factors corresponding to the error component of the choice model; where n is the number of choice alternatives. However, estimating the full covariance matrix (after normalization) does not allow inferring the underlying correlations among different alternatives. For this reason, in the current study, different correlation structures were assumed a priori (to test out different hypothesis) and the corresponding Cholesky factors were estimated. In particular, the presence of following correlation structures were explored:

i. Correlation among non-maintenance shopping, attending sports and arts events and social activity
ii. Correlation between active and passive leisure

iii. Correlation among active leisure and the rest of the discretionary activities other than passive leisure

The estimation results indicate the presence of significant correlation between active leisure and three other discretionary activities namely physical activity, attending sports and arts events and social activity (with the corresponding Cholesky factors estimated as 0.1718, 0.1193 and 0.1050 respectively). As can be seen, the correlation structure of the choice model seems to be relatively sparse. This is likely due to the fact that the inclusion of latent constructs may have accounted for the error correlations due to the common unobserved factors resulting in relatively sparse correlation structure for the choice model (Hess 2012). This is another advantage of using the HMDC (and more generally the ICLV model) i.e. to be able to isolate and parse out the factors contributing to the correlation across different choice alternatives rather than relegating the correlations to the unobserved random factors.

<u>Satiation parameter</u>

It must be noted that in addition to the baseline marginal utility, the satiation coefficients were also parameterized as a function of different exogenous variables to gain insights into the second dimension of activity engagement namely the time use dimension (i.e. amount of time spent in the discretionary activity types). The corresponding results are presented in Table 4.6. The coefficient of the exogenous variables in the satiation parameter indicates presence of statistically significant variation in satiation based on gender, age and income. Specifically, females exhibit higher satiation (meaning lower amount of consumption) for active leisure, physical activity and attending sports and arts events compared to males, while the opposite is true for non-maintenance shopping activities. Those who are in the young age group exhibit lower level of satiation (higher amount of consumption) for active leisure, non-maintenance shopping and social activities, while those in the old age group exhibit high level of satiation for social activities. In terms of income, the effect was found to be statistically significant for the two types of leisure activities. Those with higher income show higher satiation meaning lower level of consumption for both types of leisure activities.

4.4.5 Validation study

This section briefly introduces the forecasting steps for the proposed model formulation and also highlights the results of a validation study using holdout sample. The validation sample consisted of 977 observations from ATUS dataset. For forecasting the activity participation and time use choices, one needs to use the structural equation of the latent variable and the MDC choice model only. The measurement equations of the latent variable are not needed for the forecasting. More specifically, in forecasting the activity engagement choices, the below steps were carried out:

i. Predict the latent variables using the structural equation of the latent variables (i.e. Equation 4.1).

ii. Using the predicted latent variables and other exogenous variables of the MDC choice model, predict the activity participation and time use choices (i.e. consumption quantities for vector x) using the forecasting procedure proposed by Pinjari and Bhat (2011).

However, due to the presence of random error component in both the structural equation of the latent variable and the MDC choice model, the activity engagement choices are predicted with multiple draws of error (100, 200, 500, 1000, 2000, 5000, and 10000). For each set of draws, the average participation rate and average amount of time allocated to various activities are calculated for each individual. The average value of the participation rate and consumption are found to be very stable across different error draws. Also, the calculated standard deviations across draws are found to be very small even for 100 draws of error. Finally, the forecasted values of the participation rate (in percentage) and consumption average (in minutes) are compared against the corresponding observed values from the hold out sample. The forecasting errors are calculated using Equation (4.20) and (4.21).

$$Mean\ Absolute\ Error\ (MAE) = \frac{\sum_{k=1}^{K}\left|\frac{(y_k - \widehat{y_k})}{y_k}\times 100\right|}{K} \tag{4.20}$$

$$Root\ Mean\ Square\ Error\ (RMSE) = \sqrt{\frac{\sum_{k=1}^{K}(y_k - \widehat{y_k})^2}{K}} \tag{4.21}$$

where, y_k is the observed average participation rate (or consumption amount) for alternative k and $\widehat{y_k}$ is the predicted average participation rate (or consumption amount) for alternative k. The calculated MAE

and RMSE along with the predicted and observed participation rate and consumption amount are presented in Table 4.7[13]. It can be seen that, the HMDC model provides reasonable forecasts with approximately 10 percent MAE for participation rate and approximately 9 percent MAE for the average amount of time allocated. The low values of RMSE (approximately 2 and 3.5 for participation and time allocated respectively) also point to the good predicting ability of the estimated HMDC model.

Table 4.7 Validation Results of the HMDC Model using Hold out Sample

		Activity Categories					
		Active leisure	**Passive leisure**	**Physical activity**	**Non maintenance shopping**	**Attending sports and arts events**	**Social activity**
Observed	Participation Rate (%)	41.965	86.285	19.959	26.510	7.984	48.516
	Consumption (in minutes)	61.552	232.127	23.226	19.205	14.444	71.311
Predicted	Participation Rate (%)	45.038	87.764	17.668	24.716	5.754	46.62
	Consumption (in minutes)	68.618	228.426	21.608	21.657	11.774	69.782
MAE (%)	Participation Rate	9.853					
	Consumption	8.907					
RMSE	Participation Rate	2.186					
	Consumption	3.691					

4.5 Summary and Conclusions

In the travel behavior arena, researchers often explain the heterogeneity in activity-travel choices across individuals using a variety of observed explanatory variables such as socio-economic, demographic, and

[13] Reported results were produced using 1000 draws of errors. Any further increase in the number of draws did not change the predicted values of activity participation and time allocation.

built environment factors in models of the choices. With theoretical and methodological advances in the behavioral economics, there is a growing recognition that heterogeneity in the individual behaviors arises also due to differences in individual psychological factors (e.g. attitudes, preferences, and moods among others). This chapter develops a new hybrid multiple discrete continuous (HMDC) model formulation. HMDC is an Integrated Choice and Latent Variable (ICLV) implementation which allows simultaneous estimation of latent variable model and choice model in the presence of MDC kernel.

Apart from the HMDC model formulation, a major challenge in the research was to come up with a simulation free, analytical estimator for estimating the parameters of the model. CML approximation technique was employed to decompose the high dimensional integrals into lower dimensional marginal densities that can be evaluated using analytical approximation techniques. Another challenge was the variable size of the integral across observation because of the presence of the MDC kernel which resulted in varying number of marginal densities to be evaluated for each individual. To normalize the contribution from each observation to the likelihood function, a non-unit weight was used that was proportional to the size of the integral to be decomposed. The use of the *weight* significantly improved the consistent recovery of the true parameters.

In general, the proposed estimation routine provides a very good recovery of parameters both in terms of bias and asymptotic efficiency. An average absolute percentage bias (APB) value of 0.64% and an average relative asymptotic efficiency (RAE) of 1.099 were obtained across all parameters. Further, a comparison of the simulation results between weighted and unweighted CML approach reveals striking differences in recovering unbiased estimates of the parameters. An unweighted CML resulted in an average APB of 10.39% as opposed to less than 1% bias obtained using *weighted* CML. This demonstrates the importance of *weights* in setting up the CML function when the dimension of the integral to be evaluated varies across observations.

The empirical study conducted to demonstrate the feasibility of the proposed framework investigates the association between moods and the discretionary activity engagement choices of individuals on weekends. In particular, the study attempts to examine if higher levels of positive mood

(such as happiness) would be associated with participating more in activities other than passive leisure. Alternatively, the study also wanted to explore if higher levels of negative moods (such as pain, sadness, tiredness and stress) are associated with participating more in passive leisure.

To this end, data from the 2013 American Time Use Survey was used. The HMDC formulation was employed to explore the role of five moods: happiness, sadness, pain, stress and tiredness on participation and time allocation to six discretionary activities: active leisure, passive leisure, physical activity, shopping for non-maintenance, attending sports and arts events, and social activity with passive leisure serving as the reference activity type. The empirical exploration provided statistically significant evidence in support of the association between positive and negative moods and the weekend discretionary activity engagement choices after controlling for the effect of various observed explanatory variables. A validation exercise was performed using a holdout sample technique to demonstrate the validity and applicability of the HMDC model for forecasting. The results (low forecasting error) point to the ability of the HMDC model to provide valid predictions.

It can be noted that, the current empirical study explores the association between moods and discretionary activity participation propensity through the parameterization of the baseline marginal utility. Future research is needed to investigate the association between moods and satiation patterns of different discretionary activities. This would help investigate if positive (negative) moods are associated with seeking more (less) diversity in the choice of discretionary activities as posited by previous research on the influence of positive moods in variety seeking behavior (Kahn and Isen 1993).

The research presented in this chapter has both methodological and empirical contributions. First, on the methodological front, the HMDC comprises one of the first attempts to implement a MDC choice kernel into the ICLV framework. To the authors' knowledge, generalized heterogeneous data model (GHDM) proposed by Bhat et al (2016) is the only other attempt to estimate simultaneous equation system using composite marginal likelihood technique (CML) that involves latent variable model and MDC choice outcomes. However, the current chapter is perhaps the first to highlight and demonstrate the importance of using weights in setting up the CML function to estimate the parameters of an ICLV framework with MDC

choice kernel. HMDC is general enough and allows for exploration of complex error structures to accommodate correlations across latent variables, and correlations across alternatives. The formulation of HMDC is also flexible and allows for treating indicator variables used in constructing the latent variables as both ordinal and continuous.

It should be emphasized that, the empirical exploration conducted as part of the study does not intend to recommend policy interventions based on the findings – rather identifying and characterizing the additional heterogeneity (through the addition of latent constructs of moods) in the activity time allocation behavior after accounting for traditional exogenous variables was the main objective of the empirical exploration. The empirical study sheds light into the interrelationships among different types of moods throughout the day (namely happiness, pain, sadness, stress and tiredness) as well as highlight the association between daily moods and daily activity time allocation after accounting for other traditional exogenous variables. Additionally, the endogenous treatment of latent mood variables allowed the study of variation in individual moods as a function of different exogenous explanatory variables which is a topic of interest in the field of happiness and hedonic psychology.

There exist a number of avenues for future research both on the methodological and empirical fronts based on the research presented in the chapter. Research is warranted on the appropriate choice of weight in the proposed estimator. Exploring the suitable choice of weight (in terms of relative efficiency) based on different dependency structure would be a valuable addition leading to more efficient estimator. On the empirical side, the proposed HMDC formulation and estimation technique can be readily employed to explore the association between other types of psychological factors (such as life style choice and personality type) and the activity engagement choices. Also, it is believed that, with the increasing interest in studying the role of individual attitude (and other psychological factors) on various activity-travel choice decisions of interest namely household energy consumption (Abrahamse and Steg 2009, Hartmann and Apaolaza-lbanez 2012, Azadeh et al. 2014), vehicle holding and vehicle usage behavior (Siriwardena 2010, Wang et al. 2016), physical and leisure activity participation (Deforche et al. 2006) the proposed HMDC

formulation and associated estimation routine can be used due to its statistical rigor and richness in behavioral representation.

CHAPTER 5

DAY PATTERN GENERATION SYSTEM FOR JOINTLY MODELING TOURS AND STOPS: BI-LEVEL MULTIPLE DISCRETE CONTINNUOUS PROBIT (MDCP) MODEL

5.1 Introduction and Motivation

Activity-based travel demand model systems are increasingly being designed, developed, and deployed. In activity based models (ABM), various dimensions of activity engagement choices and travel choices are modeled while also acknowledging the constraints and interactions that exist, thus, resulting in a more behaviorally accurate representation of individual activity-travel patterns (Kitamura 1988, Axhausen and Gärling 1992, Bhat and Koppelman 1999).

In the literature, two different units of analysis have typically been utilized for ABMs, namely, activity (Miller and Roorda 2003, Arentze and Timmermans 2004, Pendyala et al. 2005, Auld and Mohammadian 2009, Habib 2015, Fu et al. 2016) and tour (Bowman and Ben-Akiva 2001, Bhat et al. 2004[14], Garikapati et al. 2014). The tour-based ABM approaches are the focus of the research presented in this chapter. A tour is defined as a sequence of trips that start and end at the same location. Activity-travel patterns of an individual are represented as a series of home-based (anchored at home) and work-based tours (anchored at work). Each stop represents an activity pursuit and an individual must pursue at least one activity[15]. For each tour, a primary stop is defined which also represents the purpose of the tour. In addition to the primary stop, an individual can make other activity stops, referred to as intermediate stops, en-route to the primary activity location or on the journey back home. In the state-of-the-art tour-based modeling approaches, daily activity-travel agendas pursued by individuals and households are formed in

[14] In CEMDAP, half-tours are considered.
[15] There are roundtrip tours that are also reported in surveys but representing them is a challenge and are not considered in this research.

two stages, namely, the activity pattern generation and the activity scheduling. In the activity pattern generation, characteristics of all tours are identified including tour purpose, number of stops within a tour, purpose and destination for each stop and time allocated to all tours and stops among other decisions. On the other hand, activity scheduling is concerned with the timing and placement of tours and stops within a day. The research presented contributes to the activity pattern generation stage of the tour-based ABM approach.

There are three important limitations of existing tour-based ABMs that this chapter attempts to address. First, though early literature on ABM conceptualizes time as a continuous entity (Ben-Akiva et al. 1996), almost all of the ABM systems in practice today represent time in discrete units. For example, in Bowman and Ben-Akiva (2001) the arrival-departure time combinations of different tours are modeled with plausible pairs of discrete time bins serving as alternatives. Second, the decision to participate in an activity at each stop within a tour (and amount of time to be allocated) is modeled independently (Bhat et al. 2004). Consequently, these model systems cannot explicitly address the interactions between successive activity-travel episodes within a tour and also the cascading impacts on other tours within a day. Third, related to the above, most tour-based model systems do not explicitly acknowledge the temporal constraints when modeling tours, or when modeling stops within a tour. Temporal constraints are often accommodated afterwards using heuristics and logical checks at the activity scheduling stage.

In this research, a framework and model formulation are proposed that attempts to mimic the formation of tours in a behaviorally consistent way while addressing three important limitations of existing frameworks, namely, *representation of time as a continuous entity, representation of the interrelationships between stops and tours across the day, and representation of temporal constraints*. The rest of the chapter is organized as follows. An overview of the tour generation framework is presented next. The third section presents the econometric model formulation that operationalizes the tour generation framework. The fourth section presents a case study where the model formulation was applied using data from the 2008-2009 National Household Travel Survey. The fourth section also presents result

from a replication and forecasting analysis to demonstrate the performance of the proposed framework. In the final section, findings and contributions from the research are summarized.

5.2 Model Framework

The purpose of the current research effort is to model the tour and stop making decisions of individuals in a behaviorally consistent manner while representing time as a continuous entity and explicitly acknowledging the temporal constraints. In particular, the focus of the tour generation framework is on the following four dimensions of tour-pattern of an individual: 1) *the choice of participation (whether to pursue?) in different types of home based tours* (defined based on primary activity type), and for each tour an individual participates in, 2) *the time allocation (how much time?) to the tour*, 3) *the choice of participation in different intermediate stops* within the tour and 4) *the time allocation to the stops in addition to the time allocation to the primary activity of the tour and the return home journey*[16]. There are other dimensions of tours that are necessary to complete the characterization of tour patterns of individuals namely destination of the stops, sequencing of stops within a tour, and all of the tour-and stop-level travel characteristics. It is assumed that these other dimensions are modeled using a series of independent/joint model formulations. The discussion of these other dimensions is outside the scope of this chapter.

The proposed framework assumes a bi-level decision making structure wherein the participation and time allocation decisions for the various tour types are modeled at the upper level and within each tour, participation and time allocation decisions for different stops are modeled at the lower level. Time is treated as a continuous entity thus allocations of time to tours and stops are in continuous time units. Two sets of temporal constraints govern the tour generation framework. First, total time allocation across all

[16] From this point forward any reference to stop(s) also includes the primary activity of the tour, as well as the return home journey unless explicitly noted otherwise.

tours participated is equal to the total time available in the day (e.g. 1440 minutes). This includes time spent in activities at home. Second, the time allocated to stops within the tour should add up to the time allocation for the said tour. It must be noted that the stop level time allocation includes activity dwell time and duration of the travel time to the activity location as formulated by Garikapati et al. (2014). This is also referred to as epoch duration[17]. Tour level decisions influence the stop level choices by modifying the time available to be allocated to the stops within a said tour. Also, stop level choices for a said tour can not only influence the participation and time allocation decisions directly for the tour but they can also indirectly influence the participation and time allocation decisions for other tours.

The treatment of stops within a tour and the continuous treatment of time is similar to the framework proposed by Garikapati et al. (2014). However, their framework treats one type of tour at a time. The proposed framework addresses this limitation by considering all tours pursued by individuals within a day along with stops within each tour within an unifying framework, thus, allowing for a more accurate representation of the tour formation process. Figure 5.1 presents the skeleton of the proposed framework using data from the case study. This will be described in greater detail in section four.

[17] From this time forward stop level time allocation and epoch duration are used interchangeably and refer to the sum of activity duration at the stop and also the travel time to the stop destination from the previous location.

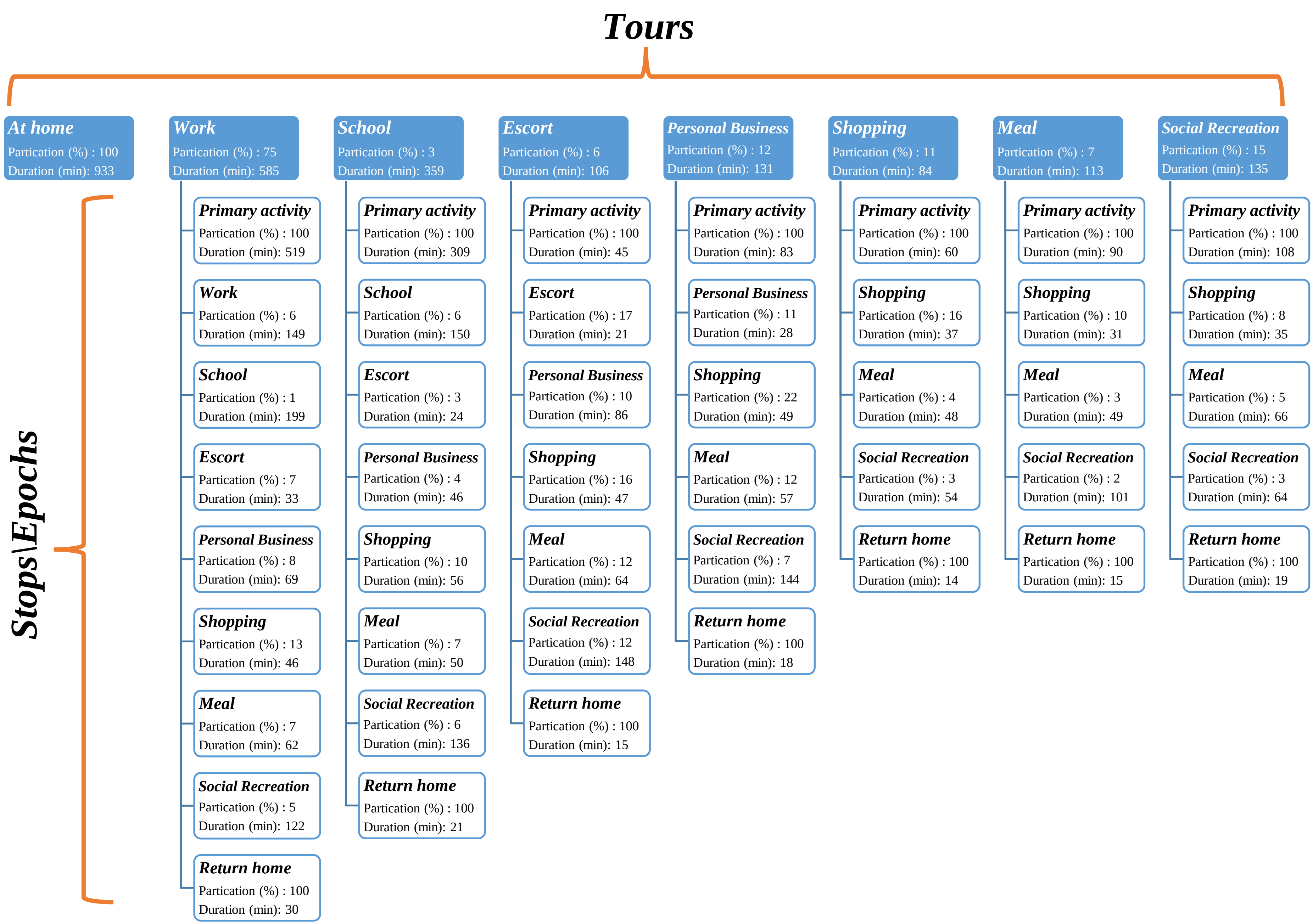

Figure 5.1 Qualitative model framework and observed participation and time allocation

5.3 Econometric Methodology

In this section, a model formulation that operationalizes the continuous time and time constrained tour generation framework is presented. The proposed model formulation adopts the multiple discrete continuous (MDC) econometric model framework proposed by Bhat (2008, 2013). This utility-maximization based Kuhn Tucker demand system has been widely used in the literature (Garikapati et al. 2014). In the proposed formulation, both the participation and time allocation choices at the upper level (for tours) and at the lower level (for stops within a tour) are treated as multiple discrete continuous choices where the participation constitutes the discrete component, time allocation constitutes the continuous component and the alternatives considered being the imperfect substitutes of one another give rise to multiple consumption scenario.

This bi-level MDC formulation is similar in spirit to the conceptual framework proposed by Deaton and Muellbauer (1980) and Chintagunta and Nair (2011) for the two level decision making involving multiple discrete continuous choices[18]. To the best of the authors' knowledge, Wang and Li (2011) offers the only other research that operationalizes the bi-level structure in the presence of multiple discrete continuous choices at each level. However, the proposed formulation is different from Wang and Li in a number of important ways, thus, comprising an important contribution to this line of inquiry. First, the current research employs a different utility specification. The proposed formulation captures the variability (across alternatives and different socio demographic groups) in the satiation effect (i.e. diminishing marginal utility with increasing consumption) thus making it an ideal candidate for the analysis of alternatives that are imperfect substitutes of one another as opposed to assuming a constant and identical satiation effect across all the alternatives. Second, Wang and Li assume an independent and

[18] In literature this two level decision making process in the presence of multiple discrete continuous choice scenario has also been referred to as two-level budgeting (see Pinjari et al. 2016).

identically distributed error structure whereas the proposed formulation assumes a flexible error structure where alternatives at the tour level are allowed to be correlated and the stop level alternatives belonging to the same tour are also allowed to be correlated. Finally, their effort relies on numerical (Monte Carlo) simulation for the estimation of the model. The proposed formulation utilizes an analytical approximation of normal cumulative distribution function proposed by Bhat (2011) which eliminates the need for any numerical simulation. Unlike numerical simulation, the analytical approximation aids the computational tractability and enables its use in practice. The econometric formulation is presented next.

The utility derived by allocating $x^l = \{x_1^l, x_2^l, x_3^l, \dots, x_{K_l}^l\}$ amount of time to different stops within a tour can be written as in Equation (5.1)[19].

$$U_s^l = \sum_{k=1}^{K_l} \gamma_k^l \psi_k^l \exp(\varepsilon_k^l) \ln(\frac{x_k^l}{\gamma_k^l} + 1) \quad (5.1)$$

Where x^l is a (K_l×1) vector of the time allocated (epoch duration) to different stops, $\gamma_k^l (> 0)$ is the translation (also serves to account for satiation effect) parameter and $\psi_k^l (> 0)$ is the baseline utility which represents the marginal utility at the point of zero consumption. The baseline marginal utility can further be parameterized as $\exp(\alpha' v_k^l)$ where v_k^l represents $D_k^l \times 1$ sized vector of exogenous variables and α represents the corresponding vector of parameters to be estimated. ε_k^l is the stochastic component which captures the idiosyncratic (unobserved) characteristics of the decision maker that impact the baseline utility. The present formulation assumes the stochastic component to be multivariate normally distributed (MVN) such that $\varepsilon^l \sim N[0_{K_l}, \Lambda^l]$ where, Λ^l is the covariance matrix of the stop level error component, ε^l. K_l is the total number of stops pertaining to tour l. In the above discussion, the subscript k represents the

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[19] The contribution of an outside good to the utility is accommodated as $\psi_k^l \exp(\varepsilon_k^l) \ln(x_k^l)$

stop k in the tour l and superscript l represents the l^{th} tour. Finally, subscript *s* is used to denote stop level utility.

Similarly, the utility derived by allocating $\{x_1, x_2, x_3, \dots, x_l\}$[20] amount of time to different tours can be written as in Equation (5.2)[21].

$$U_t = \sum_{l=1}^{L} \gamma_l \psi_l^* \exp(\varepsilon_l) \ln(\frac{x_l}{\gamma_l} + 1) \tag{5.2}$$

Note that, for the baseline marginal utility of the tour ψ_l^* is defined as $\psi_l(\prod_{k=1}^{K_l} \psi_k^l)^{w_l}$ and ψ_l is parameterized as $\exp(\beta' v_l)$ where v_l represents $D_l \times 1$ vector of exogenous variables and β represents the corresponding vectors of parameters to be estimated. Note that, the ψ_l (or equivalently, $\exp(\beta' v_l)$) component captures the tour[22] specific characteristics; where as $(\prod_{k=1}^{K_l} \psi_k^l)^{w_l}$ (or, equivalently $(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l)\,)^{w_l}$) component captures the characteristics of the stops within the tour. This specification captures the impact of the stop level participation choice(s) on the tour level participation. The exponent, w_l captures the relative contribution of the stop level characteristics on the tour level baseline marginal utility. w_l needs to be positive in order to ensure that the baseline marginal utility is positive. Also, it is desirable that the parameter takes a value between 0 and 1 to ensure that the contribution of the stop level characteristics on the baseline marginal utility of the tour is less than their contribution on the stop level baseline marginal utility. Similar to the stop level model, the stochastic component ε_l associated with the tour level alternatives is assumed to be MVN distributed such that $\varepsilon \sim N[0_L, \Lambda]$, where Λ represents the covariance matrix of the tour level error component. L represents the total number of tours (including an at home alternative). Subscript *t* is used to denote tour level utility.

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[20] It must be noted that $x_l = \sum_{k=1}^{K_l} x_k^l \;\; \forall\, l = 1,2,3, \dots, L$ represents the relationship between stop and tour level time allocation

[21] The contribution of an outside good to the utility is accommodated as $\psi_l^* \exp(\varepsilon_l) \ln(x_l)$

[22] Tour is defined based on the purpose of the activity at the primary stop.

The total utility that a decision maker derives from allocating $\{x_1, x_2, x_3, \ldots, x_l\}$ amount of time to L tours and $\{x_1^1, x_2^1, \ldots, x_{k_1}^1, x_1^2, x_2^2, \ldots, x_{k_2}^2, x_1^3, x_2^3, \ldots, x_{k_3}^3, \ldots, x_1^l, x_2^l, \ldots, x_{k_l}^l\}$ amount of time into the $\sum_{l=1}^{L} K_l$ stops can be expressed as a summation of bottom level and top level utilities as shown in Equation (5.3).

$$U = \sum_{l=1}^{L} \gamma_l \exp(\beta' v_l) \left(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l)\right)^{w_l} \exp(\varepsilon_l) \ln\left(\frac{x_l}{\gamma_l} + 1\right) +$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K_l} \gamma_k^l \exp(\alpha' v_k^l) \exp(\varepsilon_k^l) \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) \quad (5.3)$$

The decision maker is then assumed to maximize the utility in Equation (5.3) subject to the time budget constraints given by Equation (5.4).

$$\sum_{l=1}^{L} x_l = T \qquad x_l \geq 0 \ \forall\ l = 1,2,3, \ldots, L \quad (5.4a)$$

$$\sum_{k=1}^{K_l} x_k^l = x_l \qquad x_k^l \geq 0 \ \forall\ l = 1,2,3, \ldots, L \ \&\ k = 1,2,3, \ldots, K_l \quad (5.4b)$$

Equation (5.4) represents $L + 1$ budget constraints, where the top equation represents the budget constraint operating at the tour level and the bottom L equations represent the budget constraints working at the stop level for each of the L tours. The optimization problem can be solved by forming the Lagrangian, $\mathcal{L}$ and then applying the Karush-Kuhn Tucker (KKT) conditions.

$$\mathcal{L} = \sum_{l=1}^{L} \gamma_l \exp(\beta' v_l) \left(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l)\right)^{w_l} \exp(\varepsilon_l) \ln\left(\frac{x_l}{\gamma_l} + 1\right) +$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K_l} \gamma_k^l \exp\left(\alpha' v_k^l\right) \exp\left(\varepsilon_k^l\right) \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) - \lambda\left(\sum_{l=1}^{L} x_l - T\right) - \sum_{l=1}^{L} \lambda_l \left(\sum_{k=1}^{K_l} x_k^l - x_l\right) \quad (5.5)$$

Equation (5.5) provides the Lagrangian equation where λ and λ_l are the Lagrange multipliers associated with the tour and stop levels respectively. The first order KKT conditions with respect to the vector of decision variable x_l can be written as in Equation (5.6) after some manipulation, where *m* represents the good that is consumed.

$$\beta' v_l + w_l\left(\sum_{k=1}^{K_l} \alpha' v_k^l\right) - \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \varepsilon_l - \ln(\lambda - \lambda_l) =$$

$$\beta' v_m + w_m\left(\sum_{k=1}^{K_m} \alpha' v_k^m\right) - \ln\left(\frac{x_m}{\gamma_m} + 1\right) + \varepsilon_m - \ln(\lambda - \lambda_m)$$

$$\forall\ l = 1,2,3, \dots, L\ if\ x_l{}^* > 0, l = 1,2, \dots, L, l \neq m$$

(5.6)

$$\beta' v_l + w_l\left(\sum_{k=1}^{K_l} \alpha' v_k^l\right) - \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \varepsilon_l - \ln(\lambda - \lambda_l) <$$

$$\beta' v_m + w_m\left(\sum_{k=1}^{K_m} \alpha' v_k^m\right) - \ln\left(\frac{x_m}{\gamma_m} + 1\right) + \varepsilon_m - \ln(\lambda - \lambda_m)$$

$$\forall\ l = 1,2,3, \dots, L\ if\ x_l{}^* = 0, l = 1,2, \dots, L, l \neq m$$

In Equation (5.6), λ_l needs to be less than λ which makes intuitive sense since λ and λ_l respectively represents the time elasticity for the tour level and the stop level budget constraints. Next, the first order KKT conditions with respect to the vector of decision variable x_k^l for each of the l^{th} tour can be written as shown in Equation (5.7).

$$\alpha' v_k^l - \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) + \varepsilon_k^l = \alpha' v_m^l - \ln\left(\frac{x_m^l}{\gamma_m^l} + 1\right) + \varepsilon_m^l\ \forall\ k = 1,2,3, \dots, K_l\ if\ x_k^{*l} > 0,\ k \neq m$$

(5.7)

$$\alpha' v_k^l - \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) + \varepsilon_k^l < \alpha' v_m^l - \ln\left(\frac{x_m^l}{\gamma_m^l} + 1\right) + \varepsilon_m^l\ \forall\ k = 1,2,3, \dots, K_l\ if\ x_k^{*l} = 0,\ k \neq m$$

Given the above equations and assumptions about the stochastic components as preliminaries, the joint probability of allocating time into L tours and $\sum_{l=1}^{L} K_l$ stops can be given by Equation (5.8) where $\Theta = \{\alpha', \gamma_k^l, vector(\Lambda^l), \beta', \gamma_l, vector(\Lambda), w_l\}$ is the vector of parameter to be estimated and Pr denotes probability.

$$Likekihood(\Theta) = Pr\ (x_1^*, x_2^*, \dots, x_l^*, x_1^{*1}, x_2^{*1}, \dots, x_{k_1}^{*1}, x_1^{*2}, x_2^{*2}, \dots, x_{k_2}^{*2}, \dots, x_1^{*l}, x_2^{*l}, \dots, x_{k_l}^{*l})$$

$$= Pr\ (x_1^*, x_2^*, \dots, x_l^*) \times Pr\ (x_1^{*1}, x_2^{*1}, \dots, x_{k_1}^{*1}, x_1^{*2}, x_2^{*2}, \dots, x_{k_2}^{*2}, \dots, x_1^{*l}, x_2^{*l}, \dots, x_{k_l}^{*l} | x_1^*, x_2^*, \dots, x_l^*)$$

$$= Pr(x_1^*, x_2^*, \dots, x_l^*) \times \mathrm{Pr}(x_1^{*1}, x_2^{*1}, \dots, x_{k_1}^{*1} | x_1^* > 0) \times$$

$$Pr\ (x_1^{*2}, x_2^{*2}, \dots, x_{k_2}^{*2} | x_2^* > 0) \times \ldots \times Pr\ (x_1^{*l}, x_2^{*l}, \dots, x_{k_l}^{*l} | x_3^* > 0) \tag{5.8}$$

In Equation (5.8), the last equality holds because of the assumption that, the time allocation decision to different stops across tours are not correlated i.e. interdependence is facilitated at the tour level and only the stops belonging to the same tours are allowed to be correlated with each other. The probability

expression involves evaluation of MVN cumulative distribution function (CDF) which is accomplished using analytical approximation as proposed by Bhat (2011) (known as MACML approach in the literature). The likelihood function in Equation (5.8) and the associated gradients are implemented in matrix programming language GAUSS to obtain the parameter estimates $\hat{\Theta}$. The standard errors of the parameter estimates are obtained using the robust Gobambe sandwich estimator (Godambe 1960). Details regarding the estimation approach have been excluded in the interest of space and interested readers may consult Varin et al. (2011) for a general discussion about CML based estimation approach and Bhat et al. (2013) for an application of CML for estimating choice models involving MDCP choice kernel.

5.4 Empirical Study

In this section, we demonstrate the framework and model formulation using data from the 2008-2009 National Household Travel Survey. Data from two consolidated metropolitan statistical areas (CMSA) from south west portions of the US, namely, Phoenix-Mesa, AZ and Los Angeles-Riverside-Orange County, CA are used in this case study. Also, the data used for the current study only includes workers who are 16 years of age and above. Further, the analysis is limited to weekdays (i.e. Monday through Friday). The trip level data from NHTS was processed as follows:

i. All the home based tours (HBT) conducted by the individuals are identified. Note that individuals with atypical travel behavior are eliminated at this stage.

ii. A primary activity is identified for each of the HBTs based on an assumed activity priority hierarchy and dwell time at the destination. The activity hierarchy assumed for the empirical study is as follows: work is given the highest priority if the person is an adult and worker, otherwise school is given the highest priority which is followed by escort and personal business. The rest of the three activities (shopping, meal and social recreation) are given equal rank and activity with the highest dwell time at the destination is used to define the primary activity of the tour. The purpose of the primary activity is then assigned to characterize the tour. Hence, each of the HBTs were categorized into one of the following 7 activity categories: work, school, escort, personal business (PB), shopping, meal and social recreation (SR). In presence of multiple activities of the same purpose on the tour, activity with the higher dwell

time is assigned as the primary activity and the other activity is included as a stop. All activities conducted as part of the work based tours are included as part of the work activity in the current empirical exploration.

iii. In addition to the various HBTs, time spent at home (AH) was used as an alternative in the upper level. This treatment serves two main purposes. First, it allows for incorporating the natural constraint of 1440 minutes in a given day. Second, it allows capturing the tradeoffs between AH and out-of-home activity engagement (i.e. sum of HBTs); AH serves as an outside good[23] (that needs to be consumed) and thus, time allocated to HBTs is determined endogenously with respect to the time spent AH.

iv. As noted earlier, in defining the components of tours, we replace the notion of the stop with that of an epoch as defined by Garikapati et al. (2014). An epoch consists of the activity episode at each stop and the travel episode to the stop. Thus, each tour is comprised of a series of epochs and a return home episode. Subsequently, the summation of epoch duration across all stops and the duration of the return home journey equals the duration of the tour.

Figure 5.1 shows the structure of the bi-level model for the empirical case study. The model specification comprises of 8 tour alternatives. For each of the tours (except AH), the epoch alternatives are noted in the figure. The figure also presents the percentage of individuals in the subsample who participated in each of the tours and epochs. Additionally, average tour duration and average epoch durations are reported. It should be noted that, in the empirical application, participation in tours was limited to single episode of each tour type. This was in part dictated by the sample dataset. There were a small percentage of individuals who engaged in multiple episodes of the same tour types. However, this is

[23] The term “outside good” is used to refer to any alternative that an individual always participates in. In other words, a non-zero amount of time is always allocated to an outside good.

not necessarily a limitation of the proposed model formulation. Such instances can be accommodated in the current formulation by enumerating multiple tour alternatives of the same type in the tour type choice set.

5.4.1 Model estimation results

The size of the subsample used in the exploration is 5233. A variety of socio-economic, demographic, and land use variables were used to specify the model. The final model specification includes 331 parameters among which 83 are constants (pertaining to baseline marginal utility and the satiation parameters of the tour (top) and epoch (bottom) level models). The log-likelihood (LL) value of the final model at convergence is -106307.87 while final LL of the constant only model is -108166.63. The LL ratio test suggests that the model specification is significant at the 99.9% level of confidence (with LL ratio test statistic: 3717.52, Chi-square critical value: 322.56 for a degree of freedom of 248 at a level of significance of 0.001). Some of the highlights of the empirical analysis are presented next respectively for the tour (top) and the stop (bottom) level models.

5.4.2 Tour level participation and time allocation

Table 5.1 presents the parameters estimates (including baseline marginal utility and the satiation parameters) along with the robust t-statistics for the tour level of the bi-level model formulation. At home (AH) alternative is treated as the baseline alternative as well as an outside good.

5.4.2.1 Baseline marginal utility

The constants of all the seven tour types (work, school, escort, personal business (PB), shopping, meal and social recreation (SR)) are negative indicating a lower propensity of participating in different tours compared to the AH alternative. Male respondents exhibit higher propensity to participate in school tours and lower propensity to participate in escort tours. Young individuals (those who are less than 34 years old) and middle-aged adults (those who are in between 35 to 54 years old) participate more in work and school tours compared to the older adults (more than 54 years old). Middle-aged adult participate more in escort tours than individuals in other age groups. Part time workers exhibit a tendency to participate more in different types of tours such as school, escort, PB and SR and less into work tours. People living in an

urban area tend to perform more PB, shopping and SR tours compared to those living in suburban or rural areas. In terms of days of weeks, it appears like people tend to participate more in shopping, meal and SR tours and less in school tours on Fridays.

Table 5.1 Estimation Results for the Tour (Top) Level Model

Baseline Utility Specification		**Social Recreation tour (Continued)**	
Parameters	**Estimate (t-stat)**	Yearly HH income >$50K & <$100K	0.437 (3.72)
Work tour		Yearly HH income>$100K	0.387 (3.25)
Constant	-6.719 (-47.85)	Urban area indicator	0.161 (1.39)
Age 16 to 34 years	0.249 (2.92)	Friday indicator	0.142 (1.52)
Age 35 to 54 years	0.206 (3.04)	Part time worker indicator	0.352 (4.37)
Yearly HH income >$25K & <$50K	0.089 (1.84)	***Satiation Parameter Specification***	
Part time worker indicator	-1.075 (-17.22)	**Parameters**	**Estimate (t-stat)**
School tour		**Work tour**	
Constant	-12.432 (-30.35)	Constant	5.763 (96.94)
Male indicator	0.367 (2.46)	Male indicator	0.159 (5.25)
Age 16 to 34 years	2.762 (9.27)	Age 16 to 34 years	-0.213 (-2.76)
Age 35 to 54 years	1.115 (3.60)	Age 35 to 54 years	-0.161 (-2.58)
Yearly HH income >$50K & <$100K	-0.197 (-1.31)	Part time worker indicator	0.329 (5.21)
Friday indicator	-0.327 (-1.67)	Urban area indicator	-0.113 (-3.11)
Part time worker indicator	1.818 (10.97)	LA county indicator	0.099 (4.01)
LA county indicator	-0.309 (-2)	**School tour**	
Escort tour		Constant	6.543 (21.05)
Constant	-10.523 (-45.53)	Age 16 to 34 years	-0.699 (-2.38)
Male indicator	-0.371 (-3.13)	LA county indicator	0.338 (1.82)
Age 35 to 54 years	0.768 (6.07)	**Escort tour**	
Part time worker indicator	0.494 (3.63)	Constant	4.185 (23.71)
Personal Business tour		Age 35 to 54 years	-0.565 (-3.62)
Constant	-9.054 (-46.87)	Yearly HH income >$25K & <$50K	0.456 (2.11)
Age 16 to 34 years	-0.657 (-4.07)	LA county indicator	0.337 (2.37)
Age 35 to 54 years	-0.449 (-3.13)	**Personal Business tour**	
Age 55 to 64 years	-0.264 (-1.75)	Constant	4.664 (27.71)
Urban area indicator	0.192 (1.38)	Male indicator	-0.094 (-1.1)
Part time worker indicator	0.431 (4.24)	Part time worker indicator	0.251 (2.61)
Shopping tour		Urban area indicator	-0.239 (-1.46)
Constant	-9.422 (-50.51)	**Shopping tour**	
Yearly HH Income >$50K & <$100K	-0.348 (-3.26)	Constant	4.425 (33.21)
Yearly HH Income>$100K	-0.418 (-3.77)	Male indicator	-0.181 (-2.34)
Urban area indicator	0.215 (1.46)	Age 35 to 54 years	-0.128 (-1.63)
Friday Indicator	0.359 (3.34)	Urban area indicator	-0.377 (-2.88)
Part time worker indicator	0.188 (1.88)	LA county indicator	0.240 (2.97)
Meal tour		**Meal tour**	
Constant	-9.513 (-55.63)	Constant	4.912 (47.55)
Yearly HH income >$25K & <$50K	0.286 (1.87)	Male indicator	-0.206 (-2.17)
Yearly HH income >$50K & <$100K	0.331 (2.42)	Yearly HH income>$100K	-0.140 (-1.44)
Yearly HH income>$100K	0.404 (2.94)	LA county indicator	0.271 (2.92)
Friday indicator	0.453 (4.94)	**Social Recreation tour**	
Social Recreation tour		Constant	4.613 (30.8)
Constant	-9.258 (-53.87)	Urban area indicator	-0.299 (-1.99)
Age 16 to 34 years	0.088 (0.98)	Friday indicator	0.318 (2.90)
Yearly HH income >$25K & <$50K	0.253 (1.91)	LA county indicator	0.278 (3.43)

5.4.2.2 Role of weight

As noted earlier in the model formulation section, the model formation assumes that the decision to participate in a tour is not only determined by the primary activity of the tour but also depends on other stops made within the tour. However, the model formulation does not force the contribution of the stop level characteristics to influence the tour decision making. Rather, the influence is mediated through the w_l parameter. A value of w_l close to unity would imply that the influence of the stop level characteristics on the tour decision making is on the same level as their influence on the stop level decision making. On the other hand, a value of w_l close to zero implies negligible influence of stop level characteristics on the tour level decision making.

In the empirical case study, the w_l parameter was observed to be significant (with a value of 0.044 and a t-statistics of 4.245) only for the work tour baseline marginal utility specification. This can potentially be explained by the approach to data preparation. For HBTs where there is a work epoch, the purpose of the tour is coded as "work" irrespective of the activity dwell time, and distance from home. Hence, the significant w_l parameter is indicating that the utility for the work tour is not only a function of the primary activity (i.e. work) but also gets affected by other epochs' (conducted as part of the tour) participation propensities.

5.4.2.3 Satiation parameter

Male respondents tend to have high satiation (spend less time on) for PB, shopping and meal tours. On the other hand, they tend to have low satiation (spend more time on) for work tours. It is also interesting to note that, people living in urban areas tend to spend less time on different tours such as work, PB, shopping and SR. This may be attributable to the longer distances (and thus travel times) for those living in suburban and rural areas have to travel to access opportunities to pursue their activities compared to those living in urban areas.

5.4.2.4 Error correlation

The tour level model was allowed to assume a MVN error structure that is capable of accommodating both heteroscedasticity and error correlations. The below matrix shows the estimates of error covariance calculated from the corresponding lower triangular Cholesky factors.

$$
\begin{array}{cc}
 & \begin{array}{cccccccc} AH & Work & School & Escort & PB & Shopping & Meal & SR \end{array} \\
\begin{array}{c} AH \\ Work \\ School \\ Escort \\ PB \\ Shopping \\ Meal \\ SR \end{array} &
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & -0.362 & -0.584 & -0.894 & -0.751 & -0.562 & -0.463 \\
0 & -0.362 & 2.291 & 0.211 & 0.287 & 0.272 & 0.203 & 0.167 \\
0 & -0.584 & 0.211 & 4.063 & 0.522 & 0.438 & -0.358 & 0.270 \\
0 & -0.894 & -0.287 & 0.522 & 3.208 & 0.671 & -0.129 & 0.414 \\
0 & -0.751 & 0.272 & 0.438 & 0.671 & 3.419 & 0.422 & 0.348 \\
0 & -0.562 & 0.203 & -0.358 & -0.129 & 0.422 & 1.633 & -0.401 \\
0 & -0.463 & 0.167 & 0.270 & 0.414 & 0.348 & -0.401 & 2.478
\end{pmatrix}
\end{array}
$$

The error correlations provide interesting insights into participation behavior of individual due to common unobserved factors which are not captured in the deterministic portion of the utility specification. Positive correlations point to the same direction influence and negative correlations point to opposite direction influence. For example, the negative error correlation between work tour and the other type of tours reveals that the unobserved factors which influence higher participation behaviors in work tours also tend to influence lower participation in other types of tours. Another interesting observation worth pointing out is the negative correlation between meal and SR tours. This indicates that individuals are less likely to conduct tours with meal and SR as primary activities on the same day.

Table 5.2 Estimation Results for the Work Epoch (Bottom) Level Model

Baseline Utility Specification		*Baseline Utility Specification (Continued)*	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**Meal epoch**	
Constant	-3.055 (-224.55)	Constant	-12.731 (-9.44)
Work epoch		Male indicator	-0.495 (-2.69)
Constant	-14.068 (-3.59)	Age 16 to 34 years	-0.305 (-1.12)
Age 16 to 34 years	-0.203 (-1.15)	Age 35 to 54 years	-0.215 (-1.05)
Age 35 to 54 years	-0.149 (-1.14)	Yearly HH income >$50K & <$100K	0.377 (1.60)
Yearly HH income >$50K & <$100K	0.144 (1.19)	Yearly HH income >$100K	0.544 (2.28)
Flexible work schedule indicator[1]	0.295 (2.53)	Flexible work schedule indicator	0.559 (3.09)
Driver indicator[1]	4.932 (1.27)	Friday indicator	0.662 (3.20)
LA county indicator	-0.146 (-1.23)	Driver indicator	1.775 (1.38)
School epoch		**Social Recreation epoch**	
Constant	-12.817 (-14.32)	Constant	-12.643 (-9.99)
Age 16 to 34 years	2.111 (6.52)	Male indicator	-0.177 (-0.95)
Yearly HH income >$25K & <$50K	0.772 (1.34)	Yearly HH income >$100K	0.348 (1.81)
Yearly HH income >$50K & <$100K	1.394 (2.87)	Flexible work schedule indicator	0.386 (2.09)
Yearly HH income >$100K	1.332 (2.64)	Urban area indicator	0.474 (1.57)
Friday indicator	-0.741 (-1.62)	Driver indicator	1.418 (1.26)
Escort epoch		LA county indicator	-0.216 (-1.15)
Constant	-11.945 (-26.54)	*Satiation Parameter Specification*	
Male indicator	-0.435 (-2.44)	**Parameters**	**Estimate (t-stat)**
Age 16 to 34 years	1.578 (4.74)	**Work epoch**	
Age 35 to 54 years	2.139 (7.34)	Constant	5.517 (30.77)
Flexible work schedule indicator	0.519 (2.96)	**School epoch**	
LA county indicator	-0.322 (-1.82)	Constant	5.583 (12.21)
Personal Business epoch		Male indicator	1.224 (2.77)
Constant	-9.749 (-24.71)	Friday indicator	-2.063 (-5.73)
Male indicator	-0.897 (-5.05)	**Escort epoch**	
Age 16 to 34 years	-1.278 (-3.45)	Constant	2.612 (30.08)
Age 35 to 54 years	-0.854 (-2.74)	Yearly HH income >$25K & <$50K	-0.323 (-1.79)
Age 55 to 64 years	-0.487 (-1.47)	**Personal Business epoch**	
Yearly HH income >$50K & <$100K	0.192 (1.08)	Constant	3.460 (33.27)
Flexible work schedule indicator	0.810 (4.83)	Yearly HH income >$25K & <$50K	-0.455 (-2.53)
Friday indicator	0.398 (1.91)	**Shopping epoch**	
Shopping epoch		Constant	2.92 (39.98)
Constant	-11.789 (-11.35)	LA county indicator	0.168 (2.01)
Male indicator	-0.913 (-5.95)	**Meal epoch**	
Age 16 to 34 years	-0.743 (-3.17)	Constant	3.284 (28.70)
Age 35 to 54 years	-0.414 (-2.47)	Yearly HH income >$25K & <$50K	-0.375 (-1.92)
Yearly HH income >$50K & <$100K	0.206 (1.32)	**Social Recreation epoch**	
Flexible work schedule indicator	0.245 (1.64)	Constant	4.532 (36.43)
Urban area indicator	0.804 (3.12)	Friday indicator	0.376 (2.45)
Driver indicator	2.127 (2.19)		
LA county indicator	-0.217 (-1.33)		

Note: (1) Flexible work schedule indicator assumes a value 1 if flexible work schedule is exercised and 0 otherwise.
Driver indicator assumes a value 1 if person is reported to be a driver during the travel day and 0 otherwise.

5.4.3 Epoch level participation and time allocation: work

Table 5.2 presents the epoch level participation and time allocation results for the epochs pursued within work tour. The primary activity of the tour (work) and the return home journey have been treated as outside goods.

5.4.3.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Male respondents exhibit a lower tendency to undertake different maintenance and discretionary epochs (such as escort, PB, shopping, meal and SR) within the work tour compared to females. This is in line with the previous literature that alludes to complex tour structure for females compared to males (Bowman and Ben-Akiva 2001). Young people (age between 16 to 34 years) tend to perform fewer intermediate work epochs and more intermediate school epochs when compared to individuals from other age groups. It is interesting to note that, though individuals of all groups exhibited lower tendency to perform PB epochs compared to the old people (people more than 64 years old) during the work tour, they all exhibited higher tendency to perform PB epochs in other HBTs (such as escort) compared to older people. This shows the differences in epoch pursuits between different age groups for a given tour type.

5.4.3.2 Satiation parameter

In terms of variability in the satiation effect, male respondents are found to allocate more time into intermediate school epoch in a work tour than females. On Fridays, people tend to allocate more time (exhibit lower satiation) in SR epochs and less time into school epochs compared to other days of the weeks.

5.4.4 Epoch level participation and time allocation: school

Table 5.3 presents the epoch level participation and time allocation results for the epochs pursued within school tour. The primary activity of the tour (school) and the return home journey have been treated as outside goods.

Table 5.3 Estimation Results for the School Epoch (Bottom) Level Model

Baseline Utility Specification		*Satiation Parameter Specification*	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**School epoch**	
Constant	-2.694 (-36.78)	Constant	4.531 (15.91)
School epoch		Male indicator	1.474 (2.59)
Constant	-8.375 (-24.22)	**Escort epoch**	
Male indicator	0.355 (0.8)	Constant	3.883 (10.34)
Yearly HH income >$50K & <$100K	1.1 (2.68)	**Personal Business epoch**	
Escort epoch		Constant	4.326 (10.29)
Constant	-7.441 (-20.37)	**Shopping epoch**	
Age 16 to 34 years	-0.851 (-1.71)	Constant	4.465 (11.97)
Yearly HH income >$50K & <$100K	0.596 (1.23)	**Meal epoch**	
Personal Business epoch		Constant	4.561 (8.24)
Constant	-7.578 (-19.07)	Male indicator	-0.891 (-1.41)
Age 16 to 34 years	-0.733 (-1.48)	**Social Recreation epoch**	
Yearly HH income >$50K & <$100K	1.005 (2.26)	Constant	5.039 (8.63)
Shopping epoch		Male indicator	1.35 (1.65)
Constant	-5.537 (-10.21)		
Age 16 to 34 years	-1.187 (-2.98)		
Urban area indicator	-0.849 (-1.66)		
Meal epoch			
Constant	-7.385 (-39.6)		
Social Recreation epoch			
Constant	-7.831 (-29.59)		
Yearly HH income >$50K & <$100K	0.632 (1.62)		

5.4.4.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. In general, male shows higher propensity to make additional school stops within a school tour than females. People belonging to the youngest age group exhibit lower propensity to participate into additional epochs such as escort, personal business and shopping compared to the people belonging to the older age groups. This is also intuitive. Such activities are most probably not delegated to younger individuals of the family, at least not

to pursue as a part of their school tours – which presumably constitute the mandatory activity of the day for this age group. People belonging into the households with yearly income in the range of $50 to $100K show higher propensity to make additional stops (for instance social recreation, personal business and escort) within school tours compared to individuals belonging into any other income groups.

5.4.4.2 Satiation parameter

Social recreation epochs seem to have lowest satiation while performed within school tours compared to any other epochs. In other words, people tend to allocate considerably more time into social recreation epochs than in any other epochs within school tours. Similar to participation, males tend to spend more time into additional school epoch within a school tour compared to females. Males also tend to spend more time into social recreation epoch within a school tour compared to female. However, males tend to spend less time into meal epoch within school tours compared to females.

5.4.5 Epoch level participation and time allocation: escort

Table 5.4 presents the epoch level participation and time allocation results for the epochs pursued within escort tour. The primary activity of the tour (escort) and the return home journey have been treated as outside goods.

5.4.5.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. Personal business epoch has the lowest propensity to be conducted within an escort tour followed by the social recreation epoch. Male respondents exhibit lower propensity to perform additional epochs within an escort tour compared to females. People of all ages exhibit higher inclination to perform personal business epoch within an escort tour compared to the people belonging into the oldest age groups. On the other hand people belonging into age group of 16 to 64 years show lower inclination to perform meal stop within an escort tour compared to the people belonging into highest age groups.

Table 5.4 Estimation Results for the Escort Epoch (Bottom) Level Model

Baseline Utility Specification		*Satiation Parameter Specification*	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**Escort epoch**	
Constant	-0.783 (-15.89)	Constant	3 (11.96)
Escort epoch		Male indicator	0.626 (2.43)
Constant	-4.548 (-14.84)	**Personal Business epoch**	
Male indicator	-0.67 (-3.01)	Constant	6.3 (8.01)
Yearly HH income >$50K & <$100K	0.482 (2.05)	**Shopping epoch**	
Yearly HH income >$100K	0.35 (1.5)	Constant	4.403 (18.96)
LA County indicator	0.243 (1.24)	**Meal epoch**	
Personal Business epoch		Constant	4.643 (12.54)
Constant	-6.322 (-8.12)	Male indicator	0.773 (1.54)
Male indicator	-0.511 (-2.1)	**Social Recreation epoch**	
Age 16 to 34 years	0.705 (1.37)	Constant	7.571 (7.55)
Age 35 to 54 years	1.015 (2.4)		
Age 55 to 64 years	0.943 (2.03)		
Urban area indicator	0.863 (1.68)		
Shopping epoch			
Constant	-3.77 (-16.32)		
Male indicator	-0.453 (-2.19)		
Age 16 to 34 years	0.34 (1.49)		
Yearly HH income >$25K & <$50K	-1.071 (-3.16)		
Yearly HH income >$50K & <$100K	-0.653 (-2.51)		
Yearly HH income >$100K	-0.606 (-2.47)		
Meal epoch			
Constant	-3.722 (-11.02)		
Male indicator	-0.322 (-1.31)		
Age 16 to 34 years	-0.518 (-1.28)		
Age 35 to 54 years	-0.651 (-2.08)		
Age 55 to 64 years	-0.925 (-2.22)		
Yearly HH income >$25K & <$50K	-0.772 (-2.2)		
LA County indicator	-0.396 (-1.8)		
Social Recreation epoch			
Constant	-5.751 (-12.92)		
Yearly HH income >$25K & <$50K	0.416 (1)		
Yearly HH income >$50K & <$100K	0.681 (1.82)		
Yearly HH income >$100K	0.739 (1.99)		
Urban area indicator	0.422 (1.21)		

In terms of income, people with HH income more than $25K exhibit lower propensity to perform shopping stops within escort epoch compared to the people belonging to the lowest income group.

Whereas this same exogenous group of people, show increased tendency to perform social recreational stops within escort tour compared to the people belonging to the lowest income group. People living in an urban area, exhibit lower propensity to perform personal business stop and social recreational stop within an escort epoch compared to the people living in rural areas.

5.4.5.2 Satiation parameter

People tend to spend more time into social recreational stop than in any other additional stops within as escort tour. Male exhibit lower satiation, meaning tend to spend more time into escort and meal stops made within escort tour compared to females.

5.4.6 Epoch level participation and time allocation: personal business

Table 5.5 presents the epoch level participation and time allocation results for the epochs pursued within personal business tour. The primary activity of the tour (personal business) and the return home journey have been treated as outside goods.

5.4.6.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. All the rest of the epoch types have comparable magnitude of negative propensity to be pursued within a personal business tour. Males exhibit lower propensity to perform different types of stops such as shopping, meal and social recreation within a personal business tour compared to females. People belonging to the middle income group (age 35 to 64 years), shows decreased tendency to perform social recreational stop within personal business tour compared to the people belonging to the younger and older age groups. Younger people (age 16 to 34 years) shows higher tendency to perform meal stop within personal business tour. People belonging into 35 to 54 years age group show decreased tendency to perform shopping epoch within personal business tour. People tend to exhibit increased propensity to perform personal business stop and

meal stop on Fridays compared to on any other weekdays. People living in an urban area, shows increased tendency to perform shopping stop and meal stop within personal business tour compared to people living in rural area. People belonging into the highest income group (i.e. HH income greater than $100K) tend to perform more social recreational stops within personal business tour compared to people with lower HH income.

Table 5.5 Estimation Results for the Personal Business Epoch (Bottom) Level Model

Baseline Utility Specification		***Satiation Parameter Specification***	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**Personal Business epoch**	
Constant	-1.341 (-32.38)	Constant	3.515 (14.14)
Personal Business epoch		Male indicator	-0.407 (-1.73)
Constant	-5.991 (-14.99)	**Shopping epoch**	
Age 16 to 34 years	-0.969 (-2.11)	Constant	4.309 (28.57)
Age 35 to 54 years	-0.342 (-1.1)	Friday indicator	0.718 (1.59)
Age 55 to 64 years	-0.593 (-1.73)	**Meal epoch**	
Friday Indicator	0.385 (1.37)	Constant	5.093 (17.43)
LA county indicator	0.366 (1.58)	Male indicator	0.36 (1.27)
Shopping epoch		Age 16 to 34 years	-0.86 (-2.29)
Constant	-5.321 (-19.28)	Age 35 to 64 years	-0.994 (-3.59)
Male indicator	-0.403 (-2.76)	**Social Recreation epoch**	
Age 35 to 54 years	-0.239 (-1.6)	Constant	7.815 (6.05)
Urban area indicator	0.557 (2.24)		
Meal epoch			
Constant	-5.974 (-15.4)		
Male indicator	-0.242 (-1.28)		
Age 16 to 34 years	0.53 (2.1)		
Urban area indicator	0.282 (0.89)		
Friday indicator	0.339 (1.55)		
Social Recreation epoch			
Constant	-5.528 (-30.22)		
Male indicator	-0.381 (-2.09)		
Age 35 to 54 years	-0.448 (-2.22)		
Age 55 to 64 years	-0.594 (-2.55)		
Yearly HH income >$100K	0.45 (2.55)		

5.4.6.2 Satiation parameter

Similar to the epochs performed within other tours, social recreation stop has the lowest satiation, meaning people tend to spend more time into social recreational stop compared to any other additional

stops within a personal business tour. Social recreational stop is followed by meal stop. Males tend to spend less time into additional personal business epoch within a personal business tour, compared to females. However, they tend to spend more time into meal epoch compared to females. On Friday people seem to spend more time into shopping stop within a personal business tour compared to on any other weekdays.

5.4.7 Epoch level participation and time allocation: shopping

Table 5.6 presents the epoch level participation and time allocation results for the epochs pursued within shopping tour. The primary activity of the tour (shopping) and the return home journey have been treated as outside goods.

5.4.7.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. All else being equal, meal has the lowest propensity to be performed as an additional stop within a shopping tour, followed by shopping and social recreation. People reporting as drivers, tend to perform additional shopping stop within a shopping tour compared to non-drivers. On Fridays people exhibit higher propensity to perform meal stop within a shopping tour compared to on any other weekdays. People with HH income more than $25K tend to perform additional shopping stop within a shopping tour compared to people with HH income less than $25K.

5.4.7.2 Satiation parameter

People tend to exhibit similar satiation for meal stop and social recreational stop within a shopping tour, which is slightly less than the satiation for shopping stop within a shopping tour. In other words, all else being equal people tend to spend slightly more time for meal and social recreational stops within a shopping tour compared to shopping stop.

Table 5.6 Estimation Results for the Shopping Epoch (Bottom) Level Model

Baseline Utility Specification		*Satiation Parameter Specification*	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home	-1.454 (-45.74)	**Shopping epoch**	
Constant		Constant	4.643 (29.79)
Shopping epoch		**Meal epoch**	
Constant	-5.85 (-11.51)	Constant	5.496 (14.72)
Age 35 to 54 years	-0.295 (-2.13)	**Social Recreation epoch**	
Age 55 to 64 years	-0.39 (-2.26)	Constant	5.469 (12.73)
Yearly HH income >$25K & <$50K	0.254 (1.26)		
Yearly HH income >$50K & <$100K	0.458 (2.52)		
Yearly HH income >$100K	0.346 (1.78)		
Driver indicator	0.832 (1.68)		
Meal epoch			
Constant	-6.106 (-23.13)		
Yearly HH income >$50K & <$100K	0.208 (0.79)		
Yearly HH income >$100K	0.494 (2)		
Friday indicator	0.42 (1.9)		
Social Recreation epoch			
Constant	-5.385 (-18.34)		
Age 16 to 34 years	-1.304 (-2.48)		
Age 35 to 54 years	-0.502 (-1.6)		
Age 55 to 64 years	-1.495 (-3.04)		
Yearly HH income >$25K & <$50K	-0.462 (-1.17)		

5.4.8 Epoch level participation and time allocation: meal

Table 5.7 presents the epoch level participation and time allocation results for the epochs pursued within meal tour. The primary activity of the tour (meal) and the return home journey have been treated as outside goods.

5.4.8.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. All else being equal, meal has the lowest propensity to be performed as an additional stop within a meal tour followed by social recreation and shopping. People living in the urban area shows increased propensity to perform shopping

stop and social recreational stop within a meal tour compared to people living in the rural area. This observation might be indicative of the fact that, in urban areas people tend to form trip chains by performing multiple activities within the same tour, while in the rural areas comparatively simple tours are made. Respondents from LA county has the higher propensity to perform additional shopping stops within a meal tour compared to the respondents from Phoenix-Mesa in AZ.

5.4.8.2 Satiation parameter

Within meal tour, all else being equal, social recreational stop has the lowest satiation followed by meal and shopping stops. In other words, all else being equal people tend to spend more time into social recreational stop and least time into shopping stop within a meal tour.

Table 5.7 Estimation Results for the Meal Epoch (Bottom) Level Model

Baseline Utility Specification		***Satiation Parameter Specification***	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**Shopping epoch**	
Constant	-1.761 (-39.23)	Constant	3.928 (15.82)
Shopping epoch		**Meal epoch**	
Constant	-6.872 (-10.5)	Constant	4.143 (5.38)
Age 55 to 64 years	-1.26 (-2.97)	**Social Recreation epoch**	
Yearly HH income >$50K & <$100K	-0.602 (-1.63)	Constant	6.898 (10.43)
Yearly HH income >$100K	-0.787 (-2.11)		
Urban area indicator	0.647 (1.18)		
LA county indicator	0.69 (2.06)		
Meal epoch			
Constant	-7.872 (-8.19)		
Yearly HH income >$25K & <$50K	-0.888 (-1.03)		
Social Recreation epoch			
Constant	-7.109 (-14.92)		
Urban area indicator	0.643 (2.21)		

5.4.9 Epoch level participation and time allocation: social recreation

Table 5.8 presents the epoch level participation and time allocation results for the epochs pursued within social recreational tour. The primary activity of the tour (social recreation) and the return home journey have been treated as outside goods.

5.4.9.1 Baseline marginal utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Albeit, the magnitude of the constant for the return home journey is much smaller compared to any other additional epochs – which is intuitive since all HBT ought to have a return home journey. All else being equal, meal has the lowest propensity to be performed as an additional stop within a social recreational tour followed by shopping and social recreation. Males have lower propensity to perform shopping stop within a social recreational tour compared to female. People tend to perform additional meal stop within a social recreational tour more in urban areas compared to in a rural area. Respondents reporting as drivers tend to chain shopping stop within a social recreational tour more compared to a non-driver respondent.

Table 5.8 Estimation Results for the Social Recreation Epoch (Bottom) level Model

Baseline Utility Specification		***Satiation Parameter Specification***	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		**Shopping epoch**	
Constant	-1.504 (-33.13)	Constant	4.228 (15.81)
Shopping epoch		Male indicator	-0.484 (-1.54)
Constant	-6.774 (-11.79)	Age 35 to 54 years	0.689 (1.66)
Male indicator	-0.16 (-0.96)	Yearly HH income >$25K & <$50K	0.376 (1.18)
Yearly HH income >$25K & <$50K	0.356 (1.81)	Yearly HH income >$100K	0.759 (2.15)
Driver indicator	0.647 (1.27)	Friday indicator	-0.688 (-2.07)
Meal epoch		**Meal epoch**	
Constant	-6.892 (-15.94)	Constant	5.594 (23.41)
Urban indicator	0.889 (2.36)	**Social Recreation epoch**	
Social Recreation epoch		Constant	5.451 (18.31)
Constant	-6.702 (-59.57)	Male indicator	-0.752 (-1.76)

5.4.9.2 Satiation parameter

Meal stop has the lowest satiation, followed by social recreation and shopping while performed within a social recreational tour. Males tend to spend less time into shopping stop and social recreational stop while performed within a social recreational tour compared to female. People belonging into the middle age group tend to spend more time into shopping stop while performed within a social recreational tour

compared to people of any other age groups. On Fridays people tend to spend less time in executing shopping stop while performed within a social recreational tour.

5.4.10 Sample replication

The focus of this section is to validate the proposed framework and model formulation. The objective of this analysis is to illustrate the framework's ability to replicate the observations. The forecasting routine for the proposed bi-level model formulation outlined below builds on the approach proposed by Pinjari and Bhat (2011) for Kuhn-Tucker demand systems.

i. First, total daily budget of 1440 minutes is allocated across the 7 HBTs and the AH alternative. In order to capture the entire distribution of the random error term, this step is carried out 100 times using realizations from MVN distribution.

ii. Second, the tour budget (predicted in the last step) is allocated to components of the tour (including the primary epoch, the intermediate epochs and the return home journey). For each individual, and for each tour budget realization, this step is repeated 100 times using realizations from MVN distribution resulting in 100×100 realizations of time allocation to components of the tour.

iii. Third, average participation and time allocation into different tours are calculated as the average across 100 realizations across all the observations.

iv. Fourth, in order to capture the stochastic nature of the budget of the epoch level time allocation, the participation and time allocation at the epoch level are calculated similar to the last step and then averaged across the entire budget distribution.

Table 5.9 presents the replication results. The top portion of the table presents the predicted and observed percentage of the individual who participated into different tours and epochs. While the bottom portion of the table presents the predicted and observed duration (average in minutes) of the tours and the epochs within the tours. While, the predicted participation percentages very closely replicate the observed participation percentages, there are some deviations between the predicted and observed time allocation. This can partly be attributed to the specification of the satiation parameters. Enhancing the specification of the satiation parameter, will better capture the variability in the satiation effect across different

demographic groups. Also, in order to further improve the replication results for epochs, future studies may explore alternate formulations of tours, epochs and branching. One example can be to bundle different intermediate epochs together in the second level and then model participation and time allocation into each intermediate epoch in the third level.

Table 5.9 Baseline Forecasting (Replication Results)

Tour types	Participation[1] (%) Predicted (Observed)	Epoch types								
		Primary Activity	*Work*	*School*	*Escort*	*Personal Business*	*Shopping*	*Meal*	*Social Recreation*	*Return home*
		Participation[2] (%) - Predicted (Observed)								
At home	100 (100)	---	---	---	---	---	---	---	---	---
Work	67 (75)	100 (100)	8 (6)	1 (1)	7 (7)	9 (8)	13 (13)	7 (7)	6 (5)	100 (100)
School	3 (3)	100 (100)	---	7 (6)	5 (3)	6 (4)	14 (10)	10 (7)	8 (6)	100 (100)
Escort	6 (6)	100 (100)	---	---	20 (17)	13 (10)	19 (16)	14 (12)	15 (12)	100 (100)
Personal Business (PB)	10 (12)	100 (100)	---	---	---	11 (11)	23 (22)	13 (12)	9 (7)	100 (100)
Shopping	9 (11)	100 (100)	---	---	---	---	22 (16)	8 (4)	5 (3)	100 (100)
Meal	5 (7)	100 (100)	---	---	---	---	11 (10)	4 (3)	6 (2)	100 (100)
Social Recreation (SR)	12 (15)	100 (100)	---	---	---	---	9 (8)	8 (5)	4 (3)	100 (100)
Tour types	**Duration[3] (Min.) Predicted (Observed)**	**Epoch types**								
		Primary Activity	*Work*	*School*	*Escort*	*Personal Business*	*Shopping*	*Meal*	*Social Recreation*	*Return home*
		Duration[4] (Min.) - Predicted (Observed)								
At home	891 (933)	---	---	---	---	---	---	---	---	---
Work	478 (436)	599 (519)	19 (9)	4 (2)	5 (2)	13 (6)	17 (6)	9 (4)	12 (6)	40 (30)
School	11 (11)	325 (309)	---	10 (8)	2 (1)	4 (2)	13 (6)	6 (4)	13 (8)	39 (21)
Escort	8 (7)	41 (45)	---	---	6 (4)	19 (9)	13 (8)	12 (8)	27 (18)	19 (15)
Personal Business (PB)	15 (16)	77 (83)	---	---	---	5 (3)	20 (11)	12 (7)	18 (10)	23 (18)
Shopping	12 (9)	74 (60)	---	---	---	---	19 (6)	8 (2)	6 (2)	20 (14)
Meal	7 (8)	96 (90)	---	---	---	---	8 (3)	3 (2)	9 (2)	19 (15)
Social Recreation (SR)	18 (21)	101 (108)	---	---	---	---	6 (3)	8 (3)	4 (2)	32 (19)

Notes: (1) The denominator is the number of observations in the sample (5233)
(2) The denominator is the number of people who predicted (observed) to participate in the respective tour
(3) Average taken across the 5233 observations
(4) Average taken across the observations who are predicted (observed) to participate in the respective tour

5.4.11 Sensitivity analysis

The focus of this section is to highlight the model's ability to capture the interrelationships between tour level and epoch level, participation and time allocation decisions. The sensitivity analysis is carried out altering the land use variable. In particular, it was assumed that more suburbanization occurs by moving 50 percent of the households to suburban/rural areas[24].

Table 5.10 presents the change in average time allocation into different tours/epochs for the people who participated in that particular tour/epoch type[25]. A positive (negative) value indicates an increase (decrease) in time allocation from baseline scenario. In terms of tour time allocation, notable changes are observed in the work, PB, shopping and SR tours.

The results also show the ability of the model formulation to capture the interrelationships between tour and epoch level choices. There is a two level impact of the shift in the land use on the time allocation into different epochs within the tour. First, it can be seen from the table that, for the tour types with a notable change in budget (positive in current scenario analysis), overall time allocation into different epochs also increased[26] (e.g. work, PB, shop and SR tours). Such shifts can only be captured through consistent prediction of the tour budget. Specifically, for certain exogenous variables that significantly affect time allocation to tours, if change in tour budget is not forecasted correctly, it will not capture the indirect impacts on the epoch participation and time allocation decisions. Second, for tour types with slight change in the tour budget, the time allocation into different epochs mainly got redistributed[16] (e.g. school, escort and meal tours).

[24] This was achieved by randomly assigning 50% of the sub-sample to suburban/rural areas assuming baseline values are maintained for the rest of the variables
[25] The change in average time allocation across all the individual (irrespective of participation) is also reported in the parentheses
[26] This can be verified by taking the summation across all the values in the epoch duration reported in the parentheses for the respective tours.

Table 5.10 Impacts on Tour and Epoch Time Allocation Due to Land use and Demographic Changes

Impact of Change in Land Use										
Tour types	**Change in Minutes**	**Epoch types**								
		Primary Activity	*Work*	*School*	*Escort*	*Personal Business*	*Shopping*	*Meal*	*Social Recreation*	*Return home*
		Change in Minutes								
At home	-0.83 (-0.83)	---	---	---	---	---	---	---	---	---
Work	5.20 (1.03)	7.43 (7.43)	0.43(0.09)	-0.08 (0.16)	0.64 (0.1)	1.03 (0.1)	-5.56 (-2.85)	1.98 (0.45)	-1.83 (-0.89)	0.60 (0.60)
School	0.61 (0.19)	-3.27 (-3.27)	---	-4.36 (-1.82)	-0.97 (-0.26)	-2.12 (-0.66)	15.37 (8.93)	-1.09 (-0.25)	-3.15 (-1.47)	-0.59 (-0.59)
Escort	-0.92 (-0.07)	2.17 (2.17)	---	---	1.6 (0.73)	-0.99 (-5.26)	2.21 (1.17)	2.15 (1.31)	0.89 (-2.16)	1.12 (1.12)
Personal Business (PB)	6.12 (-0.38)	4.14 (4.14)	---	---	---	1.21 (0.4)	-1.53 (-2.64)	0.84 (-0.42)	4.17 (3.37)	1.27 (1.27)
Shopping	9.20 (-0.28)	4.16 (4.16)	---	---	---	---	2.53 (1.83)	3.06 (1.51)	2.21 (0.61)	1.09 (1.09)
Meal	-0.90 (0.12)	1.96 (1.96)	---	---	---	---	-2.16 (-1.67)	0.50 (0.15)	-1.73 (-2.12)	0.77 (0.77)
Social Recreation (SR)	9.66 (0.22)	7.80 (7.80)	---	---	---	---	5.83 (1.13)	-3.06 (-2.48)	4.46 (0.72)	2.49 (2.49)

Notes:
(1) Values outside the parentheses represent the change in average time allocation calculated across people who participated in the respective tour/epoch
(2) Values inside the parentheses represent the change in average time allocation calculated across all the individual (in case of tour), across all the individual who participated in the respective tour (in case of epochs)

5.5 Summary and Conclusions

In the tour-based activity based modeling (ABM), daily activity-travel agendas are formed in two stages: activity pattern generation and activity scheduling. The present work contributes to the activity pattern generation of ABMs.

The primary objective of the current research was to propose a tour generation framework that treats time as a continuous entity and explicitly accounts for temporal constraint for different tours and for different stops within the tours in a behaviorally consistent manner. The econometric formulation of the proposed framework is built on the utility theoretic Kuhn-Tucker demand system established by Bhat (2008, 2013) for multiple discrete continuous choice scenarios. The proposed approach assumes a bi-level decision making structure (where the alternatives considered at both stages are imperfect substitutes of one another) where the epoch level participation and time allocation decisions are constructed depending on the decisions made at the tour level.

The proposed framework was applied using data from NHTS 2008-2009. The empirical case study demonstrates the ability of the model formulation to model participation and allocate the daily time (1440 minutes) into different tours (including at home activities) followed by participation and time allocation into the primary epoch and intermediate epochs within the tours. Additionally, the proposed formulation offers the ability to accommodate more flexible error structure between different tour types and between different stops within the tours. The estimation routine's non-reliance on any kind of numerical simulation lends itself to be adopted in practice (Bhat 2011). The replication study conducted afterwards indicated that the framework is capable of capturing the tradeoffs underlying the tour and stop/epoch making decisions.

The proposed framework can be readily embedded into the existing tour-based ABM frameworks (e.g. Bowman and Bradley 2008). The bi-level model would replace a large number of independent model components related to day pattern generation (including number of tours, number of stops in a tour, time allocated to tours, and time allocated to stops in a tour). After the participation and time allocation decisions have been modeled using the proposed framework, other decisions relating to tour and stop

level characteristics (e.g. mode choice, destination, and occupancy among others) can be addressed using independent or joint model systems. The model implementation is also computationally very tractable. While more complex compared to traditional approaches, the proposed approach achieves efficiency by replacing a number of independent model systems and heuristics. In this study, computational overhead of the proposed framework (in terms of model estimation and forecasting) was found to be comparable to individual econometric model systems (such as MNL, MDCEV). On a Dell Latitude 620 Laptop with 2.9 GHz core i7 processor and 8GB RAM, the estimation took 1-3 hours (depending on the starting values of the parameter vector) and sensitivity analysis took about 10 minutes to run. Similar forecasting runtimes can be achieved even for a full model application (with large population sizes) by leveraging the power of parallelization. Large synthetic population can be broken down into smaller subpopulation and processed in parallel to make the application of the proposed model formulation practical.

CHAPTER 6

TIME ALLOCATION BEHAVIORS OF TWENTIETH CENTURY AMERICAN GENERATIONS

6.1 Introduction and Motivation

Researchers from different disciplines have approached the study of trends in time engagement behavior with different motivations and from varied perspectives (Gershuny and Robinson 1988 and Aguiar and Hurst 2009). Some examples include, study of gender convergence in time allocation behaviors by Fisher et al. (2007), the trend in time spent with children studied by Fox et al. (2013), the study of leisure time engagement trend by Aguiar and Hurst (2007), and the study of cross-country time engagement trend by Gimenez-Nadal and Sevilla (2012). Study of time engagement behavior has also garnered interest among transportation researchers in the recent past due to the acknowledgement of the derived nature of travel.

There is a rich body of literature on time engagement choices of individuals in the field of transportation (Bhat and Koppelman 1999, Jara-Diaz and Rosales-Sala 2017). More recently the out-of-home activity and travel engagement behavior of the Baby Boomers' and the Millennials' have sparked considerable interest among the transportation researchers due to their "atypical" activity-travel patterns (Garikapati et al. 2016). For example, Millennials' have been associated with declining rates of driving license holdings, decreasing automobile dependency, decreasing employment participation and use of virtual mobility (Delbosc and Currie 2013, McDonald 2015). These trends in the activity-travel choices of Millennials' have been attributed to their tendency to prolong education years, delay work force entry, and postpone marriage and consequently family formation (Polzin et al. 2014). On the other side of the spectrum, the aging Boomers have been characterized to be more active than the previous generations as demonstrated by increased out-of-home activity participation and late retirement tendency (Goulias 2007, Miranda-Moreno and Lee-Gosselin 2008).

The overarching goal of the current research is to compare the activity-travel behaviors of these two generations, namely Baby Boomers and Millennials with that of previous generations while

accounting for age, period, and cohort effects. In particular, the study focuses on understanding the similarities and differences in activity-travel pursuits of five American generations from the twentieth century, namely, GI Generation (1901-1924), Silent generation (1925–1943), Baby Boomer (1944–1964), Generation X (1965–1981) and Millennials (1982-2000). The analysis is conducted by combining data from four waves of American Heritage Time Use Survey (AHTUS) from 1965 through 2012 to obtain a representative sample from different generations and across different stages of life. The study attempts to separate the differences in the activity-travel patterns of different generations associated with demographic attributes from those associated with generational differences resulting from unobserved factors such as attitudes, perceptions, beliefs, and traits among others which is important for accurate prediction of the activity-travel behaviors. It can be noted that, the actual definition of the generational cohorts vary slightly from one literature to another - the definitions adopted in the current research (based on birth years) are adopted from Strauss and Howe (1991). Also, it can be noted that, in the adopted definition the number of birth years considered for different generational cohorts vary from 16 years (for Generation X) to 23 years (for GI generation).

The contribution of generational effect (also referred to as cohort effect) needs to be studied in relation to the two other types of dynamic effects such as age and period effect. These three types of effects are defined below:

i. Cohort effect refers to activity-travel behavior differences associated with being born at a specific time in the history. The cohort effect represents the attitudes, perceptions, beliefs, and traits that characterize individuals of same generation – these are formed by common epochal events that the individuals of the same generation experience (Strauss and Howe 1991). For example, Kostyniuk and Kitamura (1987) note that a person growing up during an era of motorization would continue to be inclined towards private vehicle for their mobility irrespective of other factors such as living arrangements.

ii. Age effect refers to differences associated with an individual's age. This component essentially captures the effects of life cycle stages.

iii. Period effect refers to differences associated with a specific period of time that the individual experiences. This period is also generally experienced by more than one birth cohort. The essence of period effect can be captured via the idiom “a rising tide lifts all boats”. For example, during recession, people belonging to all birth cohorts and age groups may curtail their discretionary spending and thus discretionary time allocation due to the financial and economic uncertainty they experience.

Kostyniuk and Kitamura (1987) study the impact of motorization on different cohorts using data from New York from 1963 to 1974. Newbold et al. (2005) studies the trip rate, trip duration, trip mode choice and out-of-home activity participation propensity of Canadian cohorts using data from 1986 to 1998. A similar study was conducted using a recent dataset by Scott et al. (2009) which explore trends in number of trips, trip duration, trip mode and trip timing of Canadian urban seniors. Frandberg and Vilhelmson (2011) explore the trend of motorization and individualization of travel modes of Swedish population using data from 1978 to 2006.

In spite of the growing recognition of the study of cohort effects in understanding and forecasting the activity-travel behavior, there has been limited literature exploring the influence of cohort on activity participation (what types of activities are pursued?) and time allocation choices (how much time is spent in those activities?). Further, studies have not attempted to separate the cohort effect from the two other types of effects related to age and period. The research presented in this chapter attempts to fill this gap by explicitly accounting for the cohort, age, and period when exploring the heterogeneity in activity participation and time allocation choices of Americans; the study also controls for other demographic and situational differences in exploring the heterogeneity. To the best of our knowledge, the current study is perhaps the first of its kind that sheds light on the trends in in-home and out-of-home activity participation and time allocation behaviors of all American generations from twentieth century.

The rest of the chapter is organized as follows. The next section describes the American Heritage Time Use Study (AHTUS) data. The third section presents a descriptive analysis of the trends in activity participation and time engagement behaviors of different birth cohorts of same age groups as well as depicts the demographic differences across cohorts. This section also postulates the trends in the activity-

travel behavior of the Baby Boomer and Millennial based on the previous literature as well as the exploratory analysis presented in this section. The fourth section presents a multivariate modeling framework to explore the similarities and differences in participation and time engagement behaviors across cohorts while accounting for other factors. The fifth section presents results from the multivariate modeling analysis. The sixth and the final section provides a summary of the research findings and offers suggestions for future research.

6.2 Data Composition

In this research, data from American Heritage Time Use Study (AHTUS), a database of cross-sectional time use datasets of US individuals collected over six decades was used. The current study utilizes four datasets from the AHTUS database: (1) 1965-66 dataset, (2) 1985 dataset, and (3) two waves of American Time Use Survey (ATUS) from 2005 and 2012. The four cross-sectional datasets include information on demographic characteristics and living arrangements of the respondents along with a log of activity and travel episodes pursued over a period of 24 hour. The 24 hour activity-travel log includes information about the type, location, accompaniment and mode of the reported activity and travel episodes. The process of pooling the four datasets for use in the analysis is described below.

The pooled sample that includes information from the four datasets includes 23,315 respondents: 1,154 observations from 1965-66, 2,147 observations form 1985, 10,224 observations from 2005, and 9,763 observations from 2012. The following data processing steps were applied to ensure data quality.

i. Observations with following four types of discrepancies were excluded from further consideration, namely, a) missing background information on age, sex and diary day, b) missing activity information of more than 90 minutes after imputation, c) reported activity episodes being less than 7; d) absence of at least 2 types of basic activity categories including sleep or rest, eat or drink, personal care, and, travel or exercise.

ii. Further, any respondent for whom the reported activity and travel durations do not add up to 1440 minutes were excluded from further consideration.

iii. Finally, additional checks were conducted to eliminate respondents with inconsistent and extreme activity-travel behaviors. Specific filtering criterion applied at this stage, include, a) unemployed respondents reporting work episodes, b) non-students reporting school episodes, and, c) respondents spending zero minute at-home on survey day.

Next, the episode level activity-travel information were aggregated up to the day level by activity type. At this stage, the detailed activity-travel purposes reported by AHTUS were consolidated into six broad categories, namely, maintenance, discretionary, work, education, travel, and other. Further, the maintenance and discretionary activities were disaggregated into in-home and out-of-home categories depending on the reported location. The above categorization scheme resulted in following eight activity-travel groupings: maintenance in-home (MIH), maintenance out-of-home (MOH), discretionary in-home (DIH), discretionary out-of-home (DOH), work, education, travel, and, other. Furthermore the sample was restricted to adults (i.e. individuals of 18 to 85 years of age).

Table 6.1 presents the sample size of different cohorts by age group in the pooled dataset. The rows indicate the period to which the different cohorts belong. As can be seen from the table, it was only possible to observe Silent generation and the Baby Boomers across different life cycle stages. For the rest of the generations it was only possible to capture either the older (GI generation) or the younger (Generation X, and Millennials) life cycle stages.

Table 6.1 Sample Composition of Five Cohorts by Age Groups

Age groups	18-24 years	25-34 years	35-44 years	45-54 years	55-64 years	>= 65 years	Total
Periods[1]	*GI Generation (Birth year: 1901 - 1924)*						
1965	0	0	121	254	161	0	536
1985	0	0	0	0	98	246	344
2005	0	0	0	0	0	351	351
2012	0	0	0	0	0	0	0
Total	0	0	121	254	259	597	1231
Periods[1]	*Silent Generation (Birth year: 1925 - 1943)*						
1965	99	294	161	0	0	0	554
1985	0	0	109	318	171	0	598
2005	0	0	0	0	381	1335	1716
2012	0	0	0	0	0	1489	1489
Total	99	294	270	318	552	2824	4357
Periods[1]	*Baby Boomers (Birth year: 1944 - 1964)*						
1965	64	0	0	0	0	0	64
1985	203	562	345	0	0	0	1110
2005	0	0	1031	2035	1048	0	4114
2012	0	0	0	1274	1655	524	3453
Total	267	562	1376	3309	2703	524	8741
Periods[1]	*Generation X (Birth year: 1965 - 1981)*						
1965	0	0	0	0	0	0	0
1985	95	0	0	0	0	0	95
2005	109	1796	1494	0	0	0	3399
2012	0	783	2042	558	0	0	3383
Total	204	2579	3536	558	0	0	6877
Periods[1]	*Millennials (Birth year: 1982 - 2000)*						
1965	0	0	0	0	0	0	0
1985	0	0	0	0	0	0	0
2005	644	0	0	0	0	0	644
2012	593	845	0	0	0	0	1438
Total	1237	845	0	0	0	0	2082

Note: (1) Periods refer to the survey year

6.3 Descriptive Analysis

In this subsection, a descriptive analysis is presented based on the subsample prepared using the process described above. Also, it must be noted that, the results reported in this section are based on weighted sample. The weights used in the analysis corrects for the age, gender, day of week and the location (defined by state) of the survey sample.

6.3.1 Activity participation trend across cohorts by age groups

Table 6.2 presents the percentage of people participating in different activities and travel across different cohorts of the same age group. It should be noted that the respondents used in the analysis participated in at least one episode of MIH, as a result, a hundred percent participation in MIH is observed for all cohorts by all age group. In general, participation in MOH is reducing across cohorts of different age groups with the exception of individuals transitioning into adulthood (25-34 years) and elderly (above 65 years).

Generation X and Millennials in the 25-34 years age group show a 3 to 4% higher participation in MOH activities compared to the Silent Generation and Baby Boomers. Also, elderly Boomers show a 3% higher participation in MOH activities compared to the Silent Generation alluding to the active life style of the Boomers compared to previous generations.

There is hardly any difference in DIH activity participation across cohorts in 18 to 24 years age group. For the remaining age categories, the DIH activity participation decreases across different cohorts. However, the rate of decrease is lowering with increasing age. The decrease in DIH activity participation is generally accompanied by increase in DOH activity participation by different cohorts of all age groups. The increase in DOH participation is most prominent for the youngest age group and reduces with increasing age. For example, the Millennials of 18-24 years age group show more than 20% increase in the DOH activity participation compared to the Silent generation.

Table 6.2 Participation Percentages across Cohorts by Age Groups

Age Groups	Cohorts	*MIH*	*MOH*	*DIH*	*DOH*	*Work*	*Education*	*Travel*
18 to 24 years	*Silent Generation*	100	79	89	48	57	1	92
	Baby Boomer	100	79	91	59	50	5	94
	Generation X	100	76	91	65	45	10	91
	Millennial	100	75	90	71	39	13	92
25 to 34 years	*Silent Generation*	100	77	96	52	48	0	93
	Baby Boomer	100	76	94	49	56	0	94
	Generation X	100	81	90	63	57	3	93
	Millennial	100	80	89	62	54	3	93
35 to 44 years	*GI Generation*	100	81	91	45	62	NA	95
	Silent Generation	100	76	96	51	53	NA	93
	Baby Boomer	100	79	93	57	60	NA	92
	Generation X	100	80	91	60	58	NA	91
45 to 54 years	*GI Generation*	100	80	96	40	57	NA	90
	Silent Generation	100	78	97	46	60	NA	92
	Baby Boomer	100	75	95	61	61	NA	89
	Generation X	100	74	93	58	56	NA	87
55 to 64 years	*GI Generation*	100	78	97	44	48	NA	88
	Silent Generation	100	70	98	58	38	NA	86
	Baby Boomer	100	72	96	61	47	NA	86
>= 65 years	*GI Generation*	100	57	99	49	9	NA	69
	Silent Generation	100	59	98	59	11	NA	73
	Baby Boomer	100	62	97	58	25	NA	78

Notes:
(1) MIH = Maintenance in-home
(2) MOH = Maintenance out-of-home
(3) DIH = Discretionary in-home
(4) DOH = Discretionary out-of-home
(5) NA = Not Applicable

Millennials in young age group exhibit a considerable decrease in work participation compared to the previous generations. Though the work participation of Millennials increases as they transition into adulthood, it is still 3% less compared to the Generation X. It can also be seen that the Generation X

continues to exhibit lower work activity participation compared to Baby Boomers even in the adult life stages. It is also interesting to note that Baby Boomers have higher participation in work activity compared to Silent generation for transition into old age (55-64 years) and old age (>= 65 years) groups.

On the other hand, young Millennials show higher participation in education compared to Generation X. Both Millennials and Generation X show higher participation in education compared to the Baby Boomers and Silent Generation for individuals in 25-34 years age group. It must be noted that, the participation information in education activities has been suppressed for all observations older than 34 years due to very small sample size.

In terms of travel participation, small differences were observed between different cohorts at earlier stages of lives. For example, both Millennials and the Generation X participate less in travel compared to Baby Boomers. This also brings about an important observation regarding widely held notions about Millennials' "atypical" travel patterns. It appears like, even before Millennials, the decline in travel participation was exhibited by Generation X at different life stages when compared against the Baby Boomers. Also, the old age Baby Boomers demonstrate higher participation (of 5%) in travel compared to the silent generation.

6.3.2 Time allocation trend across cohorts by age groups

Table 6.3 presents a comparison of the average daily time allocation across cohorts belonging to each of the six age groups. It must be noted that the average time allocation was calculated considering only those individuals who reported participating in at least one episode of the said activity type. MIH time allocation has considerably reduced from the GI generation to the Millennials for all age groups. MOH time allocation has increased moderately from GI generation to Baby Boomers for those younger than 54 years old. For the young Millennials (18-24 years), daily MOH time allocation is lower compared to Generation X by 6 minutes. For Millennials transitioning into adulthood, time spent in MOH is higher by 5 minutes compared to Generation X and is lower by 6 minutes compared to Boomers in the same age group.

Table 6.3 Average Daily Time Budget in Minutes across Cohorts by Age Groups

Age Groups	Cohorts	*MIH*	*MOH*	*DIH*	*DOH*	*Work*	*Education*	*Travel*
18 to 24 years	Silent Generation	742	84	182	144	500	73	98
	Baby Boomer	694	101	199	195	448	223	100
	Generation X	726	116	232	148	409	271	85
	Millennial	683	110	239	195	435	233	87
25 to 34 years	Silent Generation	789	80	201	150	468	120	81
	Baby Boomer	716	112	223	154	447	NA	96
	Generation X	719	101	207	139	459	189	88
	Millennial	713	106	216	152	465	155	84
35 to 44 years	GI Generation	755	83	183	155	460	NA	88
	Silent Generation	760	99	204	143	452	NA	93
	Baby Boomer	700	103	219	136	469	NA	89
	Generation X	723	98	214	137	464	NA	88
45 to 54 years	GI Generation	765	82	207	133	469	NA	83
	Silent Generation	709	91	248	138	441	NA	91
	Baby Boomer	678	95	256	128	465	NA	88
	Generation X	709	95	249	139	466	NA	85
55 to 64 years	GI Generation	750	92	257	149	462	NA	83
	Silent Generation	714	116	316	146	442	NA	91
	Baby Boomer	687	104	317	134	451	NA	82
>= 65 years	GI Generation	801	94	426	143	405	NA	70
	Silent Generation	745	110	437	164	360	NA	78
	Baby Boomer	717	100	400	164	422	NA	82

Notes:
(1) MIH = Maintenance in-home
(2) MOH = Maintenance out-of-home
(3) DIH = Discretionary in-home
(4) DOH = Discretionary out-of-home
(5) NA = Not Applicable

DIH time spent is higher for later generations compared to preceding generations of young age group. The spike is most significant from Generation X to Baby Boomers. Young adult Millennials (25 to 34 years) spend nearly 9 minutes more in DIH compared to Generation X and about 7 minute less compared to Boomers of the same age group. Generation X’s DIH time allocation is lower compared to

Boomers of all age groups except for the young age group. On the other hand, the Baby Boomers' DIH time allocation has increased for all age groups compared to the Silent generation except for the old age group.

Similar to DIH time allocation, the DOH time allocation of Millennials seems to mimic Boomers more closely than Generation X individuals. The young and transitioning into adult age Generation X individuals show a considerable reduction in the DOH time allocation compared to the Boomers of the same age group. However, Generation X individuals converge to the Boomers' DOH time expenditure as they age.

Both the young age (18-24 years), Generation X and Millennials show lower work time allocation compared to the Boomers. However for the transitioning into adult age (25-34 years) Generation X individuals and Millennials, the work time allocation is higher compared to that of the Boomers. The middle age (35 to 54 years) Generation X individuals again seem to be converging to the Baby Boomers. The transitioning into old and old age group Boomers seem to be working more hours than the Silent generation.

The Generation X and Millennials have significantly lower travel time allocation compared to Baby Boomers. The travel time expenditures of young Generation X individuals is significantly lower (15 minute) than the Boomers' 100 minute daily average. It can be seen that, the young Millennials' travel time budget is not lower than that of the young Generation X individuals, rather it is about 2 minutes higher. The 25 to 34 years old Generation X individuals have an 8 minute lower travel time expenditure compared to the Baby Boomers, whereas the same age Millennials have an additional 4 minute reduction in the travel time expenditure compared to the Generation Xers. The difference in the travel time allocation decreases between the 35 to 54 year old Generation X and the Baby Boomers. Whereas the old age Boomers continue to show an average 4 minute higher travel time expenditure compared to the Silent Generation.

In summary, the differences in the time allocation are most pronounced at the earlier stages of life (i.e. ages less than 35 years) and least pronounced at the middle stages of life (i.e. 35 to 54 years). On the

other hand, old Boomers seem to be different with active life styles compared to the Silent generation even at later stages in life.

6.3.3 Demographic trend across cohorts by age groups

Table 6.4 presents the demographic profiles and the living arrangements of different cohorts by age groups. In the interest of space, the presentation is limited to age groups 18-34 years, and above 54 years. In terms of living arrangement, more Generation X individuals live in urban areas compared to Boomers and more Millennials live in urban areas compared to Generation X. In terms of demographic characteristics, the percentage of student population among the 18-24 years Millennials is 45% which is nearly 15% higher compared to Generation X individuals. The proportion of Millennials who are employed is lower than Generation X individuals for those in 18–24 age category. The unemployed population is also nearly 8% higher for Millennials compared to Generation X folks in 18-24 year group. The difference in proportions of married individuals is more pronounced between Generation X and Millennials compared to between Boomers and Generation X individuals.

All of the shifts in the demography described above for the 18-24 year olds also apply to those cohorts belonging to the 25 to 34 years age groups, however, the differences are lower in magnitude.

Among the transitioning into old and old age groups, major shift can be seen in terms of retirement age. There is a 14% drop in the retired population among the 55-64 years old Boomers compared to the Silent generation. Similarly, there is a 24% decline in the retired population among the old age Boomers compared to the Silent generation.

The discussion above clearly demonstrates the demographic differences in terms of student status, (un)employment status, marital status as well as living arrangement of the young age and transition into young age groups across generations – in particular for Millennials compared to Generation X and the Baby Boomers. Also, considerable differences are observed in terms of retirement age of the Baby Boomers compared to the Silent generation.

Table 6.4 Demographic Shifts across Cohorts by Age Groups

Age group: 18 – 24 years			
	Baby Boomer	*Generation X*	*Millennial*
Percentage living in urban area	80	79	82
Student percentage	14	30	45
Worker percentage	72	65	64
Unemployed percentage	5	6	14
Married percentage	43	32	18
Age group: 25 – 34 years			
	Baby Boomer	*Generation X*	*Millennial*
Percentage living in urban area	80	79	82
Student percentage	14	30	45
Worker percentage	72	65	64
Unemployed percentage	5	6	14
Married percentage	43	32	18
Age group: 55 – 64 years			
	GI Generation	Silent Generation	Baby Boomer
Percentage living in urban area	80	74	80
Worker percentage	63	54	66
Retired percentage	18	28	14
Age group: Above 65 years			
	GI Generation	Silent Generation	Baby Boomer
Percentage living in urban area	72	77	79
Worker percentage	12	18	37
Retired percentage	81	74	48

It is plausible that the lower participation in work and education activities, the higher discretionary time allocation and lower travel time expenditures of the Millennials are due to the very different demographic composition of this generation compared to the previous generations. As the generation transition into later stages of life, the activity-travel patterns of Millennials may ultimately converge to those of the Generation X. This is what has been observed in case of the adult age Generation X individuals – the differences in the activity-travel pursuit of Generation X folks compared to Boomers was the lowest for the 35 to 54 year old age group. The next section presents a multivariate modeling

analysis of the activity participation and time allocation choices while accounting for the age, cohort as well as the period effect in addition to the contribution of different demographic characteristics.

6.3.4 Premises about the Baby Boomers' and Millennials' activity-travel behavior

This section discusses the premises of the activity-travel trend of the Millennials and the Baby Boomers which builds on the previous research on the topic as well as the exploratory analysis presented in the sections 6.3.1 through 6.3.3. Previous literature on the topic have ventured to define the profile of the Millennials based on their demographic characteristics as well as activity and travel pursuits. According to the literature Millennials tend to live in dense urban places and prefer low level of car ownership (Nielsen 2014); they also tend to delay marriage and family formation (Lamberti 2015). On the travel behavior front, the Millennials have been characterized by less driving, higher preference for alternative modes of transport, lower trip rate, and lower vehicle miles traveled (Lyons 2015). Additionally, Le Vine, Latinopoulos, and Polak (2014) argued that Millennials have been trading off lower participation in out-of-home activities with higher participation in in-home virtual activities.

Few literature have also argued that, the differences between the Millennials and Generation X individuals are not significant enough to redefine the urban landscape of America (Leanne and Brett 2015). Moreover, according to some researchers Millennials are just putting off the entry into the adulthood for few additional years compared to their immediate previous generation, i.e. generation X (Walker 2015).

The exploratory analysis presented in the previous sub-sections reveals the declining rate of travel and work force participation as well as increased rate of education and discretionary activity participation of the Millennials compared to the Generation X individuals. However, in terms of demographic characteristics, Millennials (specially the youngest age group, 18-24 years old) seem to be very different compared to the Generation X individuals. On the other hand, the descriptive analysis reveal that, the Baby Boomers are more active compared to their immediate previous generation (i.e. Silent generation) as indicated by higher work force participation and late retirement. The multivariate modelling analysis presented in the next section makes an effort to quantify and contrast the relative contribution of the

demography, period and cohort effect with the aim of predicting the activity-travel characteristics of the Millennials and Baby Boomers for the uncertain transportation future.

6.4 Econometric Methodology

The multivariate modeling analysis utilizes the multiple discrete continuous extreme value (MDCEV) framework proposed by Bhat (2008). The framework is capable of simultaneously modeling the activity participation and time allocation choices of different activity types subjected to a resource constraint. The analysis combines four cross-sectional datasets from the years 1965, 1985, 2005 and 2012 to form a pooled dataset. This approach of combining multiple cross-sectional datasets to study the dynamics of choices has been used by other researchers in the past (examples include Glenn 1977, Dargay 2002, Huang 2007, Hjorthol 2010, Sobhani et al. 2014). The MDCEV model structure is briefly described below along with a discussion of the necessary considerations for pooled dataset.

6.4.1 Multiple Discrete Continuous Extreme Value (MDCEV) model for pseudo panel data

Following Bhat (2008), the time engagement choices into different activities can be formulated as an allocation problem. According to the allocation problem, an individual allocates a certain available budget (i.e. 1440 minutes available in a day) across multiple activities such that the utility derived by engaging in the various activities is maximized.

The allocation problem where an individual allocates $x = \{x_1, x_2, \dots, x_k\}$ amounts of time to K activities can be formulated as shown in Equation (6.1) and (6.2) below.

$$\max U(x) = \Psi_1 \ln(x_1) + \sum_{k=2}^{K} \gamma_k \Psi_k \ln(\frac{x_k}{\gamma_k} + 1) \quad (6.1)$$

$$\text{subject to } \sum_{k=1}^{K} x_k = T \quad (6.2)$$

where, x is a $(K \times 1)$ vector of time allocated to activities $1,2, \dots, K$. Individuals try to maximize the total utility U given by equation (6.1) subject to the time budget constraint T given by equation 6.2. $\Psi_k (> 0)$ is known as the baseline marginal utility parameter and represents the gain in utility realized by allocating 1st unit of time to activity k. On the other hand, $\gamma_k\ (> 0)$ is known as the translation/satiation parameter

and controls the amount of time allocation into different activity types. The Ψ and γ are further parametrized as in equation (6.3) and (6.4) below.

$$\Psi = \exp(\nu\beta + \varepsilon) \tag{6.3}$$

$$\gamma = \exp(w\alpha) \tag{6.4}$$

where, Ψ and γ are $(K \times 1)$ vectors of baseline marginal utility and satiation parameters respectively, ν and w are $(K \times D)$ matrices of exogenous variables, β and α are $(D \times 1)$ vectors of coefficients, and ε is a $(K \times 1)$ vector of stochastic error term.

In the current study, ε is assumed to be independent and identically type I extreme value distributed across activities and individuals. However, the scale of the error is allowed to be different for different periods to account for the pooled nature of the dataset. More specifically, the scale of the error, σ is parameterized as in equation (6.5).

$$\sigma_i = \exp(\pi_i \delta_i) \tag{6.5}$$

where, σ_i is the scale of the error for period *i* = 1965, 1985, 2005 and 2012, π_i is a period specific parameter to be estimated along with α and β, and δ_i is an indicator variable which assumes the value 1 for period *i* and 0 otherwise. The exponentiation operator ensures that a non-negative scale is estimated for all periods.

6.5 Model Estimation Results

This section presents the estimation result of a joint model (MDCEV) of participation and time allocation into six activity types, namely: a) maintenance in-home (MIH); b) maintenance out-of-home (MOH); c) discretionary in-home (DIH); d) discretionary out-of-home (DOH); e) work; and f) education. Work (education) activity was only included in the choice set if the person was a worker (student). In addition to the demographic variables, following sets of activity specific indicators were included in the model to capture the age, period, and cohort effect:

i. age indicators which capture the age related variation irrespective of the period and cohort membership,

ii. period indicators which capture the common influence of a time period irrespective of the age group,

iii. and, age specific cohort indicators that capture the variation across different cohorts for a particular age group.

Table 6.5 and 6.6 present the coefficient estimates for the baseline marginal utility function and the translation/satiation function respectively. The final log-likelihood value of the estimated model is -117727.58 with 114 parameters compared to -119876.64 for a constant only model. The three estimated scale of the errors corresponding to years 1985, 2005 and 2012 are significantly different from 1, while the fourth scale of error (corresponding to period 1965) is fixed to 1 for normalization. The scale of the error term for the recent years are less than 1, indicating a smaller variance of the error for the recent years compared to the year 1965. Also, the scale of the error for years 2005 and 2012 are very similar in magnitude. This may be attributable to the close proximity in time for the 2005 and 2012 datasets (i.e. 7 years) compared to the datasets from other years (i.e. 1965 and 1985) used in the analysis.

6.5.1 Heterogeneity across demography

In the model, MOH was considered as the base alternative. Compared to MOH, all the five activities have lower propensity for participation as can be seen from the negative constant values. In terms of the constant of the satiation parameter, MOH and DIH have the highest satiation (lowest time allocation) tendency and work and education have the lowest satiation (highest time allocation) tendencies. Females exhibit lower tendency to participate in all types of activities compared to males. However, they tend to spend more time in MOH and less time in DOH compared to male. Students tend to participate more time in MOH, DIH and DOH compared to non-students. They also tend to spend less time in DIH activity. Similar to the students, workers tend to participate more into MOH, DIH and DOH activities. However, they tend to spend less time in all these three types of activities – this may be indicative of the time constraints experienced by workers owing to work commitments. Married people tend to participate less in all types of activities compared to MIH activity. All else being equal, retired individuals tend to spend more time in MOH, DIH and DOH activities compared to the non-retired individuals.

Table 6.5 Model Estimation Results for the Baseline Marginal Utility

	MOH	DIH	DOH	Work	Education
Constants	-6.036 (-80.18)	-4.913 (-51.2)	-7.42 (-88.33)	-6.007 (289.84)	-6.512 (-81.97)
Demographic variables					
Female Indicator	-0.092 (-6.15)	-0.17 (-13.22)	-0.115 (-7.7)	-0.203 (-10.02)	-0.192 (-3.57)
Student Indicator	0.143 (5.39)	0.051 (1.48)	0.124 (4.17)		
Worker indicator	0.473 (22.89)	0.21 (8.67)	0.349 (17.46)		
Unemployed Indicator	0.104 (3.1)				
Married Indicator	-0.062 (-4.45)	-0.109 (-8.16)	-0.122 (-8.14)	-0.068 (-4.39)	-0.127 (-1.8)
Retired Indicator	0.073 (2.79)	0.096 (3.86)	0.096 (3.2)		
Age indicators (Base: Age 65 and above)					
Age 18 to 24 years		-0.227 (-7.23)			
Age 25 to 34 years		-0.212 (-8.05)	-0.068 (-1.73)		0.206 (2.31)
Age 35 to 44 years	0.078 (3.63)	-0.158 (-6.17)	-0.037 (-1.38)	0.143 (6.3)	
Age 45 to 54 years	0.064 (3.05)	-0.112 (-5.36)	-0.483 (-2.73)	0.032 (1.11)	
Age 55 to 64 years	0.089 (4.33)				
Period Indicators (Base: Period 1965)					
Period 2 – 1985	-0.554 (-7.48)	-0.939 (-9.8)	0.711 (8.67)		
Period 3 – 2005	-0.543 (-7.4)	-0.956 (-10.22)	0.845 (10.31)		
Period 4 – 2012	-0.561 (-7.64)	-0.985 (-10.51)	0.826 (10.05)		
Cohort indicators specific to age group 18 to 24 years					
Generation X			0.114 (2.01)		0.276 (2.54)
Millennial			0.054 (1.43)	-0.151 (-3.79)	0.249 (3.11)
Cohort indicators specific to age group 25 to 34 years					
Generation X	0.091 (3.37)		0.038 (0.9)		
Millennial	0.038 (0.94)		0.055 (1.06)	-0.116 (-2.44)	-0.205 (-1.57)
Cohort indicators specific to age group 45 to 54 years					
Silent Generation			0.55 (3.05)		
Baby Boomer			0.528 (2.97)		
Generation X		-0.07 (-1.88)	0.448 (2.46)		
Cohort indicators specific to age group 55 to 64 years					
Silent Generation			0.033 (0.78)		
Baby Boomer			0.044 (1.59)		
Scale of the Error					
Period 2	0.259 (95.06[1])				
Period 3	0.302 (126.85[1])				
Period 4	0.303 (122.37[1])				

Note: (1) t -statistic with respect to 1.

6.5.2 Trend across age groups

In terms of age, people in the middle age group (35 to 64 years) tend to participate more in MOH activity compared to the people in other age groups. Comparatively young people (less than 55 years) participate less in DIH activity compared to the people in the older age group. People belonging to 35 to 54 year age group have the highest propensity to participate in work activity compared to people in other age groups. In terms of time allocation, people in 25 to 44 year age group spend less time into DIH and DOH activities compared to the people in the other age groups.

6.5.3 Trend across periods

Compared to 1965, the propensity to participate in MOH and DIH activities has decreased over the years. On the other hand, the propensity to participate in DOH activity has increased over the years compared to the MIH activity. This trend of increased discretionary activity participation is also supported by previous literature on the topic (Aguiar and Hurst 2007, 2009). In terms of time allocation or satiation tendency, all the periods exhibit an increase in the amount of time allocation in all activities compared to year 1965.

6.5.4 Trend across cohorts

Major cohort specific trends are observed in terms of DOH, work and education activity participation. For the work and education activities, the trends are observed for the people in the 18 to 34 years age group. For DOH activity, an increased tendency is observed across cohorts of all age groups. For work activity, the Millennials show a tendency to participate less in work activity compared to the previous generations of the same age groups. The youngest Millennials also show a tendency to participate more in education compared to Generation X.

In terms of time allocation, there is an increased tendency to allocate more time in work activities across different cohorts of different age groups. Generation X and Millennials belonging to 25 to 34 years age group show a decrease in MOH time allocation.

Table 6.6 Model Estimation Results for the Translation/Satiation Parameter

	MOH	DIH	DOH	Work	Education
Constants	3.31 (35.33)	3.685 (33.8)	4.835 (41.73)	5.647 (66.01)	5.441 (6.07)
Demographic variables					
Female Indicator	0.122 (3.1)		-0.169 (-3.55)	0.065 (1.07)	
Student Indicator		-0.17 (-1.9)			
Worker indicator	-0.672 (-14.48)	-0.519 (-10.32)	-0.588 (-10.23)		
Age indicators (Base: Age 65 and above)					
Age 18 to 24 years					
Age 25 to 34 years		-0.078 (-1.44)	-0.089 (-1.29)		
Age 35 to 44 years	-0.074 (-1.55)	-0.125 (-2.44)	-0.066 (-0.98)		
Period Indicators (Base: Period 1 – 1965)					
Period 2 – 1985	2.174 (20.79)	2.284 (18.55)	1.703 (12.75)	1.16 (10.51)	1.461 (1.54)
Period 3 – 2005	2.034 (22.04)	2.253 (20.26)	1.123 (9.8)	1.117 (11.15)	1.204 (1.32)
Period 4 - 2012	2 (21.43)	2.392 (21.42)	1.223 (10.62)	1.15 (11.36)	1.433 (1.55)
Cohort indicators specific to age group 18 to 24 years					
Generation X		0.316 (2.09)			
Millennials		0.205 (2.27)	0.408 (3.81)	0.611 (3.45)	
Cohort indicators specific to age group 25 to 34 years					
Baby Boomer				0.216 (1.9)	
Generation X	-0.147 (-2.22)			0.209 (2.5)	
Millennial	-0.075 (-0.67)			0.479 (2.52)	
Cohort indicators specific to age group 35 to 44 years					
Silent generation					
Baby Boomer				0.298 (3.29)	
Generation X				0.284 (3.62)	
Cohort indicators specific to age group 45 to 54 years					
Silent Generation					
Baby Boomer			-0.223 (-2.94)		
Generation X			-0.194 (-1.2)		
Cohort indicators specific to age group 55 to 64 years					
Silent Generation				0.359 (2.03)	
Baby Boomer				0.26 (2.47)	

Note: (1) t -statistic with respect to 1.

6.5.5 Relative contribution of demographic shift and cohort attitude

In order to compare and contrast the relative contribution of the demographic differences and the cohort specific changes, the percentage change in the baseline marginal utility for different activity types were calculated using equation (6.6) for different demographic variables and age specific cohort indicators.

$$\frac{\Psi_{k,d,1}-\Psi_{k,d,0}}{\Psi_{k,d,0}} \text{x}100 = 100 * [\exp(\widehat{\beta_d}) - 1] \tag{6.6}$$

where, the left hand side denotes the percentage change in the baseline marginal utility for the k^{th}activity and the d^{th}indicator variable and $\widehat{\beta_d}$ is the parameter estimate corresponding to the d^{th}indicator variable.

Based on the above calculation, it was observed that being part of a demographic group of retired individuals was responsible for about 6.57% decrease in the work activity participation propensity, whereas, being a young Millennial contribute to a 14% decrease in the work activity participation propensity. Similarly, a young age Millennial exhibits a 28% increase in the participation propensity in education activity compared to other segments of population. On the other hand, a 25 to 34 year old millennial exhibits 5.65% increase in the DOH activity participation propensity and about 12% lower propensity to participate in work activity compared to other segments. Among the 55 to 64 year old population, Silent generation shows 3.36% increase in DOH activity participation and Baby Boomers show 4.5% increase in DOH activity participation propensity.

6.6 Summary and Conclusions

This chapter examines the activity-travel participation and time allocation trends of twentieth century American generations using data from four waves (1965-66, 1985, 2005, and 2012) of American Heritage and Time Use Survey (AHTUS). The overarching goal of the research was to explore the activity-travel engagement choices of five generations, namely, GI Generation (1901-1924), Silent generation (1925–1943), Baby Boomers (1944–1964), Generation X (1965–1981) and Millennials (1982-2000). To the best of our knowledge this is one of the very first attempts to compare and contrast the activity-travel pursuit of all five twentieth century American generations while systematically isolating the age, period and cohort effects in addition to the demographic differences.

The study presented a detailed analysis of the trend in the activity-travel pursuit as well as discussed the demographic compositions of different generations at different stages of their lives. The trend analysis of the demographic composition revealed significant differences across various generations of the similar age groups. Finally, the multivariate modeling analysis was conducted to quantitatively assess the contribution of the demographic and cohort specific differences on the activity engagement heterogeneity. The key findings are summarized below:

i. The most prominent differences in the activity-travel pursuits between cohorts were observed at the early stages of individuals' lives i.e. 18 to 34 years age.

ii. The differences across cohorts are least for the middle age i.e. 35 to 54 years.

iii. Among the oldest age cohorts (i.e. above 65 years), the Boomers showed notable differences when compared with Silent generation in terms of retirement age, work participation as well as travel time allocation (an average daily increase of 4 minutes among the people who travelled on the survey day). This observation corroborates the observations from the previous literature.

iv. The most significant downward shift in the travel time allocation was noticed between the Baby Boomers to the Generation X and not between the Generation X and Millennials. However, the difference in travel time allocation tended to taper off between the Generation X and the Boomers as they enter adulthood.

v. Millennials' profile of discretionary time allocation match most closely to that of the Baby Boomers.

vi. Fewer Millennials of 18 to 34 year age group participate in work compared to the generation X individuals. However, the work time allocation of the working Millennials have seen an increase compared to the working Generation X folks.

vii. Being a Millennial accounts more for the decrease in the work force participation and the increase in the education participation than any of the demographic differences.

In general, the decreasing differences between the activity-travel pursuit of the Baby Boomers and the Generation X folks as they navigate their adulthood (i.e. 35 to 54 year age group) suggest that the

observed ‘atypical’ activity-travel pursuits of the Millennials in terms of lower participation in work force, higher engagement in educational activities, lower time allocation in travel, and higher time allocation in discretionary activities will fade out as the Millennials enter into the adult stages of their lives. Another intriguing question is whether the comparatively active life styles of the old age Boomers will be replicated by the following generations namely, the Generation X folks and Millennials or if this is solely characteristic of the Boomer generation. The answers to this will have a significant detriment to the needs of transportation systems in the future.

The presented research could be further enhanced by accounting for the built environment information that different cohorts experienced at different stages of their lives. Such data was absent especially for the older birth cohorts considered in the current study. Significant missing data for two critical demographic variables, namely, income and ethnicity hindered the exploration of the influence of these factors. The exploration and findings of the current research could be enhanced by augmenting the AHTUS dataset (rich in activity-travel information) with an outside data source that offers built environment information about different cohorts, and by imputing missing data for key demographic factors.

CHAPTER 7

CONCLUSION AND FUTURE DIRECTION

7.1 Introduction

In the last four decades, there has been a move towards disaggregate approaches for analyzing and forecasting travel behavior in the field of transportation planning. This shift in approach has in part been fueled by the shift in focus from capacity oriented policies to demand management transportation policies such as relieving congestion, spreading peak hour demand, controlling directional distribution of traffic, promoting versatile modes of transport, and promoting teleworking among others. As a result, understanding activity and travel behavior at the agent level has become important for developing effective transportation policies aimed at managing demands. The primary tenet of the dissertation was to contribute to an enhanced understanding of the of activity and travel engagement choices of transportation users. To this end, the dissertation has contributed both substantively and methodologically.

On the substantive side, the dissertation investigates individual time engagement choices by building on the theoretical research from the fields of psychology, sociology and travel behavior. On this front, the contribution of the dissertation lies in understanding the relationship between well-being and time engagement choices as well as in exploring the association between daily mood and time engagement behavior of the individual. Additionally, the dissertation proposes a framework to model the tour and stop participation and time allocation decision that overcomes major limitations of the existing tour formation frameworks. The dissertation also contribute by depicting the time engagement behavior of the twentieth century American generations with an aim to deduce such behavior for the future generations – understanding of which is essential for forecasting for an uncertain transportation future.

One of the major methodological contribution of the dissertation was to develop a hybrid choice and latent variable modeling framework with multiple discrete continuous choice kernel. The dissertation also contributes methodologically by developing a framework to mimic bi-level decision making in the presence of multiple discrete continuous choice kernels and hierarchical budget constraints. Additionally,

the dissertation also adopts various extensions of the multiple discrete continuous extreme value (MDCEV) framework to pursue the various substantive studies presented in the dissertation.

The rest of the chapter is organized as follows. The next section highlights the major substantive and methodological contributions presented by the dissertation. Policy implications of the research presented in the dissertation are presented in the third section. The fourth section highlights some of the limitations of the research pursued in the dissertation. This section also identifies ideas for future research endeavors.

7.2 Summary of Contributions

7.2.1 Theory driven exploration of time allocation

Researchers from various disciplines such as philosophy, economics, sociology, psychology, and transportation have pursued individual time allocation research from different perspectives. The primary focus of the researchers from the field of philosophy and socio-psychology has mainly been related to characterizing the motivation for individual time allocation behavior. Whereas, the transportation researchers have mostly focused on developing predictive models of time allocation behavior, so that the future time allocation behavior can be predicted with reasonable accuracy. In developing the predictive models of time allocation behavior, the transportation researchers have often ignored the motivational theories of such behavior. This tendency not only impacts the explanatory power of the time allocation models negatively but it also deteriorates the predictive ability of such modeling frameworks. The current research makes an attempt to incorporate the need based motivational theories of human time allocation in the state of the art time allocation models used in transportation planning. Borrowing from the hierarchical needs theory of Maslow (1943), socio-psychological theory of Tonn (1984) as well as the self-actualization theory of Allardt (1993), the research presented in chapter 3 postulates that, heterogeneity in the human time allocation behavior can partly be attributed to the perceived satisfaction of needs reported by individuals pertaining to different domains of life including health, marriage, job, and finance. Additionally, the research also account for various constraints, such as temporal, physical, mental, cognitive and situational constraints that contribute to the heterogeneity in the time allocation

behavior of the individuals. In operationalizing the time allocation theory postulated above the research adopts the panel multiple discrete continuous extreme value (MDCEV) framework to simultaneously model the participation and time allocation behavior of individual while accounting for the temporal constraints. In particular, the time allocation framework has been used to understand the heterogeneity in the time allocation behavior of the elderly Americans using data from Disabilities and Use of Time (DUST) survey of Panel Study of Income Dynamics (PSID). The proposed theoretical formulation can be readily deployed to investigate the heterogeneity in the time allocation behavior of other population segments in the society. The employment of this framework would yield a richer illustration of the time allocation behavior of the various population segments and would also result in better predictive abilities of the state of the art time allocation models.

Though the contribution of the research presented in chapter 4 is mostly methodological in nature; nonetheless, this chapter also contribute to the substantive objective of the dissertation by offering theory driven exploration of time engagement choices. For example, the empirical case study presented in this chapter explores the association between day level moods and discretionary activity engagement behavior of the individuals. The empirical study reveals interesting association between day level moods and discretionary activity engagement choices – it was found that, individual reporting higher levels of positive mood participate more into different types of discretionary activities compared to passive leisure and individuals reporting higher levels of negative mood participate less into different types of discretionary activities compared to passive leisure. One exception of this finding was the mood ‘stress’ – instead of being a negative emotion it was found to be positively associated with higher participation into different types of discretionary activities compared to passive leisure. Additionally, the research presented in chapter 6 explores the influence of cohort effect and period effect on the time engagement behavior of the twentieth century American generations.

7.2.2 Hybrid multiple discrete continuous choice framework

There is no implementation of an Integrated Choice and Latent Variable model capable of incorporating the influence of latent psychological factors such as individual attitude, perception and beliefs on choice

dimensions that can be represented as multiple discrete continuous (MDC) choices. One of the major methodological contributions of the dissertation is in proposing a hybrid multiple discrete continuous (HMDC) model framework to simultaneously estimate a latent variable model (i.e. multiple indicator multiple cause (mimic)) and a choice model which assumes the form of MDC kernel. The proposed framework is general enough to capture the correlation among the latent constructs as well as between the choice alternatives. The framework also provides the flexibility to treat the indicator variables as both continuous and ordinal. The development and estimation of the ICLV models have generally been saddled due to the reliance on simulated maximum likelihood estimation technique. In an attempt to address this limitation, a simulation free estimation routine that employs the composite marginal likelihood (CML) approach along with an analytical approximation of multivariate normal cumulative distribution has been proposed for estimating the parameters of the HMDC formulation. Based on the literature on CML approach (Varin et al. 2011) for clustered data, the dissertation proposes a set of values to weigh the lower dimensional marginal probabilities while decomposing the high dimensional integral using CML approach in order to normalize the contribution of each observation to the likelihood function proportional to their respective size of the integrals. Additionally, the dissertation demonstrates the applicability of the proposed set of weights and also attests the superiority of the weighted CML approach over the unweighted CML counterpart in recovering the parameters in the presence of MDC choice kernel. In simulation studies, the proposed weighted CML estimation routine was found to outperform the unweighted CML approach in recovering the unbiased and efficient estimates of the true parameters underlying the data generation process.

Lately, the MDC choice kernels have been extensively employed to model the consumer choice decisions in various fields such as energy consumption, vehicle fleet choice and composition, vacation travel choices, and, land use choices among others. However, the absence of a framework similar to HMDC has limited the exploration of the association between different attitudinal variables and the above mentioned choice dimensions. The proposed HMDC framework along with the proposed estimation routine would open up the possibility to test the association between various attitudinal factors and the

above mentioned choice dimensions. As a result it would be possible to offer enriched depictions of the choice mechanisms leading to various MDC choice outcomes.

7.2.3 Bi-level multiple discrete continuous choice framework

Another important methodological contribution of the dissertation is related to the formulation of a bi-level multiple discrete continuous extreme value probit (MDCP) model. This formulation is in spirit similar to the conceptual formulation of the two level budget problem in the presence of multiple discrete continuous choice kernel proposed by Deaton and Muellbauer (1980), and Chintagunta and Nair (2011). Typically, in multiple discrete continuous model framework, budget is treated as exogenous. Augustin et al. (2105) and Pinjari et al. (2016) provide recent synthesis on the issue of exogenous treatment of budget in the multiple discrete continuous extreme value model and propose remedial measures for the same. The bi-level MDCP formulation proposed in this dissertation allows for endogenous treatment of the budget for the MDC alternatives belonging to the bottom level. In the formulation, the decision to consume goods at the bottom level depend on the consumption decisions made at the top level. Also, the top level participation decisions (in the tour) are influenced by the bottom level participation decisions (into additional stops within the tour) according to the formulation. The bi-level MDCP formulation provides the flexibility to account for the budget constraints at both the top and bottom levels of decision making. The proposed formulation is particularly suitable for the situation, where the budget of the top level choice alternatives is exogenously determined for all individuals, while the budget for the bottom level choice alternatives varies across observation depending on their top level choices and therefore need to be treated as endogenous variables.

The framework has been used to jointly model the tour and stop participation and time allocation decisions. This framework addresses three major limitations of the tour and stop participation and time allocation models used in the state of the art activity based modeling frameworks. First, the framework explicitly accounts for the time constraints that guide the tour and stop making decisions; the tour making decisions are constrained by the time available within the day, while the stop making decisions are constrained by the time available to complete the said tour. The explicit consideration of the constraints at

the tour- and the stop-level help capture the tradeoffs within both the top- and the bottom-level decisions. Second, in the proposed framework time is represented as a continuous entity as opposed to as a discrete entity. Finally, the framework allows explicit correlation between various tours types as well as stop types belonging to the same tour. In the state of the art framework, the tour/stop participation and time allocation decisions are modeled independently and in an ad-hoc manner for each tour and stop types - often time resulting in inconsistent and unreasonable choice quantities. Compared to the state of the art formulations, the proposed formulation provides behaviorally plausible depiction of the tour- and stop-level participation and time allocation choices. The bi-level MDCP formulation is computationally very tractable as it does not rely on numerical simulation, rather the parameters of the bi-level MDCP model are estimated using analytical approximations of normal cumulative density functions (due to Bhat 2011). Finally, the proposed bi-level MDCP formulation would eliminate the need for a large number of independent models currently being used to model the tour- and stop-level decisions. This will also help gain computational efficiencies in operational travel demand models.

7.3 Policy Implications

Generally the dissertation contributes to the activity based approaches to transportation planning. Specifically, the presented studies contribute to the day pattern generation stage of activity based modeling framework. The proposed methodologies as well as the substantive findings obtained from the dissertation can be used by the different local, regional and state level planning organizations. This section briefly highlights the specific policy implications of the various studies presented in the dissertation.

7.3.1 Relationship between well-being and activity time engagement

The activity time engagement exploration of the elderly American presented in chapter 3 revealed considerable heterogeneity in the activity participation and time allocation behavior of the elderly Americans in terms of the differences in the individual and household level characteristics as well as physical and subjective well-being measures. Specifically, it was found that, elderly Americans (i.e. people above 50 years old) experience limited mobility due to physical limitation, cognitive limitation,

vehicular constraint as well as living arrangements (depending on whether living with the family or in elder care units such as in residential homes or nursing homes). It was found that, people experiencing physical or cognitive constraints participate less into different out-of-home activities compared to the people who do not experience such mobility constraints. Also, elderly people without any vehicular constraint participate more into different types of out-of-home activities compared to the people who do have vehicular constraint. On the contrary, people living in the elderly home without family members were found to participate less into different types of in-home activities and more into different types of out-of-home activities compared to the people who live with their families. The mobility restrictions faced by the elderly American due to physical, cognitive and vehicular constraint can be addressed by promoting alternate modes of transportation such as paratransit services, demand responsive services and community based shared ride services.

It can be noted that, the eligibility criterion (in terms of the manifested physical and cognitive limitations) for availing the demand responsive services often time preclude elderly with moderate to low disabilities which result in greater deprivation for this group of elderly compared to the elderly with high disabilities. Refinement of the existing regulation is needed to broaden the scope of the existing demand responsive services so that the existing services can address the need of a wider variety of elderly individuals.

Cost is another important consideration for making the alternative transportation services widely affordable among the elderly of different economic statures – often time the high cost of the prevailing services preclude elderly individuals belonging into low income households in spite of the fact that they might be in greater need for such services compared to the elderly belonging to high income households.

Lastly, most often the elderly people need to depend on the household members for getting access to the demand responsive or community based shared ride services. The alternate transportation services should strive to simplify the technology for calling such services - so that the dependency on the family members for calling such services are reasonably reduced.

7.3.2 Proposed methodological formulations: HMDC, Bi-level MDCP

The dissertation proposes couple of methodological frameworks with the aim of advancing the time engagement research in the state of the art activity based models. The primary goal of the hybrid multiple discrete continuous choice (HMDC) framework presented in chapter 4 was to augment the state of the art integrated choice and latent variable (ICLV) model formulation so that the framework can be used with multiple discrete continuous (MDC) choice kernels. The motivation behind this extension was to put forward a formulation which would enable the exploration of enriched theories of time engagement choices.

Similarly, the overarching goal of the bi-level multiple discrete continuous probit (MDCP) formulation presented in chapter 5 was to improve the representation of time in the state of the art activity based models where tour is used as a unit of analysis. In general, the bi-level MDCP formulation can be used to model bi-level choices in the presence of multiple discrete continuous (MDC) choice kernels and hierarchical budget constraints.

It can be noted that, these proposed methodological formulations help to improve the representation of the behavioral mechanism in the choice process, assist in better quantifying the choice process by improving on bias and efficiency of the parameter estimates as well as enhance the forecasting capability of the activity based choice models.

7.3.3 Time engagement behaviors of the twentieth century American generations

The descriptive and modeling explorations presented in chapter 6 reveal considerable shift in the demographic characteristics of different cohorts of same age groups in terms of their student status, (un)employment status, marital status, as well as living arrangements. However, the differences in the activity participation and time allocation profile of different cohorts were mostly found to be significant at the early stages of their lives (i.e. 18 to 34 year age groups) – after that the differences start to taper off as the behavior of the recent generations tend to coincide more and more with the previous generations. This observation allude to the fact that, providing for the transportation system based on the activity participation and time allocation trend of different generations who are still navigating the younger years

of their lives might not be all that effective - rather the activity participation and time allocation profile of the previous generations of similar age groups might be more indicative of the foreseeable future.

7.4 Limitations and Future Research

7.4.1 Unified theory of time allocation

One of the contributions of the dissertation is in conducting theory driven exploration of time allocation. The dissertation investigates the association between time engagement decisions and various motivational and psychological factors such as perceived need satisfaction, moods and cohort effects. However, the empirical investigations presented in the dissertation have mostly been motivated by the established theories from different disciplines including philosophy, psychology, and economics. It can be noted that, the dissertation does not postulate an all-encompassing theory of time allocation that unifies theories from various disciplines including those from travel behavior. Postulating an extensive theory of time allocation that unifies theories from different disciplines including philosophy, psychology, sociology, economics and travel behavior would be a valuable addition which would help advance the time engagement research in the state of the art activity based travel analysis methods.

7.4.2 Structural relationship between latent variables

In the proposed hybrid choice model (HCM) framework (i.e. in the hybrid multiple discrete continuous (HMDC) model) the structural relationship between the latent variables have been ignored (though they are still allowed to be correlated). It can be noted that, this is also the predominant practice in the existing literature. This is understandable, since the addition of multiple latent variables in the HCM framework (which is necessary for having structural relationship) increases the dimensionality of the integral and has been proven to be detrimental for simulated maximum likelihood estimation technique. In the recent years, researchers (for example Kamargianni et al. (2014), Link (2015), Motoaki and Daziano (2015)) have tried to allow structural relationship between latent variables. However, richer specification of the structural equation model of latent variables has been accomplished at the cost of simplified choice model specification where the choice kernel has been limited to binary or multinomial discrete choice kernel. The behavioral richness of the new integrated choice and latent variable (ICLV) modeling framework

with multiple discrete continuous choice kernel proposed in the dissertation can be further enhanced by allowing structural relationship between the latent variables. In order to ensure computational tractability of such behaviorally rich ICLV formulations, simulation free composite marginal likelihood based estimation routine used in the presented research can be adopted.

7.4.3 Use of longitudinal data

In the dissertation, the proposed integrated choice and latent variable (ICLV) model framework with multiple discrete continuous (MDC) choice kernel has been implemented for cross-sectional data. It can be noted that, ICLV model implementations with cross-sectional data only allow inferences of inter-individual variability of the psychological factors such as attitudes, perceptions, beliefs, and emotions and the corresponding association with the choice process. Intra-individual variability of the psychological factors and their association with the choice process therefore cannot be inferred from such dataset (Chorus and Korsen 2014). This also has the implication for policy recommendations aimed at modifying individual level activity/travel behavior by altering the psychological factors. It can be noted that, in the literature, very few ICLV implementations with discrete choice kernel have explored longitudinal data (Jansen et al. 2013, Danaf et al. 2015, Daziano 2015). Moreover, these implementations most often do not capture the dynamics in the psychological factors, i.e. the psychological factors are treated as individual traits and considered to be constant across choice occasions (Daziano 2015). Similarly, the ICLV implementations with longitudinal data most often ignore the serial correlations between the choices made across different periods.

The proposed HMDC formulation need to be extended in order to make it compatible with longitudinal data structure. The deployment of the proposed framework with longitudinal data would allow make inferences about the intra-individual variability of different psychometric factors and their associations with the choice variables. Not only that, ICLV implementations with longitudinal data and serial correlations among the choices would allow for richer depiction of the choice mechanism itself.

Similarly, the bi-level MDCP framework presented in the dissertation has been implemented with cross-sectional data. Implementing the bi-level MDCP formulation with longitudinal data and serial

correlations among the choice processes would allow for a richer depiction of the tour and stop making behavior of the individuals.

It can be noted that some of the implementation limitations identified above can be attributed to the scarcity of the longitudinal data. Deployment of longitudinal surveys crafted to capture the dynamics in the psychological factors and choice process is essential for empirical exploration of dynamic ICLV frameworks.

7.4.4 Integration into activity-based model (ABM) systems

The methodological formulations are proposed in the dissertation in order to improve the behavioral richness as well as the predictive ability of the state of the art activity based model systems. However, they have not been integrated and tested in operational activity based model systems. Also, missing is the comparison of results between the proposed formulations and existing approaches. These avenues for future studies will help assess feasibility and applicability of the proposed formulations and help promote their usage in practice.

7.4.5 Temporal and spatial transferability of the proposed frameworks

The applicability of the theoretical and methodological frameworks presented in the dissertation need to be tested in other geographic locations and for other time dimensions. For example, the time allocation theory presented in the third chapter of the dissertation has been tested only for the American elderly population. This theory can be tested for other population segments in the USA and in other parts of the world which would reveal better understanding about the influence of various individual and household level constraints on the time allocation behavior and would also reveal the association between perceived needs satisfaction and time allocation behavior at different stages of life. Also, applying the framework for different population segments dispersed in time and space would help test the robustness of the proposed theory of time allocation behavior.

Similarly, the empirical applicability of the hybrid multiple discrete choice (HMDC) framework and the bi-level multiple discrete continuous probit (MDCP) framework needs to be tested by applying these formulations in different geographic contexts and time horizons.

The trend in the time allocation behavior of the twentieth century American generations presented in the sixth chapter need to be expanded to include the similar generations of other developed and developing nations of the world. This would expand the empirical scope of the work presented in the dissertation as it would allow for the comparison of the activity engagement decisions of the similar birth cohorts across geographic locations. Additionally, research expanding the spatial and temporal scope would provide further evidence on the influence of age-, period- and cohort-effect in the evolution of activity engagement behaviors across generations.

APPENDIX

Table A.1 Simulation Results (Without weight)

Parameters	True Values	Estimated Values	Absolute Percentage Bias (APB)	Asymptotic Standard Error (ASE)	Finite Sample Standard Error (FSSE)	Relative Asymptotic Efficiency (RAE)	Confidence Interval	Contains True Value?
α_1	1.1	1.0897	0.9341	0.0375	0.0314	1.1911	(1.02) - (1.16)	Yes
α_2	1.7	1.6805	1.1489	0.047	0.0472	0.9944	(1.59) - (1.77)	Yes
α_3	1.2	1.2403	3.3614	0.0561	0.0568	0.9877	(1.13) - (1.35)	Yes
α_4	1.8	1.8498	2.7656	0.0772	0.0668	1.1554	(1.7) - (2)	Yes
α_5	1.4	1.4343	2.4496	0.0989	0.0658	1.5037	(1.24) - (1.63)	Yes
α_6	1.6	1.6188	1.1753	0.1106	0.0763	1.4493	(1.4) - (1.84)	Yes
Γ_{21}	0.5	0.5091	1.8114	0.0423	0.0264	1.6039	(0.43) - (0.59)	Yes
Γ_{31}	0.5	0.5042	0.8348	0.0493	0.0288	1.7078	(0.41) - (0.6)	Yes
Γ_{32}	0.5	0.5098	1.9626	0.0712	0.0504	1.4137	(0.37) - (0.65)	Yes
$\bar{\delta}_1$	-1.1	-1.097	0.2717	0.0565	0.0532	1.0612	(-1.21) - (-0.99)	Yes
$\bar{\delta}_2$	-1.7	-1.6881	0.6975	0.0603	0.0545	1.1072	(-1.81) - (-1.57)	Yes
$\bar{\delta}_3$	-2.5	-2.4073	3.7073	0.1418	0.1595	0.8888	(-2.69) - (-2.13)	Yes
$\bar{\delta}_4$	-2	-1.9215	3.9241	0.1047	0.1206	0.8679	(-2.13) - (-1.72)	Yes
$\bar{\delta}_5$	-2	-1.9113	4.4373	0.113	0.0932	1.2127	(-2.13) - (-1.69)	Yes
$\bar{\delta}_6$	-2.8	-2.6779	4.36	0.1636	0.1723	0.9498	(-3) - (-2.36)	Yes
$\bar{d}_{11}$	1	1.0084	0.8357	0.0235	0.0216	1.0861	(0.96) - (1.05)	Yes
$\bar{d}_{21}$	1.1	1.1083	0.7557	0.0254	0.0212	1.2028	(1.06) - (1.16)	Yes
$\bar{d}_{32}$	1.2	1.1618	3.1862	0.0832	0.0852	0.9762	(1) - (1.32)	Yes
$\bar{d}_{42}$	1	0.9697	3.0289	0.061	0.0658	0.9272	(0.85) - (1.09)	Yes
$\bar{d}_{53}$	1.1	1.0809	1.7408	0.0943	0.0719	1.3114	(0.9) - (1.27)	Yes
$\bar{d}_{63}$	1.3	1.2624	2.8941	0.1211	0.0913	1.3271	(1.03) - (1.5)	Yes
Σ_{11}	1	0.9909	0.9104	0.0238	0.0242	0.985	(0.94) - (1.04)	Yes
Σ_{22}	1	0.9885	1.1523	0.0261	0.0279	0.9365	(0.94) - (1.04)	Yes
β_1	-1	-0.4639	53.6118	0.2269	0.2239	1.0132	(-0.91) - (-0.02)	No
β_2	2	2.5258	26.291	0.2219	0.2147	1.0336	(2.09) - (2.96)	No
β_3	-2	-1.7737	11.3173	0.2423	0.2328	1.0409	(-2.25) - (-1.3)	Yes
β_4	2.5	2.9306	17.2239	0.2895	0.2758	1.0496	(2.36) - (3.5)	Yes
β_5	-1	-1.1127	11.2674	0.0835	0.091	0.9181	(-1.28) - (-0.95)	Yes
β_6	3	3.0254	0.8469	0.0938	0.1144	0.8196	(2.84) - (3.21)	Yes
β_7	-1	-1.0204	2.0402	0.0413	0.0467	0.8854	(-1.1) - (-0.94)	Yes

Table A.1 Simulation Results (Without weight) (Continued)

Parameters	True Values	Estimated Values	Absolute Percentage Bias (APB)	Asymptotic Standard Error (ASE)	Finite Sample Standard Error (FSSE)	Relative Asymptotic Efficiency (RAE)	Confidence Interval	Contains True Value?
β_8	3.5	3.8435	9.813	0.1358	0.1349	1.0069	(3.58) - (4.11)	No
β_9	-3.5	-4.1934	19.8112	0.1981	0.2005	0.9881	(-4.58) - (-3.81)	No
λ_{21}	-1.5	-1.7127	14.1815	0.085	0.0831	1.0231	(-1.88) - (-1.55)	No
λ_{22}	1.2	1.3356	11.302	0.0791	0.0674	1.1743	(1.18) - (1.49)	Yes
λ_{23}	1.1	1.2342	12.1976	0.0988	0.0806	1.2256	(1.04) - (1.43)	Yes
λ_{31}	-1.6	-1.8031	12.6915	0.0859	0.0866	0.9927	(-1.97) - (-1.63)	No
λ_{32}	1.1	1.2249	11.3508	0.0746	0.0633	1.1776	(1.08) - (1.37)	Yes
λ_{33}	1	1.1263	12.6285	0.0919	0.0723	1.2714	(0.95) - (1.31)	Yes
λ_{41}	-1.4	-1.6142	15.3007	0.083	0.0828	1.0027	(-1.78) - (-1.45)	No
λ_{42}	1.3	1.4567	12.0521	0.0846	0.075	1.1274	(1.29) - (1.62)	Yes
λ_{43}	1.1	1.2482	13.4704	0.1003	0.0774	1.2955	(1.05) - (1.44)	Yes
λ_{51}	-3	-3.5056	16.8532	0.1483	0.1466	1.0113	(-3.8) - (-3.21)	No
λ_{52}	1	1.1296	12.9568	0.0777	0.0583	1.334	(0.98) - (1.28)	Yes
λ_{53}	1	1.1545	15.449	0.0994	0.0832	1.1949	(0.96) - (1.35)	Yes
γ_1	1.5	2.3809	58.7244	0.129	0.1024	1.2593	(2.13) - (2.63)	No
γ_2	1.8	2.5996	44.4234	0.095	0.1146	0.8291	(2.41) - (2.79)	No
γ_3	2.2	3.2027	45.5769	0.0982	0.1207	0.8133	(3.01) - (3.4)	No
γ_4	2.5	3.1685	26.74	0.1037	0.0999	1.0379	(2.97) - (3.37)	No
γ_5	2.8	3.6457	30.2044	0.1491	0.1578	0.9445	(3.35) - (3.94)	No
Λ_{22}	1.1	1.0966	0.3059	0.0748	0.0814	0.9188	(0.95) - (1.24)	Yes
Λ_{32}	0.6	0.5895	1.7479	0.0846	0.078	1.0841	(0.42) - (0.76)	Yes
Λ_{33}	0.9	0.7879	12.4534	0.0375	0.0394	0.9518	(0.71) - (0.86)	No
Λ_{44}	0.8	0.8266	3.3244	0.0879	0.0924	0.9517	(0.65) - (1)	Yes
Λ_{54}	1	1.0993	9.9325	0.1541	0.1403	1.0983	(0.8) - (1.4)	Yes
Λ_{55}	0.9	1.0123	12.4738	0.1183	0.117	1.0109	(0.78) - (1.24)	Yes
$\tau_{up,1}$	1.5	1.4671	2.1965	0.0781	0.078	1.0009	(1.31) - (1.62)	Yes
$\tau_{up,2}$	1.5	1.4791	1.3957	0.0663	0.0803	0.8262	(1.35) - (1.61)	Yes
$\tau_{up,3}$	1.5	1.4886	0.7632	0.0718	0.067	1.0702	(1.35) - (1.63)	Yes
$\tau_{up,4}$	1.5	1.4699	2.0044	0.0834	0.0862	0.9669	(1.31) - (1.63)	Yes
Mean			**10.3944**			**1.0989**		

RELATED PUBLICATIONS

(1) **Enam, A.**, Konduri, K. C., Pinjari, A., & Eluru, N. (2017). An Integrated Choice and Latent Variable Model for Multiple Discrete Continuous Choice Kernels: Application Exploring the Association between Day level Moods and Discretionary Activity Engagement Choices. Journal of Choice Modelling.

(2) **Enam, A.**, & Konduri, K. C. (2017) Day Pattern Generation System for Jointly Modeling Tours and Stops: Bi-level Multiple Discrete Continuous Probit Model. Transportation Research Record: Journal of the Transportation Research Board. (Accepted)

(3) **Enam, A.**, Konduri, K. C., Eluru, N., & Ravulaparthy, S. Relationship between Well-Being and Daily Time Use of Elderly: Evidence from Disabilities and Use of Time Survey. Transportation. (Under 3rd review)

(4) **Enam, A.,** & Konduri, K. C. (2017). A Continuous Time and Temporally Constrained Tour Pattern Generation System for Jointly Modeling Daily Tours and Stops: Application of Bi-level Multiple Discrete Continuous Probit (MDCP) Model. Transportation Research Board 96th Annual Meeting (No. 17-04697). Washington DC.

(5) **Enam, A.**, Konduri, K. C., Pinjari, A. R., & Eluru, N. (2016). A Hybrid Multiple Discrete Continuous (HMDC) Model for Examining the Role of Moods on Daily Activity Engagement Choices. Transportation Research Board 95th Annual Meeting (No. 16-5180). Washington DC.

(6) **Enam, A.**, Konduri, K. C., Eluru, N., & Ravulaparthy, S. (2015). Relationship between Well-Being and Daily Time Use of Elderly: Evidence from Disabilities and Use of Time Survey. Transportation Research Board 94th Annual Meeting (No. 15-3092). Washington DC.

(7) **Enam A.**, Konduri, K. C., Eluru, N., & Pinjari, A. R. (2015). Exploring the Role of Subjective and Physical Well-being on Daily Activity Engagement Choices of Individuals: Evidence from the American Time Use Survey. 14th International Conference on Travel Behavior Research (IATBR), Windsor, UK.

(8) **Enam, A.**, & Konduri, K. C. (2015). Comparison of Activity Engagement Behaviors among Five Birth Cohorts: GI Generation, Silent Generation, Baby Boomers, Generation X, and Millennials. Women in Transportation (WTS) Transportation Mini-Series, Meriden, CT.

(9) **Enam, A.**, & Konduri, K. C. Time Allocation Behavior of Twentieth Century American Generations: GI Generation, Silent Generation, Baby Boomers, Generation X, and Millennials. Technical Paper, Department of Civil and Environmental Engineering, University of Connecticut.

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