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# A Household Daily Non-Mandatory Activity Participation and Duration Modeling Accounting for Person Level Budget Constraints

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# A HOUSEHOLD DAILY NON-MANDATORY ACTIVITY PARTICIPATION AND DURATION MODELING ACCOUNTING FOR PERSON LEVEL BUDGET CONSTRAINTS

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ABSTRACT

A HOUSEHOLD DAILY NON-MANDATORY ACTIVITY PARTICIPATION AND DURATION MODELING ACCOUNTING FOR PERSON LEVEL BUDGET CONSTRAINTS

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A key methodological and behavioral innovative component in recent Activity-Based Models (ABMs) used for transportation planning is the household-level non-mandatory activity participation component. While traditional ABMs use a series of simple models to predict non-mandatory activity participation decisions in a sequential manner (which is often not correct), the Multiple Discrete Continuous Extreme Value (MDCEV) model can model both individual and joint non-mandatory activity participation and time allocation decisions in different out-of-home activities of all household members simultaneously. A key advantage of the MDCEV framework is that it accounts for complex intra-household interactions among different household members by allocating the total household time available in a day to different household members in a utility-consistent manner. However, the earlier time-use models worked with a single household level time budget constraint. So, the model ensures consistency of time predictions with the total household available time but it can violate person level budget constraints. The primary objective of this thesis is to enhance the behavioral and prediction accuracy of the MDCEV model in the time-use context by developing an improved model that handles multiple person level budget constraints.

This thesis is dedicated to my family.

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# CHAPTER 1

# INTRODUCTION

Since the very beginning of human civilization, the community's economic success was mainly based on the transportation infrastructure and its efficiency (Guo and Bhat 2001). Since transportation systems and the characteristics of people using them keep changing, there has been a constant need to predict the transportation demand response relative to those changes. Therefore, many travel demand models were developed, so that good decisions could be made to overcome the existing day challenges and meet the future needs of transportation systems. Earlier travel demand models (TDMs) mainly focused on predicting long-term travel demand on aggregate level. For example, trip-based TDMs model total zonal trip interchanges by mode and time-of-day using zonal-level aggregate trip generation, distribution, and modal split models. However, over the past 30 years, due to rising costs of new transportation infrastructure as well as concerns about traffic congestion, there has been growing interest in travel demand management strategies such as ridesharing, telecommuting or congestion pricing, which have an impact on individual travel behavior (Pinjari and Bhat 2011). Therefore, the focus has shifted from long-term aggregate level forecasting to understanding short-term disaggregate or individual level responses to these new travel demand strategies. Given that the trip-based TDMs modeled aggregate travel outcomes, they are not suited for predicting individual travelers' responses to key policy changes, disaggregate approaches that focus on each traveler were developed. Tour-based and activity-based models (ABMs) belong to this class of disaggregate TDMs.

In the past few decades, the activity-based approach has seen significant improvement and received remarkable attention (Bhat and Koppelman 1999, Pendyala and Goulias 2002). Contrary to the trip-based approach, which focuses only on trips without considering the reason of traveling, the activity-based approach emphasizes the activity behavior and sees travel as a derived outcome which results from the need to participate in different types of activities at spatially dispersed locations during specific hours of the day (Jones, Koppelman et al. 1990, Bhat and Koppelman 1999, Davidson, Donnelly et al. 2007). Most ABMs comprise of two key components - the activity generation and the activity scheduling modules. In the activity generation component, all daily out-of-home activity participation decisions in mandatory (work, school, university) and non-mandatory (shopping, maintenance, social, recreational etc.) activity purposes of every person in the study region are modeled. Next, in the scheduling module, additional attributes including travel mode, departure time, location, and activity duration are modeled for all activities generated in the first module. Together the two modules populate the activity-travel skeleton of all people in the study region. These individual activity-travel patterns are aggregated to generate different types of travel outcomes including traffic volumes, travel times, vehicle-miles traveled (VMT), greenhouse emissions (GHG), transit ridership levels, toll revenue estimates.

The focus of this study is on the first module of ABMs, namely the activity generation component. Typically, for each traveler, first all mandatory activity participation decisions including work, school, and university activities that tend to have more spatial and temporal rigidity are modeled. Next, all non-mandatory activity participation decisions are modeled conditional on the mandatory activity choices of the traveler. The mandatory activities of a traveler act as pivots around which non-mandatory activities are later scheduled. There are two key limitations in these earlier versions of ABMs. First, the non-mandatory activity choices are modeled using a series of independent sequential models. For example, a series of three binary choices models to predict whether a person will partake in shopping, social, and recreational activities. However, the activity participation decisions in different types of activity purposes are correlated. For example, people who undertake eating out and shopping activities may be less likely to participate in other non-mandatory activities because of limited time availability during the day. *Second*, the activity participation decisions of different travelers in the same household are modeled independently in older ABMs, *i.e.*, there is no dependency due to intra-household interactions among people belonging to the same household. This assumption is clearly wrong given that household members tend to participate in joint activities as well as allocate household responsibilities to different people in the household indicating strong intra-household interactions.

This problem can be addressed by formulating the household out-of-home non-mandatory activity participation choice context as a time-budget allocation problem instead of using a series of independent choice models as has been done in the past. Every household has a fixed amount of time available for participating in out-of-home non-mandatory activities, referred to as the time budget. This time may be calculated as sum of available times of all individual household members after subtracting the mandatory activity durations associated with work, school, and/or university. Each household is assumed to allocate this time budget to different combinations of activity purposes and groups of individuals referred to as the choice alternatives. For example, consider a household with 2 people - A and B. There are 3 possible groups in this household – A, B, and (A, B). For each activity purpose, households can choose to allocate time budget to none, one, two, or all the 3 groups. So, if there are two activity purposes (e.g., shopping and maintenance), then there are a total of 6 alternatives – 3 groups for the shopping activity and 3 groups for the maintenance activity. Households can not only choose to participate in multiple combinations of activity purposes and groups but also choose to participate for different durations. All alternatives that receive some non-zero time allocation are the chosen alternatives and the time allocated to the chosen alternative is the chosen activity duration. These problems where decision-maker can choose multiple discrete alternatives as well as the budget allocated to the chosen alternatives are referred to as the Multiple Discrete Continuous (MDC) choice problems.

Bhat's Multiple Discrete Continuous Extreme Value (MDCEV) model has served as the standard workhorse model for analyzing MDC problems (Bhat 2008). The model is consistent with the utility maximization paradigm, and in the single discrete choice context, the MDCEV model collapses to the Multinomial Logit (MNL) model. Moreover, the MDCEV model also has a closed form expression for probability making the log-likelihood computation quick and easy. The MDCEV model is a budget allocation model where the decision maker is assumed to maximize his/her utility subject to budget constraint. In the time-use context, the decision-maker is the household and the budget constraint is the total time available for non-mandatory activity participation. In fact, Bhat, Goulias et al. (2013) employed the MDCEV problem to analyze the household non-mandatory activity participation problem. This model developed was also incorporated into the activity generation module of the ABM under development for the Southern California region.

However, in its current form, the MDCEV model is used to optimally allocates time to different alternatives (all possible combinations of groups of people and activity purpose) subject to a single household-level time budget constraint. The budget constraint ensures that the total time spent by household members in all types of non-mandatory activities is exactly equal to the total time available in the household. For example, let's say a household has two non-working adults. The total time each person has available in a day is 24 hours adding up to 48 hours of available time in the household. The problem with using a single household-level time budget constraint is that the MDCEV model can violate the person-level time budget constraints. For example, in the case of a household with two people, it is possible for the MDCEV model to predict that one person will spend more than 24 hours to participate in non-mandatory activities, which is not possible because each person only has 24 hours available per day. Therefore, even though the model ensures consistency with respect to the total available time in a household, it can violate one or more of the person-level time budget constraints. Moreover, in addition to inaccurate and inconsistent forecasts, ignoring the person-level time budget constraints can also lead to biased parameter estimates leading to wrong policy implications.

In this context, the primary objective of this thesis is to enhance the behavioral accuracy of the non-mandatory activity generation and allocation model by developing an improved MDCEV model that accounts for multiple person-level budget constraints. Specifically, a household-level activity pattern generation model was formulated and estimated that predicts both solo and joint activity participation decisions in different types of non-mandatory activities while maintaining consistency with respect to person-level time budget constraints. First, the older version of MDCEV model with a single household-level budget constraint was re-estimated using new household travel survey data. Next, the new MDCEV models with multiple person-level budget constraints was estimated and was compared with the older version. Based on statistical fit comparisons, the multiple-constraints MDCEV model proved to be significantly better than the single-constraint MDCEV model.

The rest of this thesis is structured as follows. The next chapter provides an overview of the existing relevant literature and its limitations. Furthermore, Chapter 3 presents methodology details of the model. Chapter 4 gives an overview of the data and provides description of the variables used for model estimation along with the relevant tables of descriptive analysis. Next, Chapter 5 shows the empirical results and the discussion about the results. Finally, Chapter 6 concludes this thesis by providing an overview of the findings of this study and its contributions.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1. Limitations of the Existing Studies

There are several examples in the previous literature of early ABMs that successfully emphasized activity participation in travel demand modeling, however they overlooked the significance of interactions between individuals in the household. For example, Lu and Pas (1999) explored relationship between activity participation and travel behavior and found that travel behavior could be explained better by activity participation choices instead of using socio-demographics alone. However, this study does not delve into the question of intra-household interactions. There are also some studies that attempted to uncover dependencies between activity choices of multiple household members. For example, Golob and McNally (1997) attempted to capture linkages between activities performed by different gender heads of household, but did not consider joint activities. So, either past studies completely ignored intra-household interactions or modeled these interactions in a limited way largely owing to the methodological complications associated with multivariate modeling of activity choices of multiple household members.

With the recent advent of the multiple-discrete continuous (MDC) choice models, the situation has changed considerably. Specifically, Bhat's MDCEV model and its variants were used to analyze activity-time use decisions in a variety of choice contexts. For example, Paleti, Copperman et al. (2011) used the nested MDCEV to analyze children's out-of-home activity time-use patterns. Even though, the need to account for joint activity participation was mentioned in this study as one of the suggestions for future studies, the study only considered individual children's activity and showed that different demographic, environmental and attitudinal characteristics influence children's activity patterns. In this example, it is necessary to account for joint activity participation. Even though there is evidence in the literature that children start developing their own identities and social needs at the age of six (Stefan and Hunt 2006), it is more likely that children's activity patterns will be a result of adult and children's decisions combined.

Similarly, Habib, Carrasco et al. (2008) modeled "with whom" interactions, however they only considered four possible alternatives: participating in activities with friends, family members, household members or family and household members together. One study of particular relevance to this research is the household-level activity time-use model developed by Bhat, Goulias et al. (2013) for the activity-based model (ABM) of Southern California region. Unlike past models, Bhat, Goulias et al. (2013)'s model explicitly accounts for intra-household interactions by modeling all activity-time use decisions, both joint and solo, within a household using a single model. However, as discussed in the introduction section, the main limitation of the model is the fact that it is based on a single household-level time budget constraint. So, even though it is ensured that model predictions don't exceed the available household time budget, it is possible for the model to come up with inconsistent predictions that violate one or more of person-level time budget constraints. For example, one of the possible forecasts of the Bhat, Goulias et al. (2013) model is a person allocating more time to a certain activity than available in a day.

## 2.2 Previous Findings

As activity-based modeling (ABM) approach was gaining its popularity, the emphasis was slowly shifting from individual to joint activity patterns. More recent ABMs stressed the need to consider interactions among individuals within a household and include joint activity participation in the model. Even our everyday experiences show that individual travel decisions usually depend on travel behavior of other household members. That can especially be seen in the example of households with the presence of children, which has gained significant attention in the most recent activity-based travel demand modeling literature. According to Reisner (2003), parents spend significant amount of time escorting children to and from different after-school activities. Several other studies also found that parents, particularly mothers, are more likely to make stops on the way to or from work due to the need of escorting children (McGuckin and Nakamoto 2004, Kato and Matsumoto 2009, Bhat, Goulias et al. 2013). The presence of children impacts joint activity participation between the adults in the household too. As found by Gliebe and Koppelman (2002), out-of-home leisure activity participation is reduced for both parents if they have children in the household. Furthermore, children's activity participations restricts adults in a way that they become unable to respond to new transportation policy changes such as congestion pricing (Bhat, Goulias et al. 2013). Even Vovsha and Bradley (2006) argued that some adults may be less responsive to such changes, because of the need to synchronize the schedules of multiple individuals in the household. For example, some employed adults may have an option of telecommuting or flexible work hours, which could help them avoid the peak hour traffic. However, with the presence of children in the household they might not have a choice, but find themselves on the road driving children to school during the rush hour. Moreover, children are likely to participate in joint activities such as shopping, entertainment and social, while they are unlikely to take part in maintenance activity purpose (Bhat, Goulias et al. 2013). Finally, it can be concluded that including children's activity patterns within the travel modeling framework is very important as it can significantly influence adults' travel patterns.

Even without the presence of children, members of the household generally don't make activity participation decisions alone. For example, a husband and a wife are more likely to go to the movies together, instead of going by themselves. Therefore, it is crucial to consider not only husband and wife's individual activity travel decisions, but joint activity decisions as well, to accurately predict their activity travel patterns. Moreover, in households with lower car ownership levels, household members tend to plan their activity-travel plans by car-pooling or synchronize their work start and end times, or allocate pick-up and drop-off responsibilities. Furthermore, according to Kapur and Bhat (2007) due to the possible sharing of responsibilities, one’s activity participation decisions are very likely to depend on the decisions of other household members. Kapur and Bhat (2007) also found that, when it comes to maintenance activities, women are more likely to take the responsibility of participating in such activities compared to men.

As Ho and Mulley (2015) mentioned in their paper, understanding the motivation for joint activity participation is not only important to better understand the travel behavior, but also to make more accurate predictions when it comes to travel demand, so that good transportation policies could be made. They performed parallel analysis comparing the models with and without taking joint travel into consideration and found that ignoring joint travel could result in overestimating or underestimating market responses to new transportation polices (Ho and Mulley 2015). Also, Srinivasan and Bhat (2006), Srinivasan and Bhat (2008) emphasized the need to accommodate inter-and-intra household interactions in analyzing activity travel behavior.

Another important finding in the previous literature is that people generally invest more time in joint activities with discretionary purpose compared to time invested in solo activities (Srinivasan and Bhat 2006). Some of their key empirical findings are as following. First, all joint activities no matter the purpose usually last longer and are often limited to some period in the weekday. In addition, differences are also observed between the activity purposes, day of the week or companion type. Also, joint participation in activities was found to be significantly greater over the weekends compared to the joint participation in activities during the weekday, which is intuitively expected since people usually use the weekend for social, entertainment or other “fun” activities. Moreover, different transportation policies may alter travel patterns of individuals in the household because of inter-personal linkages of travel behavior in the household. For example, in a household of a husband and a wife that are both employed, if a husband's travel patterns change due to flexibility in work schedule that can alter the wife's travel patterns as well. Finally, to add to the research findings of Srinivasan and Bhat (2006), some studies found that participation in joint activities implies using larger and more comfortable vehicle types such as vans or other larger vehicle types (Paleti, Pendyala et al. 2011). Even more, their study revealed that tour complexity does not have a direct impact on choosing the vehicle type, however it is the joint participation that influences the vehicle type choices. So, joint activity participation decisions also have an impact on the vehicle-use decisions having implications for accurate emissions, energy, and air quality modeling. In summary, past literature underlines the importance of modeling joint activity participation decisions and intra-household interactions to improve the accuracy and behavioral validity of transportation planning models.

# CHAPTER 3

# METHODOLOGY

## 3.1 Overview of the Modeling Approach

Traditional discrete choice models have been commonly used to study consumers and their preferences for choosing one alternative among a set of alternatives, which are available to the consumer and don't occur simultaneously. However, when it comes to travel decisions, in many occasions, consumers encounter situations where they can choose multiple alternatives at the same time. In the previous literature, those situations are described by the term "multiple discreteness" (Hendel 1999). For example, a person can decide to take part in several different activities during a day. Now, the person is not only choosing between different types of activities, but also deciding on a continuous aspect of consumption (activity duration). Therefore, the name multiple discrete continuous (MDC) choices (Bhat 2005).

While there are many ways to model MDC choices, most time-use studies are based on the fundamental micro-economic utility maximization theory that assume that individuals (or households) use their time to maximize the total utility derived from their activity participation decisions. The first models based on utility maximization theory trace back to Hanemann (1984) and Wales and Woodland (1983) Karush-Kuhn-Tucker, or so called KKT first order conditions method for constrained random utility maximization (Kuhn and Tucker 1951). Those models use utility maximization approach for estimating parameters, so it is straightforward to interpret consumer preferences. Among the more recent models that use micro-economic utility maximization approach, the MDCEV model developed by Bhat (2005), Bhat (2008) has many advantages. First, the MDCEV is very useful for situations with a great number of discrete alternatives. It also has a closed-form probability expression and in cases of consumers choosing only one alternative among a set of alternatives, it collapses to the multinomial logit (MNL) model. Also, MDCEV model is applicable to both cases with or without outside goods, which are defined as alternatives with an allocated non-zero time such as home. The standard MDCEV model used by Bhat, Goulias et al. (2013) paper assumes that the utility derived from different activities is maximized by each household and subject to a time constraint (1).

3.2 Definition of Choice Alternatives and Utility Function

Let there be P members in a household who can take part in any of the *K* activities in a day. Let *p* (=1, 2, …, *P*) be an index to represent the person-number of household members and *k* (=1, 2, …, *K*) be an index to represent out-of-home (OH) activity type alternatives. Let $g_k$ be an index to represent the different '*groups*' of household members that might participate in an activity *k*. Note that the *groups* represented by $g_k$ include multiple-member groups (for joint activities) as well as single-member groups (for solo activities). For an activity *k* in which any group of household members (or persons) might participate, there would be at most $2^P - 1$ such groups; *i.e.*, the total number of household member groups (person groups)[1] that can take part in an activity *k*, $G_k = 2^P - 1$. If all person groups can participate in all *K* activities, as discussed in Bhat et al. (2013), there would be as many as $K \times (2^P - 1)$ such activity type and person group combinations. Now, let $g_{pk}$ be an index to represent the different person groups that include person *p* for participation in activity *k*. In a household of *P* members, out of all the $G^k$ person groups that can take part in activity *k*, a person *p* can be in at most,$G_{pk} = 2^{(P-1)}$ person groups that take part in that activity; this includes a solo group where only (s)he takes part in that activity. If the person can take part in all *K* activities, (s)he can be in as many as $K \times 2^{(P-1)}$ activity type and person

[1] In the remainder of this paper, the term person group is used interchangeably with household member group (i.e., the term person is used interchangeably with household). Also, for brevity, the term group is use to referred to a group of household members.

group combinations. Of course, it is straight forward to consider that some activities may not involve certain groups of household members; for example, OH work may not involve joint participation with other household members.

Using the above notational preliminaries, let $t_{kg_k}$ be the amount of time allocation to activity $k$ by the persons in group $g_k$. If person $p$ is a part of group $g_k$ taking part in the activity, the time allocation may also be denoted as $t_{kg_{pk}}$. That is, $t_{kg_{pk}} = t_{kg_k}$ for all persons $p$ belonging to group $g_k$. Therefore, one can express $t_{kg_{pk}} = t_{kg_k} \times I[p \in g_k]$, where $I[p \in g_k]$ is an indicator function to identify if person $p$ belongs to group $g_k$ taking part in activity $k$. Lastly, let $n_{g_k} = \sum_{g_k=1}^{G_k} I[p \in g_k]$ indicate the number of people in group $g_k$.

3.3. Household-Level Single Budget MDCEV Model Formulation

The household members are assumed to make their daily activity participation and time allocation decisions to maximize the following household-level utility function:

$$\mathrm{U} = \sum_{p=1}^{P}\left(\psi_{op} \ln t_{op}\right) + \sum_{k=1}^{K} \sum_{g_k=1}^{G_k} \left\{ \{\psi_{kg_k} \gamma_{kg_k} \ln \left( \frac{n_{g_k} \times t_{kg_k}}{\gamma_{kg_k}} + 1 \right) \right\} \quad (1)$$

subject to a single household-level time constraint in a day:

$$\sum_{p=1}^{P} t_{op} + \sum_{k=1}^{K} \sum_{g_k} \left(t_{kg_k}\right) = \sum_{p=1}^{P} T_p\,,\ \ \forall_p = 1,2, \dots, P \quad (2)$$

Based on above equation, it can be noticed that this model formulation does not consider any constraints other than time constraint. There is no person-level budget constraint. Also, in the earlier version of MDCEV model developed in the Bhat, Goulias et al. (2013) paper, there are no outside goods, *i.e.*, alternatives corresponding to home activity were excluded from the choice set in the earlier version of the model. So, supplementary regression models were used to predict the total household available time for out-of-home non-mandatory activities (after excluding time spent at home), which was subsequently used the budget for the MDCEV model. However, in our revised model formulation, there is no need to use additional models to predict time spent at home since the choice set of the MDCEV model also includes home as one of the choice alternatives.

Two recent studies built upon the standard MDCEV model described above to account for multiple budget constraints (Castro 2012, Pinjari and Sivaraman 2013). Both these studies considered time and money as the two types of budgetary constraints. However, both these formulations lead to models that require evaluation of multivariate integrals (of dimension equal to the number of budget constraints) in the log-likelihood computation. The modified version of MDCEV model, developed in this thesis, assumes that households maximize the utility derived from spending time in different types of activities with different groups of people subject to multiple person-level time constraints (as opposed to time and monetary constraints). Moreover, the model formulation results in closed-form choice probability expression making model estimation computationally easy and efficient.

3.4. Person-Level Multiple Budgets MDCEV Model Formulation

The household members are assumed to make their daily activity participation and time allocation decisions to maximize the following household-level utility function:

$$\mathrm{U} = \sum_{p=1}^{P}\left(\psi_{op}\ln t_{op}\right) + \sum_{k=1}^{K}\sum_{g_k=1}^{G_k}\left\{\{\psi_{kg_k}\gamma_{kg_k}\ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)\right\} \quad (3)$$

subject to the following person-level time constraints in a day:

$$t_{op} + \sum_{k=1}^{K}\sum_{g_k s.t. p\in_{pk}}\left(t_{kg_k}\right) = T_p,\ \forall_p = 1,2,\dots,P \quad (4)$$

In the utility function of Equation (2), $\psi_{kg_k}\gamma_{kg_k}\ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)$ is the utility accrued by the household from $t_{kg_k}$amount of time allocation to an OH activity type $k$ by the household members in $g_k$. The household derives utility from time allocation to different activities $k$ (=1, 2, …, $K$) by different groups of household members $g_k$ (=1, 2,…, $G_k$). In addition, each person $p$ allocates $t_{op}$

amount of time to essential activities at home. It is assumed that $t_{op}$ serves as an outside good for person $p$'s time allocation, with a numeraire baseline utility $\psi_{op}$. The household-level utility function in Equation (2) has as many such outside goods as the number of persons in the household.[2] Note from Equation (3) that, unlike in Bhat, Goulias et al. (2013) where a single, household-level time budget constraint is considered, the model formulation includes person-level daily time constraints; as many constraints as the number of persons in the household, with each constraint representing the time budget $T_P$ available for each person $p$. Such explicit recognition of person-level constraints ensures that the sum of a person's predicted time allocations to different solo and joint activities do not exceed the daily time available to each person.

3.5. KKT Conditions of Optimal Utility

The Lagrangian function for the household's utility maximization problem is as below:

$$L = \sum_{p=1}^{P} \psi_{op} ln\left(t_{op}\right) + \sum_{k=1}^{K} \sum_{g_k=1}^{G_k} \left\{ \psi_{kg_k} \gamma_{kg_k} ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}} + 1\right) \right\} - \sum_{p=1}^{P} \lambda_p \left\{ t_{op} + \sum_{k=1}^{K} \sum_{g_k\ s.t. p\in g_k} t_{kg_k} - T_p \right\}, \quad (5)$$

where $\lambda_p$ is the Lagrangian multiplier for person $p$'s time budget constraint.

The KKT conditions of optimality for the essential goods are:

$$\frac{\partial L}{\partial t_{op}} = 0 \Rightarrow \lambda_p = \frac{\psi_{op}}{t_{op}}\ \forall\, p = 1,2, \dots . P \quad (6)$$

The KKT conditions of optimality for the non-essential goods are:

[2] It is worth noting here that joint activity participation is not considered for in-home activities in the current empirical analysis due to lack of detailed data on joint activity participation at home. Therefore, all activities conducted at home (resulting in a time allocation $t_{op}$ for each person $p$) are assumed to be solo activities. However, it is straight forward to use the same utility formulation to consider joint activities at home as well. In the presence of detailed data on in-home activity participation, every activity that could potentially involve joint participation can be considered as another inside good $k$. Since every person needs some time for his/her essential, solo activities at home (for such basic needs as sleeping and personal care), one can use the person-specific outside good $t_{op}$ to represent such activities.

$$\frac{\partial L}{\partial t_{kg_k}} = 0 \; if \; t_{kg_k} > 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K$$

$$\frac{\partial L}{\partial t_{kg_k}} < 0 \; if \; t_{kg_k} = 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K \tag{7}$$

The above KKT conditions may be rewritten as

$$\frac{\psi_{kg_k}}{\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)} = \sum_{p \in g_k} \lambda_p \;\; if \; t_{kg_k} > 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K$$

$$\frac{\psi_{kg_k}}{\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)} < \sum_{p \in g_k} \lambda_p \;\; if \; t_{kg_k} = 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K \tag{8}$$

In the above KKT conditions, the summation on the right-hand side is over all household members $p$ in group $g_k$ who participate in activity $k$. Substituting the expressions for $\lambda_p$ from the KKT conditions for essential goods in Equation (6), one can express the KKT conditions for conditions for non-essential goods in Equation (8) as:

$$\frac{\psi_{kg_k}}{\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)} = \sum_{p \in g_k} \frac{\psi_{op}}{t_{op}} \;\; if \; t_{kg_k} > 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K$$

$$\frac{\psi_{kg_k}}{\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right)} < \sum_{p \in g_k} \frac{\psi_{op}}{t_{op}} \;\; if \; t_{kg_k} = 0 \; \forall \; g_k = 1,2, \ldots G_k; k = 1,2, \ldots K \tag{9}$$

To accommodate random utility terms, one can express the baseline utility parameters $\psi_{kg_k}$ as $exp\left(\boldsymbol{\beta}'\mathbf{x}_{kg_k} + \varepsilon_{kg_k}\right)$; where $\mathbf{x}_{kg_k}$ is a vector of observed attributes of the person group $g_k$, land-use and other characteristics of the household influencing the participation and time allocation to activity $k$ by person group $g_k$; $\varepsilon_{kg_k}$ is the corresponding random error term. Further, $\gamma_{kg_k}$ may also be expressed as a function of observed attributes influencing the time allocation to activity $k$ by person group $g_k$ as: $\gamma_{kg_k} = exp\left(\boldsymbol{\theta}'\mathbf{z}_{kg_k}\right)$. With these parameterizations and after a few algebraic rearrangements, the KKT conditions in Equation (9) may be expressed as:

$$\varepsilon_{kg_k} = -\boldsymbol{\beta}'\mathbf{x}_{kg_k} + ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right) + ln\left(\sum_{p\in g_k}\frac{\psi_{op}}{t_{op}}\right)\ if\ t_{kg_k} > 0\ ;$$

$$\forall g_k = 1,2,\dots G_k; \forall k = 1,2,\dots K$$

$$\varepsilon_{kg_k} < -\boldsymbol{\beta}'\mathbf{x}_{kg_k} + ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}}+1\right) + ln\left(\sum_{p\in g_k}\frac{\psi_{op}}{t_{op}}\right)\ if\ t_{kg_k} = 0\ ;$$

$$\forall g_k = 1,2,\dots G_k; \forall k = 1,2,\dots K \qquad (10)$$

The formulation will be complete after making assumptions on the distributions of the random error terms $\varepsilon_{kg_k}$ and completing the specification of baseline utility terms $\psi_{op}$ of the outside goods. For the $\varepsilon_{kg_k}$terms, we assume an independent and identically distributed (IID) type-I extreme value distributed kernel, with the idea that inter-alternative correlations and heteroscedasticity patterns may be accommodated using mixing distributions over the IID kernel. The $\psi_{op}$ terms need to be specified keeping in view normalizations necessary for parameter identification. Specifically, as discussed in (Bhat 2008), the explanatory variables $\mathbf{x}_{kg_k}$ do not enter the $\psi_{op}$ terms because budget constraints do not allow the identification of the coefficients of those variables. In other words, if a person's budget $T_P$ is known and the person's time allocation to all the inside goods are known, his/her time allocation to the essential outside good can be estimated using his/her budget constraint; there is no need of extra parameters for the outside good. For the same reason, as typically done in the environmental economics and marketing literature (Satomura, Kim et al. 2011), there is no need to specify a random component in $\psi_{op}$. In short, it suffices to normalize $\psi_{op}$ as 1 for all persons in the household. An alternative normalization is to treat the $\psi_{op}$ terms as equal (to, say, $\psi_o = \exp(\varepsilon_0)$), where $\varepsilon_0$ is a type-1 extreme value random term IID of $\varepsilon_{kg_k}$ for all persons in the household. As discussed in Van Nostrand, Pinjari et al.

(2012),this is a valid normalization because the outside good $t_{op}$ is specific to the person $p$'s constraint in that the time $t_{op}$ is not utilized by other outside goods. In such situations with constraint-specific Hicksian outside goods, constraining the outside good baseline utility terms to be equal ($i.e.,\ \psi_{op} = \psi_o \forall p = 1, 2, \dots, P$) generates covariance across the baseline utility terms $\psi_{kg_k}$ of all other goods. To see this, assuming $i.e.,\ \psi_{op} = \psi_o \forall p = 1, 2, \dots, P$, one can rewrite the utility function in Equation (3) with a single baseline utility term $\psi_o$ for outside goods, as below:

$$U^0 = \psi_o \sum_{p=1}^{P} \left(\ln t_{op}\right) + \sum_{k=1}^{K} \sum_{g_k=1}^{G_k} \left\{ \{\psi_{kg_k} \gamma_{kg_k} \ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}} + 1\right) \right\} \tag{11}$$

Now, the optimal time allocations obtained from maximizing the above utility function would be the same as those obtained from maximizing the following function obtained after dividing $U^0$ by $\psi_o$, which generates covariance across the random components of all inside alternatives:

$$\frac{U^0}{\psi_o} = \sum_{p-1}^{P} \left(\ln t_{op}\right) + \sum_{k-1}^{K} \sum_{g_k=1}^{G_k} \left\{ \frac{\{\psi_{kg_k} \gamma_{kg_k}}{\psi_o} \ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}} + 1\right) \right\} \tag{12}$$

Using the above normalization ($i.e.,\ \psi_{op} = \psi_o \forall p = 1, 2, \dots, P$), the KKT conditions in Equation (10) may be rewritten as:

$$\varepsilon_{kg_k} - \varepsilon_0 = V_{0g_k} - V_{kg_k}\ if\ t_{kg_k} > 0\ ;\ \forall g_k = 1,2, \dots G_k; \forall k = 1,2, \dots K$$

$$\varepsilon_{kg_k} - \varepsilon_0 < V_{0g_k} - V_{kg_k}\ if\ t_{kg_k} = 0\ ;\ \forall g_k = 1,2, \dots G_k; \forall k = 1,2, \dots K \tag{13}$$

where, $V_{0g_k} = ln\left(\sum_{p \in g_k} \frac{1}{t_{op}}\right)$ and $V_{kg_k} = \boldsymbol{\beta}' \mathbf{x}_{kg_k} - ln\left(\frac{t_{kg_k}}{\gamma_{kg_k}} + 1\right); \forall g_k = 1,2, \dots G_k; \forall k = 1,2, \dots K$

3.6. Consumption Probability Expression

Using the notation described earlier, the observed time allocation vector of a given household may be denoted as:

$$\left((t_{01}, t_{02}, \ldots t_{0K}), \ldots, (t_{11}, t_{12}, \ldots, t_{1g_1}, t_{1G_1}), \ldots, (t_{k1}, t_{k2}, \ldots, t_{kG_k}), \ldots, (t_{K1}, t_{K2}, \ldots t_{KG_K})\right)$$

In this vector, only the time allocations to outside goods $(t_{01}, t_{02}, \ldots, t_{0K})$ are always positive. The time allocations to other activities by different household member groups may be positive or zero. Let the number of OH activity type ($k$) and person group ($g_k$) combinations ($kg_k$) in which the household allocates positive time is equal to *M* (i.e., the number of chosen inside goods = *M*). Let *j* denote an index to represent all the chosen OH activity types and, without loss of generality, let the first *J* OH activities be the chosen activities ($j = 1,2, \ldots J$). Let $c_j$ denote the index to represent the person groups that participate in activity *j* and, without loss of generality, let the first $C_j$ person groups be those that participate in this activity ($c_j = 1,2, \ldots C_j$). Then the time allocation to a chosen activity *j* by a household's chosen person group $c_j$ is represented as $t_{jc_j}$ and the elements of the household's optimal (i.e., chosen) time allocation vector may be regrouped as: $\left((t_{01}^*, t_{02}^*, \ldots t_{0K}^*), \ldots, (t_{j1}^*, t_{j2}^*, \ldots t_{jC_j}^*), \ldots, (t_{J1}^*, t_{J2}^*, \ldots t_{Jc_J}^*), 0,0, \ldots, 0,0,0\right)$. The consumption probability expression for such observed time allocation vector may be derived as:

$$P\left((t_{01}^*, t_{02}^*, \ldots t_{0K}^*), \ldots, (t_{j1}^*, t_{j2}^*, \ldots t_{jC_j}^*), \ldots, (t_{J1}^*, t_{J2}^*, \ldots t_{Jc_J}^*), 0,0, \ldots, 0,0,0\right) ==$$

$$|\boldsymbol{J}| \frac{\left\{\prod_{j=1}^{J} \prod_{c_j=1}^{C_j} \exp(V_{jc_j} - V_{oc_j})\right\} M!}{\left\{1 + \sum_{k=1}^{K} \sum_{g_k=1}^{G_k} \exp(V_{kg_k} - V_{og_k})\right\}^{M+1}} \tag{14}$$

where $|\boldsymbol{J}|$ is the determinant of the Jacobian matrix whose ih$^{\text{th}}$ element can be computed as

$$J_{ic_i, hc_h} = \frac{\sum_{p \in c_i \cap c_h} \frac{1}{t_{op}^2}}{\sum_{p \in c_i} \frac{1}{t_{op}}} + \frac{I[ic_i = hc_h]}{t_{ic_i} + \gamma_{ic_i}} \tag{15}$$

Note that the above likelihood expression has a closed form and resembles that of Bhat's (2008) MDCEV model.

# CHAPTER 4

# DATA ANALYSIS

## 4.1. Data Overview

The data used for this analysis was obtained from 2013 Regional Household Travel Survey conducted by Southern California Association of Governments (SCAG), which is known as the metropolitan planning organization (MPO) of the six-county Los Angeles region of California. After an extensive review of the dataset, household records with missing information were removed, as well as households that didn't participate in any out-of-home activity during the day other than work or school. Also, for this analysis, only trips starting and ending at home, or so called tours were considered. Furthermore, the household size was limited to five people, even though the original dataset contained some cases of the household size larger than five. However, it is not feasible to model joint activities of all possible sizes due to the exponential increase in the computational complexity. Moreover, the large joint activity party sizes are relatively rare. The number of individuals in the household originally varied from one to nine individuals, however the households of size five or less constituted well over 95% of all households. Table 1 shows the frequency and percentage distribution of the household size in the final dataset. As expected, the least percentage of households are those of size 5 (6.7%).

Table 1. The Frequency and Percentage Distribution of the Household Size

| Household Size | Frequency | Percentage |
|---|---|---|
| 1 | 1387 | 24.2 |
| 2 | 2141 | 37.4 |
| 3 | 961 | 16.8 |
| 4 | 851 | 14.9 |
| 5 | 382 | 6.7 |
| Total | 5722 | 100 |

This extensive cleaning of the data resulted in a final estimation dataset, which included a total of 5722 households who participated in at least one non-mandatory activity purpose during the weekday. In the original dataset, there was a total of 10 classifications for the out-of-home non-mandatory activity purposes, out of which 9 were considered for this study and 1 (“other”) was dropped from the analysis. The non-mandatory activity purposes were classified as follows: (1) escorting (pick up/drop off), (2) shopping (groceries, clothes, and electronics), (3) maintenance (bank, ATM, post office, gas station, medical/doctor appointments, and quick stops for coffee/snack), (4) social (civic/religious activities, clubs, library, and volunteer activities), (5) entertainment (going to the movies, and watching sports), (6) active recreation (gym, yoga, walking, playing sports, bicycling, and walking the dog), (7) visiting friends/family, (8) eat-out, and (9) Work-related (work-sponsored social activities such as birthday celebrations)[3]. The total of 9 activity purposes and all the possible combinations of 5 five people, results in the maximum number of 279 [$(2^5 – 1) \times 9$] alternatives. Given the aim of this study was to model intra-household interactions, the joint activity participation was only considered among the members of the household. Therefore, if the person participated in certain activities with a group of friends, that was considered as an independent participation, since no other household members were involved.

The table 2 provides the descriptive analysis of the participation rates in different types of activity purposes and of different party composition (solo versus joint) for the final estimation dataset. The first column shows the percentage of households in which no individual participates in the row activity purpose during the day. The percentages reveal that households (all individuals in the household) are most unlikely during the weekday to participate in work-related activities

[3] Even though the activity purpose classification might seem to be subjective, it was based on the activity purpose taxonomy obtained from SCAG 2010 survey which provided the sample for this analysis. Also, the work-related activity purpose is not a mandatory activity as a person can still be employed and participate in work-related activities such as birthday celebrations or other work-sponsored social or maintenance activities.

and so called discretionary activities, such as social, visiting, entertainment and active recreation. Moreover, a large percent of households did not participate in any eat-out activities, which is expected since most people use the weekend to go out. The first column also shows that households are most likely to participate in shopping and maintenance-oriented activities during the weekday. In the second column, the frequency distribution of participation rates is shown in different types of activity purposes. It can be concluded that, among the households who participate in row activity purpose, independent participations are the most common for all types of activity purposes. That is especially the case for maintenance, shopping, active recreation and work-related activities. On the other hand, entertainment, eat-out, social and escorting are more likely to be pursued in groups. Lastly, as expected, the joint participation is the most common for groups of 2 people.

From the mean durations of time invested in row activity purpose, it is noticeable that the overall high of mean durations for both solo and joint activity participation is in social, entertainment, visiting and work-related activity purposes. The least amount of time was invested in shopping, maintenance, eat-out and escorting also for both solo and joint activity durations and with each having a mean duration of about an hour or less. While there are no substantial differences between the mean duration for almost all activity types, the mean durations are found to be higher for joint activity purpose, except for escorting with a solo mean duration being higher by a few minutes compared to the joint mean duration. That can be explained by assuming that individuals are in more contact with non-household members such as colleagues, friends and other acquaintances during the weekday that they are in contact with them during the weekend, which was found to be true by Srinivasan and Bhat (2008).

Table 2. Descriptive Analysis of the Participation Rates in Different Types of Activity Purposes and of Different Party Composition

| Activity Purpose | % of households with no individuals participating in "row" activity | % of households (from among those who participate in row activity purpose) by number of participating individuals | | | | | Mean duration of time spent in row activity purpose (in minutes) | | | % of households (from among those who participate in activity purpose) who participate… | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | Overall | Solo | Joint | Only in activity purpose | In other activity purposes too |
| Escorting | 74.1 | 48.8 | 36.4 | 11.8 | 2.8 | 0.3 | 14.64 | 16.2 | 13.1 | 14.3 | 85.7 |
| Shopping | 53.4 | 81.8 | 14.6 | 2.5 | 0.8 | 0.3 | 55.67 | 53.6 | 65.1 | 16.6 | 83.4 |
| Maintenance | 54.3 | 80.6 | 16.1 | 2.6 | 0.4 | 0.3 | 62.27 | 59.0 | 76.0 | 16.1 | 83.9 |
| Social | 90 | 72.3 | 19.4 | 5.1 | 2.9 | 0.3 | 191.84 | 171.2 | 245.7 | 9 | 91 |
| Entertainment | 92.4 | 65.1 | 24.6 | 5.7 | 3.6 | 1.1 | 167.01 | 152.8 | 193.5 | 12.2 | 87.8 |
| Visiting friends/family | 79.3 | 76.6 | 15.8 | 4.7 | 2.7 | 0.3 | 172.12 | 160.5 | 210.2 | 15.6 | 84.4 |
| Active Recreation | 74.8 | 78.8 | 14.5 | 5.1 | 1.4 | 0.3 | 123.68 | 106.1 | 189.0 | 14.5 | 85.5 |
| Eat Out | 75.1 | 73.0 | 21.8 | 2.9 | 1.7 | 0.6 | 74.73 | 73.82 | 77.2 | 11.6 | 88.4 |
| Work Related | 80.1 | 94.3 | 4.9 | 0.6 | 0.2 | 0.1 | 267.1 | 265.49 | 293.6 | 20.9 | 79.1 |

The final two columns in the Table 2 show the split between households participating in only one activity purpose with those participating in other activity purposes too. So, for example, 14.3% of households that invest their time escorting during the day participate only in this activity purpose during the weekday. Meanwhile, 85.7% of households that spend time escorting also invest their time in other activity purposes too. In conclusion, this suggests that a set of households in the final estimation dataset participate in variety of activity purposes over the weekday, which strongly implies the use of MDCEV model.

### 4.2. Description of Variables used for Model Estimation

The final dataset contains three different groups of variables that were used for model estimation: individual characteristics, household demographics and zonal (TAZ) characteristics. The individual characteristics, such as work schedules and demographics were introduced in the form of individuals who establish the activity alternative. So, the variables "Latest Work End Time among People in the Alternative" were computed as the maximum work end time among the people in the group corresponding to that alternative. For example, for an alternative with a group consisting of two people- person 1 and person 2, the latest work end time was computed as the maximum of work end times of person 1 and person 2. The same logic was used in the calculation of the "Maximum Work End Time among people in the Alternative" variables. The number of young children and indicator variables for the presence of a woman adult and a child in the group were created to test the hypothesis that children and women groups have different activity patterns compared to other groups.

Regarding household socio-demographics, the SCAG survey sample provided a variety of explanatory variables to choose from. The list of all variables describing household demographics used for model estimation is presented in the Table 3 along with their frequency distributions. To estimate the effect of the number of children in the households on the time spent in different activity purposes, children were split into two groups: school going children (age more than 5 through 15) and pre-school children (age 5 or less). From Table (3), the majority of the households do not have any pre-school or school going children. However, there is still a significant number of households with one or two children. Also, as mentioned in the literature review section, it is very important to include children’s activity patterns within the modeling framework as it can significantly influence adults’ travel patterns. Therefore, the number of children (both pre-school and school variables) is expected to have a significant impact on the households’ time investments in different activity purposes. As far as the number of senior adults (age more than 65), majority of the households don’t have any, or have only one. While it is true that most of the household have at least one full-time worker, the trend is not the same for part-time workers with majority households not having even one part-time worker. The income frequency distribution shows relatively equal numbers for all three income groups which is highly desired. Lastly, the auto sufficiency variables are defined as follows: zero vehicles (no vehicles in the household), low sufficiency (less cars in the household than driving age adults), equal sufficiency (the same number of cars as the number of driving age adults in the household) and high sufficiency (more cars in the household than driving age adults. As expected, only a small percentage of household doesn’t have any cars, while most households have as many cars as driving adults.

Table 3. The Frequency and Percentage Distribution of the Household Demographics Variables

| Household Demographics Variables | Frequency | Percentage |
|---|---|---|
| Number of school children | | |
| Zero | 4459 | 77.9 |
| One | 689 | 12.0 |
| Two | 488 | 8.5 |
| Three | 84 | 1.5 |
| Four | 2 | 0.1 |
| Number of pre-school children | | |
| Zero | 5275 | 92.2 |
| One | 330 | 5.8 |
| Two | 104 | 1.8 |
| Three | 13 | 0.2 |
| Number of senior adults | | |
| Zero | 4264 | 74.5 |
| One | 1049 | 18.3 |
| Two | 404 | 7.1 |
| Three | 5 | 0.1 |
| Number of full-time workers | | |
| Zero | 2281 | 39.9 |
| One | 2381 | 41.6 |
| Two | 979 | 17.1 |
| Three | 77 | 1.3 |
| Four | 4 | 0.1 |
| Number of part-time workers | | |
| Zero | 4006 | 70.0 |
| One | 1496 | 26.1 |
| Two | 207 | 3.6 |
| Three | 13 | 0.2 |
| Income | | |
| Low | 2077 | 36.3 |
| Medium | 1978 | 34.6 |
| High | 1667 | 29.1 |
| Auto sufficiency | | |
| Zero vehicles | 291 | 5.1 |
| Low | 753 | 13.1 |
| Equal | 3994 | 69.8 |
| High | 684 | 12.0 |

The last set of variables tested describes zonal (TAZ) characteristics, or the areas (TAZ zones) where the households are located. While several zonal characteristics variables were originally tested, most of them turned out to be insignificant (t statistic less than 1.645), so they were dropped from the analysis and only a few variables describing zonal characteristics were reported in the model estimation results. Some of the variables tested that may not be reported in the model estimation results include bike lane access, household density, job density, percent of households in transit priority area etc. The indicator variable for the households that live in central business area showed that about 20% of households lives in the central business area, while only small percentage of households have at least one rail station (less than 2%).

# CHAPTER 5

# EMPIRICAL RESULTS

This chapter presents the model estimation results and compares findings with the previous research. The discussion was split into three different sub-sections as variables could be grouped based on household demographics, individual and zonal characteristics. Furthermore, the model estimation results are presented in tables six to eight, with each showing parameter estimates for different variable groups for both household-level and person-level budget constrained MDCEV models that were estimated using 80% estimation sample (the remaining 20% was excluded for validation purposes). In addition, the estimation results showing constants and translation parameters are presented in tables four and five. In the constants only model, the parameter estimates control for the preference between different types of activities. As shown in Table 4, households are least likely to participate in social and entertainment activities, while they are most likely to participate in shopping and maintenance activities during a regular weekday. Similarly, from the number of participating people parameter estimates, it is observed that households prefer to participate in solo activates compared to joint activities. When it comes to translation parameters results, as mentioned in the methodology section, higher the value of a translation parameter lower the satiation for that corresponding alternative. The translation parameter estimates in Table 5 show consistency with the relative order of activity participation durations reported in Table 2. Also, when it comes to the number of participating people, the parameter estimates indicate that the time invested in joint activities is longer compared to solo activities, which is consistent with the previous research (Srinivasan and Bhat 2008). Finally, this section discusses overall model fit and validation for both household budget and person budgets models and for both estimation and validation datasets.

Table 4. Model Estimation Results Showing Constants

| | Estimation Sample | |
|---|---|---|
| | Household Budgets | Person Budgets |
| | Parameter | Parameter |
| *Constants* | | |
| *Activity Purpose* | | |
| Escorting | -9.6259 | -9.6336 |
| Shopping | -8.5709 | -8.4864 |
| Maintenance | -8.3435 | -8.2575 |
| Social | -10.3401 | -10.3614 |
| Entertainment | -10.3957 | -10.3421 |
| Visit | -9.4348 | -9.309 |
| Active Recreation | -9.5846 | -9.4984 |
| Eat-out | -9.4546 | -9.424 |
| Work-related | -10.245 | -10.2698 |
| *Number of participating people* | | |
| Two | -0.6675 | -0.1872 |
| Three | -2.6355 | -1.3864 |
| Four | -3.3032 | -2.8242 |
| Five | -3.2578 | -0.5156 |

Table 5. Model Estimation Results Showing Translation Parameters

| | Estimation Sample | |
|---|---|---|
| | Household Budgets | Person Budgets |
| | Parameter | Parameter |
| *Translation Parameters* | | |
| *Activity Purpose* | | |
| Escorting | 1.5424 | 1.5444 |
| Shopping | 3.4051 | 3.4199 |
| Maintenance | 3.1593 | 3.1709 |
| Social | 4.9249 | 5.0343 |
| Entertainment | 4.8462 | 4.9474 |
| Visit | 4.7107 | 4.8262 |
| Active Recreation | 4.2586 | 4.3432 |
| Eat-out | 3.852 | 3.8874 |

Table 5. Continued

| | | |
|---|---|---|
| Work-related | 5.262 | 5.4903 |
| *Number of participating people* | | |
| Two | 0.8423 | 0.1326 |
| Three | 1.4287 | 0.3098 |
| Four | 1.7011 | 0.303 |
| Five | 1.7132 | 0.0711 |

5.1. Effects of Household Demographics

The model estimation results corresponding to household demographics are shown in Table 6. As it can be seen in the table, it's the parameter estimates on the number of school children in the household indicate that households with more school children, relative to households with less school children, are less likely to participate in most out-of-home non-mandatory activities except for escorting. Also, similar effects were found for the number of pre-school children in the household. The positive sign of the parameter estimate on escorting could be explained by the fact that adults in households with children (both school and pre-school) often have the responsibility to pick up/drop off children from/to school or daycare centers. Regarding the negative inclination towards out-of-home activities, perhaps it could be due to additional time pressure on adults with child-care responsibilities (Gliebe and Koppelman 2005). Also, this hypothesis was proven correct in a recent study on activity time-use patterns of couples with and without children. To be specific, Bernardo, Paleti et al. (2015) found that households with children are less likely, compared to the households without children, to invest time in non-mandatory out-of-home activities, such as maintenance, eat-out, social and recreational. Moreover, their findings conform to the hypothesis that additional child-care responsibilities in the household, along with work commitments, negatively impact the out-of-home activity time-use patterns of working parents.

Next variable on the list in Table 6 is the number of senior adults (aged more than 65) in the household. It is interesting to note that, like the number of children, households with more senior adults, relative to the households with fewer senior adults, are less likely to engage in out-of-home non-mandatory activities including escorting, maintenance, visit, eat out and work-related. The negative parameter estimate on work-related activity was expected because senior adults are retired and don't have any work responsibilities. For social activities, the effect was found to be positive, however it wasn't statistically significant and therefore it was excluded from the final model specification. The positive effect on social activities is supported by previous research, which found that the households with more senior adults, relative to the household with less senior adults tend to participate in social activities, such as voluntary, community and religious events (Habib, Carrasco et al. 2008, Bhat, Goulias et al. 2013)

About the effect of the number of workers, it seems to be the same for both full-time and part-time workers. The results indicate that the households with more workers, relative to the households with less workers are less inclined to participate in all out-of-home non-mandatory activities other than work-related activities. The negative effect on the out-of-home activities could possibly imply that households with more workers prefer to use their weekdays for work and work-related purposes only, while leaving other, non-mandatory activities, for the weekends. The negative effect on the out-of-home non-mandatory activities other than work-related could be explained by assuming that most households have at least one worker and considering the fact that households are more likely to participate in out-of-home non-mandatory activities during the weekend compared to the activity participation rates during the weekday (Srinivasan and Bhat 2008).

When exploring the effect of income, low income category (less than $50k) was chosen as a base. The results indicate that both medium (between $50k and $100k) and high income (more than $100k) households are more likely to engage in active recreation, entertainment and eat-out activities during the weekday, compared to the low-income households. The positive effect of higher income households compared to the low income households very intuitive and supported by previous studies (Bhat, Goulias et al. 2013). When it comes to eat-out activities, for instance, due to financial constraints, it anticipated that low income households would less likely to pursue compared to households with higher income. It is interesting to note that higher participation levels in active recreation for medium and low income households supports the hypothesis from the physical activity literature that households residing in higher quality areas, which are usually households with higher income, may have higher tendencies to be physically active due to feeling safe in the neighborhood (Bennett, McNeill et al. 2007). That theory is also supported by Bhat, Goulias et al. (2013).

The last explanatory variables belonging to the group of household demographics show the effects of auto sufficiency. The low sufficiency (less cars than driving age adults) was chosen as a base case. Several observations were made based on the results. While all effects were found to be positive for equal (same number of cars as driving age adults) and high sufficiency (more vehicles than driving age adults), some were not statistically significant and therefore not included in the final model estimation results. The households with zero cars compared to the households with less cars than driving age adults were found to have a negative effect on active recreation and work-related activities, however most likely due to the small sample of households with zero cars, the effects were not statistically significant. Also, based on the results in Table 6, households with zero cars are less likely to participate in joint activities (size 2 or 3) compared to households with low sufficiency. The equal sufficiency households, which represents majority of the data used for model estimation (Table 3), are more inclined to take part in out-of-home activities compared to the households with low sufficiency. Also, what is interesting, households with equal sufficiency are more likely to participate in joint activities of size 4 or 5 compared to households with low sufficiency. Intuitively, it would be expected that households with less cars than driving age adults participate in more joint activities versus solo, because they don't have as many cars to begin with. However, the model estimation results show the opposite. Perhaps, most of the households with less cars than driving age adults also belong to low income households group and therefore are less inclined to participate in out-of-home activities compared to households of higher income. Another interesting observation is that households with high sufficiency are more likely to engage in escorting compared to the households with low sufficiency. Intuitively, it would be expected that more cars in the household implied less need of escorting, however as mentioned previously that might be due to not accounting for non-household members among the participating people.

Table 6. Model Estimation Results showing Household Demographic Characteristics

| | **Household Budgets** | **Person Budgets** |
|---|---|---|
| **Explanatory Variables** | **Parameter** | **Parameter** |
| **Household Demographics** | | |
| <u>*Number of school children*</u> | | |
| *Activity Purpose (Base is home)* | | |
| Escorting | 0.5399 | 0.5484 |
| Shopping | -0.2232 | -0.2378 |
| Maintenance | -0.2874 | -0.3115 |
| Visit | -0.2268 | -0.2378 |
| Eat-out | -0.3882 | -0.4455 |
| <u>*Number of pre-school children*</u> | | |
| *Activity Purpose (Base is home)* | | |
| Escorting | 0.3824 | 0.4313 |
| Shopping | -0.4432 | -0.4434 |

Table 6. Continued

| | | |
|---|---|---|
| Maintenance | -0.5514 | -0.5457 |
| Social | -0.5072 | -0.5237 |
| Entertainment | -0.8649 | -0.9273 |
| Visit | -0.5911 | -0.5271 |
| Active Recreation | -0.4278 | -0.3977 |
| Eat-out | -0.6359 | -0.7328 |
| Work-related | -0.0922 | -0.0888 |
| *Number of senior adults* | | |
| *Activity Purpose (Base is home)* | | |
| Escorting | -0.1246 | -0.1010 |
| Maintenance | -0.2160 | -0.2255 |
| Visit | -0.2655 | -0.2467 |
| Eat-out | -0.2251 | -0.2064 |
| Work-related | -0.9425 | -0.8596 |
| *Number of full-time workers* | | |
| *Activity Purpose (Base is home)* | | |
| Shopping | -0.0825 | -0.1396 |
| Maintenance | -0.0564 | -0.1243 |
| Eat-out | -0.1239 | -0.1672 |
| Work-related | 0.5061 | 0.4655 |
| *Number of part-time workers* | | |
| *Activity Purpose (Base is home)* | | |
| Maintenance | -0.1800 | -0.2109 |
| Eat-out | -0.1824 | -0.1815 |
| Work-related | 0.4705 | 0.4868 |
| *Household Income (Base: Low Income)* | | |
| *Medium Income* | | |
| *($50K < Income < $100K)* | | |
| *Activity Purpose (Base is home)* | | |
| Entertainment | 0.3243 | 0.3242 |
| Active Recreation | 0.4002 | 0.3832 |
| Eat-out | 0.2691 | 0.2808 |
| *High Income* | | |
| *(Income > $100K)* | | |
| *Activity Purpose (Base is home)* | | |
| Entertainment | 0.3216 | 0.2909 |
| Active Recreation | 0.5377 | 0.4873 |
| Eat-out | 0.5954 | 0.6187 |
| *Auto Ownership* | | |

Table 6. Continued

| | | |
|---|---|---|
| *(Base Case: Fewer cars than driving age adults)* | | |
| *Zero cars* | | |
| *Activity Purpose (Base is home)* | | |
| Maintenance | 0.6156 | 0.6993 |
| Social | 0.1611 | 0.6354 |
| Eat-out | 0.2205 | 0.3531 |
| *Number of participating people (Base is one person)* | | |
| Two or three | -1.3233 | -2.0187 |
| *Same number of cars as driving age adults* | | |
| *Activity Purpose (Base is home)* | | |
| Shopping | 0.5020 | 0.5342 |
| Maintenance | 0.3857 | 0.3952 |
| Social | 0.2539 | 0.2958 |
| Visit | 0.3472 | 0.3491 |
| Active Recreation | 0.4812 | 0.4890 |
| Eat-out | 0.3828 | 0.4212 |
| Work-related | 0.6353 | 0.6792 |
| *Number of participating people (Base is one person)* | | |
| Four or five | 0.3368 | 1.2977 |
| *More cars than driving age adults* | | |
| *Activity Purpose (Base is home)* | | |
| Escorting | 0.1980 | 0.2393 |
| Shopping | 0.4136 | 0.4466 |
| Maintenance | 0.4189 | 0.4155 |
| Eat-out | 0.3957 | 0.4013 |
| Work-related | 0.7499 | 0.7783 |

5.2 Effects of Individual Characteristics

This group of variables describes individual characteristics such as work schedules and demographics. As mentioned in the previous chapter, these variables are introduced in the way of representing individuals who constitute a particular activity purpose. The negative effect of work end times on shopping and active recreation implies that alternatives which constitute of individuals with late work end times will usually not be pursued for the two alternatives. This effect is reasonable because individuals who work until late have less time available in their daily budget for non-work activities, as observed by Rajagopalan, Pinjari et al. (2009). In contrast, Table 7 also shows that working late doesn't stop individuals from engaging in escorting, eat-out and work-related activities. Perhaps, it's because the three activity purposes don't have a rigorous schedule and might be pursued at any time of the day. In fact, the late hours are very common to engage in activities such as eat-out. On the other hand, work duration also has an impact on the time spent in non-mandatory activities. However, it is interesting to note that alternatives involving individuals with long work hours will usually not be pursued and that is valid for any activity purpose. This could be explained by the fact that long work hours have always been associated with increased fatigue (Jungsun, Yangho et al. 2001, Caruso 2006). With individuals that work long hours are generally less inclined towards participating in any non-mandatory activities. The positive effect of work end time on escorting, eat-out and work-related activities could happen due to relatively significant number of part-time workers across all households (See table 1). In other words, working late hours doesn't necessarily imply long work hours.

The results for the number of children among the people in the alternative imply that children (both pre-school and school going) are most likely almost always going to be accompanied by an adult if they take part in certain activity purpose. While it is not feasible to assume that children less than 5 years old participate in solo activities, school going children also prefer to participate in joint activities compared to solo, so the results are reasonable.

Finally, the results show that women adults and children are very likely to participate in activities together for all activity purposes, which is very expected considering the fact that women are more likely to take care of children compared to men according to some of the previous findings (Gliebe and Koppelman 2005, Bhat, Goulias et al. 2013).

Table 7. Model Estimation Results showing Individual Characteristics

| | **Household Budgets** | **Person Budgets** |
|---|---|---|
| **Explanatory Variables** | **Parameter** | **Parameter** |
| **Individual Characteristics** | | |
| *Latest Work End time among people in the alternative (in minutes/100)* | | |
| *Activity Purpose (Base is home)* | | |
| Escorting | 0.0272 | 0.0412 |
| Shopping | -0.0173 | -0.0191 |
| Active Recreation | -0.0160 | -0.0167 |
| Eat-out | 0.0439 | 0.0384 |
| Work-related | 0.0944 | 0.0927 |
| *Maximum Work Duration among people in the alternative (in minutes/100)* | | |
| *Activity Purpose (Base is home)* | | |
| Maintenance | -0.0899 | -0.0490 |
| Entertainment | -0.1244 | -0.0851 |
| Visit | -0.1238 | -0.0929 |
| Eat-out | -0.0924 | -0.0520 |
| Work-related | -0.3244 | -0.2839 |
| *Number of children among people in the alternative* | | |
| *Number of participating people (Base is one person)* | | |
| Two | 1.957 | 2.0043 |
| Three | 2.8449 | 2.8811 |
| Four | 3.0361 | 3.4008 |
| Five | 3.1759 | 3.2902 |
| *Presence of a woman adult and a child in the alternative* | | |
| *Number of participating People (Base is one person)* | | |
| At least two | 1.1258 | 1.0899 |

5.3. Effects of Zonal Characteristics

Even though provided with many explanatory variables describing zonal characteristics, most effects discovered turned out to be statistically insignificant. Still a few effects were reported. Based on Table 8, households that reside in central business district are found to be more involved in maintenance and active recreation compared to households that don’t live in central business districts. While this effect could be justified by assuming households residing in central business districts have better access to gym or maintenance facilities compared to households that don’t reside in central business districts, we cannot say with 90% certainty that central business district doesn’t impact the time invested in maintenance activity based on estimation sample results. However, the parameter estimate for maintenance activity was still reported because of intuition.

Furthermore, the results indicate that households that live in high quality transit areas are more likely to participate in work-related activities compared to households that don’t live in high quality transit areas. While this might not be intuitively expected, the high-quality transit areas are most likely located in city downtowns or central business districts, so households might have a lot of work-related activities.

Finally, the results indicate that households that live in zones with higher stop density for Express bus and BRT are more likely to invest time in entertainment compared to the households that live in zones with lower Express bus and BRT densities. This could also be explained by if households that live in zones with higher Express bus and BRT densities may have an easier access to entertainment facilities, such as movie theaters compared to the households that live in zones with lower density of Express bus and BRT. However, similarly to the results for central business district, the parameter estimate is insignificant, but it’s reported due to intuition.

Table 8. Model Estimation Results showing Zonal Characteristics

| **Explanatory Variables** | **Household Budgets** | **Person Budgets** |
|---|---|---|
| | **Parameter** | **Parameter** |
| **Zonal (TAZ) Characteristics** | | |
| *Household lives in central business district* | | |
| *Activity Purpose (Base is home)* | | |
| Maintenance | 0.0144 | 0.024 |
| Entertainment | 0.3475 | 0.279 |
| Active Recreation | 0.3475 | 0.279 |
| *Household lives in high quality transit area* | | |
| *Activity Purpose (Base is home)* | | |
| Work-related | 0.1879 | 0.2008 |
| *Stop density for Express Bus and BRT* | | |
| *Activity Purpose (Base is home)* | | |
| Entertainment | 0.4569 | 1.1007 |

5.4. Model Fit and Validation

The log-likelihood (LL) was calculated in both estimation and validation samples and compared with the log-likelihood and for both samples estimated using the household-level and person-level budget constrained MDCEV models. The results shown in Table 8 indicate a significant improvement in the log-likelihood in the person-level model compared to the household budget model in both the estimation and validation samples. However, this is not a rigorous comparison, the improvement may not be as big as the log-likelihood values make it seem to be. Since the two models are of different structures, a more thorough forecasting exercise must be undertaken to see how the predicted activity time-use choices compare with the observed choices (instead of log-likelihood values alone). Given that the person and household budget MDCEV models are not nested models, the log-likelihood ratio test cannot be used for comparison purposes. Instead, the Bayesian Information Criterion (BIC) test statistic was used. A model with lower BIC value is preferred over a model with higher BIC value. The BIC value of a model was computed as -2*LL+*K**LN(*N*), where '*K*' is the number of model parameters and '*N*' is the number of observations. It can be seen from Table 9 that the multiple person budgets model has a much lower BIC value compared to the household budget model.

Table 9. Data Fit in Estimation and Validation Samples

| | Log-likelihood in estimation sample (N = 4575) | Bayesian Information Criterion (BIC) | Predictive log-likelihood in validation sample (N = 1147) | # Parameters |
|---|---|---|---|---|
| Household level Budget Model | -156,487 | 314423.68 | -41,227.80 | 172 |
| Person level Budgets Model | -104,448 | 210345.68 | -27,796.40 | 172 |

# CHAPTER 6

# CONCLUSIONS

To summarize, this thesis contributes to the growing literature of activity based modeling approaches that account for intra-household interactions in the activity time-use choices of household members. As discussed in the literature review section, it is crucial to include joint activity participation in modeling activity decisions for more accurate predictions. The household level activity pattern generation model was formulated and estimated that predicts both individual and joint participation decisions among all members in a household, for all possible combinations of participating individuals and non-mandatory activity purpose. This study also contributes to the existing literature by enhancing the prediction accuracy of non-mandatory activity generation and allocation model by developing an improved MDCEV model that accounts for multiple person-level time budget constraints as opposed to the standard MDCEV model that works with single household-level time budget constraint. The statistical fit comparisons, both in the estimation and validation samples, clearly demonstrated superiority data fit in the multiple-constrained MDCEV model developed in this thesis. However, there are several possible avenues for future research.

First, even though the log likelihood values for the validation sample confirm the improvement of the person level budget model over household level budget model, more rigorous validation exercises are needed to compare the predicted and observed activity time-use choices with the household and person level budget models. While there are currently methods available in the literature for predicting using single budget constrained MDCEV model, similar extensions in the case of multiple budget MDCEV models are not straightforward. Furthermore, the fact that there are outside goods (i.e., home activities) imply that households must always choose to invest some non-zero time in these alternatives. Predicting with multiple budget constrains while ensuring non-zero time allocations to outside goods is a challenge and requires further research. Second, the impact of ignoring baseline utility terms of essential good (in our case, this is the home activity) is not known and future research should take a closer look at the baseline utility terms and explore the impact they have. Furthermore, the future efforts should explore alternative mechanisms to account for different power-structures within households (*i.e.*, differential influence of different group members performing a joint activity on the utility derived from the activity). Third, both the person and household-level models in their current form can predict extremely low participation durations for chosen alternatives. For example, one possible prediction could be 1 minute of shopping which does not seem feasible from a practical standpoint. These low predictions occur because there are currently no constraints to enforce minimum time allocations. Therefore, the future studies should account for such duration constraints in addition to the budgetary constraints. Lastly, larger households with more than five people were excluded from the analysis in this study because they constitute a small sample of the entire dataset. However, these households are more likely to engage in joint activities compared to smaller households largely due to limited availability of resources (e.g., vehicles). While it is difficult to estimate the MDCEV model allowing all possible combinations of household members as alternatives (because in larger households it leads to a significant increase in the size of the choice set), imposing a reasonable party size restriction among joint activities in larger households can constraint the size of the choice set thus enabling easy and quick statistical analysis.

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# VITA

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