A MULTIPLE-DISCRETE APPROACH FOR EXAMINING VEHICLE TYPE USE FOR DAILY ACTIVITY PARTICIPATION DECISIONS

Ahmadreza Faghih Imani
PhD Student
Department of Civil Engineering and Applied Mechanics
McGill University
Ph: 514-398-6823, Fax: 514-398-7361
Email: seyed.faghihimani@mail.mcgill.ca

Golnaz Ghafghazi
Graduate student
Department of Civil Engineering & Applied Mechanics
McGill University
Ph: 514-398-6935, Fax: 514-398-7361
Email: golnaz.ghafghazi@mail.mcgill.ca

Naveen Eluru*
Assistant Professor
Department of Civil Engineering and Applied Mechanics
McGill University
Ph: 514-398-6823, Fax: 514-398-7361
Email: naveen.eluru@mcgill.ca

Abdul R. Pinjari
Assistant Professor
Department of Civil and Environmental Engineering
University of South Florida
Ph: 813-974-9671, Fax: 813-974-2957
Email: apinjari@eng.usf.edu

*corresponding author

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ABSTRACT

There is increasing recognition that the choice of vehicle type and usage decisions form a crucial element in understanding transport related GHG emissions. The traditional approach to examining these dimensions is focused on vehicle fleet purchase decisions (number and type) and annual usage. These studies aggregate the overall vehicle usage as an annual decision whereas in reality households face the choice of vehicle type for out-of-home activity participation on a daily basis. With the recent emphasis on activity-travel models, there is growing recognition that daily vehicle usage choice is affected by activity purpose choice and the travel group for the activity.This study develops a representative framework to examine daily vehicle type and usage decisions while incorporating the influence of activity type and accompaniment type choices. In our approach, we include travel mode choice by considering the various travel mode alternatives (transit, walking/bicycling) and replacing the private vehicle alternative with various vehicle type options that are available to individuals. Thus the three choice dimensions: (1) travel mode that implicitly considers vehicle type, (2) activity purpose and (3) accompaniment type are jointly analyzed by generating combination alternatives. The Mixed Multiple Discrete Continuous Extreme Value (MMDCEV) framework provides an elegant modeling approach to study these choices. In our study, the discrete component is formed as a combination of travel mode, activity purpose and accompaniment type while mileage for each combination provides the continuous component. The proposed model approach is empirically tested for workers and non-workers in New York region using the National Household Travel Survey (NHTS) 2009. The model results provide insights on how socio demographics, location and temporal attributes influence daily vehicle type and usage, activity type and accompaniment type decisions.

Keywords: Daily vehicle type and use decisions, activity type, accompaniment type, mileage, MDCEV

1. INTRODUCTION

A significant increase in greenhouse gas emissions (GHGs) and energy consumption play a key role in influencing global climate change (NRC 2010). The increased concerns about global climate change have in the past decades resulted in growing attention toward the share of the transportation sector related GHGs. It is estimated that on-road vehicle sector is responsible for about 23% of the overall GHG emissions in 2007; more alarmingly it is also the most rapidly increasing source of GHG emissions (EPA 2009). The GHG contribution from on-road vehicles is significantly influenced by household vehicle fleet ownership. The recent increase in on-road vehicle emissions can be partially attributed to a significant change in vehicle fleet composition. The 2009 National Household Travel Survey(NHTS) data reveals that the share of passenger cars (sedans) in the household vehicle fleet composition reduced by 14.4% from 1995 to 2009 while the proportion of Sport Utility Vehicles (SUV) increased by 12.5%, and the proportion of Vans and pickup trucks increased by 1% in the same time frame. The increased holdings of larger vehicles (SUVs, Vans and pickup trucks) cause a larger burden on our environment; per mile emissions from larger vehicles are substantially more than per mile emissions from smaller vehicles.

Given the importance of vehicle fleet ownership and usage decisions, a substantial number of research efforts have studied these decision processes (see Anowar et al. 2012 for a review). However, the traditional approach to examining these dimensions is focused on vehicle fleet purchase decisions (number and type) and annual usage offering useful insights on long-term household vehicle decisions (Eluru et al. 2010, Bhat et al. 2009). These studies aggregate the overall vehicle usage as an annual decision whereas in reality households face the choice of vehicle type for out-of-home activity participation on a daily basis. Towards understanding these daily decisions, a framework that considers the vehicle type choice for daily activity participation is quite critical. To be sure, Bhat and Eluru (2009) examine vehicle mileage decisions at a daily level. However, the authors consider aggregate daily mileage without any examination of activity purpose or accompaniment dimensions. With the recent emphasis on activity-travel models, there is growing recognition that daily vehicle usage choice is affected by activity purpose choice and the travel group for the activity. A cursory examination of NHTS 2009 data shows that the average vehicle occupancy is 1.78 and 2.20 for shopping and social/recreational activities, respectively, implying that these activities are undertaken more with a companion rather than alone. The vehicle miles of travel for social/recreational activities, family and personal errands and other activities are 10.9, 10.6 and 5.4, respectively, indicating that activity type influence mileage (Santos et al. 2011). Moreover, it is well recognized that larger vehicles (like SUV or Van) are more likely to be used when multiple passengers are engaged (Paleti et al. 2012). There is clear evidence of the strong association between activity purpose, vehicle type and accompaniment type of mileage decisions.

In this context, the current study develops a representative framework to examine daily vehicle type and usage decisions while incorporating the influence of activity type and accompaniment type choices. Of course, prior to considering vehicle type choice, we need to examine individuals' consideration to use the private vehicle mode (*i.e.* consider travel mode choice). In our approach, we consider travel mode choice by considering the various travel mode alternatives (transit, walking/bicycling) and replacing the private vehicle alternative with various vehicle type options that are available to individuals. The vehicle type alternatives available to an individual are conditioned based on the household vehicle ownership information. Thus the three dimensions: (1) travel mode that implicitly considers vehicle type, (2) activity purpose and (3)

accompaniment type are jointly analyzed by generating combination alternatives (an example alternative: SUV- shopping- with household members). The study considers the mileage for each combination as a continuous component. In summary, we model daily vehicle type and usage decisions for every activity type and accompaniment type combination.

The reader will note that most individuals will choose multiple alternatives in a single day. For example, a non-worker might participate in grocery shopping alone in a sedan while pick up his/her child in a SUV. A traditional discrete framework to accommodate such multiple-discreteness will result in an explosion of discrete alternatives. The Multiple Discrete Continuous Extreme Value (MDCEV) framework proposed by Bhat in 2005 provides an elegant modeling framework to study these choices. In our study, the discrete component is formed as a combination of travel mode, activity purpose and accompaniment type while mileage for each combination provides the continuous component (see Castro et al. 2011 for a similar choice of continuous variable). The proposed model approach is empirically tested for workers and non-workers in New York region using the recently released National Household Travel Survey (NHTS) 2009. The model results provide insights on how socio demographics, location and temporal attributes influence daily vehicle type and usage, activity type and accompaniment type decisions.

The remainder of the paper is organized as follows: Section 2 discusses earlier literature closely related to our research effort while positioning the current study. The econometric methodology is briefly described in Section 3. Section 4 describes the data source and sample formation procedures. In Section 5, the model estimation results are discussed. Section 6 presents a validation exercise based on a hold out sample. We conclude the paper in Section 7 by identifying study limitations and providing directions for future research.

2. EARLIER RESEARCH AND CURRENT STUDY IN CONTEXT
The different dimensions of research identified in our study –vehicle type choice, activity purpose, accompaniment type and associated mileage have received considerable attention in the recent years. A comprehensive review of earlier research on all of these dimensions is beyond the scope of this paper. We provide an overview of studies that are closely related to the objectives of our research effort. Towards this end, we categorize the earlier literature into two groups: (1) activity participation studies and (2) mileage studies.

2.1 Activity Participation Studies
The focus on activity type participation has its roots in the modeling of activity-travel patterns. The shift in the travel behavior paradigm from trip based approaches to activity based models has resulted in a number of studies exploring the activity participation decisions. The studies in this category examine one or more of the following dimensions: activity generation, time-use participation, accompaniment type and time of day. For instance, some studies examined non-work activity generation (Bhat and Misra 2002, Scott and Kanaroglou 2002). While more recent efforts consider the accompaniment type and time of day choices along with the non-work activity purposes while explicitly focussing on time-use participation as a continuous component of analysis (Sener et al. 2011, Spissu et al. 2009, Eluru et al. 2010, Rajagopalan et al. 2009, Pinjari and Bhat 2010). These research efforts consider worker and non-worker patterns separately.
A number of studies have also focussed on joint modeling of activity purpose and accompaniment type without examining time-use participation (Scott and Kanaroglou 2002, Ferdous et al. 2010, Srinivasan and Bhat 2005, Gliebe and Koppelman 2002). Some of these

studies focus on intra-household interactions (for instance, see Scott and Kanaroglou 2002, Srinivasan and Bhat 2005, Gliebe and Koppelman 2002). Of course, individuals are not required to limit their choice of accompaniment to only household members; significant activity episode participation can be found in the company of wider social network beyond the household (for example, see Sener et al. 2011, Ferdous et al. 2010, Carrasco and Miller 2009, Arentze and Timmermans 2008, Kapur and Bhat 2007). The modeling approaches considered in these studies include unordered and ordered discrete choice models, multiple-discrete continuous models and composite likelihood approaches.

In general, findings from previous literature on activity participation indicate that females are more likely to pursue maintenance activities and family care (Ferdous et al. 2010, Srinivasan and Bhat 2005, Gliebe and Koppelman 2002, Kapur and Bhat 2007). Further, younger individuals are more likely to pursue non-work activities with company, confirming the larger social networks of younger individuals (Ferdous et al. 2010). Also, earlier studies recognized that individuals have more preference to pursue leisure activities in the company of friends and family (Sener et al. 2011). During weekdays, shopping episodes are more likely to be undertaken independently (Srinivasan and Bhat 2005). Another important finding from earlier research is how financial constraints dictate disinclination towards pursuing discretionary episodes (Kapur and Bhat 2007).

2.2 Mileage Studies
The earlier research efforts that examine any form of mileage are grouped under this category. These studies examine either long-term vehicle fleet ownership decisions or short-term vehicle use decisions. In the long-term category of studies, several recent efforts have analyzed vehicle type holdings, vehicle fleet composition and the annual vehicle miles traveled (overall vehicle usage) (see Eluru et al. 2010, Bhat et al. 2009, Paleti et al. 2011, Brownstone and Golob 2009, Spissu et al. 2009, Bhat and Sen 2006, Mohammadian and Miller 2003, Mannering 1983).

In the short term category, a few studies have examined vehicle mileage decisions at a daily level (Bhat and Eluru 2009, Paleti et al. 2012, Castro et al. 2011, Konduri et al. 2011, Golob 1998). These studies do not explicitly examine the influence of activity purpose, accompaniment type and vehicle type on mileage decisions. The modeling efforts employed in these studies include discrete continuous and multiple-discrete continuous frameworks.

From the findings from long-term and short-term studies on vehicle type decisions, it is evident that measures indicative of high density and urbanization contribute negatively to the accumulation of miles (Eluru et al. 2010, Bhat et al. 2009, Paleti et al. 2012, Brownstone and Golob 2009, Spissu et al. 2009). Higher income households are likely to accumulate more miles (Eluru et al. 2010, Paleti et al. 2012, Paleti et al. 2011). The presence of children increases the household errands; thus contributes to higher miles of travel for non-work activities (Eluru et al. 2010, Castro et al. 2011, Paleti et al. 2011). On the other hand, senior adults tend to accrue lower mileage (Eluru et al. 2010, Paleti et al. 2012, Paleti et al. 2011). Besides, it appears that vehicle type affects the daily miles of travel; more miles of travel are allocated to more fuel efficient vehicles (Paleti et al. 2012). In addition, vehicle type choice is influenced by household attributes. Larger households, household with children and household with more male adults have more preference for larger vehicles (Eluru et al. 2010, Paleti et al. 2011). Moreover, in terms of accompaniment type, it is recognized that activities with company are of longer durations (Srinivasan and Bhat 2008) and tours with company have longer length (Paleti et al. 2012).

2.3 Current Study

While several studies have examined the various dimensions of interest individually, few studies explicitly address the vehicle type choice for individual's daily activity-travel patterns in the context of activity type and accompaniment type. To accurately assess the associated environmental impacts because of the use of different vehicle types, it is necessary to quantify vehicle type related usage. Earlier studies confirm that in the short-term, individuals make conscious decisions regarding vehicle type choice and tour length at the tour level, depending on attributes such as accompaniment type (see Paleti et al. 2012, Konduri et al. 2011). However, only Paleti et al. (2012) has examined these mileage choices in the context of accompaniment type. The study employs a system of simultaneous equations to generate the correlation across the various dimensions including tour complexity, passenger accompaniment, vehicle type and tour length. The approach, while simulation free, still resorts to coupling of choices through the unobserved component. In our study, we propose an approach that directly accommodates for competition across the various dimensions involved through the MDCEV framework. Further, our approach explicitly models mileage associated with activity type, accompaniment type and vehicle type on a daily basis. Thus, we propose a unified model that simultaneously allows for competition across the various alternatives within a random utility based approach. We do recognize that various alternatives of a particular dimension (for instance, all alternatives involving transit) might be affected by common unobserved factors. To accommodate for such potential correlation across the various choice dimensions we also explore the applicability of an error components MDCEV model in our analysis.

In this paper, *non-work activity purposes* are classified into five main categories:1) Shopping, 2) Social and recreational, 3) Transporting someone, 4) Meals and 5) Others. The *travel mode alternatives* are characterized as: public transit, walk/bike (these two modes are available for everyone) and three privately owned vehicle types, including: Car, SUV and other vehicles (including Van and pick up). The vehicle type dimensions are appropriately matched with the household vehicle ownership information (*i.e.* if a household does not own a SUV, the individual will not have alternatives corresponding to SUV available to him/her). The *accompaniment dimension* is classified as: alone, with household member, and with household members and non-household members. Overall, these categories result in 75 discrete alternatives (5*5*3). The mileage component associated with these discrete alternatives is provided as the continuous component of the MDCEV model. It is important to note that considering mileage as a surrogate for destination choice allows us to consider multiple episodes of the same combination.

This paper employs data for New York, Northern New Jersey and Long Island region drawn from the 2009 National Household Travel Survey (NHTS), a comprehensive database that includes individual and household socio-economic, demographic, and activity-travel information as well as temporal and residential location attributes. Since the activity-travel behavior of workers is usually constrained by their work schedule, their activity-patterns differ from non-workers. Therefore, in this paper, workers and non-workers are studied separately.

3. METHODOLOGY

This section of the paper discusses the basic structure of the MDCEV model in Section 3.1, followed by the introduction of a more elaborate error structure in Section 3.2.

3.1 The MDCEV Model Structure

The random utility function for each alternative is defined as:

$$U(x) = \sum_k \frac{\gamma_k}{\alpha_k}[\psi_k \exp(\varepsilon_k)] \cdot \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} (1)$$

where $U(x)$ is a quasi-concave, increasing, and continuously differentiable function with respect to the consumption quantity $(K\text{x}1)$-vector x ($x_k \geq 0$ for all k), and ψ_k [parameterized as $\exp(\beta' z_k)$], γ_k and α_k are parameters associated with alternative k. ψ_k represents the baseline marginal utility, γ_k enable corner solutions while simultaneously influencing satiation and α_k influences satiation. Due to the common role of γ_k and α_k, it is very challenging to identify both γ_k and α_k in empirical application (see Bhat 2008). Usually, one chooses to estimate satiation using γ_k or α_k. In our current paper the γ-profile is employed[1].

In this case the utility simplifies to

$$U(x) = \sum_k \gamma_k [\psi_k \exp(\varepsilon_k)] \cdot \ln \left(\frac{x_k}{\gamma_k} + 1 \right) (2)$$

Following Bhat, consider an extreme value distribution for ε_k and assume that ε_k is independent of z_k ($k = 1, 2, \ldots, K$) (Bhat 2005, Bhat 2008). The ε_k's are also assumed to be independently distributed across alternatives with a scale parameter of 1. Let V_k be defined as follows:

$$V_k = \beta' z_k - \ln \left(\frac{x_k}{\gamma_k} + 1 \right) (k = 1, 2, 3, \ldots, K) \tag{3}$$

The probability that the individual allocates expenditure to the first M of the K goods ($M \geq 1$) is:

$$P\left(e_1^*, e_2^*, e_3^*, \ldots, e_M^*, 0, 0, \ldots, 0\right)$$

$$= \left[\prod_{i=1}^M c_i \right] \left[\sum_{i=1}^M \frac{1}{c_i} \right] \left[\frac{\prod_{i=1}^M e^{V_i}}{\left(\sum_{k=1}^K e^{V_k} \right)^M} \right] (M-1)! \tag{4}$$

where $c_i = \left(\frac{1 - \alpha_i}{x_i + \gamma_i} \right)$

3.2 The Mixed MDCEV Model

Incorporating a general error structure is straightforward through the use of a mixing distribution, which leads to the Mixed MDCEV (or MMDCEV) model. Specifically, the error term, ε_k, may be partitioned into two components, ζ_k and η_k. The first component, ζ_k, can be assumed to be independently and identically Gumbel distributed across alternatives. The second component η_k, can be allowed to be correlated across alternatives and to have a heteroscedastic scale. Let $\eta = (\eta_1, \eta_2, \ldots, \eta_K)'$, and assume that η is distributed multivariate normal, $\eta \sim N(0, \Omega)$. For

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[1] In our empirical context, the γ-profile offered superior fit compared to the α-profile.

given values of the vector η, one can follow the preceding discussion and obtain the usual MDCEV probability that the first M of the k goods are consumed. The unconditional probability can then be computed as:

$$P\left(e_1^*, e_2^*, e_3^*, ..., e_M^*, 0, 0, ..., 0\right)$$

$$= \int_{\eta} \left[\prod_{i=1}^{M} c_i\right]\left[\sum_{i=1}^{M} \frac{1}{c_i}\right]\left[\frac{\prod_{i=1}^{M} e^{(V_i + \eta_i)}}{\left(\sum_{k=1}^{K} e^{(V_k + \eta_k)}\right)^M}\right](M-1)! \, dF(\eta). \tag{5}$$

where F is the multivariate cumulative normal distribution (see Bhat 2005, Bhat and Sen 2006, Bhat et al. 2006). The maximum simulated likelihood estimation of MMDCEV model is achieved using Halton draws (see Bhat and Eluru 2010 for examples of such approaches). The MMDCEV model discussed is estimated using a program coded in Gauss matrix programming language.

4. DATA

4.1. Data Source
The data for our research effort is drawn from National Household Travel Survey (NHTS) data conducted in 2008-2009 for New York, Northern New Jersey and Long Island region. The survey gathered information on individual and household socio-demographics, residential location characteristics and daily travel attributes. The daily travel attributes compiled include out-of-home activity episode type, the day and month on which the activity is undertaken, travel mode for every episode (including vehicle type information for automobile users) and accompanying person information (alone, household or non-household members) for the episode.

4.2. Sample Formation and Descriptive Analysis
The sample formation exercise involved a series of transformations on the original NHTS travel data set. First, the activity level information for out-of-home activities on weekdays was compiled across the three dimensions − activity purpose, travel mode and accompaniment type. Second, the relevant combination alternatives for all individuals were generated. At the same time, the associated daily mileage for each combination alternative was computed. Third, individual and household socio-demographics, residential location and contextual characteristics (day of week and the season of travel day) were appropriately added to the database. Fourth, the databases were split into two components based on whether the individual participated in work/school activity on the day; thus generating worker and non-worker profiles. Fifth, the work and school episodes were removed from the analysis database (applicable for workers only). A small hold out sample was created for both datasets to undertake validation after model estimation. Finally, several screening and consistency checks were performed on the four extracted samples, and records with missing or inconsistent data were eliminated.

Tables 1 and 2 respectively present non-workers' and workers' daily trip average millage and participation for each of 75 activity purpose-mode-accompaniment type categories by activity type, accompaniment type and travel mode. For instance, the entry for the "shopping-car- alone" cell in TABLE 1 indicates that 505non-workers (28.6% of the 1764 individuals who

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have car) participated in shopping activity alone driving a car, while the entry for the "meals-SUV-with household member" cell in TABLE 2 shows that 27workers (3.51% of the 770individuals who have SUV) participated in meals activity with only family members with SUV. The reader would note that the percentages across different dimensions do not sum to 100% because of multiple discreteness in activity purpose-mode-accompaniment types; for instance, an individual may participate in multiple social/recreational episodes on the same day, some in which the individual participates with family driving a car and others in which the individual participates alone using a bicycle. Also, the availability of vehicle is considered in the participation percentages. The results indicate that both non-workers and workers participate more in shopping activities while travelling alone in a car. From miles of travel standpoint, in general, average daily travelled millage for social/recreational trips is higher than other activity types. Besides, workers travel fewer miles for social/recreational activity pursuits compared to non-workers. The results reveal that individuals who choose to undertake bike or walk trips, not surprisingly, travel less than 2 miles. On the other hand, non-workers travel longer distances while driving a SUV for all activity and accompaniment types. Among all the activity purpose-accompaniment types, individuals allocate more private vehicle mileages for meals episodes when they have a companion.

5. EMPIRICAL ANALYSIS

5.1 Variable Specification
In the model specification, several types of variables were considered including: 1) individual demographics (gender, age, race and education level),2) household demographics (household size, presence of children and family income), 3)household location variables (urban areas and residential density) and 4) contextual variables (day of the week and seasons).Initially, a simple MDCEV model was estimated. Subsequently, the specification was enhanced by estimating an error components MDCEV model. Several different error component specifications were considered to introduce correlation across various dimensions. The error component accounts for unobserved factors across choice dimensions in the baseline utility function that may predispose individuals towards choosing a certain dimension more than others. In order to finalize the model specification, a systematic process of removing statistically insignificant variables, combining variables when their effects were not significantly different was followed. The process was guided by intuition and parsimony considerations. It should be noted that, for the continuous variables in the data (such as age), dummy variables for different ranges were tested. It was found that the dummy representation of continuous variables offered superior fit compared to the corresponding linear variables.

5.2 Model Estimation Results
The final Log-likelihood values for the error components MDECV model for the non-workers and worker samples are -17442.5 and -12028.0, respectively. The corresponding values for the MDCEV model are -18247.9 and -12338.2. The improvement in the data fit clearly illustrates the superiority of the error components MDCEV model. Tables3 and 4 present the model estimation results for non-worker and worker samples, respectively. The explanatory variable coefficient and its t-statistic are presented in the tables. In the following sections, the effect of variables on the baseline preference utility is discussed. To conserve on space, constants and gamma parameters are not presented.

5.2.1 Individual Demographics

The parameters for individual demographic characteristics underscore their importance on individual daily mileage allocation. Male non-workers are likely to travel more mileages for social/recreational and meals activities compared to women (see Ferdous et al. 2010 for similar results). Men are more likely to use Van/other vehicles and SUV for travel (see Mohammadian and Miller 2003), while they are less inclined to travel with non-household members (see Ferdous et al. 2010, Paleti et al. 2012).Among workers, men are less inclined to travel to transport someone. Also, men are likely to travel alone compared to women. The results clearly indicate that men are less likely to pursue "maintenance" chores but more likely to participate in "relaxing" activities compared to women.

Race-related coefficients of both models for workers and non-workers indicate a strong inclination toward social/recreational activities among individuals that are White. The same is true for non-workers with respect to meals activities. These results may be indicative of cultural distinctions among different races. Interestingly, there is no significant effect of race-related variables on accompaniment and travel mode dimensions of both workers and non-workers.

Non-workers with university degree travel longer for transporting someone whereas the opposite is true while they travel with a family member. The results show that workers with university degree have higher daily travelled mileages for "others" activity categories. At the same time, workers with university degree are more inclined to consider public transit and walk/bike modes for travel. On the other hand, workers with university degree have lower propensity to travel with non-family members.

The age-related variables are introduced as dummy variables, with the category of smaller than 21 being the base. The results suggest disinclination toward social/recreational, meals and "others" activity categories for individuals aged over 21.The result might be an indication that older individuals are more likely to have more responsibilities compared to younger individuals. With respect to the travel mode dimension, both workers and non-workers over 21 years old are less likely to travel longer using the public transit or walk/bicycle mode. The result probably is an indication that these individuals are more likely have access to household vehicles compared to younger individuals. Also, workers aged over 60 have lower preference to drive Van and other vehicles to get to their destinations. A possible explanation for this result is the relative difficulty of getting in and out of a Van or pickup truck for older people. Individuals in the age group of 21-60 travel smaller distances while travelling with household family members and non-family members. The same is true for people older than 60 years while travelling with non-household members. Besides, workers aged over 60 allocate less travel for activities with a household member.

5.2.2 Household Demographics

Among the household demographic variables, the coefficient of household size variable indicates that, with increasing household size, non-workers tend to transport someone more, presumably due to sharing of vehicular resources in larger families. In terms of accompaniment dimension, as the household size increases, the preference of non-workers to travel longer distances with someone, either a family member or non-family member, increases (see Paleti et al. 2012 for similar results). The same pattern is observed for workers travelling with a family member. Besides, non-workers with larger households have higher propensity to choose Van/other vehicles category as their travel mode for their daily trips (see Eluru et al. 2010 for consistent results). Further, individuals from larger households are more likely to travel by public transit

and non-motorized modes. The result is an indication of the vehicle resource constraints on individuals from larger households.

Typically, adults are responsible for chauffeuring of children to/from school and other non-school activities. The results for the presence of children variables are consist with this assumption (similar with Paleti et al. 2012). Furthermore, an individual with children younger than 15 years travels more with a family member. Workers who live in a household with a child aged less than 5, are likely to travel with non-household member while for non-workers the opposite is true. With respect to travel mode dimension, the presence of kids aged 5-15 is associated with a positive impact on Van and other vehicles or SUV use. These findings are consistent with those of earlier studies (see Eluru et al. 2010, Paleti et al. 2011, Cao et al. 2006). It is possible that individuals prefer larger vehicles in the presence of children in the household. In households with older children (>15) workers are unlikely to use larger vehicles for travel (SUV and Van/other vehicles).

The results for the household income variable show that non-workers from high income households (annual income >70K) are more likely to participate in social/recreational activities. Further, for high income workers, there is a higher disposition to travel farther for meals and "others" activity types (see Kapur and Bhat 2007 for similar results). The results reveal that non-workers from both high income and medium income (annual income between 40K and 70K) households are less likely to choose public transit as their travel mode for their activities.

5.2.3 Household Location Variables

Urban areas and areas with high residential density compared to rural areas and areas with low residential density, have better public transit accessibility and presumably are more secure and safer. The results corresponding to these variables offer expected results. Individuals residing in urban areas and highly dense neighbourhoods are less likely to travel longer for transport someone activity while they are more likely to use public transit and non-motorized modes. Workers who live in high residential density areas have higher propensity to travel longer distances for meals. With respect to accompaniment type dimension, non-workers in urban regions travel less with non-household members. On the other hand, workers residing in urban areas prefer travelling with non-household members. Non-workers residing in dense neighborhoods prefer to pursue activities alone while workers residing in dense neighborhoods are less inclined to pursue activities with household members.

5.2.4 Contextual Variables

Workers are more likely to allocate Fridays for travelling with non-household members; probably an indication of after work meet-ups. In summer, non-workers tend to allocate more travel for social/recreational and meals activities and for travel with family members. At the same time, during summer individuals (workers and non-workers) pursue less of transport someone activity (see Ferdous et al. 2010 for similar result). During summer children are usually on vacation and the need to transport them is much lower. Non-workers prefer to travel using SUVs in winter; probably reflecting preference for larger vehicles that offer more stability in winter weather.

5.2.5 Random Error Components

The final model specification included seven error components specific to the activity, accompaniment and travel mode type dimensions for non-workers and for workers. The dimensions that exhibited strong correlation for non-workers include:1) Activity type

(social/recreational), 2) Accompaniment type (with household member and with non-household member) and 3) Travel mode type (Van/other vehicles, SUV, transit and walk/bike). The dimensions that exhibited strong correlation for workers include: 1) Activity type (transport someone and others), 2) Accompaniment type (with household member and with non-household member) and 3) Travel mode type (Van/other vehicles, SUV and walk/bike).The statistically significant error component parameters indicate that unobserved component has a significant influence on individuals' vehicle type, activity purpose, accompaniment type and mileage decisions.

6. VALIDATION

The model estimates generated for non-worker and worker sample were validated using the hold-out samples set aside (200 workers and 400 non-workers). The validation exercise was employed to illustrate the application of the MMDCEV model developed. Specifically, we use the approach proposed by Pinjari and Bhat (2011) for undertaking the prediction exercise (Pinjari and Bhat 2011). To compare the results with the validation sample characteristics, we compute participation rates across the three dimensions. The computed participation rates are compared with the participation rates observed in the validation sample. The comparison exercise results for non-workers and workers are presented in TABLE5. The following observations can be made from the validation exercise. Overall, the predicted participation rates are reasonably close to the observed participation rates. The error percentages range from -48.39% to 33.33%. The MMDCEV model performs reasonable for most alternative combinations. The predictions have large errors for car usage for workers, non-hh member accompaniment and transport someone activity for non-workers. These errors might be a manifestation of the large variability in the small validation sample (*i.e.* we are predicting for 75 alternative combinations with about 400 non-workers and 200 workers). A larger sample might offer better aggregate comparison results.**7. CONCLUSION**

In recent years, the focus of transportation policy makers has shifted to reducing the share of the transportation sector related GHG emissions in face of increasing concerns about global climate change. There is growing recognition that the choice of vehicle type and usage decisions form a crucial element in understanding transport related emissions. Towards examining vehicle type and usage decisions it is important to examine the role of activity purpose and accompaniment type. The current study develops a representative framework to examine daily vehicle type and usage decisions while incorporating the influence of activity type and accompanimenttype choices. Of course prior to considering vehicle type choice, we need to examine individuals' consideration to use the private vehicle mode (*i.e.* consider travel mode choice). In our approach, we consider travel mode choice by considering the various travel mode alternatives (transit, walking/bicycling) and replacing the private vehicle alternative with various vehicle type options that are available to individuals. Thus the three dimensions: (1) travel mode that implicitly considers vehicle type, (2) activity purpose and (3) accompaniment type are jointly analyzed by generating combination alternatives (an example alternative: SUV- shopping- with household members). The study considers the mileage for each combination as a continuous component. The Mixed Multiple Discrete Continuous Extreme Value (MMDCEV) framework proposed by Bhat in 2005 provides an elegant modeling framework to study these choices. In our study, the discrete component is formed as a combination of travel mode, activity purpose and accompaniment type while mileage for each combination provides the continuous component.

The proposed model approach is empirically tested for workers and non-workers in New York region using the recently released National Household Travel Survey (NHTS) 2009 for the New York, Northern New Jersey and Long Island region. The model results provide insights on how socio demographics, location and temporal attributes influence daily vehicle type and usage, activity type, and accompaniment type decisions. For instance, the results indicate that individuals from high-income families have higher tendency to travel more with their privately owned vehicle. There are also distinct gender differences, with women traveling more for the transport someone activities. Presence of kids aged 5-15 in household increases the likelihood that non-workers use large vehicles. On the contrary, presence of children older than 15 years decreases the propensity of workers of driving large vehicles. Further, individuals are more likely to pursue activities jointly when household size increases. Age, race, education, residential location, seasons and the day of the week variables also affect individuals' choice to allocate mileage to activity purpose-mode-accompaniment type combinations. The significantly different impacts of exogenous variables for workers and non-workers reinforce the fact that there is a notable difference in travel behavior and decision making process for these two groups.

In summary, the paper underscores the need to capture and recognize the packaged nature of activity-travel choices to reflect the complex observed and unobserved linkage between several choice dimensions. The formulated model allows us to disentangle the influence of exogenous factors on mileage contribution for the different dimensions (vehicle type, activity type and accompaniment type). A model that does not explicitly model the three dimensions would aggregate these effects incorrectly. The model results provide evidence that individuals consciously consider the companionship and mode of travel when deciding to pursue non-work activities. These choice dimensions must be accommodated together within the activity-based travel modelling to provide reliable travel forecasting. The study is not without limitations. The analysis is conducted at a daily level and not at an episode level. In future research, efforts to investigate episode level vehicle type choice would be useful. The model predictions need to be undertaken on larger datasets to confirm the findings and applicability of the proposed framework. Moreover, a GEV version of the MDCEV model might also be considered as opposed to the MMDCEV model employed in our study.

REFERENCES

Anowar S., Yasmin, S., Eluru N. and Miranda-Moreno, L. (2012). "Analyzing Car Ownership in Two Quebec Metropolitan Regions: A Comparison of Latent Ordered and Unordered Response Models." Technical Paper, Department of Civil Engineering and Applied Mechanics, McGill University.

Arentze, T. and Timmermans, H. (2008). "Social Networks, Social Interactions, and Activity-Travel Behaviour: A Framework for Microsimulation." *Environment and Planning B*.Vol. 35, No. 6, pp. 1012-1027.

Bhat, C.R. (2005). "A Multiple Discrete-Continuous Extreme Value Model: Formulation and Application to Discretionary Time-Use Decisions." *Transportation Research Part B*, Vol. 39, No. 8, pp. 679-707.

Bhat, C.R. (2008). "The Multiple Discrete-Continuous Extreme Value (MDCEV) Model: Role of Utility Function Parameters, Identification Considerations, and Model Extensions." *Transportation Research Part B,* Vol. 42, No. 3, pp. 274-303.

Bhat, C.R. and Misra, R. (2002). "Comprehensive Activity-Travel Pattern Modeling System for Non-Workers with Empirical Focus on the Organization of Activity Episodes." *Transportation Research Record*, Vol. 1777, pp. 16-24.

Bhat, C.R. and Sen, S. (2006). "Household vehicle type holdings and usage: an application of the multiple discrete-continuous extreme value (MDCEV) model." *Transportation Research Part B,* Vol. 40, No. 1, pp. 35-53.

Bhat, C.R. and Eluru, N. (2009). "A Copula-Based Approach to Accommodate Residential Self-Selection Effects in Travel Behavior Modeling." *Transportation Research Part B*, Vol. 43, No. 7, pp. 749-765.

Bhat, C.R. and Eluru, N. (2010) *Recent Advances in Discrete and Discrete-Continuous Modeling Systems*, *Feasibility Decisions in Transportation Engineering*. Edited by S. Nocera, McGraw-Hill, Chapter 6, pp. 111-144.

Bhat, C.R., Sen, S. and Eluru, N. (2009). "The Impact of Demographics, Built Environment Attributes, Vehicle Characteristics, and Gasoline Prices on Household Vehicle Holdings and Use." *Transportation Research Part B*, Vol. 43, No. 1, pp. 1-18.

Bhat, C.R., Srinivasan, S. and Sen, S. (2006). "A Joint Model for the Perfect and Imperfect Substitute Goods Case: Application to Activity Time-Use Decisions." *Transportation Research Part B,* Vol. 40, No. 10, pp. 827-850.

Brownstone, D. and Golob, T.F. (2009). "The impact of residential density on vehicle usage and energy consumption." *Journal of Urban Economics*, Vol. 65, No. 1, pp. 91-98.

Cao, X., Mokhtarian, P. L. and Handy, S. L. (2006). "Neighborhood Design and Vehicle Type Choice: Evidence from Northern California." *Transportation Research Part D,* Vol. 11, No. 2, pp. 133–145.

Carrasco, J.A. and Miller, E.J. (2009). "The Social Dimension in Action: A Multilevel, Personal Networks Model of Social Activity Frequency between Individuals." *Transportation Research Part A*,Vol. 43, No. 1, pp. 90-104.

Castro, M., Eluru, N., Bhat, C.R. and R.M. Pendyala. (2011). "Joint Model of Participation in Nonwork Activities and Time-of-Day Choice Set Formation for Workers." *Transportation Research Record*, Vol. 2254, pp. 140-150.

Eluru, N., Bhat, C.R., Pendyala, R.M. and Konduri, K.C. (2010). "A Joint Flexible Econometric Model System of Household Residential Location and Vehicle Fleet Composition/Usage Choices." *Transportation*, TRB Special Issue, Vol. 37, No. 4, pp. 603-62.

Eluru, N., Pinjari, A.R., Pendyala, R.M. and Bhat, C.R. (2010). "An Econometric Multi-Dimensional Choice Model of Activity-Travel Behaviour." *Transportation Letters: The International Journal of Transportation Research,* Vol. 2, No. 4, pp. 217-230.

EPA. (2009). *U.S. Greenhouse Gas Inventory Report*. US Environmental Protection Agency.

Ferdous, N., Eluru N., Bhat, C.R. and Meloni, I. (2010). "A Multivariate Ordered Response Model System for Adults' Weekday Activity Episode Generation by Activity Purpose and Social Context." *Transportation Research Part B*, Vol. 44, No. 8-9, 2010, pp. 922-943.

Gliebe, J. P. and Koppelman, F. S. (2002). "A Model of Joint Activity Participation Between Household Members." *Transportation*, Vol. 29, pp. 49-72.

Golob, T. F. (1998). A model of household demand for activity participation and mobility. T. Garling, T. Laitila, and K. Westin, editors, *Theoretical Foundations of Travel Choice Modeling*. Oxford, UK: Pergamon, pp. 365–398.

Kapur, A. and Bhat, C.R. (2007). "On Modeling Adults' Daily Time Use by Activity Purpose and Accompaniment Arrangement." *Transportation Research Record*, Vol. 2021, pp. 18-27.

Konduri, K.C., Ye, X., Sana, B. and Pendyala, R.M. (2011). "A Joint Tour-Based Model of Vehicle Type Choice and Tour Length." *Transportation Research Record: Journal of the Transportation Research Board*, No. 2255, pp. 28-37.

Mannering, F. (1983). "An Econometric Analysis of Vehicle Use in Multivehicle Households." *Transportation Research Part A,* Vol. 17, No. 3, pp. 184–189.

Mohammadian, A. and Miller, E. J. (2003). "Empirical Investigation of Household Vehicle Type Decisions." *Transportation Research Record: Journal of the Transportation Research Board,* No. 1854, pp. 99–106.

NRC. (2010). *Advancing the Science of Climate Change*. National Research Council. The National Academies Press, Washington, DC.

Paleti, R., Eluru, N., Bhat, C.R., Pendyala, R.M., Adler, T.J. and Goulias, K.G. (2011). "Design of Comprehensive Microsimulator of Household Vehicle Fleet Composition, Utilization, and Evolution." *Transportation Research Record*, Vol. 2254, pp. 44-57.

Paleti, R., Pendyala, R.M., Bhat, C.R. and Konduri, K.C. (2012). "A Joint Tour-Based Model of Tour Complexity, Passenger Accompaniment, Vehicle Type Choice, and Tour Length*." Proceedings of 91st Annual Meeting of the Transportation Research Board, National Research Council D.C.*

Pinjari, A.R. and Bhat, C.R. (2010). "A Multiple Discrete-Continuous Nested Extreme Value (MDCNEV) Model: Formulation and Application to Non-Worker Activity Time-Use and Timing Behavior on Weekdays." *Transportation Research Part B*, Vol. 44, No. 4, pp. 562-583.

Pinjari, A.R. and Bhat, C.R. (2011). "Computationally Efficient Forecasting Procedures for Kuhn-Tucker Consumer Demand Model Systems: Application to Residential Energy Consumption Analysis." Technical paper, Department of Civil and Environmental Engineering, University of South Florida, 2011.

Rajagopalan, B.S., Pinjari, A.R. and Bhat, C.R. (2009). "Comprehensive Model of Worker Non work-Activity Time Use and Timing Behavior." *Transportation Research Record*, Vol. 2134, pp. 51-62.

Santos, A., McGuckin, N., Nakamoto, H.Y., Gray, D. and Liss, S. (2011). *Summary of Travel Trends: 2009 National Household Travel Survey*. Publication FHWA-PL-ll-022. FHWA, U.S. Department of Transportation.

Scott D.M. and Kanaroglou, P.S. (2002). "An Activity-Episode Generation Model that Captures Interactions between Household Heads: Development and Empirical Analysis." *Transportation Research Part B,* Vol. 36, pp. 875–896.

Sener, I.N., Bhat, C.R. and Pendyala, R.M. (2011). "When, Where, How Long, and With Whom are Individuals Participating in Physically Active Recreational Episodes?." *Transportation Letters: The International Journal of Transportation Research*, Vol. 3, No. 3, pp. 201-217.

Spissu, E., Pinjari, A.R., Bhat, C.R., Pendyala, R.M. and Axhausen, K.W. (2009). "An Analysis of Weekly Out-of-Home Discretionary Activity Participation and Time-Use Behaviour." *Transportation*, Vol. 36, No. 5, pp. 483-510.

Spissu, E., Pinjari, A.R., Pendyala, R.M. and Bhat, C.R. (2009). "A Copula-Based Joint Multinomial Discrete-Continuous Model of Vehicle Type Choice and Miles of Travel." *Transportation*, Vol. 36, No. 4, pp. 403-422.

Srinivasan, S. and Bhat, C.R. (2005). "Modeling Household Interactions in Daily In-Home and Out-of-Home Maintenance Activity Participation." *Transportation*, Vol. 32, No. 5, 2005, pp. 523-544.

Srinivasan, S. and Bhat, C.R. (2008). "An Exploratory Analysis of Joint-Activity Participation Characteristics Using the American Time Use Survey." *Transportation*, Vol. 35, No. 3, pp. 301-328.

TABLE 1 Non-Workers' Daily Trip Average Millage and Participation by Activity Type, Accompaniment Type and Travel Mode Type.

	Activity Type / Travel mode	Shopping		Social/ Recreational		Transport Someone		Meals		Others	
		Average Millage	Participation (%)	Average Millage	Participation (%)	Average Millage	Participation (%)	Average Millage	Participation (%)	Average Millage	Participation (%)
Alone	Car	6.734	28.63	14.446	14.62	4.917	6.07	4.159	5.27	8.986	11.84
	Van/Other Vehicles	5.656	14.46	11.052	7.5	3.525	5.18	2.933	2.14	7.821	6.43
	SUV	8.282	20.8	12.378	9.69	5.146	7.09	6.488	4.37	9.324	9.34
	Transit	6.317	2.36	16.723	2.47	3.222	0.22	8.674	0.55	7.288	3.46
	Walk/Bike	0.803	11.97	1.259	13.04	0.485	1.33	0.675	3.94	0.938	6.04
With HH Member	Car	8.621	14.73	47.378	9.47	6.667	5.67	10.623	7.31	11.738	7.77
	Van/Other Vehicles	8.675	10.36	12.188	8.39	8.266	7.68	4.184	2.50	13.048	5.89
	SUV	9.814	11.58	28.730	9.81	5.961	7.92	26.101	5.20	18.170	6.62
	Transit	2.802	0.52	23.506	0.33	18.000	0.11	4.000	0.40	13.278	0.59
	Walk/Bike	1.194	0.74	0.620	0.70	0.481	0.11	0.453	0.70	1.000	0.33
With Non-HH Member	Car	9.429	5.84	23.507	6.29	13.015	4.93	9.069	4.37	15.139	3.63
	Van/Other Vehicles	8.451	2.86	14.222	5.00	4.884	3.75	11.139	2.86	21.601	3.93
	SUV	14.430	4.26	33.980	4.85	16.524	6.15	20.224	3.66	32.759	1.89
	Transit	4.352	0.44	14.825	0.52	6.200	0.18	7.400	0.18	12.617	0.33
	Walk/Bike	0.389	0.22	2.012	0.33	0.000	0.00	2.005	0.44	0.822	0.18

TABLE 2 Workers' Daily Trip Average Millage and Participation by Activity Type, Accompaniment Type and Travel Mode Type.

Activity Type / Travel mode	Shopping Average Millage	Shopping Participation (%)	Social/ Recreational Average Millage	Social/ Recreational Participation (%)	Transport Someone Average Millage	Transport Someone Participation (%)	Meals Average Millage	Meals Participation (%)	Others Average Millage	Others Participation (%)
Alone										
Car	9.117	20.94	10.350	9.85	6.298	6.61	4.420	9.04	9.650	8.30
Van/Other Vehicles	9.761	11.43	5.304	3.49	8.007	4.76	5.584	4.60	13.545	3.97
SUV	7.284	13.38	7.242	7.14	8.831	5.97	5.271	6.62	6.612	5.45
Transit	6.484	1.59	8.212	2.31	8.284	0.46	10.615	0.67	22.034	3.59
Walk/Bike	0.729	7.79	1.227	11.90	0.363	1.64	0.384	7.69	0.834	8.31
With HH Member										
Car	6.224	4.63	9.288	4.70	5.823	6.98	17.786	4.11	7.632	3.45
Van/Other Vehicles	7.204	6.83	6.862	4.44	5.856	10.00	3.174	3.65	11.187	3.81
SUV	11.407	4.81	17.397	5.97	4.038	8.31	11.698	3.51	13.826	2.86
Transit	13.028	0.21	0	0	0.111	0.05	0	0	28.400	0.26
Walk/Bike	0.230	0.36	0.810	0.36	0.333	0.10	0.333	0.15	0.889	0.21
With Non-HH Member										
Car	7.840	3.01	12.028	3.82	7.076	4.63	4.769	3.23	19.591	1.62
Van/Other Vehicles	9.214	0.95	6.251	3.17	10.205	5.87	1.270	0.95	1.685	0.95
SUV	13.278	1.04	6.125	2.08	4.702	3.25	17.206	1.86	7.111	0.91
Transit	1.778	0.10	7.556	0.36	6.481	0.15	1.667	0.10	7.986	0.21
Walk/Bike	0.333	0.31	1.156	0.77	0.407	0.15	0.468	2.21	0.633	0.26

TABLE 3 The Mixed MDCEV Model Results for Non-worker Sample: Baseline Parameter Estimates.

	Individual Socio-demographics					Household (HH) Socio-demographics					
	Male	White	University degree	21<Age<60	Age>60	HH size	Kids of age <5 yrs present	Kids of age 5-15 yrs present	Kids of age >15 yrs present	HH annual income >70k	40k < HH annual income >70k
'Activity Purpose' Dimension _(Baseline: Shopping)_											
Social/Recreational	0.210 (2.67)	0.480 (4.016)		-1.268 (-8.12)	-1.402 (-8.98)					0.282 (3.52)	
Transport Someone			0.436 (2.73)	0.553 (3.34)		0.225 (2.99)	0.780 (2.58)	1.308 (5.24)	0.712 (2.12)		
Meals	0.277 (2.67)	0.739 (4.34)		-0.911 (-4.62)	-1.220 (-6.19)						
Others				-0.805 (-4.39)	-0.821 (-4.53)						
'Accompaniment' Dimension _(Baseline: Alone)_											
With Household Member			-0.344 (-1.90)	-0.723 (-3.84)		0.423 (4.64)	1.738 (4.99)	1.134 (3.99)			
With Non-household Member	-0.503 (-2.74)			-1.948 (-6.65)	-2.429 (-7.27)	0.223 (2.938)	-0.715 (-2.14)				
'Travel Mode' Dimension _(Baseline: Car)_											
Van/Other Vehicles	0.888 (2.03)					0.664 (4.52)		0.909 (1.97)			
SUV	0.698 (1.55)							1.534 (3.19)			
Transit				-1.098 (-3.24)	-1.836 (-4.79)	0.302 (3.582)				-0.694 (-2.97)	-0.802 (-2.79)
Walk/Bike				-1.049 (-4.23)	-1.372 (-4.97)	0.206 (3.38)					

TABLE 4(Continued) The Mixed MDCEV Model Results for Non-worker Sample: Baseline Parameter Estimates.

	HH Location Variables		Contextual Variables			Random Error Components
	Urban area	Residential density>10,000 (per sq miles)	Friday	Winter	Summer	
'Activity Purpose' Dimension _(Baseline: Shopping)_						
Social/Recreational					0.272 (2.96)	1.693 (12.06)
Transport Someone	-0.392 (-2.12)	-0.817 (-3.58)			-0.410 (-2.05)	
Meals					0.353 (3.00)	
Others						
'Accompaniment' Dimension _(Baseline: Alone)_						
With Household Member		-1.727 (-6.99)			0.455 (2.26)	2.684 (17.34)
With Non-household Member	-0.458 (-2.15)	-0.314 (-1.39)				-2.282 (-13.67)
'Travel Mode' Dimension _(Baseline: Car)_						
Van/Other Vehicles			0.820 (1.53)			3.665 (8.75)
SUV				1.628 (2.78)		4.678 (7.89)
Transit		2.942 (12.2)				-1.032 (-4.39)
Walk/Bike		2.114 (11.45)				1.300 (9.956)

TABLE 4 The Mixed MDCEV Model Results for Worker Sample: Baseline Parameter Estimates.

	Individual Socio-demographics					Household (HH) Socio-demographics					
	Male	White	University degree	21<Age<60	Age>60	HH size	Kids of age <5 yrs present	Kids of age 5-15 yrs present	Kids of age >15 yrs present	HH annual income >70k	40k < HH annual income >70k
'Activity Purpose' Dimension *(Baseline: Shopping)*											
Social/Recreational		0.459 (3.27)		-1.242 (-9.05)	-1.863 (-9.48)						
Transport Someone	-0.738 (-5.03)						2.350 (10.68)	1.878 (10.22)	0.905 (3.36)		
Meals				-0.389 (-2.31)	-0.696 (-3.23)					0.280 (1.82)	
Others			0.426 (2.78)	-1.068 (-5.04)	-1.149 (-4.37)					0.496 (3.99)	
'Accompaniment' Dimension *(Baseline: Alone)*											
With Household Member	-0.375 (-2.49)			-1.478 (-7.84)	-1.223 (-4.29)	0.181 (2.87)	0.872 (3.506)	1.166 (5.97)			
With Non-household Member	-0.531 (-3.77)		-0.505 (-2.97)	-1.473 (-7.21)	-1.889 (-6.58)		0.443 (3.51)				
'Travel Mode' Dimension *(Baseline: Car)*											
Van/Other Vehicles					-0.883 (-1.09)				-2.686 (-3.25)		
SUV									-1.607 (-2.58)		
Transit			0.865 (2.45)	-1.669 (-5.57)	-1.994 (-5.19)						
Walk/Bike			0.753 (4.55)	-0.976 (-4.66)	-1.581 (-5.80)						

	HH Location Variables		Contextual Variables			Random Error Components
	Urban area	Residential density>10,000 (per sq miles)	Friday	Winter	Summer	
'Activity Purpose' Dimension _(Baseline: Shopping)_						
Social/Recreational						
Transport Someone		-0.546 (-2.517)			-0.543 (-2.59)	-1.316 (-9.17)
Meals		0.332 (2.52)				
Others	-0.395 (-2.34)					1.197 (8.28)
'Accompaniment' Dimension _(Baseline: Alone)_						
With Household Member		-0.805 (-3.905)				-1.445 (-10.24)
With Non-household Member	0.458 (2.19)		0.328 (1.75)			1.173 (7.24)
'Travel Mode' Dimension _(Baseline: Car)_						
Van/Other Vehicles						-3.837 (-7.22)
SUV						-3.476 (-8.18)
Transit		2.159 (9.37)				
Walk/Bike		1.812 (9.11)				1.000 (7.07)

TABLE 5 Validation Results for Worker and Non-worker Samples by Activity Type, Accompaniment Type and Travel Mode Type.

		Accompaniment			Activity					Travel Mode				
		Alone	With HH Member	With Non-HH Member	Shopping	Social/ Recreational	Transport Someone	Meals	Others	Car	Van/ Other Vehicles	SUV	Transit	Walk/Bike
Worker	Predicted Participation	144	63	30	80	85	36	54	43	108	29	41	22	62
	Observed Participation	140	52	33	82	68	36	59	43	81	24	39	20	63
	Percentage Difference	2.86	21.15	-9.09	-2.44	25.00	0.00	-8.47	0.00	33.33	20.83	5.13	10.00	-1.59
Non-worker	Predicted Participation	324	156	48	226	205	51	86	135	235	38	104	44	112
	Observed Participation	277	154	93	223	171	82	82	137	210	36	89	38	132
	Percentage Difference	16.97	1.30	-48.39	1.35	19.88	-37.80	4.88	-1.46	11.90	5.56	16.85	15.79	-15.15