A MULTIPLE DISCRETE-CONTINUOUS MODEL OF ACTIVITY TYPE CHOICE AND TIME ALLOCATION FOR HOME-BASED NON-WORK TOURS

Daehyun You
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 965-3589; Fax: (480) 965-0557
Email: dae.you@asu.edu

Venu M. Garikapati
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 965-3589; Fax: (480) 965-0557
Email: venu.garikapati@asu.edu

Karthik C. Konduri
University of Connecticut, Department of Civil and Environmental Engineering
Unit 3037, Storrs, CT 06269-3037. Tel: (860) 486-2992; Fax: (860) 486-2298
Email: kkonduri@engr.uconn.edu

Ram M. Pendyala
Arizona State University, School of Sustainable Engineering and the Built Environment
Room ECG252, Tempe, AZ 85287-5306. Tel: (480) 727-9164; Fax: (480) 965-0557
Email: ram.pendyala@asu.edu

Peter S. Vovsha
Parsons Brinckerhoff
1 Penn Plaza, 3rd Floor, New York, NY 10119. Tel: (212) 465-5511; Fax: (212) 465-5096
Email: vovsha@pbworld.com

Vladimir Livshits
Maricopa Association of Governments
302 North First Avenue, Suite 300, Phoenix, AZ 85003. Tel: (602) 452-5079; Fax: (602) 254-6490
Email: vlivshits@azmag.gov

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ABSTRACT
In the activity-based modeling arena, tour-based approaches to modeling travel demand have been implemented in practice in a number of geographical contexts. In the tour context, there are a number of choice dimensions wherein the choice of the alternatives and the amount to consume is made simultaneously. In particular, the choice of different activity types and the amount of time allocated to various activity types within a tour is of considerable interest. The simulation of these choice processes must be done while also recognizing the dependencies and interactions across choice contexts within the tour. It is desirable to model the choice context of multiple discrete choices (activity types) and the associated continuous variable (time spent on the activity types) under a single unifying framework to accurately capture the interrelationships across the choice dimensions within a tour. Data from the latest wave of the NHTS is used to estimate a joint model of activity type choice and continuous time allocation using the multiple discrete-continuous extreme value model. In addition, history of activity participation is explicitly captured in the model specification as explanatory variables. Results from the empirical exercise provide plausible results and support the case for modeling these choice dimensions simultaneously to accurately capture the inter-relationship between activity type choice and activity time allocation. History of activity participation was found to be significant with notable trade-off and complementarity effects exhibited by individuals for selected non-work activity types.

Keywords: multiple discrete-continuous extreme value model, tour-based model, activity type, activity duration, home-based non-work tours

INTRODUCTION

In the activity-based modeling arena, tour-based approaches have been implemented in practice due their computational feasibility and appealing behavioral paradigm. In these approaches, a tour comprising a series of stops is the basic unit of analysis. Tour-based models generate activity-travel patterns by explicitly accounting for the interdependencies across stops within a tour. Tour-based models often break up a person's daily activity-travel engagement pattern into a set of primary and secondary tour choices. For each tour, the number of stops on the tour, the purpose of the activity episode on each stop, the sequencing of stops/activities, the destination for each activity stop, the mode of travel for individual trips and the tour as a whole, and activity timing are modeled using appropriate choice model formulations (Shiftan 1998; Bowman and Ben-Akiva 2001; Yagi and Mohammadian 2010). The different dimensions of tours are often modeled independently, but connected together through a nested logit model structure that feeds logsum terms through a chain of models. Doherty and Mohammadian (2011) developed ordered response choice models for different tour sizes, attempting to predict the choice order of the planned activity in the tour as a function of activity type, activity characteristics and individual characteristics. Bowman and Ben-Akiva (2001) conceptualized the timing of activities as the choice between morning, afternoon or evening based on the notion that certain types of actives are more attractive in certain periods of the day.

While the sequential treatment of choice dimensions has served the transportation community well, especially in operationalizing and implementing tour-based model systems, there has been a growing body of literature which supports the notion of simultaneity in choice dimensions and makes the case for employing advanced joint modeling frameworks that can accurately capture the simultaneity and potential endogeneity effects across choice dimensions. Ettema, et al (2007) proposed a model for the simultaneous choice of the timing and duration of activities and travel mode. Ye, et al (2007) studied the relationship between mode choice and complexity of trip chaining patterns by testing alternative causal structures. Despite the large body of literature dedicated to joint modeling of activity-travel choices, a topic that has not been adequately addressed is the modeling of activity engagement dimensions across choice contexts (stops) within a tour while recognizing the dependencies and interactions that individuals experience as they plan and execute tours. The questions that motivate the model development effort in this study are: what are the different activity types pursued within a tour, what is the frequency of the episodes for each activity type, how is time allocated to different activity types and further to individual activity episodes, and what are the transactions and trade-offs that individuals make across activity type choices within a tour.

The choice of activity types and the amount of time spent on each activity type are two key dimensions of activity engagement decisions. Time is a limited resource (1440 minutes) and individuals allocate the time to engage in different types of activities over the course of day. There is some literature exploring these two dimensions in the context of daily activity engagement behavior. Bhat (2005) explores the activity allocation decisions of individuals to discretionary activity types during weekend days. Pinjari and Bhat (2010) study non-worker daily activity engagement behavior. However, these studies are limited to daily allocations and do not explore the nature of activity engagement at a disaggregate level of individual tours as dealt with in tour-based models. At the tour-level there have been some studies exploring activity engagement. Limanond et al (2005) specified a tour-based neighborhood shopping model and calibrated it using the travel data collected from three sample neighborhoods located in the Puget Sound region. Krygsman et al (2007) studied the mutual interaction between transport mode choice and trip chaining choice for a given work tour. While these comprise studies exploring attributes at a tour-level, they do not account for the dependencies across tour dimensions or choice contexts (e.g., across stops, or across activity types within a tour). One of the key goals of this study is to explore and model the choice of activity types and activity time allocation for home-based non work tours while recognizing the interactions across choice contexts within the tour.

The modeling of activity engagement decisions across activity types within a tour involves specification and estimation challenges. A typical approach to model this choice dimension is to enumerate all possible combinations of activity types and model using traditional random utility-based single discrete choice models. However, this approach doesn't account for diminishing marginal returns of consuming an alternative and hence fails to capture the transactions and tradeoff behaviors that individuals exhibit when making decisions of multiple activity types and the amount of time they wish to spend on different activities. Further, the situation calls for modeling multiple discrete alternatives (choice of activity types) and multiple continuous variables (durations associated with activity types) simultaneously within a tour. The multiple discrete-continuous extreme value (MDCEV) methodology proposed by Bhat (2005, 2008) is adopted in this study to model the choice of different types of activities pursued on a tour and the time spent pursuing those activity types. Further, the MDCEV formulation has a neat closed form solution and affords the ability to efficiently estimate models.

In the context of understanding activity engagement behavior, an important consideration is the history of activity participation and its role in shaping activity engagement patterns in subsequent time steps of the day. For example, if an individual has already participated in a shopping episode in an earlier part of the day, the probability that he or she will engage in another shopping activity later in the day is potentially lower. There are a number of studies that have showed the history of activity participation and the types of substitution and complementarity effects displayed by individuals as they shape their activity agendas (Konduri et al., 2011; Kasturirangan et al., 2002). It is important to capture the role of history of activity participation to accurately model the dynamics of activity-travel engagement exhibited by individuals as they plan their daily activity schedules.

The study aims to add to the literature on tour-based modeling by making contributions along the following three lines of inquiry. First, a tour-level joint model of activity engagement decisions is presented. In particular, the choice of all activity types and the amount of time spent on each activity type is modeled at a tour level. This effort comprises a unique attempt to understand activity engagement behavior at an individual tour level while recognizing the interactions and dependencies across choice contexts within a tour (stops). Second, the study explores the role of history dependency in modeling activity engagement in the context of tours – a topic that is not yet well understood. The empirical exercise involves estimating a tour-level activity type and time allocation model on the Maricopa county add-on sample from the latest (2009) wave of the National Household Travel Survey (NHTS).

The rest of the paper is organized as follows. In the next section, an overview of the joint modeling framework (MDCEV) is presented. In the third section, the data utilized in this study is presented along with an exploratory analysis to identify trends in the data. In the fourth section, the joint model results are presented; this is followed by a discussion of the results and some concluding thoughts in the final section.

METHODOLOGY

As noted in the previous section, one of the main aims of the study was to model the choice of activity type and duration for all activities undertaken on the tour simultaneously. This entails choice of multiple (more than one) discrete alternatives (activity types) and the allocation of time durations to various activity types to construct a tour profile. This modeling context is ideally suited to the application of the multiple discrete-continuous extreme value (MDCEV) methodology proposed by Bhat (2005, 2008). In the following subsections, an overview of the MDCEV methodology is presented with a view to apply this method to simultaneously model the activity-type(s) choice and duration for each tour.

Utility Model Specification

Several consumer choices are characterized by multiple-discreteness (i.e., simultaneous choice of one or more alternatives that are imperfect substitutes of one another). Examples include a household owning different kinds of vehicles (Bhat and Sen, 2006) or a firm owning different brands of computers. Such situations can be modeled using traditional random utility-based (RUM) single discrete choice models, but since these models allow only a single alternative to be chosen among a set of mutually exclusive alternatives, one should identify all combinations of elemental alternatives and treat each combination as a 'composite alternative' (Bhat, 2008). This list will explode as the number of alternatives increase. Also, RUM single discrete choice models do not take into account the diminishing marginal returns of consuming an alternative. To overcome these limitations of the single discrete choice model in such multiple discrete choice contexts, Bhat (2005) formulated a model that allows for multiple-discreteness in the choice behaviors, as well as satiation associated with consuming an alternative. This model is referred to as the multiple discrete-continuous extreme value (MDCEV) model. The functional form of utility proposed by Bhat (2008) is based on a generalized variant of constant elasticity of substitution (CES) function:

$$U(\boldsymbol{x}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}; \tag{1}$$

$$\psi_k > 0,\ \gamma_k > 0,\ \alpha_k \leq 1$$

where $U(\boldsymbol{x})$ is a quasi-concave and continuously differentiable function with respect to consumption quantity vector $\boldsymbol{x}$ ($x_k \geq 0$ for all k). ψ_k represents the baseline marginal utility or the marginal utility at the zero consumption point. Suppose there are two goods *i* and *j*. If good *i* has a higher baseline marginal utility compared with good *j*, it implies that a consumer can increase whole utility by consuming good *i* instead of good *j.* A higher value of ψ_k implies less likelihood for zero consumption for good *k*. α_k is the satiation parameter which accounts for diminishing marginal utility with increasing consumption of good *k*. If α_k equals 1 for all goods, it implies no satiation effects or constant marginal utility. As α_k approaches 0, it means there is an increase of satiation effects for good *k*. If the baseline utility of all goods is the same, lower values of α_k imply a smaller budget spent on good *k*. When $\alpha_k \to -\infty$, immediate and full satiation can be expected for good *k*. γ_k, the translation parameter governs the level of satiation and also enables corner solutions (i.e., zero consumption of some goods). As γ_k increases, it represents a higher preference for good *k*.

The baseline marginal utility, ψ_k is written in the following functional form to introduce the impact of observed and unobserved alternative attributes (Bhat, 2008):

$$\psi_k(z_k, \varepsilon_k) = \exp(\beta' z_k + \varepsilon_k) \tag{2}$$

where z_k is a set of attributes characterizing the alternative k and ε_k captures unobserved characteristics that impact the baseline utility for good k. It is assumed that ε_k is independent of z_k and is independently distributed across alternatives with a scale parameter of σ (σ can be normalized to 1 in case of no price variation across goods). Substituting equation (2) for ψ_k in the utility function in equation (1) results in the following:

$$U(\boldsymbol{x}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} [\exp(\beta' z_k + \varepsilon_k)] \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{3}$$

From the analyst's perspective, the choice-maker is maximizing random utility given by equation (3) subject to a linear budget constraint wherein the budget allocated to each alternative t_k satisfies the condition that:

$$\sum_{k=1}^{K} t_k = T \tag{4}$$

where T is the total budget ($t_k \geq 0$), $t_k = p_k x_k$, and p_k is the unit price of a good. In the context of this study the unit price of choosing any of the alternatives is equal (no price variation), hence $p_k = p$, $\forall$ k.The optimal budget allocations can be obtained by forming the Lagrangian and applying the Kuhn–Tucker (KT) conditions. The Lagrangian function is given as (Bhat, 2008):

$$\mathcal{L} = \sum_k \frac{\gamma_k}{\alpha_k}[\exp(\beta' z_k + \varepsilon_k)]\left\{\left(\frac{t_k}{\gamma_k p_k}+1\right)^{\alpha_k} - 1\right\} - \lambda\left[\sum_{k=1}^{K} t_k - T\right] \tag{5}$$

where λ is the Lagrangian multiplier associated with budget constraint. The KT first order conditions for optimal budget allocations (the t_k^* values) are (Bhat, 2008):

$$\begin{aligned}
&\left[\frac{\exp(\beta' z_k+\varepsilon_k)}{p_k}\right]\left\{\left(\frac{t_k^*}{\gamma_k p_k}+1\right)^{\alpha_k-1} - 1\right\} - \lambda = 0, \text{ if } t_k^* > 0,\ k = 1, 2, 3, \ldots, K \\
&\left[\frac{\exp(\beta' z_k+\varepsilon_k)}{p_k}\right]\left\{\left(\frac{t_k^*}{\gamma_k p_k}+1\right)^{\alpha_k-1} - 1\right\} - \lambda < 0, \text{ if } t_k^* = 0,\ k = 1, 2, 3, \ldots, K
\end{aligned} \tag{6}$$

The optimal consumption satisfies the first order conditions as well as equation 4 (budget constraint). Bhat (2008) specified the error structures and derived the MDCEV model where an individual allocates the available budget to first M of the K available alternatives as:

$$\begin{aligned}
&P(t_1^*, t_2^*, t_3^*, \ldots, t_M^*, 0, 0, \ldots, 0) = \frac{1}{\sigma^{M-1}}|J|\left[\frac{\prod_{i=1}^{M} e^{V_i/\sigma}}{\left(\sum_{k=1}^{K} e^{V_k/\sigma}\right)^M}\right](M-1)!\ ; \\
&V_k = \beta' z_k + (\alpha_k - 1)\ln\left(\frac{t_k^*}{\gamma_k p_k}+1\right) - \ln p_k \ \ (k = 1, 2, 3, \ldots, K)
\end{aligned} \tag{7}$$

where $|J|$ is the Jacobian derived by Bhat (2008) for the case of no price variation across alternatives:

$$|J| = \left(\prod_{i=1}^{M} c_i\right)\left(\sum_{i=1}^{M} c_i\right), \qquad \text{where } c_i = \left(\frac{1-\alpha_i}{t_i^*+\gamma_i p_i}\right) \tag{8}$$

The expression in equation (7) collapses to a standard MNL model, in the case when only one alternative is chosen ($M = 1$), diminishing marginal utility is not accounted for ($\alpha_k = 1, \forall k$) and the Jacobian (continuous component) drops out, as all budget is allocated to good 1. The likelihood function for the MDCEV model has a neat closed form solution that makes it possible to estimate parameters using standard maximum likelihood estimation methods. A program was written in R to estimate the MDCEV model and optimization algorithms within R were used to search for parameter estimates that maximize the likelihood function.

DATA DESCRIPTION

The analysis in this study was conducted using data from the latest wave of the National Household Travel Survey (NHTS 2009). NHTS collects data about all trips that were pursued by a representative sample of households and persons in a region. The data for this analysis was limited to the Maricopa County add-on sample to minimize any regional biases in activity engagement behaviors. NHTS includes a trip diary survey (as opposed to an activity diary) and hence activity engagement and tour information is not readily available. Activity engagement profiles were derived for this study by using a combination of trip purpose to, trip purpose from, and dwell time variables in the dataset. Further, tours were constructed from trip records by using home or work as the anchors. All activities pursued between the departure from- and arrival at- the anchor locations were defined as stops and tours were tagged as home-based or work-based depending on the anchor location. The analysis was limited to individuals 18 years and older who reported trips on a weekday (Monday through Friday). The activity engagement analysis in this study was limited to home-based non-work tours undertaken by non-workers (anybody who reported absolutely no work trip on the travel survey day) because of the flexibility afforded by home-based tours for non-work type activities. All of the non-work episodes considered in this study were classified into the following seven categories:

- Personal Business
- Meal
- Shopping
- Serve Passenger
- Recreational & Sports
- Social Visit
- Other

In addition to constructing tours, variables representing history of activity participation were computed for each tour by calculating the amount of time spent on the above activity types up to the tour under consideration. The time allocation budget (continuous time budget constraint) for the MDCEV model was computed as an aggregate of all activity time allocations for stops within the tour. Activity durations at anchor locations were not included in the budget. It is plausible to argue that the true budget is the sum of all activity durations and travel durations within a tour; however, due to the absence of a destination choice model component in the current empirical study, the budget was limited to an aggregation of activity time allocations. The behavioral paradigm assumed here is one where individuals separately allocate a travel budget and an activity time budget for each tour. The activity time budget is then apportioned across activity types according to the MDCEV model. When zero time is allocated to an activity type, that activity type is not pursued at all in the tour.

The data preparation process described above resulted in 4486 tours pursued by 2546 survey respondents. Table 1 provides summary statistics for the respondent subsample. It should be noted that the survey subsample is dominated by older people with about 46 percent of the survey respondents older than 65 years of age. As a result, the mean age for the sample is 61 years. There is a higher percentage of female respondents comprising about 60 percent of the subsample. The household attributes are also reflective of the older demographic. The average household size is about 2.42 with about 0.4 children per household. It is also interesting to note that the number of workers within these households is 0.67, a low figure reflecting the large number of households with retired individuals. These observations of household structure may also be reflective of the filtering criterion employed to create the subsample wherein only home-based non-work tours on weekdays were selected for analysis; presumably most workers report at least one work trip on a weekday and they are not included in the subsample. The subsample is also dominated by automobile-oriented households as can be seen from the high car ownership levels, with about 65 percent of the households reporting two or more vehicles in the household. The subsample has a significant amount of households with Caucasian householders (90 percent of households) mostly living in urban environments (nearly 82 percent live in urban areas).

Table 2 shows the profile of home-based non-work tours and provides some important insights into the activity-travel engagement patterns of respondents in the subsample. The count refers to the actual number of tours that included a specific activity type. For example, of the 4486 tours in the sample, 249 were tours that only included the single activity type of Personal Business. The average time allocation to personal business for those 249 tours is 76.1 minutes (average computed across tours that actually included the activity type). If, however, the average is computed across all single activity type tours (i.e., 2952 tours, many of which have no personal business activity participation), then the average time allocation (including zero values) is 6.4 minutes. Beyond the statistics shown in the table, it is found that tour durations increase as the number of activity types pursued within the tour increases. It is interesting to note that the non-zero averages are typically highest for social visit, recreation & sports, and meal types of activities regardless of the number of activity types pursued on the tour. These findings are consistent with expectations in that eat meal activities typically last for an hour or so, and social recreation activities are likely to be longer than maintenance type activities (such as shopping and personal business). It is also found that the average number of home-based non-work tours per person in the sample is 1.76 per day. In the table, it is found that 40 percent of the tours involve the pursuit of more than one activity type. In addition, not shown in the table is the statistic that 60 percent of the tours have more than one stop episode (although multiple episodes may be devoted to the same activity type); these observations support the need for a modeling paradigm (multiple discrete-continuous formulation) that can model activity engagement by type for home-based non-work tours.

MODEL ESTIMATION RESULTS

A variety of household socio-demographics (income, household size, number of children in the household), individual demographics (age, gender, race), land use characteristics, and tour level attributes (history of activity participation and tour start time) were explored to explain the activity type choice and time allocation behavior. In the current effort, the translation parameters (γ_j) are fixed (γ_j = 1,$\forall j$), and the coefficients of the explanatory variables in the baseline preference (β') and the satiation parameters (α_j) for all alternatives are estimated. The "other" activity type is considered as the base alternative for estimation. Various combinations of variables were tried and variables that were statistically significant and behaviorally intuitive were retained for each of the alternatives. Table 3 provides the joint model of activity type choice and time allocation to activity types at an individual tour level for home-based non-work tours pursued by non-workers on a weekday.

Household Level variables

Individuals with household income less than $35,000 had lesser baseline preference for pursuing personal business, recreation and meal stops on the tour. This is intuitive as lower income households might not be able to spend resources on recreation and meals outside home. On the other hand, individuals with household income between $35,000 and $50,000 had higher preference for making social stops and allocating time to such activities compared to other types of activity. Individuals with a larger number of people in the household had lesser baseline preference for recreational stops. This is probably due to the need to take care of household obligations (in larger households), resulting in a higher level of maintenance and recreational activity engagement at home. Vehicle availability defined as a ratio of the number of vehicles to number of persons in the household was observed to be significant. Individuals from households with higher vehicle ratio had higher baseline preference for personal business and social stops. It is possible that high availability of vehicles provides travelers greater flexibility in pursuing personal business and social activity type stops outside home without feeling constrained to rush back home because another individual in the household needs to use the car.

Consistent with expectations, the household structure also appears to affect activity engagement patterns associated with non-work tours. Individuals in households with children have lesser baseline preference for shopping, social visit, and meal stops. Presumably the presence of children makes it difficult for parents to plan and participate in discretionary activity types, especially on a weekday. Land use variables, particularly the location of home, appears to play a role in shaping the types of activities pursued on a tour. Tours undertaken by individuals living in urban clusters have a lower propensity to include the serve-passenger activity type. This observation can be attributed to mixed land use characteristics of the household's location (in urban settings), which might encourage people to walk/bike to the destinations (such as shopping/school) without another household member requiring to drop off or pick them up.

Individual Level Variables

In addition to household-level variables, individual-level variables were also explored in the model specification. Individuals more than 65 years of age have a higher propensity to engage in personal business stops. On the other hand, tours made by people in the age group 36 to 45 years were more likely to include shopping and serve passenger activity types. The difference in the preference for the types of activities pursued on the tour can be attributed to the differing needs and lifecycle stages of the two age groups. The elderly may be participating in personal business type activities for meeting health care needs, while the middle aged group may be engaging in shopping and serve passenger type activities to fulfill their household responsibilities and serve their children or other members of the household. Gender was also observed to play a significant role in defining the types of activities pursued on non-work tours. Tours made by females had a higher likelihood of including social stops, while those made by males had higher propensity to include recreational stops. This result is intuitive and can be attributed to the kinds of gender differences that have been documented extensively in the travel and time use literature.

Tour Level attributes

In addition to the household- and person-level socio-demographic attributes, a number of tour related attributes including start time of the tour and history of activity participation on prior tours of the day were explored. The history of activity participation was calculated as the total time spent in a particular activity type on all previous tours. Tours of individuals who have already spent time shopping on prior tours show a lower propensity to include both personal business and shopping stops. It is possible that satiation is reached quickly in these activity types (see the next section). Once an individual has already pursued shopping, then he or she is unlikely to desire pursuing maintenance type activities again in subsequent tours. It is interesting, however, to see that tours, undertaken by individuals who already spent some time on social visit activity (prior to the current tour), are more likely to include another social visit stop. This can be attributed to the low level of satiation associated with social visit stops (Konduri et al. 2011).

A number of tour start time indicators were explored to capture the differences in activity engagement by time of day. In the early morning hours of 7 am to 9 am, tours are more likely to include serve passenger stops. This may, at least in part, be due to the "drop off child at school" event. For tours starting in the morning (9 am – 11 am), individuals have low baseline preference to make a recreation stop, which is intuitive as not a lot of people would want to participate in a recreational stop at the start of the day. Tours starting mid-day (11 am – 1 pm) and evening (5 pm – 7 pm) are more likely to include time allocation to a meal stop. This result is logical as these are the lunch and dinner periods. Shopping is more likely to be included in tours post lunch (1 pm – 3 pm). The early afternoon period appears to be conducive to engaging in a shopping stop. Tours in the early afternoon are also likely to include serve passenger stops, presumably to pick up children from school. Social visit stops are more likely to be part of tours starting in the evening. This may be plausible because social visits with friends and relatives typically take place towards the latter part of the day.

Other Model Parameters

In addition to all the coefficients described above, the MDCEV formulation also includes a number of satiation parameters. There is variation in the satiation parameters across different activity types, which calls for the use of multiple discrete choice models as opposed to single discrete choice models (which assume satiation for all activities to be the same and equal to 1). Satiation for serve passenger is higher compared to other types of stops and satiation for recreational activity is the lowest indicating that people do not want to spend a large amount of their time serving others, but would like to spend it on recreational or social activities. Satiation for meal stop is lower than that for shopping and serve passenger type activities. This can be partially attributed to the nature of a meal stop wherein a person is likely to enjoy eating a meal away from home and allocates an adequate period of time to fulfill the activity.

Goodness of Fit

The signs of all explanatory variables are statistically significant and consistent with expectations. Log-likelihood value of the final model at convergence is -18151.27 with 37 degrees of freedom and that for the model with only constants in the baseline preference terms and satiation parameters is -18613.28. The likelihood ratio is 924.02 which is substantially greater than the critical chi-squared ($\chi^2_{0.001}$) value at 31 degrees of freedom supporting the model specification presented in Table 3.

DISCUSSION AND CONCLUSIONS

The study aims to add to the literature on tour-based modeling along the following fronts. First, a joint tour-based model of multiple activity type engagement and activity time allocation is estimated using a multiple discrete-continuous modeling approach. This is one of the few explorations of activity engagement behaviors at the most disaggregate unit of analysis, namely, tour. The multiple discrete-continuous extreme value (MDCEV) formulation proposed by Bhat (2005, 2008) is employed in this effort to accurately capture the interrelationships between the different activity type participation contexts within a tour. Second, the study explores the role of history of activity participation in the formation of activity schedules in subsequent tours of the day.

Data from the latest wave of the National Household Travel Survey was used in this study. The model was limited to home-based non-work tours because of the extra flexibility afforded by the lack of fixed activities and their time-space prism constraints. The model results are very plausible. A host of socio-economic and demographic attributes were found to affect tour-level activity engagement and time allocation patterns. History of activity participation also significantly influenced activity type engagement within tours and interesting trade-off and complementarity effects were observed even in the presence of explicit satiation parameters inherent to the MDCEV formulation. The study highlights the applicability of the MDCEV modeling framework for modeling tour-level decisions and the following discussion identifies some follow-up research directions of immediate interest.

In this empirical study, two key dimensions of tour-based choices, namely, the choice of activity type and the duration spent on the activity types is modeled using a joint modeling approach (MDCEV model). It should be noted that the empirical model presented in this paper needs to be extended further to be applied in tour-based models. The empirical context explored in this paper provides insights on the proclivity of individuals to engage in different types of activities within non-work tours and allocate time to the pursuit of those activity types. There are two key dimensions that one needs to model to fully understand the activity engagement patterns of individuals and subsequently simulate the behaviors in a forecasting exercise. First, to fully generate tours, the numbers of stops of different activity types need to be identified, and for each of those stops, the time spent on the activity type/episode needs to be determined. Similar to the choice situation explored in this paper, the choice of activity type for each stop needs to be modeled in a joint modeling framework to accurately capture the interrelationships across stops within a tour. The modeling framework presented in this paper can easily be extended to not only model the stop-level activity type choice and duration, but also the frequency of the stops of each activity type. This can be achieved by altering the way in which discrete alternatives are enumerated in MDCEV. In the current paper, there are seven possible alternatives for the activity type choice and the individual can engage in zero duration for any of the seven activity types. If each discrete alternative is defined to represent a stop-level activity episode, the discrete set of alternatives can be enumerated so that a multitude of instances of each activity type is allowed subject to a maximum number of such episodes observed in survey data. The individual now has the choice of multiple activities of the same type and based on the number of alternatives chosen (with non-zero duration), the stop frequency is implicitly determined along with activity type choice at each stop (activity episode) and the activity duration. The MDCEV modeling framework offers the ability to accurately capture any transaction decisions and tradeoff behaviors. One might argue that multiple episodes of the same activity type may share some common unobserved attributes and that error correlations need to be accommodated to make accurate inferences. MDCEV offers a very robust framework and mixed extensions of the formulation can easily accommodate error correlations across choice alternatives.

The second key dimension that is of interest to generate tours in their entirety is the sequencing of stops within a tour. While modeling the frequency of stops, activity types, and time spent at the stops can be achieved through simple extensions of the MDCEV model, the incorporation of the sequencing dimension is not that straightforward and constitutes an important topic for research and inquiry. An extension of the MDCEV dubbed the MDCEV-MNL that jointly models multiple discrete-continuous choice variables (stop type choice and duration) with a multinomial discrete choice variable (sequence order) may be a potential candidate (Bhat et al., 2009). However, the size of the choice set may explode in the enumeration of all possible choice alternatives with increasing number of stops, making the computation and implementation of the model system cumbersome. Alternative approaches that one could explore include methods from the data mining literature to understand stop sequencing behavior (e.g., sequence alignment procedures, pattern matching techniques).

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Table 1. Summary of the Household- and Person-Level Attributes of the Respondent Subsample

Characteristic	**Mean**	**Standard Deviation**
Household attributes		
Number of vehicles in the household	1.93	1.02
Household size	2.42	1.24
Number of adults in the household	2.01	0.70
Number of children in the household (age less than 18 years)	0.4	0.93
Number of workers in the household	0.67	0.84
Number of drivers in the household	1.91	0.73
% household with two or more vehicles	65.20%	0.48
% household with two or more persons	83.70%	0.37
% household with two or more adults	83%	0.38
% household with children (at least one)	19.90%	0.40
% household with two or more drivers	76.50%	0.42
% households where race of the householder: White	89.60%	0.31
% households where race of the householder: Hispanic	3.30%	0.18
% households residing in urban	81.90%	0.39
% households residing in urban cluster	4.50%	0.21
% households residing in 1 million or more population areas	75.50%	0.43
% households owning residence	91.10%	0.29
% households with income less than $50,000	45.40%	0.50
Person attributes		
Age of the respondents in years	61.34	16.29
% persons with age > 65 years	45.60%	0.50
% male	40.10%	0.49
% persons who purchase goods at least one time through internet in past month	36.60%	0.48
Sample Size, N	2,546 Respondents	

Table 2. Profile of Types of Activities and Average Time Allocations by Activity Type for Home-Based Non-Work Tours

Tour Activity Type Count	Duration (minutes)	Personal Business	Shopping	Social Visit	Recreation & Sports	Meal	Serve Passenger	Other	Full Tour
One activity type	Non-zero Average	76.1	40.0	139.5	73.1	62.1	15.3	75.1	
	Count	*249*	*831*	*251*	*631*	*297*	*416*	*277*	*2952*
	Including Zero Average	6.4	11.3	11.9	15.6	6.2	2.2	7.0	60.6
Two activity types	Non-zero Average	66.1	31.8	111.6	108.4	50.9	21.3	67.8	
	Count	*120*	*712*	*86*	*129*	*156*	*182*	*133*	*759*
	Including Zero Average	10.5	29.8	12.6	18.4	10.5	5.1	11.9	98.8
Three activity types	Non-zero Average	59.3	31.3	87.0	106.9	48.2	21.3	62.1	
	Count	*94*	*671*	*70*	*73*	*146*	*168*	*95*	*439*
	Including Zero Average	12.7	47.8	13.9	17.8	16.0	8.2	13.4	129.8
Four activity types	Non-zero Average	33.3	31.5	90.1	89.1	47.0	23.1	52.3	
	Count	*55*	*353*	*30*	*34*	*88*	*77*	*51*	*172*
	Including Zero Average	10.7	64.7	15.7	17.6	24.1	10.4	15.5	158.5
Five activity types	Non-zero Average	42.6	22.0	98.5	79.7	54.8	9.9	55.7	
	Count	*37*	*228*	*28*	*19*	*45*	*66*	*37*	*92*
	Including Zero Average	17.1	54.6	30.0	16.5	26.8	7.1	22.4	174.5
Five or more activity types	Non-zero Average	33.4	27.5	125.8	59.5	39.7	21.7	60.5	
	Count	*48*	*283*	*18*	*17*	*44*	*50*	*27*	*72*
	Including Zero Average	22.3	108.0	31.4	14.0	24.2	15.1	22.7	237.8
Total tour count	*4486*								

Note: All durations are in minutes.

Table 3. Model Estimation Results for MDCEV Model of Activity Type Choice and Time Allocation: Home-based Non-work Tours

Household Attributes			Tour Level Attributes			Person Attributes		
Explanatory Variables	**Coef**	**t-stat**	**Explanatory Variables**	**Coef**	**t-stat**	**Explanatory Variables**	**Coef**	**t-stat**
Low annual income households			***History of shopping activity in the day***			***Age 36-45 years***		
Personal Business	-0.3801	-3.2	Personal Business	-0.005	-2.46	Shopping	0.3531	3.29
Recreational	-0.2141	-2.44	Shopping	-0.0029	-2.9	Serve Passenger	1.1023	9.58
Meal	-0.2887	-2.97	***History of social visit in the day***			***Age > 65 years***		
Medium annual income households			Social Visit	0.0047	3.62	Personal Business	0.3835	3.59
Social Visit	0.2472	1.96	***Start time of tour (7 am - 9 am)***			***Male***		
Household size			Serve Passenger	1.0757	10.34	Recreation	0.184	2.46
Recreation	-0.2632	-7.01	***Start time of tour (9 am - 11am)***			***Female***		
Vehicle ratio			Recreation	-0.5215	-5.43	Social Visit	0.2904	2.66
Personal Business	0.4275	4.63	***Start time of tour (11 am - 1 pm)***			***White***		
Social Visit	0.2601	2.27	Personal Business	-0.2863	-2.21	Recreation	0.4511	3.17
Serve Passenger	-0.8362	-7.74	Meal	0.5246	5.27	Meal	0.3317	2.19
Number of children			***Start time of tour (1 pm - 3 pm)***					
Shopping	-0.2891	-8.01	Shopping	0.6832	8.35			
Social Visit	-0.2737	-4.36	Serve Passenger	0.7455	6.26			
Meal	-0.3775	-6.9	***Start time of tour (5 pm - 7 pm)***					
Employed status indicator			Social Visit	0.7601	5.13			
Personal Business	0.3016	2.61	Meal	1.2596	11.09			
Urban / Rural indicator								
Serve Passenger	-0.7754	-2.76						

Baseline Constants			Satiation Parameters			Goodness of fit Statistics	
Explanatory variables	**Coef**	**t-stat**	**Activity Type**	**Coef**	**t-stat**		
Personal Business	-0.4036	-3.32	Personal Business	0.9155	96.06	Log-likelihood of final model at convergence	-18151.27
Shopping	1.4334	24.5	Shopping	0.8523	118.77	Degrees of freedom of final model	37
Social Visit	-0.7684	-4.83	Social Visit	0.9771	189.3	Log-Likelihood of base model at convergence	-18613.28
Recreation	0.6193	3.36	Recreation	0.9867	260.46	Degrees of freedom of base model	6
Meal	-0.0026	-0.02	Meal	0.8632	77.54	Likelihood ratio	924.02
Serve Passenger	0.2787	1.87	Serve Passenger	0.8115	57.28	$\chi^2_{31,0.0001}$	61.1
			Other	0.9393	119.28		