# A Household-Level Activity Pattern Generation Model for the Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT) System in Southern California


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**ABSTRACT**

This paper develops and estimates a Multiple Discrete Continuous Extreme Value (MDCEV) model of household activity generation that jointly predicts the activity participation decisions of all individuals in a household by activity purpose and the precise combination of individuals participating. The model is estimated on a sample obtained from the Post Census Regional Household Travel Survey conducted by the South California Association of Governments (SCAG) in the year 2000. The model has been embedded within the larger activity-based modeling structure for the Southern California region (labeled as Simulator of Activities, Greenhouse Emissions, Networks, and Travel or SimAGENT).

# 1. INTRODUCTION

The emphasis of the activity-based approach to travel modeling is on activity participation and scheduling over a specified time period (usually a weekday in the U.S.), with travel being viewed as a derivative of out-of-home activity participation and scheduling decisions. While the detailed structures of activity-based models (ABMs) vary substantially, it is typical for operational ABMs to model "mandatory" activity decisions such as out-of-home work-related decisions (employed or not, duration of work, location of work, and timing of work) and education-related decisions (student or not, duration of study, location of study, and timing of study) as precursors to the generation of out-of-home non-work activity participations and the overall activity-travel schedules of individuals (including the scheduling of work and non-work episodes). Within the context of the generation of out-of-home non-work activity participation, while early activity-based travel studies and operational models ignored the interactions between individuals within a household (see, for example, Mannering *et al.*, 1994, Lu and Pas, 1999), more recent studies and models have emphasized the need to explicitly consider such interactions and model joint activity participations within a household. This is motivated by several considerations. <u>First</u>, individuals within a household usually do not make their activity engagement decisions in isolation. As articulated by Gliebe and Koppelman (2002) and Kapur and Bhat (2007), an individual's activity participation decisions are likely to be dependent on other members of the household because of the possible sharing of household maintenance responsibilities, joint activity participation in discretionary activities, and pick-up/drop-off of household members with restricted mobility. These interactions in activity decisions across household members are important to consider to accurately predict activity-travel patterns. For instance, a husband's and wife's activity schedules are necessarily linked because of the spatial and temporal overlap when they both watch a movie or an opera at a theatre. In this regard, considering the husband's and wife's activity-travel patterns independently without maintaining the time-space linkage will necessarily result in less accurate activity travel pattern predictions for each one of them. <u>Second</u>, there is a certain level of rigidity in joint activity participations (since such participations necessitate the synchronization of the schedules of multiple individuals in time and space), because of which the responsiveness to transportation control measures such as pricing schemes may be less than what would be predicted if each individual were considered in isolation (Vovsha and Bradley, 2006, Timmermans and Zhang, 2009). <u>Third</u>, the activity-travel attributes of joint activity participations are systematically different from individual activity participations, even beyond the issue of rigidity in schedule. For instance, studies indicate that, in general, joint discretionary activity episode participations entail longer travel distances and longer participation durations relative to individual episode participations (Srinivasan and Bhat, 2006). Moreover, when a joint activity episode participation entails joint travel of some or all members participating jointly in the activity episode, the travel is more likely to be undertaken using larger and more spacious vehicles such as sports utility vehicles and vans, impacting the vehicle composition by type in the region, a key determinant of vehicular emissions (Konduri *et al.*, 2011).

The emphasis on joint intra-household activity decisions has led to (or perhaps also been motivated by) another key substantive issue that has been receiving attention only more recently in the activity-based travel modeling literature. This pertains to the explicit modeling of children's activity decisions, and the inclusion of both adults' and children's activity-travel patterns within the travel demand modeling framework. After all, as Reisner (2003) indicates, parents spend considerable time and resources transporting children to and from after-school activities, while other studies have found that parents, especially mothers, make frequent stops on the commute to work and to, or from, non-work activities due to the need to escort children to activities (McGuckin and Nakamoto, 2004; see also Kato and Matsumoto, 2009 for extended discussions on this topic). The participation of children in activities, therefore, necessarily constrains adults' activity-travel patterns in important ways and may make an adult unresponsive to policy changes that attempt to modify travel mode, time of travel, or destination of travel. For instance, a parent driving a child to school during the morning peak is unlikely to shift away from the morning peak because of a congestion pricing strategy, even if the parent has a flexible work schedule. Similarly, in the case of a parent dropping a child off at soccer practice, it is the child's activity episode and its location that determines the temporal and spatial dimensions of the trip. In this context, Stefan and Hunt (2006) indicate that children as young as six years of age start developing their own independent activity participation needs that are then fulfilled by the logistical planning of their parents. Finally, the presence of children in the household can also increase joint activity participation in such activities as shopping, going to the park, walking together, and other social-recreational activities. Overall, modeling children's activity engagement (and the interactions between these engagements and those of adults) within activity-based travel model systems is an important pre-requisite for accurate travel forecasting in response to shifts in population demographics and land-use/transportation policies.

The discussion above motivates the current study. Specifically, we formulate and estimate a household-level activity pattern generation model that at once predicts, for a typical weekday, the independent and joint activity participation decisions of *all individuals (adults and children) in a household, for all types of households, for all combinations of individuals participating in joint activity participations, and for all disaggregate-level activity purposes*. To our knowledge, this is the first such comprehensive household-level pattern generation model in the literature. The model has been embedded within the larger activity-based modeling structure for the Southern California region (labeled as Simulator of Activities, Greenhouse Emissions, Networks, and Travel or SimAGENT). In addition to providing richness in behavioral detail, the model contributes to the run speed of SimAGENT by obviating the need for several hierarchical sub-models typically used in extant activity-based systems to generate activity patterns.

The rest of this paper is structured as follows. The next section provides an overview of the analysis approach. Section 3 discusses the details of the modeling methodology. Section 4 provides an overview of the data source and the sample. Section 5 presents the empirical findings, model validation results, and a brief discussion explaining how the current model has been embedded into the broader SimAGENT modeling framework. Finally, Section 6 concludes the study by highlighting contributions and findings.

## 2. AN OVERVIEW OF THE ANALYSIS APPROACH

In this section, we provide a brief overview and motivation for the analysis approach used in the current paper (the reader is referred to the unabridged and unpublished version of this paper by Bhat *et al*. (2011) for a detailed review and synthesis of earlier research in the area of intra-household interactions and the position of the current paper within this broader context (see http://www.caee.utexas.edu/prof/bhat/ABSTRACTS/IntrahouseholdInteractions_unabridged.pdf).

There are several possible ways to model intra-household interactions in activity engagement decisions, including rule-based approaches (see Arentze and Timmermans, 2004, Miller and Roorda, 2003) and econometric approaches (see Bhat *et al*., 2011). One common econometric approach is based on the micro-economic time allocation framework (see Zhang and Fujiwara, 2006 and Kato and Matsumoto, 2009). In the class of such time allocation models, the Multiple Discrete Continuous Extreme Value (MDCEV) model proposed by Bhat, 2008 is a simple and parsimonious way to accommodate intra-household interactions. It also is based on the notion that individuals determine the activity purposes to participate in, make decisions regarding with whom to participate in activities, and allocate time to different "activity purpose-with whom" combinations based on satiation and variety seeking behavior. Given these appealing behavioral characteristics of the MDCEV model, several recent studies have used the structure and its variants in the context of activity time use modeling (Habib and Miller, 2008, Xia *et al*., 2009, Paleti *et al.*, 2010). However, these earlier applications of the MDCEV model have been individual-level models of time-use among multiple activity purposes, sometimes with aggregate representations of the "with whom" context of activity participations. They are fundamentally not household-level models of activity pattern generation. At the same time, the use of the MDCEV framework for household-level activity generation lends itself nicely to incorporation within a larger activity-based model system, and does not have the explosion problem that characterizes the traditional discrete choice methods discussed in the previous paragraph. This is because the MDCEV framework allows the choice of multiple alternatives at the same time, while traditional discrete choice frameworks allow only one alternative to be chosen. As a result, the number of composite alternatives (activity purpose – participating individual combinations) that need to be defined in the traditional discrete model choice set with $I$ out-of-home disaggregate activity purpose alternatives and $P$ individuals in the household is $2^{I*(2^P-1)}-1$, while the corresponding number in the MDCEV model choice set is only $I*(2^P-1)$.[1] Consider the case of three disaggregate out-of-home (OH) activity purposes (say $A_1$, $A_2$, and $A_3$). For a single individual in the household, there are eight alternatives in the traditional model ($A_1$ only, $A_2$ only, $A_3$ only, $A_1A_3, A_2A_3, A_2A_3, A_1A_2A_3$), but only three alternatives ($A_1$, $A_2$, and $A_3$) in the MDCEV model. The difference in the number of alternatives becomes stark as the number of individuals increases. With just three household members, the number of alternatives in the choice set for the traditional discrete choice model explodes to over 2 million, while the corresponding number is only 22 in the MDCEV set-up.

In this study, we use the MDCEV model to analyze the joint and individual activity participation decisions of all household members in out-of-home (OH) activities on weekdays.

## 3. METHODOLOGY

In this section, we present an overview of the MDCEV model structure. The reader is referred to Bhat (2005) and Bhat (2008) for the details of the model structure. Also, we suppress the index for households and present the structure for a single household with $K$ out-of-home (OH) "activity purpose-participating individuals" combination alternatives (for ease in presentation, we will refer to the OH activity purpose-participating individual combination alternatives simply as activity alternatives in the rest of this paper). Note that, in reality, $K$ will vary across households based on the number of individuals in the household. Let $t_k$ be the amount of time

[1] Of course, these formulas will need to be adjusted in minor ways to accommodate for the fact that there is no jointness in work-related activity, and that this activity purpose applies only to employed individuals in the household. But the formulas provide a clear magnitude effect assuming there were no restrictions on any of the $I$ activity purposes. Also, technically speaking, there needs to be an additional alternative in both the discrete choice and the MDCEV structures that corresponds to all individuals in the household staying at home for the entire day. However, as will be discussed in the next section, we consider this alternative outside the MDCEV framework.

invested in activity alternative $k$ ($k$ = 1, 2, …, $K$) over the course of the weekday, where $k$ is an index for activity alternatives. Define the vector $\boldsymbol{t} = (t_1, t_2, ..., t_K)$, and let $\sum_{k=1}^{K} t_k = T$, where $T$ represents the total time across all household members that is available for OH non-work activity participation.

An important point here is in order here. We are not including the household-level activity alternative that corresponds to all individuals staying at home for the entire day in the way we have defined our $K$ alternatives. This is because the duration for this alternative can be as high as 1440×$Q$, where $Q$ is the number of individuals in the household. This very large duration for a single alternative leads to difficulties when estimating the non-linear utility functions in the MDCEV model. Thus, we first estimate a simple binary choice model to predict whether or not a household has any OH non-work participation at all (across all its household members), based on household and individual characteristics (such as age of adults, presence of children, family structure, commute times, work characteristics of individuals, *etc.*).[2] Then, we only consider those households that have a non-zero OH work participation time in the MDCEV model, which also then does not have the alternative corresponding to all individuals staying at home. This way of inclusion of households implies that each household must choose at least one alternative for participation in the MDCEV model from the $K$ activity alternatives (of course, this does not preclude the possibility that specific individuals in the household will have no OH activity during the day; for instance, if all the alternatives involving individual $q$ ($q$ = 1, 2, …, $Q$) have no time allocation, it implies that individual $q$ stays at home the entire day).

The MDCEV model still, however, needs the value of $T$, corresponding to the total time available for OH non-work activity participation. To obtain this, we first remove the work duration of each individual $q$ ($q$ = 1, 2, …, $Q$) in the household from the total duration in a day to obtain the available non-work time (in minutes) as follows: $NWTIME_q = 1440 - WTIME_q$ (in minutes). Next, the total non-work time at the household level may be computed as $HNWTIME = \sum_{q=1}^{Q} NWTIME_q$. However, $HNWTIME$ includes travel times to OH activities as well as the in-home times (including sleep times) of individuals. So, we need to remove these times from $HNWTIME$ (note that travel times are determined only later in the scheduling phase, and are not available at the activity generation phase). We proceed by estimating a fractional split model (see Sivakumar and Bhat, 2002 for details of this model structure) for each household, so that we are able to split $HNWTIME$ into at-home time, travel time, and out-of-home non-work activity time ($T$). In this paper, we do not provide details of the fractional split model, and focus primarily on the MDCEV model and its results.

Consider the following additive, non-linear, household-level functional form to represent the household-level utility accrued by time investments in the activity alternatives:

$$U(\boldsymbol{t}) = \sum_{k=1}^{K} \gamma_k \psi_k \ln\left(\frac{x_k}{\gamma_k} + 1\right) = \sum_{k=1}^{K} \gamma_k \exp\left(\beta' z_k + \varepsilon_k\right) \ln\left(\frac{x_k}{\gamma_k} + 1\right) \qquad (1)$$

$z_k$ is a vector of exogenous determinants (including a constant) specific to alternative $k$. The $\psi_k$ term represents the random marginal utility of one unit of time investment in alternative $k$ for

[2] In the SCAG survey sample used in the empirical estimation of the current paper, 23.4% of households did not have any non-work activity participation at all during the weekday.

household $q$ at the point of zero time investment for the alternative and is specified as $\exp(\beta' z_k + \varepsilon_k)$. It controls the discrete choice participation decision in alternative $k$ and is usually referred to as the baseline preference for alternative $k$. $\gamma_k$ ($\gamma_k > 0$) is a translation parameter which serves two purposes – (1) it plays the role of satiation parameter reducing the marginal utility with increasing consumption of alternative $k$; higher values of $\gamma_k$ imply lower satiation effects (*i.e.*, higher durations of time investments, subject to any time investment at all in alternative $k$) and (2) it allows the presence of corner solutions (that is, zero consumptions of alternatives).

From the analyst's perspective, households are maximizing random utility $U(\boldsymbol{t})$ subject to the time budget constraint that $\sum_k t_k = T$. Assuming that the error terms $\varepsilon_k$ ($k$ = 1, 2, …, $K$) are independent and identically distributed across alternatives with a type 1 extreme value distribution, the probability that household allocates time to the first $M$ of the $K$ alternatives (for duration $t_1^*$ in the first alternative, $t_2^*$ in the second, … $t_M^*$ in the $M^{th}$ alternative) is given by:

$$P(t_1^*, t_2^*, t_3^*, ..., t_M^*, 0, 0, ..., 0) = \left[\prod_{i=1}^{M} c_i\right]\left[\sum_{i=1}^{M} \frac{1}{c_i}\right]\left[\frac{\prod_{i=1}^{M} e^{V_i}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right](M-1)!, \text{ where } c_k = \left(\frac{1}{t_k^* + \gamma_k}\right) \quad (2)$$

and $V_k = \beta' z_k - \ln\left(\frac{t_k}{\gamma_k} + 1\right)$ ($k$ = 1, 2, 3,…, $K$).

Once estimated, the MDCEV model may be used to predict the amount of time allocated to each activity alternative using the forecasting algorithm proposed by Pinjari and Bhat (2010). This algorithm is very fast, and facilitates the use of the MDCEV model within the SimAGENT micro-simulation platform. The resulting discrete choice predictions and the time investments are used further downstream in the activity scheduling component of SimAGENT, as discussed in more detail in Section 5.6.

## 4. DATA

The data for our analysis is drawn from the 2000 Post Census Regional Household Travel Survey conducted by the South California Association of Governments (SCAG), which is the metropolitan planning organization (MPO) of the six-county Los Angeles region of California.

### 4.1 Determination of Joint Activity Participation and Associated Daily Duration

The survey data obtained point information or closest cross-street intersection information for all locations (home locations, work locations, and all other activity locations) of each trip end of each individual in the survey. This was translated by SCAG to spatial coordinates, and served as the basis to determine joint activity participation decisions among household members. Specifically, the trip end information was converted to activity episode information, and each activity episode was assigned as an independent episode or a joint episode based on examining the reported activity locations of all household members. If the reported locations of activity episodes were the same across two or more household members, and the time of day of the episode start was reported within a "buffer-window" of ten minutes, the corresponding episode was designated as a joint activity episode involving the appropriate household members. The activity purpose of the episode was then determined. In some cases, one or more participating members reported the activity purpose of participation as "accompanying another individual". In such cases, the activity purpose of the participating individual who reported a purpose other than "accompanying another individual" was designated as the joint activity purpose. Finally, the durations of episodes were aggregated by purpose and participating individuals to obtain the weekday durations, and served as the dependent variables of the MDCEV model.

### 4.2 Sample Formation

In the current paper, we consider maintenance and discretionary activity purposes, with a disaggregate activity purpose classification as follows: (1) shopping (grocery shopping, clothes shopping, and window shopping), (2) non-shopping maintenance (ATM and other banking, purchasing gas, quick stop for coffee/newspaper, visiting post office, paying bills, and medical/doctor visits), which we will refer to simply as "maintenance" in the rest of this paper, (3) social (community meetings, political/civic event, public hearing, occasional volunteer work, church, temple and religious meeting), (4) entertainment (watching sports, going to the movies/opera, going dancing, and visiting a bar), (5) visiting friends and family, (6) active recreation (going to the gym, playing sports, biking, walking, and camping), (7) eat-out, (8) work-related, and (9) other (includes an "other" category as presented to respondents in the survey, as well as child-care and school-care activities).[3] Of these nine purposes, no joint participation was observed for work-related activity. Thus, we allow joint activity participation in eight purposes, and only independent participation in the work-related purpose category.

The number of individuals in the household varied from one to nine individuals. However, households of size five or less constituted well over 97% of all households. For these households, the maximum number of alternatives is 253 (= $(2^5-1)*8+5$). In estimation, we focus on these households, because of the reasonable number of alternatives. However, once the model is estimated with 253 alternatives, it can be applied to households of any size because of the manner in which the model is specified.

The final sample for estimation included 8900 households (with less than or equal to five household members). These correspond to households that had at least one non-work out-of-home (OH) activity participation during the course of the day. The household size distribution of these households was as follows: 1 individual (30.8%), 2 individuals (36.6%), 3 individuals (14.5%), 4 individuals (12.7%), and 5 individual (5.5%).

[3] Note that "serve-passenger" does not appear as an activity purpose, because we consider this as a travel arrangement. In SimAGENT, "serve passenger trips" fall under the purview of activity-travel scheduling. Thus, if a child is driven to a soccer practice and dropped off, this would appear as an independent activity for the child in physically active recreation in the household-level activity pattern generation model of this paper. This independent activity is then assigned to a driving-age individual in the household in the scheduling phase. Also, in SimAGENT, the assignment of travel mode to school for a young child, and who among the driving-age individuals serves the young child (if the travel mode to school is car for the young child), is determined prior to the non-work activity pattern generation model of the current paper. The reader is referred to Section 5.6 for an overview of the SimAGENT model structure and to Goulias *et al.*, 2011 for a more detailed presentation of the SimAGENT structure.

### 4.3 Construction of Accessibility Measures

In addition to the 2000 SCAG survey data set, several other secondary data sets were used to obtain residential neighborhood accessibility measures that may influence household-level activity participation behavior. All these variables were computed at the level of the residential traffic analysis zone (TAZ) of each household and considered in our model specifications. The secondary data sources included geo-coded block group and block data within the SCAG region obtained from Census website, SCAG roadway and transit network skims from SCAG, the employment data from the Census Transportation Planning Package (CTPP) and Dun & Bradstreet (D&B), and the 2000 Public-Use Microdata Samples (PUMS) from Census 2000 and the marginal distributions (population and household summary tables) from SCAG.

Two types of accessibility measures were constructed in the current analysis. The first set of accessibility measures are opportunity-based indicators which measure the number of activity opportunities by twelve different industry types that can be reached within 10 minutes from the home zone during the morning peak period (6am to 9am). The reader is referred to Chen *et al.*, 2011 for details. The second set of accessibility indicators correspond to Hansen type measures (Bhat and Guo, 2007), which take the following form:

$Acc_{i,\tilde{t}} = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{\text{Size Measure}_{\text{j}}}{\text{Impedance}_{\text{ij},\tilde{\text{t}}}}\right)$, where *i* is the index for zone, $\tilde{t}$ is the index for the time period, and *N* is the total number of zones in the study region (four time periods were used in our analysis: AM peak (6:30 am-9 am), midday (9 am-4 pm), PM peak (4 pm-6:30 pm), and evening (6:30 pm-6:30am)). $\text{Impedance}_{\text{ij},\tilde{\text{t}}}$ is the composite impedance measure of travel between zones *i* and *j* at time period $\tilde{t}$ and is obtained as: $\text{Impedance}_{\text{ij},\tilde{\text{t}}} = IVTT_{ij,\tilde{t}} + \lambda Cost_{ij,\tilde{t}}$, where $IVTT_{ij,\tilde{t}}$ and $Cost_{ij,\tilde{t}}$ are the auto travel time (in minutes) and auto travel cost (in cents), respectively, between zones *i* and *j* in time period $\tilde{t}$, and $\lambda$ is the inverse of the money value of travel time. We used $\lambda$ = 0.0992 in the current study, which corresponds to about $6 per hour of implied money value of travel time. For the zonal size measure in the accessibility formulation, we considered four variables -- retail employment, retail and service employment, total employment, and population. Finally, the time period-specific accessibility measures computed as discussed above were weighted by the durations of each time period, and a composite daily accessibility measure (for each size measure) was computed for each traffic analysis zone, and appended to sample households based on the residence TAZs of households.

### 4.4 Descriptive Analysis

Table 1 presents the descriptive statistics of household-level activity participation decisions in the final estimation dataset, including the (1) percentage of households in which no individual participates at all during the day in the row activity purpose (the first numeric column), (2) percentage of households (from among those who participate in the row activity purpose) with only single individual (or independent) activity participations over the course of the day (the second numeric column), (3) percentage of households (from among those who participate in the row activity purpose) with joint activity participations of two or more individuals (the third through sixth columns; note that the sum of the second through sixth numeric columns is 100% for each row), (4) the mean duration of daily time investment among households who participate in each activity purpose in the overall, and by individual or joint activity engagement (the seventh and eight columns), and (5) the percentage of households participating in each activity purpose who solely participate in that activity and who also participate in other activity purposes (the last two columns; the sum of these last two columns is 100% for each row).

The descriptive statistics in the first numeric column of Table 1 reveal that households (*i.e.*, across all individuals in the household) are most unlikely during the weekday to participate in relatively discretionary activities (social, entertainment, visiting, active recreation), work-related activity, and the catch-all "other" activity purpose. The most likely participation is in the maintenance-oriented purposes of shopping and other maintenance activities. Among households who participate in each activity purpose, not surprisingly, independent participations are the most common (see the second numeric column; note, however, that the statistics here are not for episodes of participation, but for daily participations). Independent participations are particularly frequent for the maintenance, active recreation, and visiting activity purposes (of course, , all work-related participations in the day were pursued alone). On the other hand, shopping, entertainment, eat-out, and "other" activities (relative to the remaining activity purposes) are more likely to be pursued jointly with other household members (see the higher percentages corresponding to these purposes in the third through sixth numeric columns of the table). Also, as expected, the most frequent type of joint activity participation for all activity purposes is with two participating individuals in the household (though the number of individuals participating jointly is also a function of the number of individuals in the household).

The "mean duration of daily time investment among households who participate" column shows the high overall daily time investments of participating households in entertainment and work-related purposes. The purposes with the least time investments are the shopping and eat-out purposes, with each having a mean duration of less than an hour. Also interesting to note is the difference in daily time durations based on independent (that is, single individual) versus joint (that is, multiple individual) participation. While there are no substantial differences for the shopping, maintenance, and eat-out activity purposes, the daily time investments on joint participation for the relatively discretionary purposes (social, entertainment, visiting, and "other") are lower than for independent participations in these purposes.

The final two columns in Table 1 indicate the split between single activity purpose participation (*i.e.*, household participation in only one activity purpose category) and multiple activity purpose participation (*i.e.*, household participation in multiple activity purpose categories) for each activity purpose. Thus, for instance, 14.7% of households who participate in shopping activity during the course of the day participate only in this activity during the weekday, while 85.3% of households who participate in shopping activity also participate in other activity purposes (note that these participations refer to the participations across all individuals in the household). Clearly, this indicates the variety of activity purposes in which households participate over the course of a weekday, and reinforces the use of the MDCEV model for modeling household-level activity participation.

## 5. EMPIRICAL RESULTS

The model estimation process was guided by the findings of earlier studies, intuitiveness, and parsimony considerations. In the most general way of specifying an MDCEV model, the number of coefficients for each covariate in the $\boldsymbol{z}_k$ independent variable vector would be of the order of the number of alternatives, which is 253 for a household with five individuals. However, this way of specifying alternative-specific coefficients is not efficient, and also not behaviorally sound because the specification should accommodate the specific characteristics of the household as a whole and each individual in the household (rather than "label" each member as

A or B or C). Besides, a full "labeling" approach of estimation will not also work because of the few households that have four and five individuals. In addition, the approach is not amenable to application in forecasting for households that have more than five individuals.

In our empirical analysis, the baseline preference utility of the independent (single person participating) activity alternatives for any household is specified as a function of household, individual characteristics, and residential neighborhood accessibility, while the utility of joint (multiple individuals participating) activity alternatives is specified as a function of household, combination of individual characteristics constituting the alternative (for example, whether the alternative includes a child or not), and residential variables. In general, covariates may impact the utilities of the "joint activity purpose-participating individual" activity alternatives through (1) the "activity purpose" dimension, (2) the "participating individuals" dimension, (3) dual, but independent, effects on the "activity purpose" and the "participating individuals" dimensions, and/or (4) an interaction effect on the "activity purpose" and the "participating individuals" dimensions. We consider all of these possible effects on the baseline utilities of alternatives in developing a parsimonious specification. In our presentation of results, we will explicitly identify the "base" category for the first, second, and third groups of covariate effects. For the fourth group of covariate effects, the "base" category will be implicit from the alternatives not listed (it is not space-efficient to list all the base alternatives in this case).

Table 2 presents the model estimation results of the best MDCEV model specification obtained in our study. The model results are discussed under five sections - effects of household demographics (Section 5.1), effects of individual characteristics (Section 5.2), effects of accessibility measures (Section 5.3), baseline preference constants (Section 5.4), and translation parameters (Section 5.5).

### 5.1 Effects of Household Demographics

The effects of the first two variables in Table 2 under "household demographics" indicate that households with many children (aged less than or equal to 15 years) are most likely to participate in the "Other" activity purpose. This is not surprising because, by definition, the "Other" activity purpose involves child care, school care, and after school care activities. Also, these households are less inclined toward eat-out and shopping activity participation on a typical weekday, perhaps because of a preference to undertake these activities more leisurely during the weekends without the time pressures of work/school and child-care responsibilities of the typical weekday (Gliebe and Koppelman, 2005). However, it is interesting that such time pressures do not appear to extend to active recreation activities when school going children are present. Indeed, the presence of school going children increases the baseline preference for these activity purposes, perhaps because of school-related active recreation of children as well because children can drive the activity recreation participation decisions of the household (see, Mallett and McGuckin, 2000, Stefan and Hunt, 2006 and Rajagopalan *et al.*, 2009). Another point to note is that households with non-school going children (a proxy for very young children in the household) are not likely to partake in social activities during a typical weekday.

As expected, and as also observed by Habib and Miller, 2008, households with several senior adults (aged more than 65 years) have a predisposition to partake in activities other than work-related activity. This is particularly so for social activities such as community meetings, voluntary activities, and religious events, which provide the opportunity for senior adults to connect with other individuals and forge new social relationships. The effects of high household income get manifested in the generally higher likelihood to engage in work-related and active recreation activities relative to other non-work activities. The higher levels of participation in work-related activity is perhaps a sign of the higher job responsibilities and workaholic tendencies among individuals in such households, while the higher participation levels in active recreation is likely a result of financial affordability to access gyms and health clubs. The latter result that individuals in higher income households are more likely than individuals in low (and even moderate) income households to pursue active recreation is a recurring theme in the physical activity literature (see Bennett *et al*., 2007). There have been suggestions that, while active recreation can be pursued in and around neighborhoods without much financial implications, the quality of the environment in which low income households reside may have a bearing on their low active recreation tendencies. As stated by Bennett *et al*. (2007), "residing in a neighborhood that is perceived to be unsafe at night is a barrier to regular physical activity among individuals, especially women, living in urban low-income housing. Feeling unsafe may also diminish confidence in the ability to be more physically active." Table 2 also shows another effect of high household income, which is that non-work activity participations in such households are likely to be pursued solo. Finally, in the class of household demographics, the effects of the number of vehicles in the household mirrors the effects of high household income with one important difference – households with several vehicles, but not in the high income group (>100K per year), have a tendency to participate in visiting activities more so than those with relatively fewer vehicles but in the high income group. This is suggestive of conscious lifestyle choices and lifestyle preferences; for instance, households with high income and low number of motorized vehicles may be pre-disposed to a physically active lifestyle with lower preference for visiting activities.

### 5.2 Effects of Individual Characteristics

In this class of variables, we include the effects of individual characteristics such as work schedules and demographics. These variables get introduced in the form of representations of individuals who constitute an activity alternative (they cannot be introduced directly because the model being developed is a household-level model). Thus, for example, variables for work end time and work duration are created for each "activity purpose-participating individual" combination alternative as the latest work end time and maximum work duration among all participating individuals in that combination alternative. If an alternative corresponds to solo (independent) participation in a certain activity type for a certain individual, then (and only then) does the latest work end time variable for the alternative collapse to the work end time of the individual.

The results for work end time suggest that activity alternatives involving individuals with late work end times will generally not be pursued, which is reasonable because the post-work time window for non-work activities gets squeezed (Rajagopalan *et al.*, 2009). However, the table also shows that this time window constraint is not very active for maintenance, visiting, and eat-out activities, perhaps because these activities do not have a rigid schedule and may be pursued even late at night (unlike, for example, entertainment events and other social events that may start at a certain time in the evening). Work duration also has an influence on the preferences for activity alternatives. Specifically, it is not likely that shopping, maintenance, social, and active recreation participations will be pursued by (or with) individuals who work long hours, though eat-out and work-related participations are likely to increase for (or with) individuals working long hours. The increased work-related participation may simply be a reflection of the "workaholic" tendency that led to a long work duration in the first place (note that work-related participations are never pursued jointly).

The "number of children among participating people" variable has a negative sign, indicating that children are almost always going to be accompanied by an adult individual, regardless of activity purpose. Other results indicate that children, when present in the household, are likely to be involved in joint activities for shopping, social, and entertainment, but are unlikely to be companions in joint maintenance activity pursuits (such as when paying the bills or banking). The next variable in the table suggests that those adults who have the responsibility of dropping off/picking up children at/from school are also likely to pursue shopping, maintenance, and eat-out activities by themselves or with other individuals in the household; these adults are unlikely to be involved in work-related activities. The introduction of this variable captures the effects of being the primary child-care and household maintenance "point person" (note that the assignment of who drops off/picks up children at/from school is determined prior to the application of the proposed MDCEV model, and that assignment is based on individual demographics as well as work-related characteristics).

Finally, the results show that a child and a woman adult are more likely to participate together in activities of all purposes, either by themselves or with other household members. This is consistent with the findings of several earlier studies (see, for example, Gliebe and Koppelman, 2005) that women tend to be more responsible for the activities of children.

### 5.3 Accessibility Measures

In the current empirical context, none of the accessibility measures in the first set of opportunity-based accessibility measures (see Section 4.3) turned out to be statistically significant. In the second group of Hansen-type accessibility indicators, two measures (one corresponding to retail plus service employment as the size measure and another corresponding to population as the size measure) have significant impacts. Specifically, we found that households residing in zones with high retail and service employment accessibility are more likely to invest time in active recreation, eat-out, entertainment, shopping, and maintenance activities relative to work-related activities. This is a direct consequence of increased activity participation opportunities, and is consistent with the results from several earlier studies of the effects of the built environment on activity generation (see, for instance, Pinjari *et al.*, 2009, Cervero and Duncan, 2003, and Fan and Khattak, 2009). On the contrary, households in zones with high population accessibility are less likely to participate in active recreation, eat-out, entertainment, shopping, and maintenance activities, perhaps because zones with high population accessibility are not rich in land-use mix, thus inhibiting activity participation.

### 5.4 Baseline Preference Constants and Satiation Parameters

The baseline constants for different activity purposes, in general, capture generic tendencies to participate in different activity purposes. However, in our specification with many continuous variables, the baseline constants do not have a straightforward interpretation and serve as overall adjustors to fit the data best given the exogenous variables. We do not present the baseline constants here, but these are available in Bhat *et al*. (2011).

As discussed earlier in the methodology section, a higher value for the translation parameter $\gamma_k$ for alternative $k$ implies higher preference and less satiation (*i.e.*, higher durations of time investment conditional on participation) in alternative $k$. The translation parameter estimates (not shown in Table 2 to conserve on space) indicated substantial variation in the translation parameters across the activity purpose categories and across the "number of participating individuals" categories. These variations are statistically significant based on the estimated standard errors. Also, the satiation parameters were consistent with the high mean value of participation duration in entertainment, and the low mean values of participation duration in maintenance, shopping, and eat-out activities (see Table 1).

### 5.5 Model Fit and Validation

The log-likelihood value at convergence for the model in Table 2 is -136922.89, while the log-likelihood value for the naïve model with only the baseline preference constants and the translation parameters is 139023.13. The log-likelihood ratio test statistic value for the comparison between our model specification and the naïve model is 4200.54, which is much higher than the critical chi-squared value with 72 degrees of freedom at any level of significance. This is clear evidence of the contribution of explanatory variables in predicting household-level activity participations and durations. We also undertook an aggregate validation exercise, which indicated that the MDCEV model does very well in predicting the observed participation levels in each "activity purpose-number of participating individuals" category (see Bhat *et al.*, 2011).

### 5.6 Model Application: Integration with SimAGENT

SimAGENT includes many components that act together to generate activity-travel patterns, network flows by vehicle type, and travel-related greenhouse gas (GHG) emissions. SimAGENT includes a population synthesizer, an accessibility generator, a land-use/demographic micro-simulator, an activity-travel pattern generator and scheduler, a traffic assignment modeler, and an emissions and fuel consumption predictor. A complete overview of the SimAGENT system is provided in Goulias *et al*. (2011), but we provide a brief discussion in the next paragraph of the position of the proposed MDCEV model within the larger SimAGENT system.

The household level activity pattern generator module of this paper is embedded within the activity-travel pattern generator and scheduler component of SimAGENT. This component of SimAGENT simulates activity-travel patterns of all individuals in the region for a 24 hour period along the continuous time axis. The component includes an (a) activity generation step in which work and school activity participation and timing decisions of all individuals in the household are created, children's travel needs to school are predicted, an allocation of school escort responsibilities to parents takes place, and household-level activity patterns in non-work activity participation decisions are modeled; and an (b) activity scheduling step that produces the sequence of activities, with the departure and arrival times, the participating individuals, activity durations, mode(s) used and accompanying individuals during the travel to each activity, the vehicle type used in the travel, and the location of each activity.

The current MDCEV model resides in, and is the last module of, the generation step. Then, during activity scheduling, the household-level participations and durations are used to inform all scheduling decisions. However, we do not require the activity schedules to be perfectly consistent with the participation and duration predictions from the activity generator. For example, assume that the MDCEV model predicts the following two activities in a household with 2 people (say, A and B)- 30 minutes of independent shopping activity by A and 30 minutes (in actual time) of joint eat-out activity by A and B. The scheduler will work toward meeting the above predictions by using the predictions to constantly inform the activity-travel patterns of all individuals in the household as these patterns unfold during the course of the day, but it can so happen that individual A, because of his/her time availability constraints, participates only for 15 minutes in the independent shopping activity and 20 minutes in the joint activity. The reader is referred to Goulias *et al.* 2011 for a complete and detailed discussion of all the components of SimAGENT.

## 6. CONCLUSION

This study has formulated and estimated a household-level activity pattern generation model that at once predicts, for a typical weekday, the independent and joint activity participation decisions of *all individuals (adults and children) in a household, for all types of households, for all combinations of individuals participating in joint activity participations, and for all disaggregate-level activity purposes*. The model uses a host of household, individual, and residential neighborhood accessibility measures as inputs, and has been embedded within the larger activity-based modeling structure for the Southern California region. In addition to providing richness in behavioral detail, the model contributes to the run speed of SimAGENT by obviating the need for several hierarchical sub-models typically used in extant activity-based systems to generate activity patterns. The forecasting algorithm recently proposed by Pinjari and Bhat (2010) is used to predict household-level participation levels and durations, which then informs the scheduling of activity episodes and travel for each household member.

The empirical results are intuitive and insightful, and illustrate the behavioral richness of the MDCEV formulation. The validation exercise undertaken in the study also shows that the MDCEV predictions match closely with the observed data. Ongoing and future efforts will continue to refine and update the model using new survey data, undertake extensive sensitivity testing and validation exercises, and employs the proposed model as part of the larger SimAGENT model system to assess a variety of policy scenarios in terms of behavioral changes, traffic congestion, and GHG emissions.

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**TABLE 1 Descriptive Analysis of Household-Level Participation and Daily Time Investment by Activity Purpose and Number of Participating Individuals**

| Activity Purpose | % of households in which no individual participates in "row" activity purpose | % of households (from among those who participate in row activity purpose) by number of participating individuals | | | | | Mean duration of daily time investment (minutes) across households who participate in row activity purpose | | | % of households (from among those who participate in activity purpose) who participate… | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | Overall | Independent (single individual) | Joint (multiple individuals) | Only in activity purpose | In other activity purposes too |
| Shopping | 48.9 | 81.7 | 14.1 | 3.1 | 0.9 | 0.2 | 55.3 | 54.3 | 59.8 | 14.7 | 85.3 |
| Maintenance | 51.5 | 89.1 | 10.4 | 0.5 | -- | -- | 90.3 | 90.4 | 89.7 | 14.1 | 85.9 |
| Social | 91.4 | 83.9 | 13.5 | 1.5 | 0.9 | 0.2 | 134.8 | 137.8 | 119.6 | 8.8 | 91.2 |
| Entertainment | 89.9 | 80.9 | 15.5 | 3.1 | 0.5 | -- | 302.2 | 315.8 | 244.1 | 9.2 | 90.8 |
| Visiting | 80.6 | 85.3 | 11.1 | 2.5 | 0.9 | 0.2 | 195.8 | 198.9 | 137.8 | 11.9 | 88.1 |
| Active Recreation | 83.8 | 85.5 | 11.4 | 2.6 | 0.4 | 0.1 | 143.0 | 141.6 | 152.2 | 12.0 | 88.0 |
| Eat-out | 67.6 | 79.4 | 16.6 | 2.8 | 1.0 | 0.2 | 56.2 | 55.6 | 58.3 | 9.3 | 90.7 |
| Other | 79.8 | 80.1 | 15.7 | 3.1 | 1.0 | 0.1 | 191.6 | 208.4 | 124.3 | 7.9 | 92.1 |
| Work-related | 87.8 | 100.0 | -- | -- | -- | -- | 294.5 | 294.5 | -- | 15.9 | 84.1 |

**TABLE 2 MDCEV Model Estimation Results**

| Explanatory Variables | Parameter | T-Statistic |
|---|---|---|
| **Household Demographics** | | |
| <u>*Number of school going children*</u> | | |
| *Activity Purpose (Base is maintenance activity purpose)* | | |
| Shopping | -0.1310 | -4.64 |
| Entertainment | -0.0685 | -1.71 |
| Visiting Friends | 0.0245 | 0.76 |
| Active Recreation | 0.1937 | 6.40 |
| Eat-out | -0.2837 | -8.99 |
| Other | 0.6362 | 21.60 |
| Work-related | 0.2141 | 5.57 |
| <u>*Number of non-school going children*</u> | | |
| *Activity Purpose (Base is maintenance activity purpose)* | | |
| Shopping | -0.1552 | -6.48 |
| Social | -0.3225 | -5.90 |
| Eat-out | -0.1614 | -5.59 |
| Other | 0.6661 | 24.31 |
| Work-related | 0.1396 | 4.70 |
| <u>*Number of senior adults*</u> | | |
| *Activity Purpose (Base is work-related activity purpose)* | | |
| Shopping | 0.7655 | 13.85 |
| Maintenance | 0.8667 | 15.97 |
| Social | 0.9842 | 14.32 |
| Entertainment | 0.7563 | 11.06 |
| Visiting Friends | 0.6253 | 10.03 |
| Active Recreation | 0.7765 | 12.44 |
| Eat-out | 0.7329 | 12.15 |
| Other | 0.4794 | 6.57 |
| <u>*High Income Household (Income> $100K)*</u> | | |
| *Activity Purpose (Base is work-related and active recreation purposes)* | | |
| Shopping | -0.2266 | -5.02 |
| Maintenance | -0.2331 | -5.13 |
| Social | -0.4273 | -4.46 |
| Entertainment | -0.3192 | -4.20 |
| Visiting Friends | -0.6557 | -10.40 |
| Other | -0.3073 | -4.65 |
| *Number of participating people* | | |
| One | 0.5217 | 6.21 |
| At least two people | 0.1014 | 1.22 |
| <u>*Total number of vehicles*</u> | | |
| *Activity Purpose (Base is work-related activity purpose)* | | |
| Shopping | -0.2408 | -10.32 |
| Maintenance | -0.2830 | -12.71 |
| Social | -0.1679 | -4.92 |
| Entertainment | -0.2340 | -7.38 |
| Visiting Friends | -0.1243 | -4.66 |
| Active Recreation | -0.1513 | -5.30 |
| Eat-out | -0.2391 | -9.45 |
| Other | -0.2753 | -9.05 |

**TABLE 2 (Continued) MDCEV Model Estimation Results**

| Explanatory Variables | Parameter | T-Statistic |
|---|---|---|
| **Individual Characteristics** | | |
| *Latest Work End time among people in the alternative (in minutes/100)* | | |
| *Activity Purpose* | | |
| Shopping | -1.3213 | -7.84 |
| Social | -1.0581 | -2.40 |
| Entertainment | -0.6481 | -5.59 |
| Active Recreation | -0.7700 | -2.71 |
| Other | -2.3252 | -7.84 |
| Work-related | -3.1325 | -14.32 |
| *Maximum Work Duration among people in the alternative (in minutes/100)* | | |
| *Activity Purpose* | | |
| Shopping | -1.1533 | -19.09 |
| Maintenance | -1.1533 | -19.09 |
| Social | -0.3768 | -1.44 |
| Active Recreation | -0.0230 | -0.13 |
| Eat-out | 0.1888 | 4.41 |
| Other | 0.3310 | 1.96 |
| Work-related | 0.8254 | 6.70 |
| *Number of children among the people in the alternative* | | |
| *Number of participating people* | | |
| One | -0.6390 | 4.83 |
| *Interaction of Number of participating people and activity purpose* | | |
| Shopping*At least two participating people | 0.4571 | 9.44 |
| Maintenance*At least two participating people | -0.6403 | 7.53 |
| Social*At least two participating people | 0.4571 | 9.44 |
| Entertainment*At least two participating people | 0.0400 | 0.55 |
| *Number of adults with school drop-off/pick-up commitments in the alternative* | | |
| *Activity Purpose* | | |
| Shopping | 0.5599 | 7.53 |
| Maintenance | 0.3900 | 4.83 |
| Eat-out | 0.8028 | 9.44 |
| Work-related | -0.5051 | -3.34 |
| *Presence of a woman adult and a child in the alternative* | | |
| *Number of participating people* | | |
| *At least two people* | 0.0362 | 1.32 |
| **Accessibility Measures** | | |
| *Retail and Service Employment Accessibility* | | |
| *Activity Purpose* | | |
| Shopping | 0.0137 | 2.30 |
| Maintenance | 0.0107 | 1.82 |
| Entertainment | 0.0221 | 2.13 |
| Active Recreation | 0.0709 | 8.57 |
| Eat-out | 0.0458 | 6.69 |
| *Population Accessibility* | | |
| *Activity Purpose* | | |
| Shopping | -0.0077 | -4.09 |
| Maintenance | -0.0058 | -3.10 |
| Entertainment | -0.0082 | -2.51 |
| Active Recreation | -0.0230 | -8.45 |
| Eat-out | -0.0174 | -7.86 |