A Comprehensive Model of Workers' Non-Work Activity Time-Use and Timing Behavior

Bharath S. Rajagopalan
The University of Texas at Austin
Dept of Civil, Architectural and Environmental Engineering
1 University Station C1761
Austin, TX 78712-0278
Phone: 512-471-4535, Fax: 512-475-8744
E-mail: bharath.s.rajagopalan@gmail.com

Abdul Rawoof Pinjari
University of South Florida
Department of Civil & Environmental Engineering
4202 E. Fowler Avenue, ENC 2503
Tampa, FL 33620
Phone: (813) 974-9671, Fax: (813) 974-2957
E-mail: apinjari@eng.usf.edu

and

Chandra R. Bhat *(corresponding author)*
The University of Texas at Austin
Dept of Civil, Architectural and Environmental Engineering
1 University Station C1761
Austin, TX 78712-0278
Phone: 512-471-4535, Fax: 512-475-8744
E-mail: bhat@mail.utexas.edu

ABSTRACT

This study contributes to the literature on activity time-use and activity timing analysis by developing a comprehensive, high resolution, out-of-home non-work activity generation model that considers daily activity time-use behavior and activity timing preferences in a unified random utility framework. The empirical analysis is undertaken using data from the 2000 Bay Area Travel Survey. Several important household and commuter demographics, commute characteristics, and activity-travel environment attributes are found to be significant determinants of workers' non-work activity time-use and timing behavior. The comprehensive model developed in this paper can serve as an activity generation module in an activity-based travel demand microsimulation framework.

1. INTRODUCTION

A fundamental difference between the trip-based and the activity-based approaches to travel modeling is in the way "time" is considered and treated in the analysis framework (*1*, *2*). In the trip-based approach, time is reduced to being simply a "cost" of making a trip. The activity-based approach, on the other hand, treats time as an all-encompassing entity within which individuals make activity/travel participation decisions (*3*). Because of the treatment of time as the "building block" for activity-travel patterns in the activity-based approach, a significant amount of research has focused on two specific aspects of the time-dimension of activity participation behavior: (1) Activity time-use, and (2) Activity timing. Each of these is discussed in turn in the next two sections.

1.1 Activity Time-Use Analysis

The central basis of the activity-based approach is that individuals' activity-travel patterns are a result of their time-use decisions (*2*, *4*, *5*). That is, individuals have 24 hours in a day (or multiples of 24 hours for longer periods of time) and decide how to use that time among various activities distributed in time and space subject to their sociodemographic, spatial, temporal, transportation system, and other contextual constraints.

The subject of activity time use research has gained substantial attention in the travel demand field in the past two decades, with several threads of research efforts. For example, from a conceptual/analytical framework standpoint, some past studies have been based on economic utility theories of time allocation [see (*6*), (*7*), (*8*) and (*9*)], while others are based on theories other than utility theory (*10-13*). From an activity purpose viewpoint, several previous studies have focused on discretionary activity participation (*8*, *14*), while others have focused on maintenance activity participation (*15-17*). In addition, some studies have investigated the trade-offs and substitution effects between in-home and out-of-home activity participation (*16*, *18*), and several recent research studies are starting to examine time-use in the context of such related dimensions of activity-travel behavior as inter-personal interdependencies (*19*) and multi-day/weekly time-use behavior (*20, 21*).

Despite the increasing number of activity time-use studies in the travel demand field, most earlier time-use studies examine only activity participation and time-use during the course of a day or a week, and fail to consider the timing dimension of activities during the day (*i.e., when* an activity is undertaken). On the other hand, the utility derived by an individual from participating in an activity is likely to depend both upon the time allocated to that activity and the time at which the activity is undertaken.

1.2 Activity Timing Analysis

The timing of activities and travel is an important aspect of activity-travel behavior. Hence, models of activity and/or travel timing are at the core of several activity-based systems that are designed for travel forecasting and evaluating travel demand management policies (*22-24*).

Earlier research in the activity timing analysis area has focused largely on modeling individuals' travel timing (*i.e.,* trip/tour departure time) decisions, by using either discrete time approaches (*25-27*) or continuous-time approaches (*28*, *29*). More recently, due to the recognition that travel timing decisions depend to a large extent on individual preferences regarding activity time-use and activity timing (*30*), a handful of studies has examined activity time-use behavior jointly with activity timing during the day, or focused on activity time-use behavior during specific periods of the day (*13*, *30-32*). While very significant contributions in and of their own right, these studies are limited in one of the following ways: (1) They focus narrowly on only certain classes of activity purposes [such as a single maintenance activity purpose category in Pendyala and Bhat (*33*) or a few discretionary activity purpose categories in Yamamoto *et al.* (*31*)], or (2) They do not distinguish between activities by purpose (*30*, *32*, *34*), or (3) They consider the list of activities by purpose for participation as pre-determined before duration/timing decisions of activities (*35*), or (4) They focus narrowly on only certain specific time-periods of the day [such as the post-home arrival period of workers in Bhat (*13*)] or independently (and separately) model activity time-use across different time periods of the day [such as in Chu (*34*)].

1.3 Current Study

This study contributes to the literature on activity time-use and activity timing analysis by developing a comprehensive, high resolution, out-of-home non-work activity generation model for workers that considers daily activity time-use behavior and activity timing preferences in a unified framework. More specifically, a random utility maximization-based model is formulated to predict workers' activity participation and time allocation patterns in seven out-of-home non-work activity purposes at various time periods of the day: (1) Meals, (2) Recreation, (3) Non-maintenance shopping, (4) Maintenance shopping, (5) Personal business, (6) Socializing, and (7) Pick-up/drop-off. The time periods of the day are defined based on the representation framework used by Bhat and Singh (*36*) to describe the daily activity-travel patterns of workers. According to this framework, based on the temporal fixities of the work schedule, a worker's day is divided into the following five broad time periods: (1) Before home-to-work commute period (or before work period)[1], (2) Home-to-work commute period, (3) Work-based period, (4) Work-to-home commute period, and (5) Post home-arrival period. Thus, the model developed in this paper predicts the discrete choice of participation in, and the continuous choice of the time allocated to, each of the activity purposes in each of the broad time periods (*i.e.,* to each activity purpose-time period combination alternative). Such a joint activity time-use and activity timing (in the five broad time periods) choice model considers that the benefit derived from activity participation (and the time allocation) is dependent on both the type of activity undertaken and the timing of the activity. This allows for substitution effects in activity participation and time allocation behavior across different types of activities as well as across different time periods of the day. Also, the knowledge of the activities (and the corresponding time allocations and timing decisions) predicted by this model can be used for the subsequent sequencing/scheduling of activities and travel (tour/stop sequencing, temporal scheduling of stops, activity location choice, and travel mode/route choices) to obtain the complete individual activity-travel pattern at a fine resolution of time (see Figure 1 for a schematic of the plausible position of the model developed in this paper within regional activity-based travel demand microsimulation systems). The model in the paper can, therefore, serve as an important component of a comprehensive behavioral tool to analyze the impact (on activity-travel patterns) of policy actions or changes in household/individual demographics. For instance, consider a policy action that releases some workers at 4 pm instead of 5 pm (as part of either a work staggering policy or an early-release policy to reduce peak-period traffic congestion). Such a policy may not have the intended effect because such workers may make more out-of-home activity stops after work (either during the commute, or after arriving home at the end of the commute). Even those workers who do not

[1] For the sake of conciseness, we will use the term "before work" period for "before home-to-work commute" period.

change the number of out-of-home activity stops may now spend more time at each non-work stop they make. Another possible response of individuals may be to shift non-work stops made earlier during the day to the evening commute and/or the post home-arrival period. Of course, individuals may also change their activity-travel behavior using a combination of the responses just identified. These potentially complex responses to policy actions in (a) participation in non-work activities (by activity type), (b) duration of participation, and (c) timing of participation can all be examined using the proposed comprehensive model system.

From a methodological standpoint, this paper employs a state-of-the-art utility maximization-based discrete continuous modeling framework to model activity time-use and timing decisions. Specifically, the paper is based on the multiple discrete-continuous extreme value (MDCEV) framework, originally developed by Bhat (*37*), which recognizes the possibility of a worker participating in more than one type of non-work activity during more than one time period in the day. This framework uses a non-linear, additive, utility structure that accommodates diminishing marginal utility (or satiation) effects associated with increasing duration of participation in any activity type at any time period. Furthermore, we use the nested version of the MDCEV model structure (referred to as the multiple discrete-continuous nested extreme value or MDCNEV model) proposed by Pinjari and Bhat (*38*) in the current paper, which allows for flexible substitution patterns by capturing correlations among the unobserved utilities of different activity type-timing combination alternatives.

The rest of the paper is organized as follows. Section 2 provides details of the modeling methodology. Section 3 presents the empirical analysis. Finally, Section 4 concludes the paper by summarizing the salient features of the study and identifying potential future research directions.

2. MODEL STRUCTURE

Consider, without loss of generality, that the first alternative corresponds to in-home activity. As one would expect, all individuals in our empirical sample invest some non-zero amount of time on in-home activities. Let there be (K–1) additional alternatives that correspond to the different out-of-home non-work activity purpose-activity timing combinations. In the empirical analysis of the current paper, K–1 = 35 activity purpose-timing combinations formed from 7 activity purpose categories and 5 activity timing categories. Let t_k be the time invested in alternative k (k = 1, 2,…, K), and consider the following additive, non-linear, functional form to represent the utility accrued by an individual (the index for the individual is suppressed in the following presentation):

$$U = \exp(\beta' z_1 + \varepsilon_1)\ln(t_1) + \sum_{k=2}^{K} \gamma_k \exp(\beta' z_k + \varepsilon_k)\ln\left(\frac{t_k}{\gamma_k} + 1\right) \quad (1)$$

In the above expression, z_k (k = 1, 2,…, K) is the vector of individual-related exogenous variables specific to alternative k (k = 1, 2,…, K). The term $\exp(\beta' z_k + \varepsilon_k)$, labeled as the baseline preference for alternative k (k = 1, 2,…, K), represents the random marginal utility of one unit of time investment in alternative k at the point of zero time investment for the alternative. Thus, $\exp(\beta' z_k + \varepsilon_k)$ controls the discrete participation decision of the individual in alternative k. The γ_k ($\gamma_k > 0$) terms are translational parameters that allow for the possibility that the individual invests no time in certain alternatives k (k = 2, 3,…, K). There is no γ_1 term for the first alternative because all individuals invest some positive amount of time in in-home activities. The γ_k terms, in addition to serving as translation parameters, also serve the role of satiation parameters that reduce the marginal utility accrued from investing increasing amounts of time in any alternative (*37*). Note that, to distinguish the activity purpose-specific satiation and activity timing-specific satiation, we reparameterize γ_k as $\gamma_k = \gamma_{l_k} \times \gamma_{h_k}$, where γ_{l_k} and γ_{h_k} are the purpose-specific and timing-specific satiation parameters, respectively, corresponding to the activity purpose–activity timing combination alternative *k*.

From the analyst's perspective, the individual is maximizing random utility (*U*) subject to the time budget constraint $\sum_{k=1}^{K} t_k = T$, where *T* is the time available to participate in in-home and out-of-home non-work activities[2]. Assume now that the joint probability density function of the ε_k terms in Equation (1) is $g(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$, and let *M* alternatives be chosen out of the available *K* alternatives. Let the time allocations to the *M* alternatives be $(t_1^*, t_2^*, t_3^*, \ldots, t_M^*)$. Also, define the following:

$$V_1 = -\ln t_1^* \text{ and} \tag{2}$$

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

Then, as given in Bhat (*37*), the joint probability expression for the time allocation pattern is as follows:

$$P(t_1^*, t_2^*, t_3^*, \ldots, t_M^*, 0, 0, \ldots, 0) = |J| \int_{\varepsilon_1=-\infty}^{+\infty} \int_{\varepsilon_{M+1}=-\infty}^{V_1-V_{M+1}+\varepsilon_1} \int_{\varepsilon_{M+2}=-\infty}^{V_1-V_{M+2}+\varepsilon_1} \cdots \int_{\varepsilon_{K-1}=-\infty}^{V_1-V_{K-1}+\varepsilon_1} \int_{\varepsilon_K=-\infty}^{V_1-V_K+\varepsilon_1}$$
$$g(\varepsilon_1, V_1-V_2+\varepsilon_1, V_1-V_3+\varepsilon_1, \ldots, V_1-V_M+\varepsilon_1, \varepsilon_{M+1}, \varepsilon_{M+2}, \ldots, \varepsilon_{K-1}, \varepsilon_K) \tag{3}$$
$$d\varepsilon_K d\varepsilon_{K-1} \ldots d\varepsilon_{M+2} d\varepsilon_{M+1} d\varepsilon_1 ,$$

where *J* is the Jacobian whose elements are given by Bhat (*37*)

$$J_{ih} = \frac{\partial[V_1 - V_{i+1} + \varepsilon_1]}{\partial t_{h+1}^*} = \frac{\partial[V_1 - V_{i+1}]}{\partial t_{h+1}^*}; \; i, h = 1, 2, \ldots, M-1.$$

The specification of $g(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$ (*i.e.*, the distribution of error terms) determines the form of the probability expression above. To derive the MDCNEV probability expressions, Pinjari and Bhat (*38*) used a nested extreme value distributed structure that has the following joint cumulative distribution:

$$F(\varepsilon_1, \varepsilon_2, .., \varepsilon_K) = \exp\left[-\sum_{\mathcal{S}=1}^{S_K}\left\{\sum_{i \in \mathcal{S}^{\text{th}}\text{nest}} \exp\left(-\frac{\varepsilon_i}{\theta_{\mathcal{S}}}\right)\right\}^{\theta_{\mathcal{S}}}\right] \tag{4}$$

---

[2] The total time (*T*) available for in-home and out-of-home non-work activities is considered to be exogenous in the current analysis. *T* is computed as 24 hours minus the time invested in sleep, work/work-related and education activities, and travel.

In the above expression, $\eth(=1,2,...,S_M,...,S_K)$ is the index to represent a nest of alternatives, S_K is the total number of nests the K alternatives belong to, and S_M is the total number of nests the chosen M alternatives belong to. $\theta_\eth(0<\theta_\eth \le 1; \eth = 1,2,...,S_K)$ is the (dis)similarity parameter introduced to capture correlations among the stochastic components of the utilities of alternatives belonging to the $\eth^{th}$ nest.

Next, let $q_1, q_2, \ldots q_{S_M}$ be the number of chosen alternatives in each of the S_M nests (hence $q_1 + q_2 + \ldots + q_{S_M} = M$). Using this notation, and with the nested extreme value distributed error terms, the expression in Equation (3) simplifies to the following probability expression for the MDCNEV model [see Pinjari and Bhat (*38*) for the derivation]:

$$P(t_1^*, t_2^*, ... t_M^*,\ 0,...,0) =$$

$$|J| \frac{\prod_{i \in \{\text{chosen alternatives}\}} e^{\frac{V_i}{\theta_i}}}{\prod_{\eth=1}^{S_M} \left(\sum_{i \in \eth^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\eth}} \right)^{q_\eth}} \sum_{r_1=1}^{q_1} \ldots \sum_{r_\eth=1}^{q_\eth} \ldots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\eth=1}^{S_M} \left[\frac{\left(\sum_{i \in \eth^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\eth}} \right)^{\theta_\eth}}{\sum_{\eth=1}^{S_k} \left\{ \left(\sum_{i \in \eth^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\eth}} \right)^{\theta_\eth} \right\}} \right]^{q_\eth - r_\eth + 1} \left(\prod_{\eth=1}^{S_M} sum(X_{r\eth}) \right) \left(\sum_{\eth=1}^{S_M} (q_\eth - r_\eth + 1) - 1 \right)! \right\} \quad (5)$$

In the above expression, $sum(X_{r\eth})$ is the sum of elements of a row matrix $X_{r\eth}$ that takes a form given in Pinjari and Bhat (*38*). The parameters are estimated using a maximum likelihood estimation approach.

3. EMPIRICAL ANALYSIS

3.1 Data Sources and Sample Description

The primary source of data used for this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS), designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC). The survey collected information on all activity episodes (in-home and out-of-home) undertaken by individuals from over 15,000 households in the Bay Area for a two-day period. Information characterizing the context (activity type, start and end times of the activity, and location of participation) of each activity episode was collected. Furthermore, data on individual and household socio-demographics was also obtained. In addition to the 2000 BATS data, several other secondary data sources were used to derive spatial variables characterizing the activity-travel environment in the region.[3]

The final estimation sample consists of 4903 workers in the San Francisco Bay area. Each worker in the sample commuted to her/his workplace on the travel day. A descriptive analysis of the sample revealed the strong presence of multiple discreteness. That is, a significant percentage of workers in the sample chose more than one combination of activity purpose and timing during the course of the day.

[3] The details of these secondary data sources and the sample formation process are being suppressed here due to space considerations, but are available from the authors.

3.2 Empirical Results

The final specification results of the MDCNEV model are presented in Table 1. The in-home activity purpose serves as the base activity purpose category and the before work time period serves as the base activity timing category for most (but not all) variables. Further, the model is specified (and the results are presented) in such a way that the effect of each variable is first identified separately along the activity purpose and activity timing dimensions. Subsequently, any interaction effects of the variable over and beyond the unidimensional effects are identified. A '-' entry corresponding to the effect of a variable for a particular activity purpose in the top "activity purpose dimension" panel of Table 1 indicates no significant effect of the variable on the corresponding activity purpose utility. The same holds for the "activity timing dimension" panel and the "activity purpose-activity timing" panel. Further, the effects of variables on the baseline utilities have been constrained to be equal in Table 1 if coefficient equality cannot be rejected based on statistical tests.

3.2.1 Effects of Household Demographics on Baseline Utility

Among the household demographic variables, household structure was introduced into the baseline utility as three sets of dummy variables (one each for single member households, couple households, and households with children), and two ordinal variables (one each for the number of unemployed adults and the number of employed adults). Among the dummy variables, the coefficients on the single member household variable indicate that workers who live alone are more likely to participate in out-of-home (OH) socializing and OH recreational activities, compared to workers not living alone. This is perhaps a reflection of the basic human need to socialize and interact with other individuals. Further, such individuals may have a relatively larger amount of time available for socializing/recreation due to lesser household responsibilities [see (*6*) for similar results]. With respect to the timing of OH non-work activity participations, workers living alone have the highest propensity of participation during the post home-arrival period and the least propensity during the commutes. These effects are similar to the findings of other studies (*14, 39*). The preference for the post home-arrival time period could be a manifestation of lesser household responsibilities and greater available free time after coming home from work (relative to workers who are non-single).

The coefficients on the couple family household dummy variable indicate that workers in couple households are associated with a lower baseline preference toward pickup/drop-off activities, when compared to workers living alone or those with children. With respect to the timing of OH non-work activities, the most preferred time period for workers living as a couple is the post home-arrival period (although this preference is not as strong as for workers living alone). As with workers living alone, workers living as a couple may have less familial responsibilities and greater available time (when compared to workers with children at home) to pursue non-work activities after their mandatory work activities in the day.

The coefficients associated with households with children offer very plausible interpretations. For example, workers from households with young children (of less than 5 years of age) are more inclined toward in-home activities (perhaps, activities such as child-care and household chores) and pickup/drop-off activities (quite possibly for trips to/from day care centers). Also, as one would expect, the OH non-work activities of these workers (which are more likely to be pickup/drop-off trips from/to day care centers, as identified before) are most likely to be during their commutes. Interestingly, with the presence of older children (of age between 5 and 15 years) in the household, workers are more likely to undertake pickup/drop-off activities than workers from households with younger children. This is perhaps a manifestation of the older children being school-goers and the resulting need for parents to escort these children to/from school and other activity centers (sports training, music classes, *etc.*).

The next set of household structure variables are the number of unemployed and employed adults in the household. Workers in households with several unemployed adults are more likely to spend time on OH socializing activities compared to other activity purposes. This is probably an indication of the additional time available for these workers, given that the non-workers are more likely to undertake household chores and maintenance activities for the day. With respect to activity timing, with increasing number of unemployed adults, workers are less likely to participate in OH non-work activities during commutes and post home-arrival periods relative to the before-work and work-based time periods [see (*32*) for a similar result]. Perhaps, non-worker presence at home reduces the need for worker(s) to make maintenance activity stops during the commute, and increases the propensity to spend time with other (non-working) adults at home after returning from work. Next, with the increasing number of employed individuals in the household, a worker is more likely to spend time on OH socializing and pickup/drop-off activities, compared to other non-work activities. The reason behind the effect of employed individuals on OH socializing is not clear and needs to be explored further. However, the effect on pickup/drop-off activities is reasonable, as workers from multi-worker households are likely to co-ordinate and share pickup/drop-off responsibilities. Similar to the effect of non-working adults, workers from multi-worker households are less likely to pursue their OH non-work activities during the commute periods and post home-arrival periods. This result has also been found in some earlier studies (*40*), and may suggest a preference to spend time together during the non-work times on weekdays, and pursue non-work activities jointly on weekend days.

The effect of household income is introduced in the form of dummy variables, with the "*low income*" category (annual income < 45K) being the base. The coefficient on the high income dummy variable (income > 100K) in Table 1 indicates that workers from high income households are less likely to participate in maintenance shopping and socializing on working days. One possible reason for this is that, relative to middle and low income workers, high income wage earners may have increased office responsibilities, thus being more time-constrained on workdays. With respect to activity timing, the income coefficients in the second panel of Table 1 reveal that workers from higher income households are more inclined than workers from lower income households to undertake non-work activities during the work-based and post home-arrival periods (*32, 39*).

The race variable effects suggest a lower participation propensity of Asian workers (relative to workers of Caucasian and other races) for OH recreation, shopping and socializing activities. However, there appears to be no race-based differences in activity timing preferences.

Finally, within the category of household demographics, the coefficients on the number of bicycles show a positive association between bicycle ownership and OH recreational activity participation. Further, high bicycle ownership in a household decreases the worker's preference for OH non-work activity participation during the home-to-work and work-to-home commutes, but increases the preference for OH non-work activity participation during the before-work period. This may be because bicycle owners are health/environment-conscious and, consequently, may bike to work (hence reducing the likelihood of commute stops) and/or participate in physically active recreational activities/travel during early morning hours as a way of maintaining physical fitness. These findings suggest that policies and educational campaigns aimed at increasing bicycle ownership not only can lead to traffic congestion alleviation, but can also play an important role in improving public health (*14*).

3.2.2 Effects of Individual Demographics on Baseline Utility

Among the individual demographic variables, the female sex dummy variable highlights the role of gender in non-work activity time-use and timing. Specifically, female workers, relative to male workers, are more inclined to participate in OH personal business, socializing, non-maintenance shopping and pickup/drop-off activities during the working day [see (*41*) for a similar finding]. Also, female workers are more likely to participate in OH non-work activities during the work-to-home commute, and less likely to do so during work-based and post home-arrival periods. The timing preferences of female workers could be related to their higher household responsibilities and child care needs at home in the post home-arrival period (*13, 42*). Further, female workers who use automobiles to commute to work have a high likelihood of participating in pickup/drop-off activities during the home-to-work commute period, and in OH maintenance shopping activities during the work-to-home commute and post home-arrival periods (*9, 41*).

The age variable effects show that older workers, relative to younger workers, are less likely to participate in OH meal, recreation and pickup/drop-off activities. On the other hand, older workers are more likely to participate in maintenance shopping and personal business activities. The relatively lower propensity of older workers to participate in leisure activities, and higher likelihood to participate in basic maintenance activities, has been well documented in the literature (*6*). Older workers are also less likely to pursue OH non-work activities in the post home-arrival period and more likely to participate in OH non-work activities during the work-to-home commute [see Steed and Bhat (*26*) for similar findings].

The next variable is associated with workers' work schedule flexibility (respondents reported whether they had no flexibility in start/end times, about 30 minutes (but not more) of flexibility at either end, or complete flexibility at both ends). The results suggest that workers with fully flexible work schedules show a strong preference toward all OH non-work activities relative to in-home activities. With regard to the timing decisions, these workers are less likely to undertake OH non-work trips during the work-to-home commute and post home-arrival periods, relative to the earlier parts of the day. While the activity participation increase due to flexible work schedules is expected (*32*), the effect of flexible work arrangements on timing decisions is rather interesting. Perhaps, workers choose to undertake non-work activities (jogging, drop-off of child at school, trip to the bank, paying bills, shopping for groceries, *etc.*) either before getting to work (due to the flexibility in work start time) or during work (again due to flexibility). Another likely explanation is that workers who choose to spend more of post home-arrival time at home with their family may be self-selecting themselves into work arrangements with flexible schedules. Given that flexible work arrangements are linked to job satisfaction, employee productivity and the overall health of the employees (*43*), the impacts of such arrangements on worker's activity-travel patterns is an important area for policy analysis. With more and more organizations adopting such flexible work schedule policies, the results obtained in this study should be examined further in future research efforts.

There are no main effects of full-time employment on the activity purpose dimension. However, in terms of activity timing, full-time employed individuals show a generally higher propensity than part-time employees to participate in OH non-work activities before their arrival home at the end of the workday, after which they are more likely to remain at home. The interaction effects of the full-time employment variable in the third panel of Table 1 further indicate that full-time employees are more likely to undertake pickup/drop-off activities during the home-to-work commute, OH meal activities during the work-based period, and OH recreation activities during the post home-arrival period.

The final individual demographic variable is the natural logarithm of the "length of the time window available for non-work activities (in minutes)" during different time periods of the day. This variable is computed as the time duration between the work start time and 3 AM minus the direct home-to-work auto commute time for the before-work period, the duration between the work start and end times minus the reported work duration time for the work-based period, and the duration between 3 AM of the next day and work end time minus the work-to-home auto commute time for the after-work period. As expected, the results suggest an increase in OH non-work activity participation as the length of the available time window of a time period increases.

3.2.3 Effects of Commute Characteristics on Baseline Utility

Three specific commute characteristics turned out to be statistically significant in the final model specification: (1) one-way no-stop commute time (in minutes), (2) one-way no-stop commute cost (in $), and (3) a dummy variable for the worker's commute mode choice being auto.

From the corresponding estimation results in Table 1, it can be observed that as commute time increases, workers are more likely to participate in in-home activities, and less likely to pursue OH non-work activities in the before-work period. These are clear manifestations of time constraints imposed by the longer commute. Another likely reason for the preference to stay at home is the fatigue associated with longer travel, which may make the commuters averse to additional travel for OH non-work activities.

The commute cost effect is interesting, and suggests that workers tend to chain non-work activities with their commutes, or pursue non-work activities during the before-work period, as commute costs increase. The commute chaining effect is potentially a strategy adopted by commuters to reduce overall transportation costs, by obviating the need to pursue separate out-of-home travel from home. To our knowledge, this is the first study to document this increased chaining effect in response to an increase in commute costs. The suggestion is that there may be more traffic delays and congestion caused by chaining in the rush hours in today's era of rising fuel prices.

Finally, workers who commute by auto have a high baseline preference for OH maintenance shopping, personal business and pickup/drop-off activities. With respect to the timing preferences, workers who commute by auto are more likely to pursue OH non-work activities during the home-work commute, work-home commute, and the work-based periods of the day. These effects are intuitive and reasonable, as personal vehicles lend greater mobility to the worker, facilitating additional activity stops that may be made during commutes and while at work (*39*).

3.2.4 Effect of Activity-Travel Environment Attributes on Baseline Utility

The coefficients of the activity-travel environment variables show the effects of the availability of activity opportunities on workers' OH non-work activity participation. For example, a high retail employment density (per acre) within a 0.25 mile radius of a worker's household is associated with a high baseline preference for non-work activity participation during the home-to-work commute, work-to-home commute, and post home-arrival periods. It is interesting, however, that retail employment density variable is not associated with any differences in preference among various OH non-work activity types.

In the context of service employment, individuals working in high service employment density zones show a high propensity to participate in OH meals and personal business activities, both during the work-based period. Also, a high density of eat-out centers in a worker's home zone significantly increases his/her baseline preference for OH meal activities. The eat-out center density, however, does not have an impact on activity timing preferences.

Finally, among the activity-travel environment attributes, the length of bicycle lanes within a 0.25 mile radius of a household is associated with a higher participation of workers in OH recreational pursuits, possibly for physically active recreation such as bicycling for fun.

An important note is in order here regarding the interpretation of the effect of household location variables. In the current analysis, household residential location is considered as an exogenous choice in the modeling of activity timing and time-use. However, it is conceivable that households choose their location of residence based on their time-allocation and timing preferences, in which case the location effects are really correlations and not causal effects. Accommodating this self selection of households into neighborhoods and investigating its effect on activity timing and time-use is beyond the scope of the current research [see Pinjari *et al.* (*14*) for related research].

3.2.5 Baseline Preference Constants

The baseline preference constants (final part of Table 1) do not have any substantive interpretations. They capture generic tendencies to participate in each activity type-time period category as well as accommodate the range of the continuous independent variables in the model. However, all the baseline preference constants are negative, indicating the high participation level of workers in in-home activities relative to OH non-work activities.

3.2.6 Satiation Parameters

The satiation parameter γ_k (k = 2, 3,..., K) for the "inside" goods (*i.e.*, the 35 activity purpose-timing alternatives) influence the length of participation in any alternative. Specifically, the higher the value of γ_k, the less is the satiation effect in the consumption of the alternative k (*37*).

The last part of Table 1 provides the estimated values of γ_k and the corresponding t-statistic values. The satiation parameters are introduced dimension-wise in the model specification. That is, instead of estimating 35 satiation parameters (one for each activity purpose-timing combination alternative), 11 satiation parameters were estimated to distinguish the satiation effects for each of the 7 OH non-work activity purposes and an additional 4 satiation parameters were estimated to distinguish satiation effects for four time periods (the before-work time period satiation parameter was fixed at 1.00 due to "estimability" considerations, given the low sample size of participations in this period). The dimension-wise estimates are shaded in Table 1. From such dimension-wise γ estimates, as explained in Section 2.1, the satiation parameters for each of the 35 activity purpose-timing combination alternatives have been obtained through appropriate combination of the dimension-wise estimates.[4] From the t-statistics provided in Table 1, it can be observed that significant satiation effects exist in the time

[4] Hence, from Table 5, the γ_k estimate for work-based-meals is (0.992)×(30.646) = 30.401. The appropriate t-statistics (against zero) are also shown in the table.

investment patterns of each activity purpose-timing combination. Overall, the results show that post home-arrival time period activity participations and OH socializing activity participations are associated with low satiation (hence high durations), while the before-work period activity participations and OH pickup/drop-off activity participations are associated with high satiation (hence low durations). It can also be observed that workers have very low satiation for (*i.e.*, spend long durations on) OH socializing and recreation in the post home-arrival period. On the other hand, workers show the highest satiation for (*i.e.*, spend short durations on) pickup/drop-off activities undertaken during the home-to-work commute period.

3.2.7 Nesting Parameters

Several nesting structures were considered and later refined based on intuitive and statistical considerations. The final specification included three nests – (1) Nest 1 includes all pickup/drop-off activities undertaken through the day, starting from the home-to-work commute, (2) Nest 2 includes OH socializing and recreation during the work-to-home commute, along with all activity types during the post home-arrival period, except OH personal business, and (3) Nest 3 includes OH meals in both commutes and work-based periods, OH personal business during work-based and work-home commute, OH maintenance and non-maintenance shopping during work-home commute. Figure 2 graphically represents these nests, along with parameter estimates for each nest. The nesting parameter for Nest 1 is 0.80 (with a t-statistic of 5.76), while those of Nests 2 and 3 are 0.94 (t-statistic of 3.01) and 0.93 (t-statistic of 2.86), respectively.[5]

3.2.8 Likelihood-Based Measures of Fit

The log-likelihood value for the MDCEV model with only the constants in the baseline preference (and with the satiation/translation parameters) is -43,523.5. The log-likelihood value at convergence of the MDCEV model with the above-discussed explanatory variables is -41,434.4. For the MDCNEV model with the above-discussed explanatory variables and with three additional parameters for the three nests (see Figure 2), the log-likelihood at convergence is -39,307.5. The likelihood ratio between the final MDCNEV and the MDCEV models is 4253.8, which is substantially larger than the critical chi-square value with 3 restrictions (one for each nest) at any reasonable level of significance. Further, the adjusted Rho-bar squared value (relative to the constants-only model) increases from 0.05 for the MDCEV model to 0.10 for the MDCNEV model, indicating the importance of nesting structure from a goodness-of-fit standpoint.

4. SUMMARY AND CONCLUSIONS

This study contributes to the literature on activity time-use and activity timing analysis by developing a comprehensive, high resolution, out-of-home non-work activity generation model that considers daily activity time-use behavior and activity timing preferences in a unified framework. More specifically, a random utility maximization-based model is formulated to predict workers' activity participation and time allocation patterns in seven types of out-of-home non-work activities at various time periods of the day. From a methodological standpoint, this study uses an advanced multiple discrete-continuous nested extreme value (MDCNEV) model, which recognizes the possibility of multiple activity/timing choices for a given time period/activity type. In addition to the recognition of such multiple choices, the model accommodates activity type specific and activity timing specific satiation effects in time

[5] These statistics are computed for the null hypothesis that the nesting parameters are equal to 1.

allocation behavior. Further, the “nested extreme value” model structure allows for flexible substitution patterns in activity time-use behavior across activity purposes and time periods. At the same time, the model provides closed form probability expressions. Finally, an appealing feature of the unified, closed-form, comprehensive model presented in this study is its applicability in regional activity-based travel demand microsimulation models. The knowledge of the activities (and the corresponding time allocations and timing decisions) predicted by this model can be used for subsequent detailed scheduling and sequencing of activities and related travel in an activity-based microsimulation framework. Empirical analysis using data from the 2000 Bay Area Travel Survey provides several insights into the determinants of workers’ non-work activity time-use and timing decisions. The model developed in the current study was also used to predict the impact of policy measures (such as an increase in commute time and commute cost, and changes in accessibility indices) on activity-timing and time-use. These details have been suppressed here due to space considerations. Interested readers are referred to Rajagopalan (*44*) for more details on these policy analyses.

The research in this paper may be extended to jointly model activity time-use and timing decisions, activity sequencing and scheduling decisions, and travel-related decisions. This is an important area for future research that the authors are currently pursuing.

ACKNOWLEDGEMENTS

The authors acknowledge the helpful comments of four anonymous reviewers on an earlier version of the paper. The authors are also grateful to Lisa Macias for her help in typesetting and formatting this document.

REFERENCES

1. Pas, E.I., and A.S. Harvey. Time Use Research and Travel Demand Analysis and Modeling. In Stopher, P.R., and Lee-Gosselin, M. (eds.) *Understanding Travel Behavior in an Era of Change*, pp. 315-338, Elsevier, Oxford, 1997.

2. Bhat, C.R., and F.S. Koppelman. Activity-Based Modeling of Travel Demand. In R.W. Hall (ed.) *The Handbook of Transportation Science*, Kluwer Academic Publishers, Norwell, Massachusetts, 1999, pp. 35-61.

3. Kurani, K.S., and M.E.H. Lee-Gosselin. Synthesis of Past Activity Analysis Applications. Presented at the Travel Model Improvement Program (TMIP) Conference on Activity-Based Travel Forecasting, New Orleans, June 2-5, 1996.

4. Pendyala, R.M., and K.G. Goulias. Time Use and Activity Perspectives in Travel Behavior Research. *Transportation*, Vol. 29, No. 1, 2002, pp. 1-4.

5. Arentze, T.A., and H.J.P. Timmermans. A Learning-Based Transportation Oriented Simulation System. *Transportation Research Part B,* Vol. 38, No. 7, 2004, pp. 613-633.

6. Yamamoto, T., and R. Kitamura. An Analysis of Time Allocation to In-Home and Out-of-Home Discretionary Activities across Working Days and Non-Working Days. *Transportation*, Vol. 26, No. 2, 1999, pp. 211-230.

7. Bhat, C.R., and R. Misra. Discretionary Activity Time Allocation of Individuals Between In-home and Out-of-home and between Weekdays and Weekends. *Transportation,* Vol. 26, No. 2, 1999, pp. 119-139.

8. Meloni, I., E. Spissu, and M. Bez. A Model of the Dynamic Process of Time Allocation to Discretionary Activities. *Transportation Science,* Vol. 41, No. 1, 2007, pp. 15-28.

9. Chen, C., and P. Mokhtarian. Tradeoffs between Time Allocations to Maintenance Activities/Travel and Discretionary Activities/Travel. *Transportation*, Vol. 33, No. 3, 2006, pp. 223-240.

10. Lu, X., and E.I. Pas. Socio-Demographics, Activity Participation and Travel Behavior. *Transportation Research Part A,* Vol. 33, No. 1, 1999, pp. 1-18.

11. Meka, S., R.M. Pendyala, and M.A. Wasantha Kumara. A Structural Equations Analysis of Within-Household Activity and Time Allocation between Two Adults. Presented at the 81st Annual Meeting of the Transportation Research Board, Washington, D.C., 2002.

12. Fujii, S., R. Kitamura, and K. Kishizawa. Analysis of Individuals' Joint Activity Engagement Using a Model System of Activity-Travel Behavior and Time Use. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1676,* Transportation Research Board of the National Academies, Washington, D.C., 1999, pp.11-19.

13. Bhat, C.R. A Model of Post Home-Arrival Activity Participation Behavior. *Transportation Research Part B,* Vol. 32, No. 6, 1998, pp. 387-400.

14. Pinjari, A.R., C.R. Bhat, and D.A. Hensher. Incorporating Residential Self-Selection Effects in Activity Time-use Behavior: Formulation and Application of a Joint Mixed Multinomial Logit – Multiple Discrete-Continuous Extreme Value Model. Technical paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, 2007.

15. Srinivasan, K.K., and S.R. Athuru. Analysis of Within-Household Effects and Between Household Differences in Maintenance Activity Allocation. *Transportation*, Vol. 32, No. 5, 2005, pp. 495-521.

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

17. Vovsha P., E. Petersen, and R. Donnelly. A Model for Allocation of Maintenance Activities to the Household Members. Presented at the 83rd Annual Meeting of the Transportation Research Board, Washington, D.C, 2004.

18. Kuppam, A.R. and R.M. Pendyala. A Structural Equations Analysis of Commuter Activity and Travel Patterns. *Transportation*, Vol. 28, No. 1, 2001, pp. 33-54.

19. Gliebe, J.P., and F.S. Koppelman. A Model of Joint Activity Participation Between Household Members. *Transportation*, Vol. 29, No. 1, 2002, pp. 49-72.

20. Kharoufeh, J.P., and K.G. Goulias. Nonparametric Identification of Daily Activity Durations using Kernel Density Estimators. *Transportation Research Part B*, Vol. 36, No. 1, 2002, pp. 59-82.

21. Lee, M., and M.G. McNally. On the Structure of Weekly Activity/Travel Patterns. *Transportation Research Part A*, Vol. 37, No. 10, 2003, pp. 823-839.

22. Ben-Akiva, M., and J.L. Bowman. Integration of an Activity-based Model System and a Residential Location Model. *Urban Studies,* Vol. 35, No. 7, 1998, pp. 1131-1153.

23. Pinjari, A.R., N. Eluru, R. Copperman, I.N. Sener, J.Y. Guo, S. Srinivasan, and C.R. Bhat. Activity-Based Travel-Demand Analysis for Metropolitan Areas in Texas: CEMDAP Models, Framework, Software Architecture and Application Results. Research Report 4080-8, Center for Transportation Research, The University of Texas at Austin, 2006.

24. Arentze, T.A., and H.J.P. Timmermans. Albatross Version 2: A Learning-Based Transportation Oriented Simulation System. European Institute of Retailing and Services Studies, Eindhoven, The Netherlands, 2005.

25. Small, K.A. The Scheduling of Consumer Activities: Work Trips. *The American Economic Review*, Vol. 72, No. 3, 1982, pp. 467-479.

26. Steed, J., and C.R. Bhat. On Modeling the Departure Time Choice for Home-Based Social/Recreational and Shopping Trips. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1706*, Transportation Research Board of the National Academies, Washington, D.C., 2000, pp. 152-159.

27. Hess, S., J.W. Polak, A.J. Daly, and G. Hyman. Flexible Substitution Patterns in Models of Mode and Time-of-day Choice: New Evidence from the UK and The Netherlands. *Transportation,* Vol. 34, No. 2, 2007, pp. 213-238.

28. Ettema, D., A. Borgers, and H.J.P. Timmermans. Competing Risk Hazard Model of Activity Choice, Timing, Sequencing, and Duration. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1493*, Transportation Research Board of the National Academies, Washington, D.C., 1995, pp. 101-109.

29. Bhat, C.R., and J.L. Steed. A Continuous-Time Model of Departure Time Choice for Urban Shopping Trips. *Transportation Research Part B*, Vol. 36, No. 3, 2002, pp. 207-224.

30. Ettema, D., F. Bastin, J. Polak, and O. Ashiru. Modelling the Joint Choice of Activity Timing and Duration. *Transportation Research Part A,* Vol. 41, No. 9, 2007, pp. 827-841.

31. Yamamoto, T., S. Fujii, R. Kitamura, and H. Yoshida. Analysis of Time Allocation, Departure Time, and Route Choice Behavior under Congestion Pricing. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1725*, Transportation Research Board of the National Academies, Washington, D.C., 2000, pp. 95-101.

32. Chu, Y. Modeling Workers' Daily Nonwork Activity Participation and Duration. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1926*, Transportation Research Board of the National Academies, Washington, D.C., 2005, pp. 10-18.

33. Pendyala, R.M. and C.R. Bhat. An Exploration of the Relationship between Timing and Duration of Maintenance Activities. *Transportation,* Vol. 31, No. 4, 2004, pp. 429-456.

34. Ashiru, O., J.W. Polak, and R.B. Noland. The Utility of Schedules: A Theoretical Model of Departure Time Choice and Activity Time Allocation with Application to Individual Activity Schedules. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1894*, Transportation Research Board of the National Academies, Washington, D.C., 2004, pp. 84-98.

35. Joh, C-H., T. Arentze, F. Hofman, and H.J.P. Timmermans. Activity Pattern Similarity: A Multi-Dimensional Sequence Alignment Method. *Transportation Research Part B,* Vol. 36, No. 7, 2002, pp. 385-403.

36. Bhat, C.R., and S.K. Singh. A Comprehensive Daily Activity-Travel Generation Model System for Workers. *Transportation Research Part A,* Vol. 34, No. 1, 2000, pp. 1-22.

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

38. Pinjari, A.R., and C.R. Bhat. A Multiple Discrete Continuous Nested Extreme Value Model: Formulation and Application to Non-workers' Activity Time-use and Timing Decisions. Working Paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, 2008.

39. Gangrade, S., R.M. Pendyala, and R.G. McCullough. Nested Logit Model of Commuters' Activity Schedules. *Journal of Transportation and Statistics,* Vol. 5, No. 2-3, 2002, pp. 19-36.

40. Zhang, J., H.J.P. Timmermans, and A. Borgers. Utility-Maximizing Model of Household Time Use for Independent, Shared, and Allocated Activities Incorporating Group Decision Mechanisms. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1807,* Transportation Research Board of the National Academies, Washington, D.C., 2002, pp. 1-8.

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

42. Bradley, M., and P. Vovsha. A Model for Joint Choice of Daily Activity Pattern Types of Household Members. *Transportation*, Vol. 32, No. 5, 2005, pp. 545-571.

43. Martens, M.F.J., F.J.N. Nijhuis, M.P.J. van Boxtel, and J.A. Knottnerus. Flexible Work Schedules and Mental and Physical Health: A Study of a Working Population with Non-Traditional Working Hours. *Journal of Organizational Behavior,* Vol. 20, No. 1, 1999, pp. 35-46.

44. Rajagopalan, B.S. Modeling Workers' Non-work Timing and Time-use Behavior. M.S. Thesis, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, Austin, Texas, 2008.

LIST OF FIGURES

LIST OF TABLES

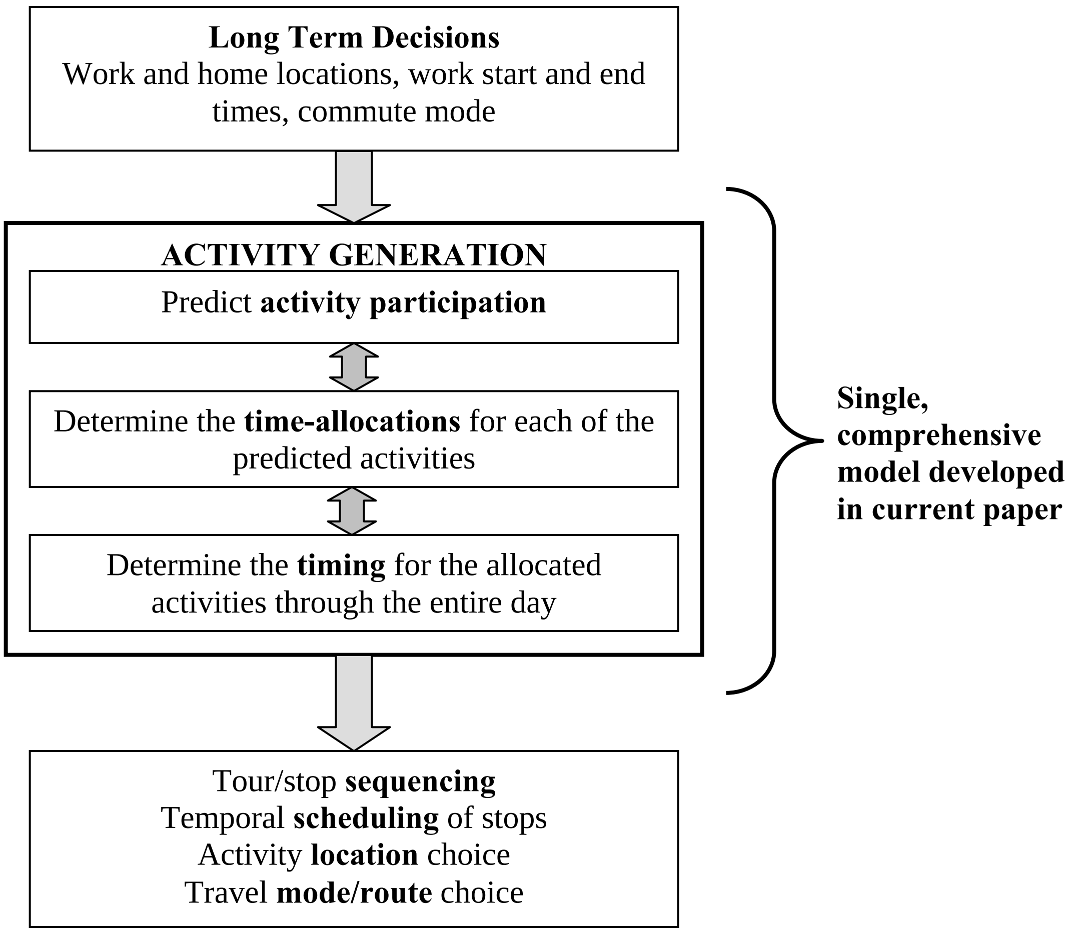

FIGURE 1 Schematic positioning of current paper's work in an activity-based travel demand microsimulation framework.

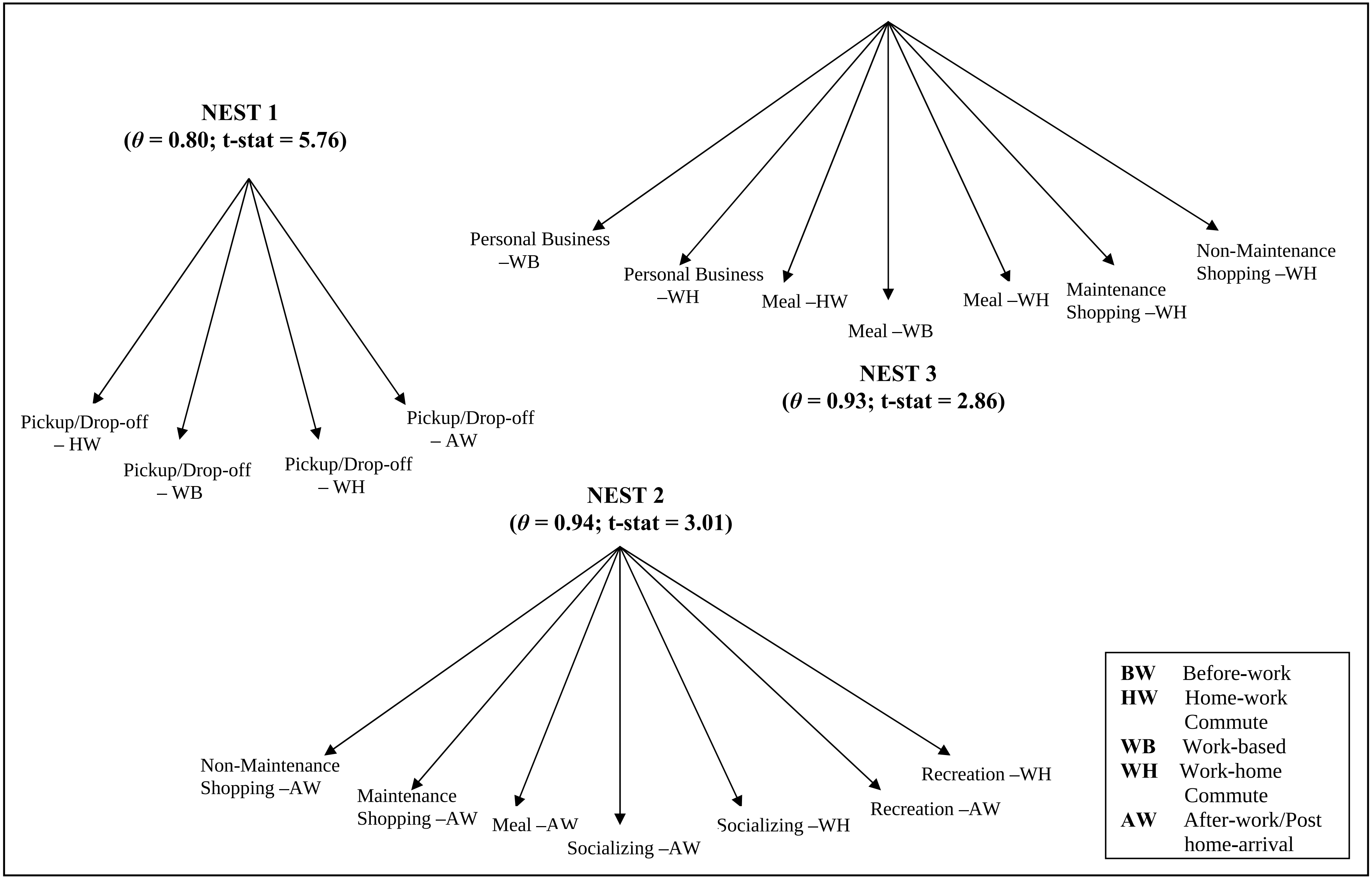

FIGURE 2 Schematic representation of the nests implemented in the MDCNEV model and their parameter estimates.

TABLE 1 The MDCNEV Model Results: Baseline Utility Parameters

	Household Demographics							
	Household Structure						Household Annual Income (1,000s of dollars)	
	Single Member	Couple (married/ unmarried)	Kids of age < 5yrs present	Kids of age 5-15 yrs present	# of unemployed adults in HH	# of employed adults in HH	Medium (45-100)	High (>100)
'Activity Type' Dimension								
In-home Activities (Outside good)	-	-	0.336 (4.87)	-	-	-	-	-
OH Meal	-	-	-	-	-	-	-	-
OH Recreation	0.212 (2.44)	-	-	-	-	-	-	-
OH Non-Maintenance Shopping	-	-	-	-	-	-	-	-
OH Maintenance Shopping	-	-	-	-	-	-	-	-0.294 (-3.73)
OH Personal Business	-	-	-	-	-	-	-	-
OH Socializing	0.212 (2.44)	-	-	-	0.202 (1.32)	0.109 (1.21)	-	-0.294 (-3.73)
OH Pickup/Drop-off	-	-0.237(-1.82)	0.705 (6.78)	1.404 (14.71)	-	0.345 (5.13)	-	-
'Activity Timing' Dimension								
Before Work	-	-	-	-	-	-	-	-
Home-work Commute	-0.248 (-2.32)	-	0.336 (4.87)	-	-0.436 (-3.53)	-0.311 (-3.62)	-	-
Work-Based	0.192 (2.28)	-	-	-	-	-	0.176 (3.23)	0.328 (3.71)
Work-Home Commute	-0.248 (-2.32)	-	0.336 (4.87)	-	-0.558 (-4.64)	-0.343 (-4.22)	-	-
Post home-arrival	0.245 (2.59)	0.156 (2.58)	-	-	-0.123 (-1.55)	-0.080 (-1.40)	0.176 (3.23)	0.395 (6.00)
Activity Type-Activity Timing	-	-	-	-	-	-	-	-
Pickup/Drop-off – Home-work Commute	-	-	-	-	-	-	-	-
Maintenance Shopping – Work-Home Commute	-	-	-	-	-	-	-	-
Maintenance Shopping – Post home-arrival	-	-	-	-	-	-	-	-
Meal – Work-based	-	-	-	-	-	-	-	-
Personal Business – Work-based	-	-	-	-	-	-	-	-
Recreation – Post home-arrival	-	-	-	-	-	-	-	-
Maintenance Shopping – Post home-arrival	-	-	-	-	-	-	-	-

TABLE 1 (continued) The MDCNEV Model Results: Baseline Utility Parameters

	HH Demographics		Individual Demographics					
	Race							
	Asian	#of bicycles in HH	Female	Female interacted with "Auto Commute"	Worker's Age (Continuous Variable)	Fully Flexible Work Hours	Full-time Employed?	Length of Time Window for Non-Work Activities (natural log)
'Activity Type' Dimension								
In-home Activities (Outside good)	-	-	-	-	-	-	-	-
OH Meal	-0.205 (-2.21)	-	-	-	-0.011 (-4.96)	0.133 (2.36)	-	-
OH Recreation	-0.273 (-2.93)	0.087 (3.33)	-	-	-0.011 (-4.96)	0.133 (2.36)	-	-
OH Non-Maintenance Shopping	-0.273 (-2.93)	-	0.191 (2.15)	-	-	0.133 (2.36)	-	-
OH Maintenance Shopping	-	-	-	-	0.012 (4.01)	0.133 (2.36)	-	-
OH Personal Business	-	-	0.437 (6.74)	-	0.012 (4.01)	0.133 (2.36)	-	-
OH Socializing	-0.273 (-2.93)	-	0.257 (2.29)	-	-	0.133 (2.36)	-	-
OH Pickup/Drop-off	-	-	0.437 (6.74)	-	-0.011 (-4.96)	0.133 (2.36)	-	-
'Activity Timing' Dimension								
Before Work	-	0.089 (2.16)	-	-	-	-	0.237 (1.57)	3.744 (20.84)
Home-work Commute	-	-0.014 (-0.76)	-	-	-	-	0.506 (4.52)	-
Work-Based	-	-	-0.064 (-1.38)	-	-	-	0.661 (3.23)	2.096 (17.06)
Work-Home Commute	-	-0.014 (-0.76)	0.119 (1.47)	-	0.008 (2.04)	-0.229 (-2.57)	0.506 (4.52)	-
After Work	-	-	-0.064 (-1.38)	-	-0.016 (-6.44)	-0.133 (-2.36)	-	0.641 (21.49)
'Activity Type-Activity Timing'	-	-			-	-	-	-
Pickup/Drop-off – Home-work Commute	-	-	-	0.186(2.33)	-	-	0.296 (2.18)	-
Maintenance Shopping – Work-Home Commute	-	-	-	0.186(2.33)	-	-	-	-
Maintenance Shopping – After-work	-	-	-	0.186(2.33)	-	-	-	-
Meal – Work-based	-	-	-	-	-	-	0.589 (2.23)	-
Personal Business – Work-based	-	-	-	-	-	-	-	-
Recreation – After-work	-	-	-	-	-	-	0.296 (2.18)	-
Maintenance Shopping – After-work	-	-	-	-	-	-	-	-

TABLE 1 (continued) The MDCNEV Model Results: Baseline Utility Parameters

	Commute Characteristics			Activity-Travel Environment Attributes			
	Commute Time (mins)	Commute Cost ($)	Is Commute Mode Auto?	Retail employment density within 0.25 mile radius from household (per acre)	Service Employment Density in Work Zone (per acre)	Density of eat-out centers in home zone (per acre)	Bicycling facility (kms of bike lane) within 0.25 mile radius from household
‘Activity Type’ Dimension							
In-home Activities (Outside good)	0.011 (2.32)	-	-	-	-	-	-
OH Meal	-	-	-	-	-	1.200 (3.71)	-
OH Recreation	-	-	-	-	-	-	0.034 (1.32)
OH Non-Maintenance Shopping	-	-	-	-	-	-	-
OH Maintenance Shopping	-	-	0.371 (3.41)	-	-	-	-
OH Personal Business	-	-	0.371 (3.41)	-	-	-	-
OH Socializing	-	-	-	-	-	-	-
OH Pickup/Drop-off	-	-	0.804 (3.46)	-	-	-	-
‘Activity Timing’ Dimension							
Before Work	-0.012 (-2.61)	-	-	-	-	-	-
Home-work Commute	-	-	1.414 (6.49)	0.038 (1.91)	-	-	-
Work-Based	-	-0.039 (-1.57)	0.489 (4.09)	-	-	-	-
Work-Home Commute	-	-	1.467 (6.68)	0.038 (1.91)	-	-	-
Post home-arrival	-	-0.039 (-1.57)	-	0.016 (1.15)	-	-	-
Activity Type-Activity Timing		-		-	-	-	-
Pickup/Drop-off – Home-work Commute	-	-	-	-	-	-	-
Maintenance Shopping – Work-Home Commute	-	-	-	-	-	-	-
Maintenance Shopping – Post home-arrival	-	-	-	-	-	-	-
Meal – Work-based	-	-	-	-	0.002 (2.73)	-	-
Personal Business – Work-based	-	-	-	-	0.002 (2.73)	-	-
Recreation – Post home-arrival	-	-	-	-	-	-	-
Maintenance Shopping – Post home-arrival	-	-	-	-	-	-	-

TABLE 1 (continued) The MDCNEV Model Results: Baseline Preference Constants

ACTIVITY TIMING	ACTIVITY TYPE							
	In-home Activities *(base alternative)*	Out-of-home Non-work Constants (t-statistics)						
		Meal	Recreation	Non-Maintenance Shopping	Maintenance Shopping	Personal Business	Socializing	Pickup/ Drop-off
Before-work	-	-32.847 (-26.86)	-31.687 (-27.54)	-33.368 (-27.91)	-33.835 (-28.66)	-33.586 (-28.40)	-34.407 (-27.59)	-33.983 (-28.42)
Home-work Commute	-	-10.712 (-32.96)	-14.146 (-20.99)	-12.039 (-34.83)	-12.121 (-35.25)	-12.271 (-35.44)	-13.873 (-26.19)	-12.528 (-29.72)
Work-based	-	-11.844 (-38.66)	-13.296 (-41.77)	-13.076 (-44.50)	-14.262 (-42.04)	-14.345 (-41.71)	-14.799 (-37.42)	-15.734 (-38.42)
Work-home Commute	-	-11.769 (-31.84)	-13.722 (-30.34)	-11.659 (-31.64)	-12.110 (-32.94)	-12.829 (-33.77)	-13.575 (-30.09)	-12.900 (-32.63)
Post home-arrival	-	-21.221 (-26.70)	-21.659 (-26.45)	-22.113 (-27.49)	-23.158 (-28.80)	-22.523 (-27.61)	-22.470 (-27.80)	-23.992 (-28.17)

TABLE 1 (continued) The MDCNEV Model Results: Satiation (γ) Parameters

ACTIVITY TIMING	γ estimates for activity timing (t-statistics)	Gamma Estimates for Activity Types (t-statistics)							
		In-home Activities	Out-of-home Non-work Activities						
			Meal	Recreation	Non-Maintenance Shopping	Maintenance Shopping	Personal Business	Socializing	Pickup/ Drop-off
		-	30.646 (6.70)	64.988 (5.89)	21.785 (6.11)	15.770 (5.83)	16.016 (6.64)	87.997 (4.80)	7.209 (6.94)
Before-work	-	-	30.646 (6.69)	64.988 (5.89)	21.785 (6.11)	15.770 (5.83)	16.016 (6.64)	87.997 (4.80)	7.209 (6.94)
Home-work Commute	0.411 (5.91)	-	12.596 (4.43)	26.710 (4.17)	8.954 (4.25)	6.481 (4.15)	6.583 (4.42)	36.167 (3.73)	2.963 (4.50)
Work-based	0.992 (6.36)	-	30.401 (4.61)	64.468 (4.32)	21.611 (4.40)	15.644 (4.30)	15.888 (4.59)	87.293 (3.83)	7.151 (4.68)
Work-home Commute	0.796 (6.23)	-	24.394 (1.87)	51.730 (1.76)	17.341 (1.79)	12.553 (1.75)	12.749 (1.87)	70.046 (1.56)	5.738 (1.90)
Post home-arrival	1.812 (7.08)	-	55.531 (4.83)	117.758 (4.49)	39.474 (4.58)	28.575 (4.46)	29.021 (4.80)	159.451 (3.94)	13.063 (4.91)