

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

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## **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 framework. More specifically, a random utility maximization-based model is formulated to simultaneously 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 choices of activity purpose and timing. Further, the "nested extreme value" model structure allows for flexible substitution patterns in activity time-use behavior across different activity types and/or across different time periods. At the same time, the model provides closed-form probability expressions. 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' activity time-use and timing behavior. The results have several important policy applications. Also, 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 (see Pas and Harvey, 1997; and Bhat and Koppelman, 1999). 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 (see Kurani and Lee-Gosselin, 1996). 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 (Bhat and Koppelman, 1999; Pendyala and Goulias, 2002; Arentze and Timmermans, 2004). 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 (for example, see Yamamoto and Kitamura, 1999; Bhat and Misra, 1999; Jara-Diaz and Guevara, 2003; Meloni *et al.*, 2007; Bhat, 2005; and Chen and Mokhtarian, 2006), while others are based on theories other than utility theory (see, for example, Lu and Pas, 1999; Meka *et al.*, 2002; Fujii *et al.*, 1999; and Bhat, 1998). From an activity purpose viewpoint, several previous studies have focused on discretionary activity participation (Goulias and Henson, 2006; Meloni *et al.*, 2007; and Pinjari *et al.*, 2007), while others have focused on maintenance activity participation (Srinivasan and Athuru, 2005; Srinivasan and Bhat, 2005; Vovsha *et al.*, 2004). In addition, some studies have investigated the trade-offs and substitution effects between in-home and out-of-home activity participation (Yamamoto and

Kitamura, 1999; Kuppam and Pendyala, 2001; and Srinivasan and Bhat, 2005), 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 (see, for example, Gliebe and Koppelman, 2002; and Zhang *et al.*, 2004) and multi-day/weekly time-use behavior (see, for example, Kharoufeh, and Goulias, 2002; and Lee and McNally, 2003).

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 (see, for example, Ben-Akiva and Bowman, 1998; Pinjari *et al.*, 2006; and Arentze and Timmermans, 2005).

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 (Small, 1982; Steed and Bhat, 2000; and Hess *et al.*, 2007) or continuous-time approaches (Ettema *et al.*, 1995; and Bhat and Steed, 2002). 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 (see Ettema *et al.*, 2007), 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 (see Bhat, 1998; Yamamoto *et al.*, 2000; Joh *et al.*, 2002; Ashiru *et al.*, 2004; Chu, 2005; and Ettema *et al.*, 2007). 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, 2004 or a few discretionary activity purpose categories in Yamamoto *et al.*, 2000), or (2) They do not distinguish between

activities by purpose (see Ettema *et al.*, 2007, Ashiru *et al.*, 2004; and Chu, 2005), or (3) They consider the list of activities by purpose for participation as pre-determined before duration/timing decisions of activities (Joh *et al.*, 2002), 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, 1998) or independently (and separately) model activity time-use across different time periods of the day (such as in Chu, 2005).

### 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. The seven out-of-home activity purposes considered in this study include: (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 (2000) 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: (1) Before home-to-work commute period (or before work period)<sup>1</sup>, (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 at each of the time periods (*i.e.*, to each activity purpose-time period combination alternative). Such a joint activity time-use and activity timing 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

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<sup>1</sup> For the sake of conciseness, we will use the term "before work" period for "before home-to-work commute" period.

time allocations and timing decisions) predicted by this model can be used for the subsequent scheduling and sequencing of activities and related travel (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).

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 (2005) and Bhat (2008), 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 (2008) 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. Details of the modeling methodology are provided in Section 2. Specifics about the data source and descriptive statistics are presented in Section 3. The model estimation results are discussed in Section 4, and policy simulation results with the model are examined in Section 5. Finally, Section 6 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, and is evident from the data (see Section 3), all individuals 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  $k$  ( $k = 1, 2, \dots, K$ ), 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)<sup>2</sup>:

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

In the above expression,  $z_k$  ( $k = 1, 2, \dots, K$ ) is the vector of individual-related exogenous variables specific to alternative  $k$  ( $k = 1, 2, 3, \dots, K$ ). The term  $\exp(\beta' z_k + \varepsilon_k)$  ( $k = 1, 2, \dots, K$ ) 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  $k$ . We will refer to this term as the baseline preference for alternative  $k$ . The  $\gamma_k$  ( $\gamma_k > 0$ ) terms for  $k = 2, 3, \dots, K$  are translational parameters that allow corner solutions for the individual's time allocation problem. That is, these terms allow for the possibility that the individual invests no time in certain alternatives  $k$  ( $k = 2, 3, \dots, K$ ). There is no  $\gamma_1$  term for the first alternative because all individuals invest some positive amount of time in in-home activities (*i.e.*, only interior solutions are allowed for in-home activity). The  $\gamma_k$  terms ( $k = 2, 3, \dots, K$ ), 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. For the inside "goods" ( $k = 2, 3, \dots, K$ ), values of  $\gamma_k$  closer to zero imply higher satiation effects (*i.e.*, lower durations of time investment, subject to any time investments at all, in activity  $k$ ; see Bhat, 2008). Note that, to distinguish the activity purpose-specific satiation and activity timing-specific satiation, we reparameterize  $\gamma_k$  as  $\gamma_k = \gamma_{l_k} \times \gamma_{h_k}$ , where  $\gamma_{l_k}$  and  $\gamma_{h_k}$  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 that  $\sum_{k=1}^K t_k = T$ , where  $T$  is the time available to participate in in-home

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<sup>2</sup> Several other additive, non-linear, utility forms, as proposed by Bhat (2008), were also considered. However, the one provided below was the best form in the empirical analysis of the current paper.

and out-of-home non-work activities<sup>3</sup>. The optimal time investments  $t_k^*$  ( $k = 1, 2, \dots, K$ ) can be found by forming the Lagrangian function (corresponding to the problem of maximizing random utility  $U$  under the time budget constraint  $T$ ) and applying the Kuhn-Tucker (KT) conditions. After several algebraic manipulations, the KT conditions collapse to (see Bhat, 2008):

$$\begin{aligned}
 V_k + \varepsilon_k &= V_1 + \varepsilon_1, \text{ if } t_k^* > 0 \text{ (} k = 2, 3, \dots, K \text{)} \\
 V_k + \varepsilon_k &< V_1 + \varepsilon_1, \text{ if } t_k^* = 0 \text{ (} k = 2, 3, \dots, K \text{)}, \text{ where} \\
 V_1 &= -\ln t_1^* \text{ and} \\
 V_k &= \beta' z_k - \ln \left( \frac{t_k^*}{\gamma_k} + 1 \right) \text{ (} k = 2, 3, \dots, K \text{)}
 \end{aligned} \tag{2}$$

The stochastic KT conditions of Equation (2) can be used to write the joint probability expression of time allocation patterns if the density function of the stochastic terms (*i.e.*, the  $\varepsilon_k$  terms) is known. In the general case, let the joint probability density function of the  $\varepsilon_k$  terms be  $g(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_K)$ , and let  $M$  alternatives be chosen out of the available  $K$  alternatives. Let the time allocations to the  $M$  alternatives be  $(t_1^*, t_2^*, t_3^*, \dots, t_M^*)$ . As given in Bhat (2008), the joint probability expression for this time allocation pattern is as follows:

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

where  $J$  is the Jacobian whose elements are given by (see Bhat, 2005)

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

The specification of  $g(\varepsilon_1, \varepsilon_2, \dots, \varepsilon_K)$  (*i.e.*, the distribution of error terms) determines the form of the probability expression above. To derive the MDCNEV probability expressions,

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<sup>3</sup> 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.



Pinjari and Bhat (2008) used a nested extreme value distributed structure that has the following joint cumulative distribution:

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

In the above expression,  $\delta (= 1, 2, \dots, S_M, \dots, S_K)$  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.  $\theta_\delta (0 < \theta_\delta \leq 1; \delta = 1, 2, \dots, S_K)$  is the (dis)similarity parameter introduced to capture correlations among the stochastic components of the utilities of alternatives belonging to the  $\delta^{\text{th}}$  nest.<sup>4</sup>

Next, let  $q_1, q_2, \dots, q_{S_M}$  be the number of chosen alternatives in each of the  $S_M$  nests (hence  $q_1 + q_2 + \dots + q_{S_M} = M$ ). Using this notation, and with the nested extreme value distributed error terms, the expression in Equation (3) simplifies to the following probability expressions for the MDCNEV model (see Pinjari and Bhat, 2008 for the derivation):

$$P(t_1^*, t_2^*, \dots, t_M^*, 0, \dots, 0) = |J| \frac{\prod_{i \in \{\text{chosen alternatives}\}} e^{\frac{V_i}{\theta_i}}}{\prod_{\delta=1}^{S_M} \left( \sum_{i \in \delta^{\text{th}} \text{nest}} e^{\frac{V_i}{\theta_\delta}} \right)^{q_\delta}} \sum_{r_1=1}^{q_1} \dots \sum_{r_\delta=1}^{q_\delta} \dots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\delta=1}^{S_M} \frac{\left( \sum_{i \in \delta^{\text{th}} \text{nest}} e^{\frac{V_i}{\theta_\delta}} \right)^{\theta_\delta}}{\sum_{\delta=1}^{S_k} \left\{ \left( \sum_{i \in \delta^{\text{th}} \text{nest}} e^{\frac{V_i}{\theta_\delta}} \right)^{\theta_\delta} \right\}} \right\}^{q_\delta - r_\delta + 1} \left( \prod_{\delta=1}^{S_M} \text{sum}(X_{r_\delta}) \right) \left( \sum_{\delta=1}^{S_M} (q_\delta - r_\delta + 1) - 1 \right)! \quad (5)$$

In the above expression,  $\text{sum}(X_{r_\delta})$  is the sum of elements of a row matrix  $X_{r_\delta}$  that takes a form described in Appendix A.

As indicated in Pinjari and Bhat (2008), the equation above represents the probability expressions for any time allocation pattern with a two-level nested extreme value error structure. This expression can be used in the log-likelihood formation and subsequent maximum likelihood

<sup>4</sup> This error structure assumes that the nests are mutually exclusive and exhaustive (*i.e.*, each alternative can belong to only one nest and all alternatives are allocated to one of the  $S_K$  nests).

estimation of the parameters for any dataset with mutually exclusive groups (or nests) of interdependent multiple discrete-continuous choice alternatives (*i.e.*, mutually exclusive groups of alternatives with correlated utilities). Further, it may be verified that the MDCNEV probability expression in Equation (5) simplifies to Bhat's (2008) MDCEV probability expression when each of the utility functions are independent of one another (*i.e.*,  $\theta_{\delta} = 1$  and  $q_{\delta} = 1 \forall \delta$ , and  $S_M = M$ ).

### 3. DATA SOURCES AND SAMPLE INFORMATION

#### 3.1 Data Sources

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.<sup>5</sup> The derived spatial variables include the following for each traffic analysis zone (TAZ) in the San Francisco Bay Area: (1) zonal household, population, and employment density measures, obtained from the land-use data file, (2) zonal land-use composition measures (percentage area of residential, commercial/industrial, and other categories, and land-use mix diversity), constructed from the land-use data file, (3) regional accessibility measures such as shopping accessibility and recreational accessibility, computed from the level-of-service data, (4) zonal demographics such as median income, derived from the Census 2000 population and housing data summary file, (5) zonal activity opportunity variables, such as activity center intensity/density for each of the following activity types, (extracted from the InfoUSA business establishments data): (a) maintenance (grocery stores, gas stations, food stores, car wash, automotive businesses, banks,

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<sup>5</sup> 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.

medical facilities, *etc.*), (b) recreation (fitness/sports centers, parks/gardens, theatres/amusement centers/arcades, *etc.*), and (d) eat-out (restaurants and eateries), and (6) Zonal transportation network measures, such as bikeway density and local roadway density, extracted from the GIS layers of bikeways and roadways.

The density measures, land-use composition measures, activity opportunity variables, and transportation network measures discussed above were computed not only at the zonal level, but also at higher levels of geographic resolution. Specifically, these variables were computed for 0.25 mile, 1 mile, and 5 mile radii around the residence of each individual in the sample (see Guo and Bhat, 2004 for the variable computation procedure). This latter approach of using circular areas is not only of a higher spatial resolution than that of a zone, but is also likely to provide better measures of a household's immediate neighborhood (Guo and Bhat, 2004).

### 3.2 Sample Description

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. In this section, we present a descriptive analysis of activity time allocation by activity purpose (Section 3.3.1), activity time allocation by activity timing (Section 3.3.2) and activity participation by activity purpose and timing combination (Section 3.3.3).

#### 3.3.1 Activity Time Allocation by Activity Purpose

Table 1 presents the descriptive statistics of participation in (and the time allocated to) each of the activity purposes defined in the study. The second and third columns of the table show the total number (and percentage) of workers participating, and the average amount of time invested, respectively, in each activity purpose. As is evident from the second row (*i.e.*, the row labeled "In-home Activities"), all workers in the sample participate in in-home activities. Also, the mean duration of time investment in in-home activities is rather high, at about 7 hours (or 417 minutes). The remaining rows provide descriptive statistics for out-of-home (OH) non-work activity participation levels and time investments by activity purpose. The OH activity participation percentages in the second column indicate that the lowest participation rate corresponds to OH socializing activities (only 6.9% of the workers in the sample pursue such activities). However, when undertaken, OH socializing activities are allocated, on average, the

largest amount of time (about two hours). Further, consistent with expectations, OH pickup/drop-off activities are allocated the least amount of time. These activity participation and duration statistics for workers are reasonable, given the nature of the activity purposes under discussion. Overall, the results indicate a high baseline preference and low satiation toward in-home activities. Among the OH non-work activities, there is a low baseline preference and low satiation for socializing activities.

The last two columns in Table 1 indicate the split between participation in only one type of activity and participation in multiple types of activities. For example, 41% (*i.e.*, 2021) of the 4093 workers who participated in in-home activities did so only in in-home activities, while the remaining 59% participated in one or more types of out-of-home non-work activities along with in-home activities. Similarly, 43% of the 1177 workers who participated in OH meal activity did not participate in any other OH non-work activity, while the remaining 57% participated in one or more types of OH non-work activities other than OH meal. These results clearly illustrate the prevalence of workers participating in multiple activity purposes on the same day, warranting a detailed analysis of multiple activity choices and necessitating the use of a multiple discrete choice modeling framework (as opposed to a standard single discrete choice model).

### 3.3.2 Activity Time Allocation by Activity Timing

Table 2 provides the descriptive statistics of participation in, and the time allocated to, OH non-work activities during each time period of the worker's day.<sup>6</sup> The second and third columns of the table show the total number (and percentage) of workers participating, and the average amount of time invested, respectively, in OH non-work activities during each time period of the day. It can be observed from the second column that, among the workers who participated in OH non-work activities, only about 8% did so during the before work period, while a significant 55% did so during the post home-arrival period, followed by 31% in the work-based period, and about 20% during each commute. The third column in Table 2 indicates that, if workers participate in OH non-work activities, their time investment in those activities is the lowest during the home-to-work commute (mean duration is about 8 minutes) and the highest during the post home-arrival period (mean duration is about 1 hour and 45 minutes). The lowest time investment

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<sup>6</sup> The numbers in the parentheses adjacent to each time period label in the first column represent the average amount of time available in each of the time periods.

during the home-to-work commute can be explained by the smaller amount of time available during the home-to-work commute period as well as inflexibility due to the need to start work at a relatively fixed time. On the other hand, the highest time investment during post home-arrival period can be explained by the larger amount of time available in that period. Overall, these numbers suggest a high baseline preference (*i.e.*, high level of participation) and a low satiation (*i.e.*, large amount of duration) for OH non-work activities undertaken in the post home-arrival period. The statistics also suggest a low baseline preference for OH activities during the before-work time period and a high satiation for OH activities during the home-to-work commute period.

The last two columns of the table indicate that workers' OH non-work activity participation is spread over multiple time periods of the day, warranting the use of a multiple discrete choice modeling framework in the context of activity timing decisions. Another interesting observation is that a large proportion (71%) of workers who participate in OH non-work activities during the home-to-work commute also participate in OH non-work activities during other time periods.

### *3.3.3 Activity Participation by Activity Purpose and Activity Timing Combination*

The focus of the current analysis is on the interactions of activity purpose and activity timing. Tables 1 and 2, on the other hand, only show the marginal distributions along each of the activity purpose and activity timing dimensions. In Table 3, we present the activity participation levels in OH non-work pursuits by activity purpose and activity timing combination categories. The unidimensional activity participation statistics are reproduced in grey shaded cells in the first two number columns (for activity purpose) and in the first number row (for timing). The remainder of the rows and columns provide the descriptive statistics for the activity purpose and timing combination categories. Thus, the entries in the "OH meal before work" cell indicate that 26 workers (or 2.2% of all workers participating in OH meal activity) participate in OH meals during the before-work period. It is to be noted here that the percentages for each row across the timing categories sum to more than 100% because of multiple discreteness. For example, a worker can participate in OH meals during both the before-work and work-based periods).

The descriptive statistics associated with the activity purpose and timing combination categories indicate that workers are more likely to participate in OH meals during the work-

based and post home-arrival periods. Also, while OH social and OH recreational pursuits are more likely to take place during the post home-arrival period, pickup/drop-off activities are more likely to take place during commutes and the post home-arrival period.

## **4. EMPIRICAL ANALYSIS**

### **4.1 Variables Considered**

Several types of variables were considered in the joint modeling system. These included: (1) household socio-demographics (household size, family structure and household composition, income, race/ethnicity, vehicle and bicycle ownership, whether or not household owned or rented its residence, dwelling type, availability of internet, *etc.*), (2) individual demographics and work characteristics (gender, age, license holding to drive, flexibility of work hours, full-time/part-time employment type, number of hours of work in the day, corresponding length of time windows before work-start time, between work-start and work-end times, and after work-end time), (3) commute characteristics (no-stop home-to-work and work-to-home commute time and commute cost, and commute mode), (4) contextual variables such as season of the year, day of the week, rainfall (and the amount of rainfall) in the day, temperature (minimum and maximum values in the day, and the variation in the day), (5) a host of activity-travel environment variables (discussed in section 3.3), and (6) the interactions of the activity-travel environment variables with household and individual socio-demographics.

In the next section (Section 4.2), we discuss the results of the MDCNEV model. Section 4.3 focuses on likelihood-based measures of data fit.

### **4.2 Empirical Results**

The final specification results of the MDCNEV model are presented in Tables 4 and 5. Table 4 presents the parameter estimates of the baseline utility specification and Table 5 presents the satiation parameter estimates. 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 4 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 4 if coefficient equality cannot be rejected based on statistical tests.

#### *4.2.1 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 Yamamoto and Kitamura, 1999 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 (see Gangrade *et al.*, 2002; and Pinjari *et al.*, 2007). 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 Chu, 2005 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 (such as Zhang *et al.*, 2002), 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 4 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 (note from the descriptive statistics in Table 1 that the duration of OH socializing activities tends to be very high, which makes socializing activities less attractive for high income workers with tight time constraints). With respect to activity timing, the income coefficients in the second panel of Table 4 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 (see Chu, 2005 and Gangrade *et al.*, 2002 for similar findings).

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 (Pinjari *et al.*, 2007).

#### *4.2.2 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 Srinivasan and Bhat, 2008 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 (Bradley and Vovsha, 2005; Bhat, 1998). 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 (see Chen and Mokhtarian, 2006, and Srinivasan and Bhat, 2008 for similar gender-based results in activity participation).

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 (see, for example, Yamamoto and Kitamura, 1999). 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, 2000 for similar findings).

The next variable is associated with workers' work schedule flexibility. 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 (Chu, 2005), 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 (Martens *et al.*, 1999), 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 4 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. Overall, full-time employed individuals prefer to spend the post home-arrival period at home with their family, instead of pursuing OH non-work activities – except for some recreational pursuits.

The final individual demographic variable is the natural logarithm of the length of the time window available for non-work activities during different time periods of the day. 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.

#### *4.2.3 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 4, 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 (see Gangrade *et al.*, 2002).

#### *4.2.4 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.*, 2007 for related research).

#### 4.2.5 Baseline Preference Constants

The baseline preference constants (final part of Table 4) 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.

#### 4.2.6 Satiation Parameters

The satiation parameter  $\gamma_k$  ( $k = 2, 3, \dots, K$ ) 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  $\gamma_k$ , the less is the satiation effect in the consumption of the alternative  $k$  (Bhat, 2008).

Table 5 provides the estimated values of  $\gamma_k$  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 5. From such dimension-wise  $\gamma$  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.<sup>7</sup> From the t-statistics provided in Table 5, it can be observed that significant satiation effects exist in the time 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.

#### 4.2.7 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.<sup>8</sup>

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<sup>7</sup> Hence, from Table 5, the  $\gamma_k$  estimate for work-based-meals is  $(0.992) \times (30.646) = 30.401$ . The appropriate t-statistics (against zero) are also shown in the table.

<sup>8</sup> These statistics are computed for the null hypothesis that the nesting parameters are equal to 1.

#### 4.2.8 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.

### 5. MODEL DEMONSTRATION

In this section, we demonstrate the application of the model estimated in this paper by analyzing the effects of two policies on workers' activity time-use and timing behavior: (1) An increase in the commute travel cost by 25% and (2) An increase in the time available during the post-home arrival period by one hour. These changes were applied to each commuter in the sample. Subsequently, the model was applied to predict (and then aggregate) the activity time-use and timing patterns before and after the changes. The effect of the policies on activity time-use and timing decisions was quantified using two measures: (1) The change (per commuter) in the *proportion* of time (expressed in percentage points) allocated to each activity purpose-timing combination alternative, and (2) The change (per commuter) in the *duration* of time allocated to each activity purpose-timing combination alternative. Table 6 presents the policy simulation results. The table contains the policy impact measures for only those alternatives that showed discernible changes in the time-use patterns due to the policy under consideration. Any cell in the table that is labeled “-” indicates that the proposed policy (*i.e.*, the policy in the corresponding row) did not have a discernible impact on that particular alternative and hence, the impact is not reported.

Several important observations may be drawn from Table 6. First, in response to a 25% increase in commute cost, there is an increase in the proportion of time spent on in-home

activities (by 3 percentage points) and a decrease in the proportion of time spent in OH non-work activities (see third column of the first numeric row in Table 6). The results also indicate a decrease in the proportion of time allocated for out-of-home non-work activities in the post home-arrival period, specifically for the out-of-home meal and recreation activities (see the last two columns). Furthermore, in response to the 25% increase in commute cost, there is an increase in the proportion of time allocated for non-work activities during the work-to-home commute period, although it is not as high (at 0.6 percentage points) in magnitude as the changes identified earlier. The above-mentioned aggregate changes in the proportions of time allocations translate into the following aggregate changes in time allocation patterns (see second row under the commute cost variable): (1) A 45 minute increase in the total time spent on in-home activities, (2) a 20 minute decrease in time spent on out-of-home non-work activities in the post home-arrival period (including a 10 minute decrease for out-of-home recreation and an 8 minute decrease for out-of-home meals; see the last two columns), and (3) a 4 minute increase in time spent during the work-to-home commute. These changes are reflective of the negative coefficient of the commute cost variable on the post home-arrival period (see Section 4.2.3). As identified in the empirical results, these effects are possibly due to the workers' need to reduce overall travel costs outside of commuting (by trip chaining during commute), thus leading to more proportions of time spent on activities at home and during commutes and lesser during the post home-arrival period.

Second, due to an additional hour available for commuters in the post home-arrival period (which may be due to, for example, either an "early work end time" policy or a "reduced work duration" policy), there is a decrease in the proportion of time spent (or a reduction of 13 minutes in the time spent) on in-home activities. In addition, there is also a significant increase in the proportion of time spent (or a 15 minute increase in time spent) on out-of-home non-work activities in the post home-arrival period. These changes are expected, given that the empirical results (see Section 4.2.2) indicate the increased participation of a commuter in out-of-home non-work activities in a given time period as the available time window for non-work activities increases in that period. Overall, the policy simulation results show intuitive effects of the two policies on the non-work activity time-use and timing patterns of commuters.



## **6. 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 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. Further, policy simulations reiterate some of the findings of the model estimation results.

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.

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**APPENDIX A:**  
Form of  $X_{r_\delta}$  matrix

For  $r_\delta = 1$ ,  $X_{r_\delta} = \{1\}$ .

$$\text{For } r_\delta = 2, X_{r_\delta} = \left\{ \frac{(q_\delta - 1)(1 - \theta_\delta)}{\theta_\delta} + \frac{(q_\delta - 2)(1 - \theta_\delta)}{\theta_\delta} + \dots + \frac{2(1 - \theta_\delta)}{\theta_\delta} + \frac{1(1 - \theta_\delta)}{\theta_\delta} \right\}.$$

For  $r_\delta = 3, 4, \dots, q_\delta$ ,  $X_{r_\delta}$  is a matrix of size  $\begin{bmatrix} q_\delta - 2 \\ r_\delta - 2 \end{bmatrix}$  which is formed as described below:

Consider the following row matrices  $A_{q_\delta}$  and  $A_{r_\delta}$  (with the elements arranged in the descending order, and of size  $q_\delta - 1$  and  $r_\delta - 2$ , respectively):

$$A_{q_\delta} = \left\{ \frac{(q_\delta - 1)(1 - \theta_\delta)}{\theta_\delta}, \frac{(q_\delta - 2)(1 - \theta_\delta)}{\theta_\delta}, \frac{(q_\delta - 3)(1 - \theta_\delta)}{\theta_\delta}, \dots, \frac{3(1 - \theta_\delta)}{\theta_\delta}, \frac{2(1 - \theta_\delta)}{\theta_\delta}, \frac{1(1 - \theta_\delta)}{\theta_\delta} \right\}$$

$$A_{r_\delta} = \{r_\delta - 2, r_\delta - 3, r_\delta - 4, \dots, 3, 2, 1\}$$

Choose any  $r_\delta - 2$  elements (other than the last element,  $\frac{1 - \theta_\delta}{\theta_\delta}$ ) of the matrix  $A_{q_\delta}$  and arrange

them in the descending order into another matrix  $A_{i_{q_\delta}}$ . Note that we can form  $\begin{bmatrix} q_\delta - 2 \\ r_\delta - 2 \end{bmatrix}$  number of

such matrices. Subsequently, form another matrix  $A_{ir_{q_\delta}} = A_{i_{q_\delta}} + A_{r_\delta}$ . Of the remaining elements in

the  $A_{q_\delta}$  matrix, discard the elements that are larger than or equal to the smallest element of the

$A_{i_{q_\delta}}$  matrix, and store the remaining elements into another matrix labeled  $B_{ir_{q_\delta}}$ . Now, an element

of  $X_{r_\delta}$  (i.e.,  $x_{ir_{q_\delta}}$ ) is formed by performing the following operation:

$x_{ir_{q_\delta}} = \text{Product}(A_{ir_{q_\delta}}) \times \text{Sum}(B_{ir_{q_\delta}})$ ; that is, by multiplying the product of all elements of the matrix  $A_{ir_{q_\delta}}$  with the sum of all elements of the matrix  $B_{ir_{q_\delta}}$ . Note that the number of such elements of

the matrix  $X_{r_\delta}$  is equal to  $\begin{bmatrix} q_\delta - 2 \\ r_\delta - 2 \end{bmatrix}$ .

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**LIST OF FIGURES**

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

**LIST OF TABLES**

Table 1. Descriptive Statistics of Activity Time Allocation by Activity Type

Table 2. Descriptive Statistics of Activity Time Allocation by Activity Timing

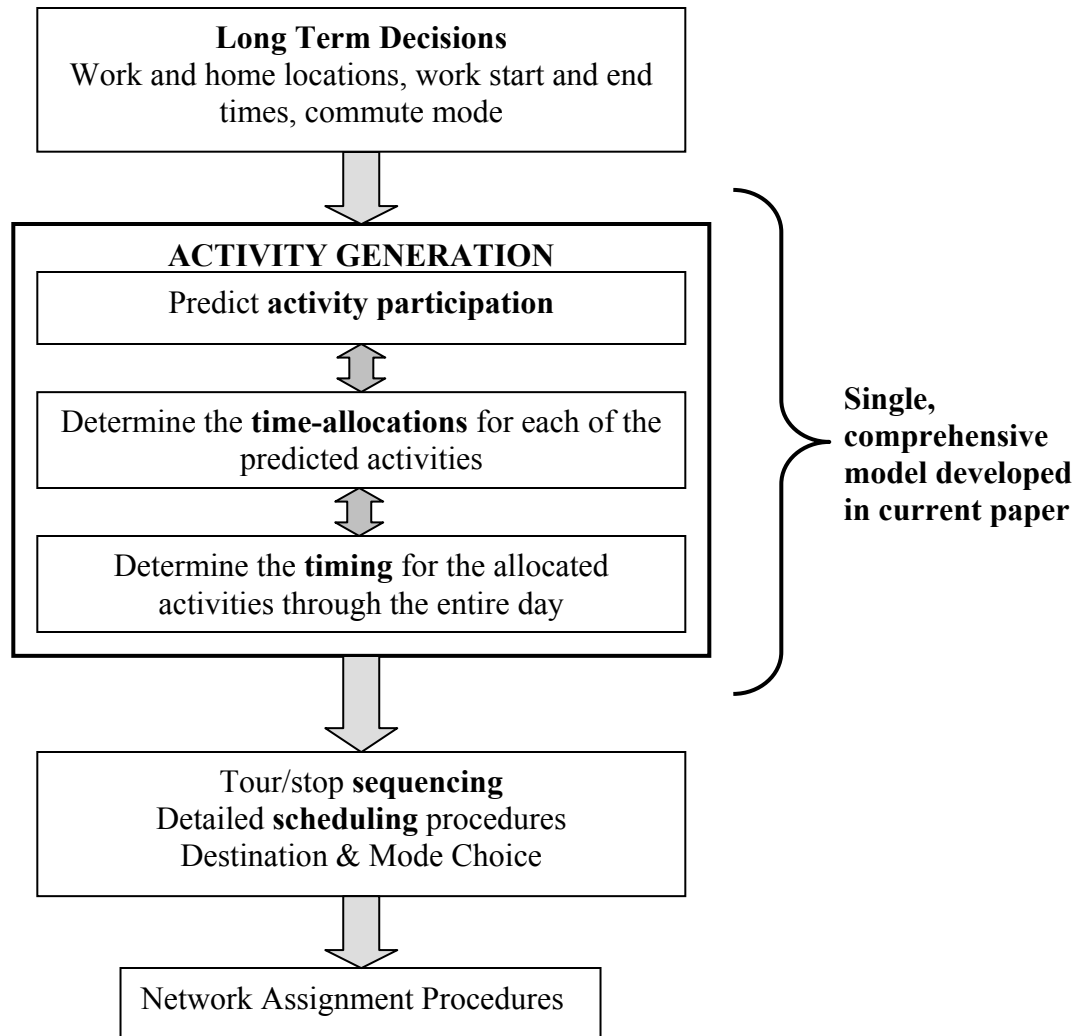
Table 3. Distribution of Participation in Out-of-Home Non-work Activities by Purpose and Timing

Table 4. The MDCNEV Model Results

Table 5. Satiation ( $\gamma$ ) Parameters

Table 6. Policy Impacts on Workers' Non-Work Activity Time-Use and Timing Behavior





**Figure 1. Schematic Positioning of Current Paper's Work in an Activity-Based Travel Demand Microsimulation Framework**

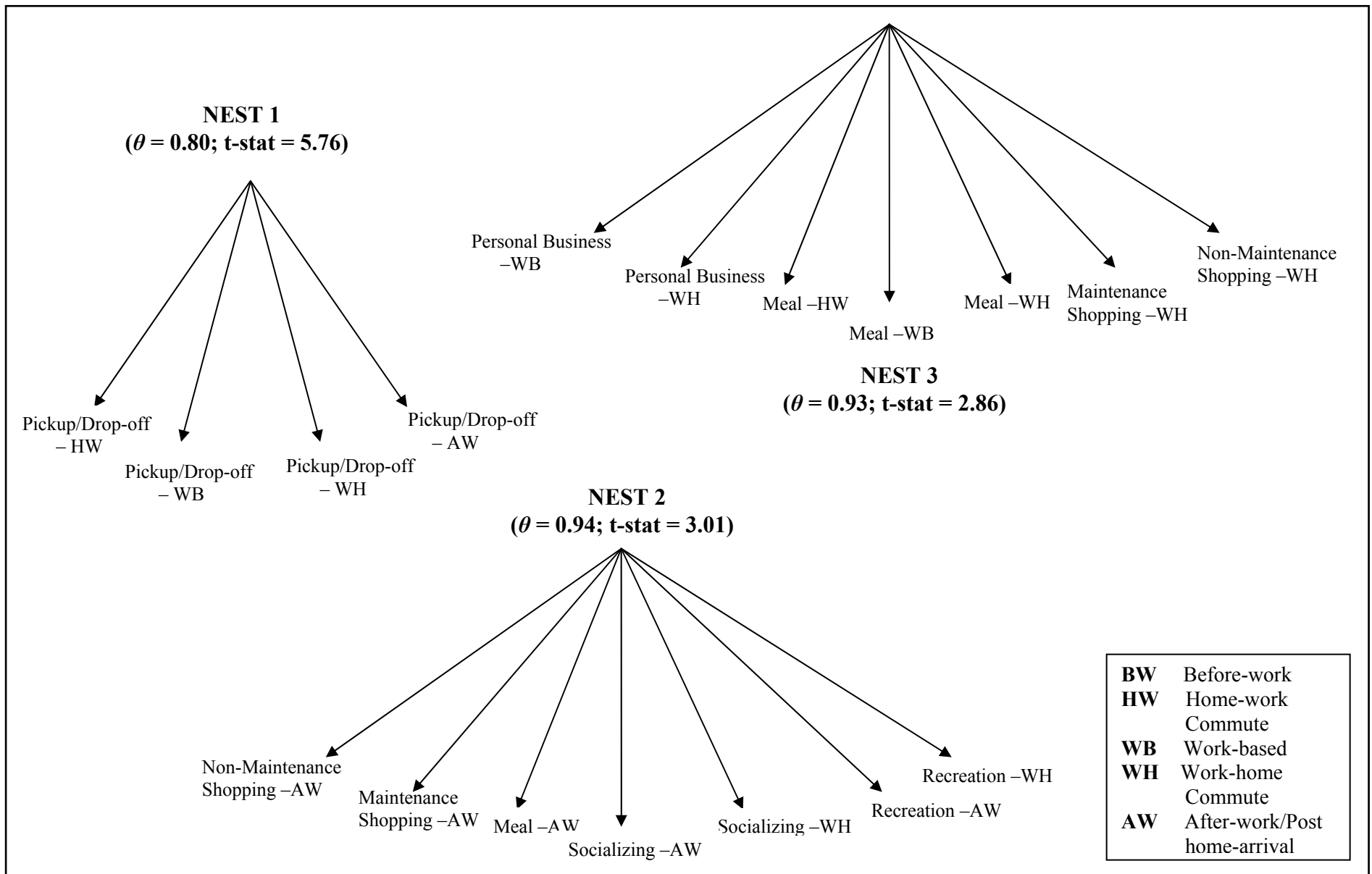


Figure 2. Schematic Representation of the Nests Implemented in the MDCNEV Model and their Parameter Estimates

**Table 1. Descriptive Statistics of Activity Time Allocation by Activity Type**

Activity purpose	Total number (%) of workers participating	Mean duration of participation among those participating (min.)	Number of individuals (% of total number participating) who participate....	
			Only in this activity purpose	In this activity purpose and other OH non-work activity purposes
In-home Activities	4903 (100%)	417.80	2021 (41%)*	2882 (59%)*
OH Meal	1177 (24.0%)	61.85	506 (43%)†	671 (57%)†
OH Recreation	623 (12.7%)	92.37	247 (40%)	376 (60%)
OH Non-Maintenance Shopping	578 (11.7%)	39.78	181 (31%)	397 (69%)
OH Maintenance Shopping	583 (11.8%)	22.89	198 (34%)	385 (66%)
OH Personal Business	650 (13.2%)	35.24	110 (17%)	540 (83%)
OH Socializing	341 (6.9%)	115.01	180 (53%)	161 (47%)
OH Pickup/Drop-off	610 (12.4%)	13.83	265 (43%)	345 (57%)

\* These numbers imply that 2021 (41%) of the 4903 workers who participated in in-home activities did so without participating in any out-of-home non-work activity, while the remaining 2882 (59%) participated in one or more of the out-of-home non-work activity purposes along with in-home activities.

† Similarly, 506 (43%) of the 1177 workers who participated in OH meals did not participate in any other OH non-work activity, while the remaining 671 (57%) workers participated in one or more of the OH non-work activity purposes other than OH meal.

**Table 2. Descriptive Statistics of Activity Time Allocation by Activity Timing**

Time Period (mean duration of time available in the time period in minutes)	Total number (% of those who participated in OH non-work activity) of workers participating	Mean duration of participation among those participating (min.)	Number of workers (% of total number participating) who participate....	
			Only in this time period	In this time period and other time periods
Before-to-Work (288.43)	243 (8.4%) <sup>‡</sup>	59.23	115 (47%)	128 (53%)
Home-to-Work Commute (25.13)	596 (20.7%)	8.16	172 (29%)	424 (71%)
Work-Based (537.01)	894 (31.0%)	45.67	398 (45%)	496 (55%)
Work-to-Home Commute (36.42)	662 (23.0%)	19.45	294 (44%)	368 (56%)
Post Home-Arrival (543.00)	1588 (55.1%)	103.46	972 (61%)	616 (39%)

<sup>‡</sup> The percentages in this column are out of the 2822 workers who participated in at least one out-of-home non-work activity during the survey day. It should be noted, however, that the percentages for each row across the all time periods may sum to more than 100% because of multiple discreteness; for example, a worker can participate in OH meals during both before work and work-based periods.

**Table 3. Distribution of Out-of-Home Non-work Activity Participation by Purpose and Timing**

ACTIVITY PURPOSE	# of workers participating ...	% of workers participating ...	ACTIVITY TIMING									
			Before-Work		Home-work Commute		Work-Based		Work-Home Commute		Post Home-Arrival	
			#	%	#	%	#	%	#	%	#	%
			243	8.4% <sup>§</sup>	596	20.7%	894	31.0%	662	23.0%	1588	55.1%
<b>OH Meal</b>	1177	40.8% <sup>§</sup>	26	2.2 <sup>**</sup>	152	12.9	630	53.5	68	5.8	458	38.9
<b>OH Recreation</b>	623	21.6%	99	15.9	3	0.5	54	8.7	11	1.8	475	76.2
<b>OH Non-Maintenance Shopping</b>	578	20.1%	25	4.3	35	6.1	93	16.1	134	23.2	315	54.5
<b>OH Maintenance Shopping</b>	583	20.2%	32	5.5	68	11.7	60	10.3	202	34.6	244	41.9
<b>OH Personal Business</b>	650	22.6%	55	8.5	80	12.3	156	24.0	124	19.1	275	42.3
<b>OH Socializing</b>	341	11.8%	12	3.5	7	2.1	21	6.2	24	7.0	281	82.4
<b>OH Pickup/Drop-off</b>	610	21.2%	68	11.1	276	45.2	51	8.4	184	30.2	230	37.7

<sup>§</sup> Percentages are based on total number of workers who participate in at least one out-of-home non-work activity during the survey day; *i.e.*, out of 2882 workers.

<sup>\*\*</sup> Percentages are based on total number of workers participating in row activity type  $[(26/1177) \times 100 = 2.2\%]$ .





**Table 4. (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
<b><i>'Activity Type' Dimension</i></b>							
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)	-	-	-	-
<b><i>'Activity Timing' Dimension</i></b>							
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)	-	-	-
<b><i>Activity Type-Activity Timing</i></b>							
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 4. (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 5. The MDCNEV Model Results: Satiation ( $\gamma$ ) Parameters**

ACTIVITY TIMING	$\gamma$ 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
<b>ACTIVITY TIMING</b>		-	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)
<b>Before-work</b>	-	-	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)
<b>Home-work Commute</b>	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)
<b>Work-based</b>	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)
<b>Work-home Commute</b>	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)
<b>Post home-arrival</b>	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)

**Table 6. Policy Impacts on Workers' Non-Work Activity Time-Use and Timing Behavior**

<b>Policy</b>	<b>Dimension of change</b>	<b>In-home Activities</b>	<b>Activity Timing Alternatives</b>		<b>Activity Purpose-Timing Combination Alternatives</b>	
			<b>Post Home-Arrival Period</b>	<b>Work-Home Commute</b>	<b>OH Meals in Post Home-Arrival Period</b>	<b>OH Recreation in Post Home-Arrival Period</b>
25% Increase in Commute Cost	Change in proportion of time allocated to activity purpose/timing (in percentage points)	+3.00	-3.60	+0.60	-1.50	-2.00
	Net change in duration of participation in activity purpose/timing	+45 minutes	-20 minutes	+4 minutes	-8 minutes	-10 minutes
One hour increase in the time available during the post home-arrival time period	Change in proportion of time allocated to activity purpose/timing (in percentage points)	-2.20	+2.50	-	-	-
	Net change in duration of participation in activity purpose/timing	-13 minutes	+15 minutes	-	-	-