A Continuous Time and Temporally Constrained Tour Pattern Generation System for Jointly Modeling Daily Tours and Stops: Application of Bi-level Multiple Discrete Continuous Probit (MDCP) Model

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ABSTRACT

The primary objective of the current paper is to contribute to the literature on activity pattern generation. In this research, a new framework is proposed to simultaneously model the following tour and stop making decisions: the number and purpose of tours conducted on a day, time allocated to different tours, the number and purpose of stops conducted within each tour, and time allocated to different stops. The framework represents time as a continuous entity and explicitly considers the time constraints within which an individual operates when generating tours and stops. Additionally, the framework is capable of accounting for the interrelationships across different tour- and stop-level decisions. The model formulation that operationalize the proposed framework imitates a bi-level structure where the participation (whether to pursue?) and time allocation (how much time?) decisions to daily tours are modeled at the upper level. Within each participated tour, participation and time allocation decisions for different stops are modeled at the lower level. The model formulation for the bi-level structure builds on the utility theoretic multiple discrete continuous probit (MDCP) modeling approach. The proposed framework and model formulation are demonstrated using an empirical case study employing data from the 2008-2009 National Household Travel Survey. Replication and forecasting results are presented to demonstrate the feasibility and applicability of the proposed framework and model formulation. The results provide evidence in support of the bi-level structure and its ability to reasonably capture the various constraints and interrelationships across tour- and stop-level participation and time allocation decisions.

Keywords: activity pattern generation, time budget, multiple discrete continuous probit, Bi-level model, tour generation, stop generation

INTRODUCTION

Activity-based travel demand model systems are increasingly being designed, developed, and deployed. In ABM, various dimensions of activity engagement choices and travel choices are modeled while also acknowledging the constraints and interactions that exist, thus, resulting in a more behaviorally accurate representation of individual activity-travel patterns (Kitamura 1988, Axhausen and Gärling 1992, Bhat and Koppelman 1999).

In the literature, two different units of analysis have typically been utilized in ABMs, namely, activity Miller and Roorda 2003, Arentze and Timmermans 2004, Pendyala et al. 2005, Auld and Mohammadian 2009, Habib 2015, Fu et al. 2016) and tour (Bowman and Ben-Akiva 2001, Bhat et al. 2004[1], Garikapati et al. 2014). The tour-based ABM approaches are the focus of the research presented in this paper. A tour is defined as a sequence of trips that start and end at the same location. Activity-travel patterns of an individual are represented as a series of home-based (anchored at home) and work-based tours (anchored at work). Each stop represents an activity pursuit and an individual must pursue at least one activity[2]. For each tour, a primary stop is defined which also represents the purpose of the tour. In addition to the primary stop, an individual can make other activity stops, referred to as intermediate stops, en-route to the primary activity location or on the journey back home. In the state-of-the-art tour-based modeling approaches, daily activity-travel agendas pursued by individuals and households are formed in two stages, namely, the activity pattern generation and the activity scheduling. In the activity pattern generation, characteristics of all tours are identified including tour purpose, number of stops within a tour, purpose and destination for each stop and time allocated to all tours and stops among other decisions. On the other hand, activity scheduling is concerned with the timing and placement of tours and stops within a day. The research presented contributes to the activity pattern generation stage of the tour-based ABM approach.

There are three important limitations of existing tour-based ABMs that this paper attempts to address. First, though early literature on ABM conceptualizes time as a continuous entity (Ben-Akiva et al. 1996), almost all of the ABM systems in practice today represent time in discrete units. For example, in Bowman and Ben-Akiva (2001) the arrival-departure time combinations of different tours are modeled with plausible pairs of discrete time bins serving as alternatives. Second, the decision to participate in an activity at each stop within a tour (and amount of time to be allocated) is modeled independently (Bhat et al. 2004). Consequently, these model systems cannot explicitly address the interactions between successive activity-travel episodes within a tour and also the cascading impacts on other tours within a day. Third, related to the above, most tour-based model systems do not explicitly acknowledge the temporal constraints when modeling tours, or when modeling stops within a tour. Temporal constraints are often accommodated afterwards using heuristics and logical checks at the activity scheduling stage.

In this research, a framework and model formulation are proposed that attempts to mimic the formation of tours in a behaviorally consistent way while addressing three important limitations of existing frameworks, namely, *representation of time as a continuous entity*, *representation of the interrelationships between stops and tours across the day, and*

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[1] In CEMDAP, half-tours are considered.

[2] There are roundtrip tours that are also reported in surveys but representing them is a challenge and are not considered in this research.

representation of temporal constraints. The rest of the paper is organized as follows. An overview of the tour generation framework is presented next. The third section presents the econometric model formulation that operationalizes the tour generation framework. The fourth section presents a case study where the model formulation was applied using data from the 2008-2009 National Household Travel Survey. The fourth section also presents result from a replication and forecasting analysis to demonstrate the performance of the proposed framework. In the final section, findings and contributions from the research are summarized.

CONTINUOUS TIME AND TEMPORALLY CONSTRAINED TOUR GENERATION FRAMEWORK

The purpose of the current research effort is to model the tour and stop making decisions of individuals in a behaviorally consistent manner while representing time as a continuous entity and explicitly acknowledging the temporal constraints. In particular, the focus of the tour generation framework is on the following four dimensions of tour-pattern of an individual: 1) *the choice of participation (whether to pursue?) in different types of home based tours* (defined based on primary activity type), and for each tour an individual participates in, 2) *the time allocation (how much time?) to the tour*, 3) *the choice of participation in different intermediate stops* within the tour and 4) *the time allocation to the stops in addition to the time allocation to the primary activity of the tour and the return home journey*[3]. There are other dimensions of tours that are necessary to complete the characterization of tour patterns of individuals namely destination of the stops, sequencing of stops within a tour, and all of the tour-and stop-level travel characteristics. It is assumed that these other dimensions are modeled using a series of independent/joint model formulations. The discussion of these other dimensions is outside the scope of this paper.

The proposed framework assumes a bi-level decision making structure wherein the participation and time allocation decisions for the various tour types are modeled at the upper level and within each tour, participation and time allocation decisions for different stops are modeled at the lower level. Time is treated as a continuous entity thus allocations of time to tours and stops are in continuous time units. Two sets of temporal constraints govern the tour generation framework. First, total time allocation across all tours participated is equal to the total time available in the day (e.g. 1440 minutes). This includes time spent in activities at home. Second, the time allocated to stops within the tour should add up to the time allocation for the said tour. It must be noted that the stop level time allocation includes activity dwell time and duration of the travel time to the activity location as formulated by Garikapati et al. (2014). This is also referred to as epoch duration[4]. Tour level decisions influence the stop level choices by modifying the time available to be allocated to the stops within a said tour. Also, stop level choices for a said tour can not only influence the participation and time allocation decisions directly for the tour but they can also indirectly influence the participation and time allocation decisions for other tours.

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[3] From this point forward any reference to stop(s) also includes the primary activity of the tour, as well as the return home journey unless explicitly noted otherwise.

[4] From this time forward stop level time allocation and epoch duration are used interchangeably and refer to the sum of activity duration at the stop and also the travel time to the stop destination from the previous location.

The treatment of stops within a tour and the continuous treatment of time is similar to the framework proposed by Garikapati et al. (2014). However, their framework treats one type of tour at a time. The proposed framework addresses this limitation by considering all tours pursued by individuals within a day along with stops within each tour within an unifying framework, thus, allowing for a more accurate representation of the tour formation process. Figure 1 presents the skeleton of the proposed framework using data from the case study. This will be described in greater detail in section four.

MODEL FORMULATION

In this section, a model formulation that operationalizes the continuous time and time constrained tour generation framework is presented. The proposed model formulation adopts the multiple discrete continuous (MDC) econometric model framework proposed by Bhat (2008, 2013). This utility-maximization based Kuhn Tucker demand system has been widely used in the literature (Garikapati et al. 2014). In the proposed formulation, both the participation and time allocation choices at the upper level (for tours) and at the lower level (for stops within a tour) are treated as multiple discrete continuous choices where the participation constitutes the discrete component, time allocation constitutes the continuous component and the alternatives considered being the imperfect substitutes of one another give rise to multiple consumption scenario.

This bi-level MDC formulation is similar in spirit to the conceptual framework proposed by Deaton and Muellbauer (1980) and Chintagunta and Nair (2011) for the two level decision making involving multiple discrete continuous choices[5]. To the best of the authors' knowledge, Wang and Li (2011) offers the only other research that operationalizes the bi-level structure in the presence of multiple discrete continuous choices at each level. However, the proposed formulation is different from Wang and Li in a number of important ways, thus, comprising an important contribution to this line of inquiry. <u>First</u>, the current research employs a different utility specification. The proposed formulation captures the variability (across alternatives and different socio demographic groups) in the satiation effect (i.e. diminishing marginal utility with increasing consumption) thus making it an ideal candidate for the analysis of alternatives that are imperfect substitutes of one another as opposed to assuming a constant and identical satiation effect across all the alternatives. <u>Second</u>, Wang and Li assume an independent and identically distributed error structure whereas the proposed formulation assumes a flexible error structure where alternatives at the tour level are allowed to be correlated and the stop level alternatives belonging to the same tour are also allowed to be correlated. <u>Finally</u>, their effort relies on numerical (Monte Carlo) simulation for the estimation of the model. The proposed formulation utilizes an analytical approximation of normal cumulative distribution function proposed by Bhat (2011) which eliminates the need for any numerical simulation. Unlike numerical simulation, the analytical approximation aids the computational tractability and enables its use in practice. The econometric formulation is presented next.

The utility derived by allocating $x^l = \left\{x_1^l, x_2^l, x_3^l, \ldots, x_{K_l}^l\right\}$ amount of time to different stops within a tour can be written as in equation (1)[6].

[5] In literature this two level decision making process in the presence of multiple discrete continuous choice scenario has also been referred to as two-level budgeting (see Pinjari et al. 2016).

[6] The contribution of an outside good to the utility is accommodated as $\psi_k^l \exp(\varepsilon_k^l) \ln(x_k^l)$

$$U_s^l = \sum_{k=1}^{K_l} \gamma_k^l \psi_k^l \exp(\varepsilon_k^l) \ln(\frac{x_k^l}{\gamma_k^l} + 1) \qquad (1)$$

Where x^l is a (K_l×1) vector of the time allocated (epoch duration) to different stops, $\gamma_k^l (> 0)$ is the translation (also serves to account for satiation effect) parameter and $\psi_k^l (> 0)$ is the baseline utility which represents the marginal utility at the point of zero consumption. The baseline marginal utility can further be parameterized as $\exp(\alpha' v_k^l)$ where v_k^l represents $D_k^l \times 1$ vectors of exogenous variables and α represents the corresponding vectors of parameters to be estimated. ε_k^l is the stochastic component which captures the idiosyncratic (unobserved) characteristics of the decision maker that impact the baseline utility. The present formulation assumes the stochastic component to be multivariate normally distributed (MVN) such that $\varepsilon^l \sim N\left[0_{K_l}, \Lambda^l\right]$. K_l is the total number of stops pertaining to tour l. In the above discussion, the subscript k represents the stop k in the tour l and superscript l represents the l^{th} tour.

Similarly, the utility derived by allocating $\{x_1, x_2, x_3, \dots, x_l\}$[7] amount of time to different tours can be written as in equation (2)[8].

$$U_t = \sum_{l=1}^{L} \gamma_l \psi_l^* \exp(\varepsilon_l) \ln(\frac{x_l}{\gamma_l} + 1) \qquad (2)$$

Note that, for the baseline marginal utility of the tour ψ_l^* is defined as $\psi_l (\prod_{k=1}^{K_l} \psi_k^l)^{w_l}$ and ψ_l is parameterized as $\exp(\beta' v_l)$ where v_l represents $D_l \times 1$ vector of exogenous variables and β represents the corresponding vectors of parameters to be estimated. Note that, the ψ_l (or equivalently, $\exp(\beta' v_l)$) component captures the tour[9] specific characteristics; where as $(\prod_{k=1}^{K_l} \psi_k^l)^{w_l}$ (or, equivalently $(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l))^{w_l}$) component captures the characteristics of the stops within the tour. This specification captures the impact of the stop level participation choice(s) on the tour level participation. The exponent, w_l captures the relative contribution of the stop level characteristics on the tour level baseline marginal utility. w_l needs to be positive in order to ensure that the baseline marginal utility is positive. Also, it is desirable that the parameter takes a value between 0 and 1 to ensure that the contribution of the stop level characteristics on the baseline marginal utility of the tour is less than their contribution on the stop level baseline marginal utility. Similar to the stop level model, the stochastic component ε_l associated with the tour level alternatives is assumed to be MVN distributed such that $\varepsilon \sim N[0_L, \Lambda]$. L represents the total number of tours (including an at home alternative).

The total utility that a decision maker derives from allocating $\{x_1, x_2, x_3, \dots, x_l\}$ amount of time to L tours and $\{x_1^1, x_2^1, \dots, x_{k_1}^1, x_1^2, x_2^2, \dots, x_{k_2}^2, x_1^3, x_2^3, \dots, x_{k_3}^3, \dots, x_1^l, x_2^l, \dots, x_{k_l}^l\}$ amount of time into the $\sum_{l=1}^{L} K_l$ stops can be expressed as a summation of bottom level and top level utilities as shown in equation (3).

[7] It must be noted that $x_l = \sum_{k=1}^{K_l} x_k^l \ \forall \ l = 1,2,3, \dots, L$ represents the relationship between stop and tour level time allocation

[8] The contribution of an outside good to the utility is accommodated as $\psi_l^* \exp(\varepsilon_l) \ln(x_l)$

[9] Tour is defined based on the purpose of the activity at the primary stop.

$$U = \sum_{l=1}^{L} \gamma_l \exp(\beta' v_l) \left(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l)\right)^{w_l} \exp(\varepsilon_l) \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \sum_{l=1}^{L} \sum_{k=1}^{K_l} \gamma_k^l \exp(\alpha' v_k^l) \exp(\varepsilon_k^l) \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) \quad (3)$$

The decision maker is then assumed to maximize the utility in equation (3) subject to the following temporal budget constraints.

$$\sum_{l=1}^{L} x_l = T \qquad x_l \geq 0 \; \forall \; l = 1,2,3,\ldots,L \quad (4a)$$
$$\sum_{k=1}^{K_l} x_k^l = x_l \qquad x_k^l \geq 0 \; \forall \; l = 1,2,3,\ldots,L \;\&\; k = 1,2,3,\ldots,K_l \quad (4b)$$

Equation (4) represents $L + 1$ budget constraints, where the top equation represents the budget constraint operating at the tour level and the bottom L equations represent the budget constraints working at the stop level for each of the L tours. The optimization problem can be solved by forming the Lagrangian and then applying the Karush-Kuhn Tucker (KKT) conditions.

$$\mathcal{L} = \sum_{l=1}^{L} \gamma_l \exp(\beta' v_l) \left(\prod_{k=1}^{K_l} \exp(\alpha' v_k^l)\right)^{w_l} \exp(\varepsilon_l) \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \sum_{l=1}^{L} \sum_{k=1}^{K_l} \gamma_k^l \exp\left(\alpha' v_k^l\right) \exp\left(\varepsilon_k^l\right) \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) - \lambda\left(\sum_{l=1}^{L} x_l - T\right) - \sum_{l=1}^{L} \lambda_l \left(\sum_{k=1}^{K_l} x_k^l - x_l\right) \quad (5)$$

Equation (5) provides the Lagrangian equation where λ and λ_l are the Lagrange multipliers associated with the tour and stop levels respectively. The first order KKT conditions with respect to the vector of decision variable x_l can be written as in equation (6) after some manipulation.

$$\beta' v_l + w_l\left(\sum_{k=1}^{K_l} \alpha' v_k^l\right) - \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \varepsilon_l - \ln(\lambda - \lambda_l) = \beta' v_m + w_m\left(\sum_{k=1}^{K_m} \alpha' v_k^m\right) - \ln\left(\frac{x_m}{\gamma_m} + 1\right) + \varepsilon_m - \ln(\lambda - \lambda_m)$$
$$\forall \; l = 1,2,3,\ldots,L \; if \; x_l^* > 0, l = 1,2,\ldots,L, l \neq m$$
$$(6)$$
$$\beta' v_l + w_l\left(\sum_{k=1}^{K_l} \alpha' v_k^l\right) - \ln\left(\frac{x_l}{\gamma_l} + 1\right) + \varepsilon_l - \ln(\lambda - \lambda_l) < \beta' v_m + w_m\left(\sum_{k=1}^{K_m} \alpha' v_k^m\right) - \ln\left(\frac{x_m}{\gamma_m} + 1\right) + \varepsilon_m - \ln(\lambda - \lambda_m)$$
$$\forall \; l = 1,2,3,\ldots,L \; if \; x_l^* = 0, l = 1,2,\ldots,L, l \neq m$$

In equation (6), λ_l needs to be less than λ which makes intuitive sense since λ and λ_l respectively represents the time elasticity for the tour level and the stop level budget constraints. Next, the first order KKT conditions with respect to the vector of decision variable x_k^l for each of the l^{th} tour can be written as shown in equation (7).

$$\alpha' v_k^l - \ln\left(\frac{x_k^l}{\gamma_k^l} + 1\right) + \varepsilon_k^l = \alpha' v_m^l - \ln\left(\frac{x_m^l}{\gamma_m^l} + 1\right) + \varepsilon_m^l \; \forall \; k = 1,2,3,\ldots,K_l \; if \; x_k^{*l} > 0, \; k \neq m$$
$$(7)$$

$$\alpha' v_k^l - \ln\left(\frac{x_k^l}{\gamma_k^l}+1\right) + \varepsilon_k^l < \alpha' v_m^l - \ln\left(\frac{x_m^l}{\gamma_m^l}+1\right) + \varepsilon_m^l \;\forall\; k = 1,2,3,\ldots,K_l \;if\; x_k^{*l} = 0,\; k \neq m$$

Given the above equations and assumptions about the stochastic components as preliminaries, the joint probability of allocating time into L tours and $\sum_{l=1}^{L} K_l$ stops can be given by equation (8) where $\Theta = \{\alpha', \gamma_k^l, vector(\Lambda^l), \beta', \gamma_l, vector(\Lambda), w_l\}$ is the vector of parameter to be estimated.

$$L(\Theta) = Pr\,(x_1^*, x_2^*, \ldots, x_l^*, x_1^{*1}, x_2^{*1}, \ldots, x_{k_1}^{*1}, x_1^{*2}, x_2^{*2}, \ldots, x_{k_2}^{*2}, \ldots, x_1^{*l}, x_2^{*l}, \ldots, x_{k_l}^{*l})$$

$$= Pr\,(x_1^*, x_2^*, \ldots, x_l^*) \times Pr\,(x_1^{*1}, x_2^{*1}, \ldots, x_{k_1}^{*1}, x_1^{*2}, x_2^{*2}, \ldots, x_{k_2}^{*2}, \ldots, x_1^{*l}, x_2^{*l}, \ldots, x_{k_l}^{*l} | x_1^*, x_2^*, \ldots, x_l^*)$$

$$= Pr(x_1^*, x_2^*, \ldots, x_l^*) \times \Pr(x_1^{*1}, x_2^{*1}, \ldots, x_{k_1}^{*1} | x_1^* > 0) \times$$
$$Pr\,(x_1^{*2}, x_2^{*2}, \ldots, x_{k_2}^{*2} | x_2^* > 0) \times \ldots \times Pr\,(x_1^{*l}, x_2^{*l}, \ldots, x_{k_l}^{*l} | x_3^* > 0) \quad (8)$$

In equation (8), the last equality holds because of the assumption that, the time allocation decision to different stops across tours are not correlated i.e. interdependence is facilitated at the tour level and only the stops belonging to the same tours are allowed to be correlated with each other. The probability expression involves evaluation of MVN cumulative distribution function (CDF) which is accomplished using analytical approximation as proposed by Bhat (2011) (known as MACML approach in the literature). The likelihood function in equation (8) and the associated gradients are implemented in matrix programming language GAUSS to obtain the parameter estimates $\hat{\Theta}$. The standard errors of the parameter estimates are obtained using the robust Gobambe sandwich estimator (Godambe 1960). Details regarding the estimation approach have been excluded in the interest of space and interested readers may consult Varin et al. (2011) for a general discussion about CML based estimation approach and Bhat et al. (2013) for an application of CML to estimate choice models involving MDCP choice kernel.

EMPIRICAL CASE STUDY

In this section, we demonstrate the framework and model formulation using data from the 2008-2009 National Household Travel Survey. Data from two consolidated metropolitan statistical areas (CMSA) from south west portions of the US, namely, Phoenix-Mesa, AZ and Los Angeles-Riverside-Orange County, CA are used in this case study. Also, the data used for the current study only includes workers who are 16 years of age and above. Further, the analysis is limited to weekdays (i.e. Monday through Friday). The trip level data from NHTS was processed as follows:

- All the home based tours (HBT) conducted by the individuals are identified. Note that individuals with atypical travel behavior are eliminated at this stage.
- A primary activity is identified for each of the HBTs based on an assumed activity priority hierarchy and dwell time at the destination[10]. The purpose of the primary activity is then

[10] The activity hierarchy for the current exploration is as follows: work is given the highest priority if the person is an adult and worker, otherwise school is given the highest priority which is followed by escort and personal

assigned to characterize the tour. Hence, each of the HBTs were categorized into one of the following 7 activity categories: work, school, escort, personal business (PB), shopping, meal and social recreation (SR). In presence of multiple activities of the same purpose on the tour, activity with the higher dwell time is assigned as the primary activity and the other activity is included as a stop. All activities conducted as part of the work based tours are included as part of the work activity in the current empirical exploration.

- In addition to the various HBTs, time spent at home (AH) was used as an alternative in the upper level. This treatment serves two main purposes. First, it allows for incorporating the natural constraint of 1440 minutes in a given day. Second, it allows capturing the tradeoffs between AH and out-of-home activity engagement (i.e. sum of HBTs); AH serves as an outside good[11] (that needs to be consumed) and thus, time allocated to HBTs is determined endogenously with respect to the time spent AH.
- As noted earlier, in defining the components of tours, we replace the notion of the stop with that of an epoch as defined by Garikapati et al. (2014). An epoch consists of the activity episode at each stop and the travel episode to the stop. Thus, each tour is comprised of a series of epochs and a return home episode. Subsequently, the summation of epoch duration across all stops and the duration of the return home journey equals the duration of the tour.

Figure 1 shows the structure of the bi-level model for the empirical case study. The model specification comprises of 8 tour alternatives. For each of the tours (except AH), the epoch alternatives are noted in the figure. The figure also presents the percentage of individuals in the subsample who participated in each of the tours and epochs. Additionally, average tour duration and average epoch durations are reported. It should be noted that, in the empirical application, participation in tours was limited to single episode of each tour type. This was in part dictated by the sample dataset. There were a small percentage of individuals who engaged in multiple episodes of the same tour types. However, this is not necessarily a limitation of the proposed model formulation. Such instances can be accommodated in the current formulation by enumerating multiple tour alternatives of the same type in the tour type choice set.

Estimation Results

The size of the subsample used in the exploration is 5233. A variety of socio-economic, demographic, and land use variables were used to specify the model. The final model specification includes 331 parameters among which 83 are constants (pertaining to baseline marginal utility and the satiation parameters of the tour (top) and epoch (bottom) level models). The log-likelihood (LL) value of the final model at convergence is -106307.87 while final LL of the constant only model is -108166.63. The LL ratio test suggests that the model specification is significant at the 99.9% level of confidence (with LL ratio test statistic: 3717.52, Chi-square critical value: 322.56 for a degree of freedom of 248 at a level of significance of 0.001). Some of the highlights of the empirical analysis are presented next respectively for the tour (top) and the stop (bottom) level models.[12]

business. The rest of the three activities (shopping, meal and school) are given equal rank and activity with the highest dwell time at the destination is used to define the primary destination of the tour.

[11] The term "outside good" is used to refer to any alternative that an individual always participates in. In other words, a non-zero amount of time is always allocated to an outside good."

[12] In the interest of space, only key observations are discussed. Additionally, the empirical case study was performed primarily to illustrate the feasibility of the model formulation.

Tour Level Participation and Time Allocation

Table 1 presents the parameters estimates (including baseline marginal utility and the satiation parameters) along with the robust t-statistics for the tour level of the bi-level model formulation. At home (AH) alternative is treated as the baseline alternative as well as an outside good.

Baseline Marginal Utility

The constants of all the seven tour types (work, school, escort, personal business (PB), shopping, meal and social recreation (SR)) are negative indicating a lower propensity of participating in different tours compared to the AH alternative. Male respondents exhibit higher propensity to participate in school tours and lower propensity to participate in escort tours. Young individuals (those who are less than 34 years old) and middle-aged adults (those who are in between 35 to 54 years old) participate more in work and school tours compared to the older adults (more than 54 years old). Middle-aged adult participate more in escort tours than individuals in other age groups. Part time workers exhibit a tendency to participate more in different types of tours such as school, escort, PB and SR and less into work tours. People living in an urban area tend to perform more PB, shopping and SR tours compared to those living in suburban or rural areas. In terms of days of weeks, it appears like people tend to participate more in shopping, meal and SR tours and less in school tours on Fridays.

Role of w_l

As noted earlier in the model formulation section, the model formation assumes that the decision to participate in a tour is not only determined by the primary activity of the tour but also depends on other stops made within the tour. However, the model formulation does not force the contribution of the stop level characteristics to influence the tour decision making. Rather, the influence is mediated through the w_l parameter. A value of w_l close to unity would imply that the influence of the stop level characteristics on the tour decision making is on the same level as their influence on the stop level decision making. On the other hand, a value of w_l close to zero implies negligible influence of stop level characteristics on the tour level decision making.

In the empirical case study, the w_l parameter was observed to be significant (with a value of 0.044 and a t-statistics of 4.245) only for the work tour baseline marginal utility specification. This can potentially be explained by the approach to data preparation. For HBTs where there is a work epoch, the purpose of the tour is coded as “work” irrespective of the activity dwell time, and distance from home. Hence, the significant w_l parameter is indicating that the utility for the work tour is not only a function of the primary activity (i.e. work) but also gets affected by other epochs’ (conducted as part of the tour) participation propensities.

Satiation Parameter

Male respondents tend to have high satiation (spend less time on) for PB, shopping and meal tours. On the other hand, they tend to have low satiation (spend more time on) for work tours. It is also interesting to note that, people living in urban areas tend to spend less time on different tours such as work, PB, shopping and SR. This may be attributable to the longer distances (and thus travel times) for those living in suburban and rural areas have to travel to access opportunities to pursue their activities compared to those living in urban areas.

Error Correlation

The tour level model was allowed to assume a MVN error structure that is capable of accommodating both heteroscedasticity and error correlations. Equation (9) shows the parameters of the variance covariance matrix (VCM) calculated from estimates of the corresponding lower triangular Cholesky Factors.

$$\begin{array}{c} \\ AH \\ Work \\ School \\ Escort \\ PB \\ Shopping \\ Meal \\ SR \end{array} \begin{array}{c} \begin{array}{cccccccc} AH & Work & School & Escort & PB & Shopping & Meal & SR \end{array} \\ \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -0.362 & -0.584 & -0.894 & -0.751 & -0.562 & -0.463 \\ 0 & -0.362 & 2.291 & 0.211 & 0.287 & 0.272 & 0.203 & 0.167 \\ 0 & -0.584 & 0.211 & 4.063 & 0.522 & 0.438 & -0.358 & 0.270 \\ 0 & -0.894 & -0.287 & 0.522 & 3.208 & 0.671 & -0.129 & 0.414 \\ 0 & -0.751 & 0.272 & 0.438 & 0.671 & 3.419 & 0.422 & 0.348 \\ 0 & -0.562 & 0.203 & -0.358 & -0.129 & 0.422 & 1.633 & -0.401 \\ 0 & -0.463 & 0.167 & 0.270 & 0.414 & 0.348 & -0.401 & 2.478 \end{pmatrix} \end{array} \quad (9)$$

The error correlations provide interesting insights into participation behavior of individual due to common unobserved factors which are not captured in the deterministic portion of the utility specification. Positive correlations point to the same direction influence and negative correlations point to opposite direction influence. For example, the negative error correlation between work tour and the other type of tours reveals that the unobserved factors which influence higher participation behaviors in work tours also tend to influence lower participation in other types of tours. Another interesting observation worth pointing out is the negative correlation between meal and SR tours. This indicates that individuals are less likely to conduct tours with meal and SR as primary activities on the same day.

Epoch Level Participation and Time Allocation

Table 2 presents the epoch level participation and time allocation results. In the interest of space, presentation of the bottom level model estimation results is limited to the epochs pursued within work tour. It should be noted that, for all the 7 bottom level models, the primary activity of the tour and the return home journey have been treated as outside goods.

Baseline Marginal Utility

All the constants in the baseline marginal utility are estimated to be negative indicating lower propensity to participate in any intermediate epochs compared to the primary activity of the tour. Male respondents exhibit a lower tendency to undertake different maintenance and discretionary epochs (such as escort, PB, shopping, meal and SR) within the work tour compared to females. This is in line with the previous literature that alludes to complex tour structure for females compared to males (Bowman and Ben-Akiva 2001). Young people (age between 16 to 34 years) tend to perform fewer intermediate work epochs and more intermediate school epochs when compared to individuals from other age groups. It is interesting to note that, though individuals of all groups exhibited lower tendency to perform PB epochs compared to the old people (people more than 64 years old) during the work tour, they all exhibited higher tendency to perform PB epochs in other HBTs (such as escort) compared to older people. This shows the differences in epoch pursuits between different age groups for a given tour type.

Satiation Parameter

In terms of variability in the satiation effect, male respondents are found to allocate more time into intermediate school epoch in a work tour than females. On Fridays, people tend to allocate more time (exhibit lower satiation) in SR epochs and less time into school epochs compared to other days of the weeks.

Sample Replication

The focus of this section is to validate the proposed framework and model formulation. The objective of this analysis is to illustrate the framework's ability to replicate the observations. The forecasting routine for the proposed bi-level model formulation outlined below builds on the approach proposed by Pinjari and Bhat (2011) for Kuhn-Tucker demand systems.

- First, total daily budget of 1440 minutes is allocated across the 7 HBTs and the AH alternative. In order to capture the entire distribution of the random error term, this step is carried out 100 times using realizations from MVN distribution.
- Second, the tour budget (predicted in the last step) is allocated to components of the tour (including the primary epoch, the intermediate epochs and the return home journey). For each individual, and for each tour budget realization, this step is repeated 100 times using realizations from MVN distribution resulting in 100×100 realizations of time allocation to components of the tour.
- Third, average participation and time allocation into different tours are calculated as the average across 100 realizations across all the observations.
- Fourth, in order to capture the stochastic nature of the budget of the epoch level time allocation, the participation and time allocation at the epoch level are calculated similar to the last step and then averaged across the entire budget distribution.

Table 3 presents the replication results. The top portion of the table presents the predicted and observed percentage of the individual who participated into different tours and epochs. While the bottom portion of the table presents the predicted and observed duration (average in minutes) of the tours and the epochs within the tours. While, the predicted participation percentages very closely replicate the observed participation percentages, there are some deviations between the predicted and observed time allocation. This can partly be attributed to the specification of the satiation parameters. Enhancing the specification of the satiation parameter, will better capture the variability in the satiation effect across different demographic groups. Also, in order to further improve the replication results for epochs, future studies may explore alternate formulations of tours, epochs and branching. One example can be to bundle different intermediate epochs together in the second level and then model participation and time allocation into each intermediate epoch in the third level.

Sensitivity Analysis

The focus of this section is to highlight the model's ability to capture the interrelationships between tour level and epoch level, participation and time allocation decisions. The sensitivity analysis is carried out altering the land use variable. In particular, it was assumed that more suburbanization occurs by moving 50 percent of the households to suburban/rural areas[14].

[14] This was achieved by randomly assigning 50% of the sub-sample to suburban/rural areas assuming baseline values are maintained for the rest of the variables

Table 4 presents the change in average time allocation into different tours/epochs for the people who participated in that particular tour/epoch type[15]. A positive (negative) value indicates an increase (decrease) in time allocation from baseline scenario. In terms of tour time allocation, notable changes are observed in the work, PB, shopping and SR tours.

The results also show the ability of the model formulation to capture the interrelationships between tour and epoch level choices. There is a two level impact of the shift in the land use on the time allocation into different epochs within the tour. First, it can be seen from the table that, for the tour types with a notable change in budget (positive in current scenario analysis), overall time allocation into different epochs also increased[16] (e.g. work, PB, shop and SR tours). Such shifts can only be captured through consistent prediction of the tour budget. Specifically, for certain exogenous variables that significantly affect time allocation to tours, if change in tour budget is not forecasted correctly, it will not capture the indirect impacts on the epoch participation and time allocation decisions. Second, for tour types with slight change in the tour budget, the time allocation into different epochs mainly got redistributed[16] (e.g. school, escort and meal tours).

CONCLUSION

In the tour-based activity based modeling (ABM), daily activity-travel agendas are formed in two stages: activity pattern generation and activity scheduling. The present work contributes to the activity pattern generation of ABMs.

The primary objective of the current research was to propose a tour generation framework that treats time as a continuous entity and explicitly accounts for temporal constraint for different tours and for different stops within the tours in a behaviorally consistent manner. The econometric formulation of the proposed framework is built on the utility theoretic Kuhn-Tucker demand system established by Bhat (2008, 2013) for multiple discrete continuous choice scenarios. The proposed approach assumes a bi-level decision making structure (where the alternatives considered at both stages are imperfect substitutes of one another) where the epoch level participation and time allocation decisions are constructed depending on the decisions made at the tour level.

The proposed framework was applied using data from NHTS 2008-2009. The empirical case study demonstrates the ability of the model formulation to model participation and allocate the daily time (1440 minutes) into different tours (including at home activities) followed by participation and time allocation into the primary epoch and intermediate epochs within the tours. Additionally, the proposed formulation offers the ability to accommodate more flexible error structure between different tour types and between different stops within the tours. The estimation routine's non-reliance on any kind of numerical simulation lends itself to be adopted in practice (Bhat 2011). The replication study conducted afterwards indicated that the framework is capable of capturing the tradeoffs underlying the tour and stop/epoch making decisions.

The proposed framework can be readily embedded into the existing tour-based ABM frameworks (e.g. Bowman and Bradley 2008). The bi-level model would replace a large number

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[15] The change in average time allocation across all the individual (irrespective of participation) is also reported in the parentheses

[16] This can be verified by taking the summation across all the values in the epoch duration reported in the parentheses for the respective tours.

of independent model components related to day pattern generation (including number of tours, number of stops in a tour, time allocated to tours, and time allocated to stops in a tour). After the participation and time allocation decisions have been modeled using the proposed framework, other decisions relating to tour and stop level characteristics (e.g. mode choice, destination, and occupancy among others) can be addressed using independent or joint model systems. The model implementation is also computationally very tractable. While more complex compared to traditional approaches, the proposed approach achieves efficiency by replacing a number of independent model systems and heuristics. In this study, computational overhead of the proposed framework (in terms of model estimation and forecasting) was found to be comparable to individual econometric model systems (such as MNL, MDCEV). On a Dell Latitude 620 Laptop with 2.9 GHz core i7 processor and 8GB RAM, the estimation took 1-3 hours (depending on the starting values of the parameter vector) and sensitivity analysis took about 10 minutes to run. Similar forecasting runtimes can be achieved even for a full model application (with large population sizes) by leveraging the power of parallelization. Large synthetic population can be broken down into smaller subpopulation and processed in parallel to make the application of the proposed model formulation practical.

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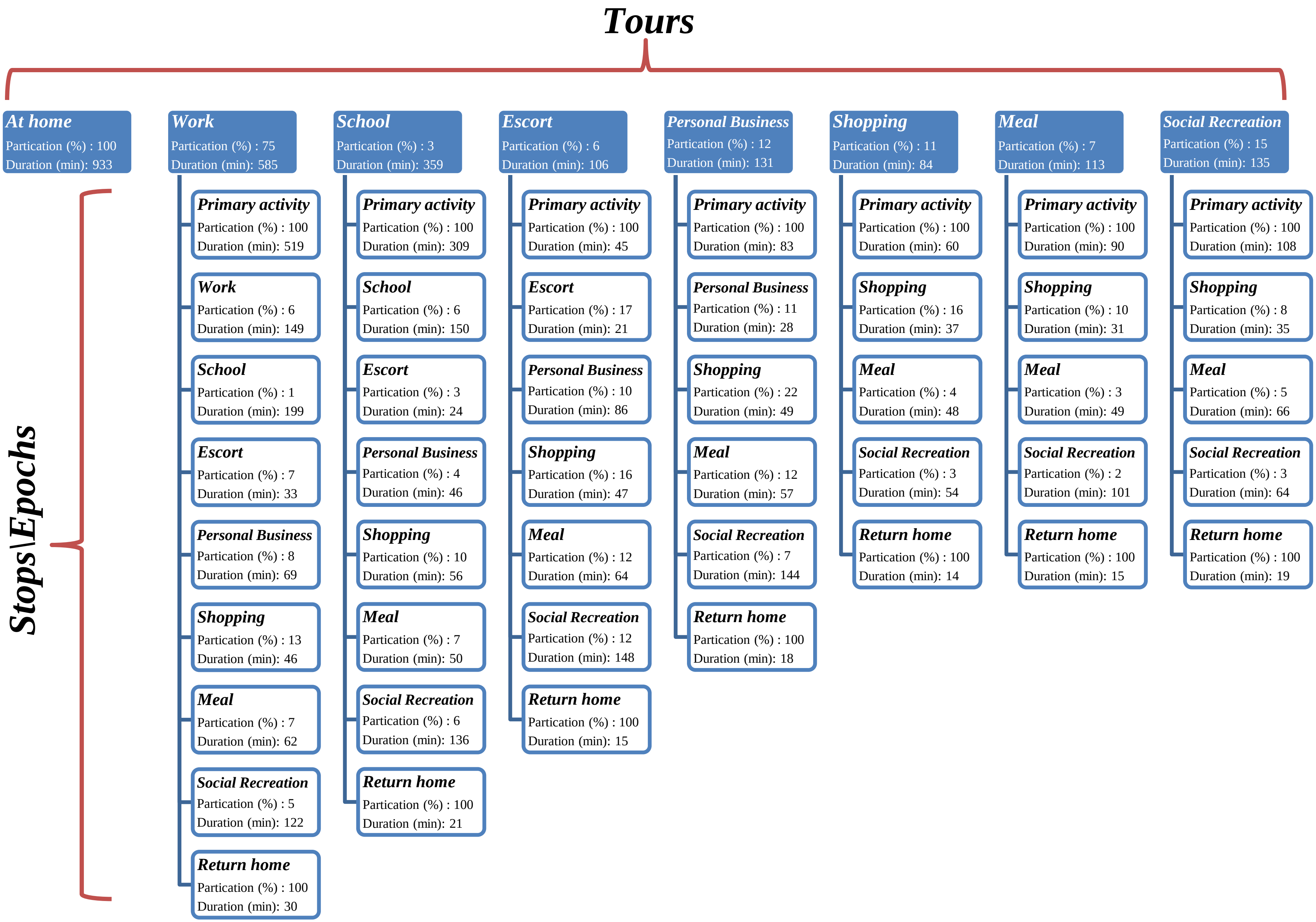

FIGURE 1: Qualitative model framework and observed participation and time allocation.

Note: Average durations are calculated across the individuals who reported to participate in the respective tour and stop/epoch.

Table 1: Estimation Results for the Tour (Top) level Model

Baseline Utility Specification		*Satiation Parameter Specification*	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Work tour		***Work tour***	
Constant	-6.719 (-47.85)	Constant	5.763 (96.94)
Age 16 to 34 years	0.249 (2.92)	Male indicator	0.159 (5.25)
Age 35 to 54 years	0.206 (3.04)	Age 16 to 34 years	-0.213 (-2.76)
Yearly HH Income >$25,000 & <$50,000	0.089 (1.84)	Age 35 to 54 years	-0.161 (-2.58)
Part time worker indicator	-1.075 (-17.22)	Part time worker indicator	0.329 (5.21)
School tour		Urban area indicator	-0.113 (-3.11)
Constant	-12.432 (-30.35)	LA County Indicator	0.099 (4.01)
Male indicator	0.367 (2.46)	***School tour***	
Age 16 to 34 years	2.762 (9.27)	Constant	6.543 (21.05)
Age 35 to 54 years	1.115 (3.60)	Age 16 to 34 years	-0.699 (-2.38)
Yearly HH Income >$50,000 & <$100,000	-0.197 (-1.31)	LA County Indicator	0.338 (1.82)
Friday Indicator	-0.327 (-1.67)	***Escort tour***	
Part time worker indicator	1.818 (10.97)	Constant	4.185 (23.71)
LA County Indicator	-0.309 (-2)	Age 35 to 54 years	-0.565 (-3.62)
Escort tour		Yearly HH Income >$25,000 & <$50,000	0.456 (2.11)
Constant	-10.523 (-45.53)	LA County Indicator	0.337 (2.37)
Male indicator	-0.371 (-3.13)	***Personal Business tour***	
Age 35 to 54 years	0.768 (6.07)	Constant	4.664 (27.71)
Part time worker indicator	0.494 (3.63)	Male indicator	-0.094 (-1.1)
Personal Business tour		Part time worker indicator	0.251 (2.61)
Constant	-9.054 (-46.87)	Urban area indicator	-0.239 (-1.46)
Age 16 to 34 years	-0.657 (-4.07)	***Shopping tour***	
Age 35 to 54 years	-0.449 (-3.13)	Constant	4.425 (33.21)
Age 55 to 64 years	-0.264 (-1.75)	Male indicator	-0.181 (-2.34)
Urban area indicator	0.192 (1.38)	Age 35 to 54 years	-0.128 (-1.63)
Part time worker indicator	0.431 (4.24)	Urban area indicator	-0.377 (-2.88)
Shopping tour		LA County Indicator	0.240 (2.97)
Constant	-9.422 (-50.51)	***Meal tour***	
Yearly HH Income >$50,000 & <$100,000	-0.348 (-3.26)	Constant	4.912 (47.55)
Yearly HH Income>$100,000	-0.418 (-3.77)	Male indicator	-0.206 (-2.17)
Urban area indicator	0.215 (1.46)	Yearly HH Income>$100,000	-0.140 (-1.44)
Friday Indicator	0.359 (3.34)	LA County Indicator	0.271 (2.92)
Part time worker indicator	0.188 (1.88)	***Social Recreation tour***	
Meal tour		Constant	4.613 (30.8)
Constant	-9.513 (-55.63)	Urban area indicator	-0.299 (-1.99)
Yearly HH Income >$25,000 & <$50,000	0.286 (1.87)	Friday Indicator	0.318 (2.90)
Yearly HH Income >$50,000 & <$100,000	0.331 (2.42)	LA County Indicator	0.278 (3.43)
Yearly HH Income>$100,000	0.404 (2.94)		
Friday Indicator	0.453 (4.94)		
Social Recreation tour			
Constant	-9.258 (-53.87)		
Age 16 to 34 years	0.088 (0.98)		
Yearly HH Income >$25,000 & <$50,000	0.253 (1.91)		
Yearly HH Income >$50,000 & <$100,000	0.437 (3.72)		
Yearly HH Income>$100,000	0.387 (3.25)		
Urban area indicator	0.161 (1.39)		
Friday Indicator	0.142 (1.52)		
Part time worker indicator	0.352 (4.37)		

Table 2: Estimation Results for the Work Epoch (Bottom) level Model

Baseline Utility Specification		***Baseline Utility Specification (Cont.)***	
Parameters	**Estimate (t-stat)**	**Parameters**	**Estimate (t-stat)**
Return home		***Meal epoch***	
Constant	-3.055 (-224.55)	*Constant*	-12.731 (-9.44)
Work epoch		*Male indicator*	-0.495 (-2.69)
Constant	-14.068 (-3.59)	*Age 16 to 34 years*	-0.305 (-1.12)
Age 16 to 34 years	-0.203 (-1.15)	*Age 35 to 54 years*	-0.215 (-1.05)
Age 35 to 54 years	-0.149 (-1.14)	*Yearly HH Income >$50,000 & <$100,000*	0.377 (1.60)
Yearly HH Income >$50,000 & <$100,000	0.144 (1.19)	*Yearly HH Income>$100,000*	0.544 (2.28)
Flexible work schedule indicator[17]	0.295 (2.53)	*Flexible work schedule indicator*	0.559 (3.09)
Driver Indicator[18]	4.932 (1.27)	*Friday Indicator*	0.662 (3.20)
LA County Indicator	-0.146 (-1.23)	*Driver Indicator*	1.775 (1.38)
School epoch		***Social Recreation epoch***	
Constant	-12.817 (-14.32)	*Constant*	-12.643 (-9.99)
Age 16 to 34 years	2.111 (6.52)	*Male indicator*	-0.177 (-0.95)
Yearly HH Income >$25,000 & <$50,000	0.772 (1.34)	*Yearly HH Income>$100,000*	0.348 (1.81)
Yearly HH Income >$50,000 & <$100,000	1.394 (2.87)	*Flexible work schedule indicator*	0.386 (2.09)
Yearly HH Income>$100,000	1.332 (2.64)	*Urban area indicator*	0.474 (1.57)
Friday Indicator	-0.741 (-1.62)	*Driver Indicator*	1.418 (1.26)
Escort epoch		*LA County Indicator*	-0.216 (-1.15)
Constant	-11.945 (-26.54)	***Satiation Parameter Specification***	
Male indicator	-0.435 (-2.44)	**Parameters**	**Estimate (t-stat)**
Age 16 to 34 years	1.578 (4.74)	***Work epoch***	
Age 35 to 54 years	2.139 (7.34)	*Constant*	5.517 (30.77)
Flexible work schedule indicator	0.519 (2.96)	***School epoch***	
LA County Indicator	-0.322 (-1.82)	*Constant*	5.583 (12.21)
Personal Business epoch		*Male indicator*	1.224 (2.77)
Constant	-9.749 (-24.71)	*Friday Indicator*	-2.063 (-5.73)
Male indicator	-0.897 (-5.05)	***Escort epoch***	
Age 16 to 34 years	-1.278 (-3.45)	*Constant*	2.612 (30.08)
Age 35 to 54 years	-0.854 (-2.74)	*Yearly HH Income >$25,000 & <$50,000*	-0.323 (-1.79)
Age 55 to 64 years	-0.487 (-1.47)	***Personal Business epoch***	
Yearly HH Income >$50,000 & <$100,000	0.192 (1.08)	*Constant*	3.460 (33.27)
Flexible work schedule indicator	0.810 (4.83)	*Yearly HH Income >$25,000 & <$50,000*	-0.455 (-2.53)
Friday Indicator	0.398 (1.91)	***Shopping epoch***	
Shopping epoch		*Constant*	2.92 (39.98)
Constant	-11.789 (-11.35)	*LA County Indicator*	0.168 (2.01)
Male indicator	-0.913 (-5.95)	***Meal epoch***	
Age 16 to 34 years	-0.743 (-3.17)	*Constant*	3.284 (28.70)
Age 35 to 54 years	-0.414 (-2.47)	*Yearly HH Income >$25,000 & <$50,000*	-0.375 (-1.92)
Yearly HH Income >$50,000 & <$100,000	0.206 (1.32)	***Social Recreation epoch***	
Flexible work schedule indicator	0.245 (1.64)	*Constant*	4.532 (36.43)
Urban area indicator	0.804 (3.12)	*Friday Indicator*	0.376 (2.45)
Driver Indicator	2.127 (2.19)		
LA County Indicator	-0.217 (-1.33)		

[17] Flexible work schedule indicator assumes a value 1 if flexible work schedule is exercised and 0 otherwise.
[18] Driver indicator assumes a value 1 if person is reported to be a driver during the travel day and 0 otherwise.

Table 3: Baseline Forecasting (Replication Results)

Tour types	*Participation[a] (%) Predicted (Observed)*	*Epoch types*								
		Primary Activity	*Work*	*School*	*Escort*	*Personal Business*	*Shopping*	*Meal*	*Social Recreation*	*Return home*
		Participation[b] (%) - Predicted (Observed)								
At home	100 (100)	---	---	---	---	---	---	---	---	---
Work	67 (75)	100 (100)	8 (6)	1 (1)	7 (7)	9 (8)	13 (13)	7 (7)	6 (5)	100 (100)
School	3 (3)	100 (100)	---	7 (6)	5 (3)	6 (4)	14 (10)	10 (7)	8 (6)	100 (100)
Escort	6 (6)	100 (100)	---	---	20 (17)	13 (10)	19 (16)	14 (12)	15 (12)	100 (100)
Personal Business (PB)	10 (12)	100 (100)	---	---	---	11 (11)	23 (22)	13 (12)	9 (7)	100 (100)
Shopping	9 (11)	100 (100)	---	---	---	---	22 (16)	8 (4)	5 (3)	100 (100)
Meal	5 (7)	100 (100)	---	---	---	---	11 (10)	4 (3)	6 (2)	100 (100)
Social Recreation (SR)	12 (15)	100 (100)	---	---	---	---	9 (8)	8 (5)	4 (3)	100 (100)
Tour types	*Duration[c] (Min.) Predicted (Observed)*	*Epoch types*								
		Primary Activity	*Work*	*School*	*Escort*	*Personal Business*	*Shopping*	*Meal*	*Social Recreation*	*Return home*
		Duration[d] (Min.) - Predicted (Observed)								
At home	891 (933)	---	---	---	---	---	---	---	---	---
Work	478 (436)	599 (519)	19 (9)	4 (2)	5 (2)	13 (6)	17 (6)	9 (4)	12 (6)	40 (30)
School	11 (11)	325 (309)	---	10 (8)	2 (1)	4 (2)	13 (6)	6 (4)	13 (8)	39 (21)
Escort	8 (7)	41 (45)	---	---	6 (4)	19 (9)	13 (8)	12 (8)	27 (18)	19 (15)
Personal Business (PB)	15 (16)	77 (83)	---	---	---	5 (3)	20 (11)	12 (7)	18 (10)	23 (18)
Shopping	12 (9)	74 (60)	---	---	---	---	19 (6)	8 (2)	6 (2)	20 (14)
Meal	7 (8)	96 (90)	---	---	---	---	8 (3)	3 (2)	9 (2)	19 (15)
Social Recreation (SR)	18 (21)	101 (108)	---	---	---	---	6 (3)	8 (3)	4 (2)	32 (19)

[a]: The denominator is the number of observations in the sample (5233)
[b]: The denominator is the number of people who predicted (observed) to participate in the respective tour
[c]: Average taken across the 5233 observations
[d]: Average taken across the observations who are predicted (observed) to participate in the respective tour

Table 4: Impacts on Tour and Epoch Time Allocation Due to Land use and Demographic Changes

Impact of Change in Land Use										
		Epoch types								
Tour types	***Change in Minutes***	***Primary Activity***	***Work***	***School***	***Escort***	***Personal Business***	***Shopping***	***Meal***	***Social Recreation***	***Return home***
		Change in Minutes								
At home	-0.83 (-0.83)	---	---	---	---	---	---	---	---	---
Work	5.20 (1.03)	7.43 (7.43)	0.43 (0.09)	-0.08 (0.16)	0.64 (0.1)	1.03 (0.1)	-5.56 (-2.85)	1.98 (0.45)	-1.83 (-0.89)	0.60 (0.60)
School	0.61 (0.19)	-3.27 (-3.27)	---	-4.36 (-1.82)	-0.97 (-0.26)	-2.12 (-0.66)	15.37 (8.93)	-1.09 (-0.25)	-3.15 (-1.47)	-0.59 (-0.59)
Escort	-0.92 (-0.07)	2.17 (2.17)	---	---	1.6 (0.73)	-0.99 (-5.26)	2.21 (1.17)	2.15 (1.31)	0.89 (-2.16)	1.12 (1.12)
Personal Business (PB)	6.12 (-0.38)	4.14 (4.14)	---	---	---	1.21 (0.4)	-1.53 (-2.64)	0.84 (-0.42)	4.17 (3.37)	1.27 (1.27)
Shopping	9.20 (-0.28)	4.16 (4.16)	---	---	---	---	2.53 (1.83)	3.06 (1.51)	2.21 (0.61)	1.09 (1.09)
Meal	-0.90 (0.12)	1.96 (1.96)	---	---	---	---	-2.16 (-1.67)	0.50 (0.15)	-1.73 (-2.12)	0.77 (0.77)
Social Recreation (SR)	9.66 (0.22)	7.80 (7.80)	---	---	---	---	5.83 (1.13)	-3.06 (-2.48)	4.46 (0.72)	2.49 (2.49)

Note:

(1) Values outside the parentheses represent the change in average time allocation calculated across people who participated in the respective tour/epoch

(2) Values inside the parentheses represent the change in average time allocation calculated across all the individual (in case of tour), across all the individual who participated in the respective tour (in case of epochs)