A UNIFIED MODEL SYSTEM OF ACTIVITY TYPE CHOICE, ACTIVITY DURATION, ACTIVITY TIMING, MODE CHOICE, AND DESTINATION CHOICE

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August 2009

ABSTRACT

Recent evidence suggests that many activity-travel choices are inter-dependent with one another and hence inextricably linked in ways that need to be better understood to help inform the specification of activity-based travel model systems. Model systems in practice often sequentially link a series of choice dimensions into a deeply nested logit model where accessibility variables (logsum terms) from lower nests cascade up through the structure to the higher levels in the model structure. While these model systems are convenient from a practical standpoint, they ignore the potential jointness in choice-making processes and do not effectively and directly capture the effects of spatial land use and built environment characteristics on activity generation. In this paper, a unified model of activity type choice (generation), time of day choice, mode choice, destination choice, and time use allocation (duration) is formulated and estimated on a survey sample data set drawn from the 2000 San Francisco Bay Area Travel Survey (BATS). The model system constitutes a joint multiple discrete continuous extreme value (MDCEV) – multinomial logit (MNL) model, in which all discrete choices, except for destination choice, and the continuous duration dimension are modeled using the MDCEV, and destination choice is modeled as a MNL (with sampling of alternatives) nested and therefore integrated with the MDCEV model component. The parameter estimates of the joint model offer behaviorally intuitive results that support the integrated treatment of these choice dimensions as a choice "bundle". The potential applicability of the model system is demonstrated through a policy simulation example that shows how changes in travel cost and time variables lead to changes in out-of-home discretionary activity participation.

Keywords: activity type choice, time of day choice, activity duration, mode and destination choice, joint model, simultaneous equations model, integrated model, MDCEV-MNL model

1. INTRODUCTION AND MOTIVATION

Emerging policy issues of interest, including concerns regarding global climate change and the desire to better understand how pricing policies and technological innovations impact travel demand, enhanced understanding of activity-travel behavior dimensions garnered over decades of behavioral research, and advances in microsimulation-based computational approaches have all contributed to a new era in travel demand modeling and forecasting (Pendyala *et al*, 2005; Pinjari *et al*, 2006). This era is characterized by an increasing shift towards activity-based travel demand modeling approaches that explicitly recognize that travel is undertaken to fulfill activity needs and desires dispersed in space and time (Meloni *et al*, 2004). The move towards microsimulation-based approaches facilitates the disaggregate representation of behavioral agents and their interactions, while simultaneously incorporating the ability to analyze policy impacts and address equity concerns at the level of the individual traveler or any sub-market segment of interest (Miller and Roorda, 2003).

Within the scope of this paper, it is not possible to thoroughly review the developments in activity-based models over the past decade and the gradual implementation of tour-based models in practice in several urban areas in the United States and other parts of the world. Regardless of the specific model design adopted, it is found that activity and tour-based model systems universally strive to mimic and replicate activity-travel choice processes of individuals. These choice processes include such dimensions as activity type choice, time of day choice, trip chaining or linking choice, joint versus solo activity engagement choice, destination choice, mode choice, activity sequencing decisions, and activity time allocation (duration) decisions. Many of these choice processes are discrete in nature (e.g., activity type choice, time of day period choice, mode and destination choices), while a few may be more continuous in nature (e.g., activity duration). Given the large number of choices that are involved in the behavioral process, many models, particularly the tour-based models in practice, resort to the adoption of deeply nested logit models (Ben-Akiva and Lerman, 1985) where one choice process is nested within another choice process and so on, forming a long chain of inter-connected nests to complete the representation of the behavioral process (Bowman, 1995; Bowman and Bradley, 2006; PB Consult, 2005). As it is virtually impossible to estimate such long chains of nested logit models simultaneously (i.e., in one single step), components of the nested logit model are usually estimated one step (or maybe two steps) at a time and the logsum from one level is carried up to the next higher level, resulting in a sequential estimation and model application approach. Although there are other behavioral model systems that attempt to move away from such deeply nested logit specifications, such as those based on computational process modeling and heuristic approaches (Arentze and Timmermans, 2005), the fact remains that most activity-based model systems break down the behavioral decision process so that one is modeling only one or two choice processes at any step in the model system.

Although a sequential treatment of choice mechanisms is convenient from a practical model estimation and application standpoint, it is unclear whether such model systems truly replicate behavioral processes. While tour-based and activity-based models in practice can be lauded for their ability to model activity engagement patterns, consider interactions among activities and trips, and microsimulate activity-travel patterns at the level of the individual traveler, the issue arises as to whether these model systems can be challenged and questioned from a behavioral standpoint not unlike the traditional four-step travel modeling process. The four-step travel modeling process has been consistently criticized for its sequential nature of treatment of the travel demand process. To what extent activity and tour-based models in practice overcome this issue is potentially open to debate, although there is no question that even limited information maximum likelihood (LIML) specifications of deeply nested logit models allow one to model correlated choice processes better than was done in the four-step travel modeling process.

While it is arguably true that people have limited cognitive abilities and therefore exercise choices in a limited, sequential way, there is considerable evidence that many choices are made jointly or simultaneously and that there are significant unobserved factors that simultaneously impact multiple choice dimensions (see, for example, Pinjari and Bhat, 2009a). In fact, one could argue that the limited information sequential model specifications have been adopted in the activity-based modeling realm because of the estimation challenges and computational complexity associated with specifying, identifying, and estimating simultaneous equations model systems that represent joint choice processes in which individuals and households are making a "package" of activity-travel choices as a "bundle". In other words, it is conceivable that individual agents are making choices regarding the type of activity to pursue, the mode and destination, and the time allocation to the activity in one swoop, thus motivating the adoption of a "joint" choice model specification in which unobserved factors unknown to the analyst may be simultaneously impacting multiple dimensions of interest (Jara-Diaz *et al*, 2007).

The growing interest in the ability to model multiple choice dimensions simultaneously, where the endogeneity of many choice variables is explicitly recognized in the activity-travel behavior modeling arena, motivates this paper. Specifically, this paper presents a joint model system of five choice dimensions:

- Activity type choice
- Activity time of day choice (treated as discrete time intervals)
- Mode choice
- Destination choice
- Activity duration (continuous choice dimension)

These five choice dimensions are of critical interest to any activity-based model system regardless of the model design that might be adopted. Thus, this paper aims to specify and estimate a comprehensive econometric model system that jointly models these five choice dimensions in a holistic unifying utility-maximization framework. The model system explicitly includes consideration of built environment attributes including level of service variables and spatial land use characteristics to capture the potential impacts of such variables on the activity generation process, a key area that warrants additional research. Such a model specification provides the ability to examine induced and suppressed demand effects in response to changes in system capacity and level of service.

The modeling methodology adopted in this paper builds on previous work by the authors and constitutes a joint multiple discrete continuous extreme value model and multinomial logit model system (Bhat 2005, Bhat et al., 2006, Bhat 2008). The multiple discrete continuous extreme value (MDCEV) model component is used to jointly analyze activity type choice, activity time of day choice, mode choice, and activity duration. Specifically, the MDCEV model is used to represent activity participation (discrete choice) and time use (continuous choice) for different types of activities at different time periods of the day by different travel modes. The activity location choice is modeled using a multinomial logit (MNL) model nested within the MDCEV framework. The model system is estimated for a survey sample drawn from the 2000 San Francisco Bay Area Travel Survey (BATS), a comprehensive database that includes detailed household and personal socio-economic, demographic, and activity-travel information together with a host of secondary transportation level-of-service and land use variables.

The next section presents the modeling methodology in detail. This is followed by a description of the dataset and survey sample. The fourth and fifth sections present model estimation and policy simulation results, while the sixth and final section offers concluding remarks.

2. MODELING METHODOLOGY

This section presents the modeling methodology for the joint MDCEV-MNL model structure. First, the utility structure is presented, second, the econometric model specification is presented, and finally the procedure for sampling of location choice alternatives is discussed. An intuitive behavioral interpretation of the model structure is offered as well.

2.1 Utility Structure

Consider the following utility specification for the integrated analysis of individuals' activity time-use, timing, mode choice, and location choice decisions:

$$U(\boldsymbol{x}) = \{\psi_1 \ln x_1\} + \left\{\gamma_2 \psi_2 \ln\left(\frac{x_2}{\gamma_2} + 1\right)\right\} + \sum_{ptm=3}^{62} \left\{\gamma_{ptm} \psi_{ptm} \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1\right)\right\} \tag{1}$$

In the above equation, the first term $\psi_1 \ln x_1$ corresponds to the utility contribution of the total daily time invested (x_1) in all maintenance activities, and the second term corresponds to the utility contribution of the total daily time invested (x_2) in all in-home (IH) discretionary activities. The next set of terms correspond to the utility contribution due to the time investment (x_{ptm}) in out-of-home (OH) discretionary activity episode types (indexed by *ptm*), with each activity episode type defined by its purpose (*p*), timing (*t*), and mode of travel (*m*). In the current empirical context considered in this paper, there are five OH discretionary activity purposes (volunteering, socializing, recreation, meals, and shopping), six time periods (3am-7am or early morning, 7am-9am or morning, 9am-12noon or late morning, 12noon-4pm or afternoon, 4pm-7pm or evening, and 7pm-3am or night), and two modes of travel (auto, and non-auto), yielding 60 different types of OH discretionary activity episodes (or *ptm* combinations). Thus, there are a total of 62 MDCEV choice alternatives in that one or more of these alternatives may be chosen by an individual through the course of a day.[1] For each of these alternatives, the ψ terms $(\psi_1, \psi_2, \text{and}\, \psi_{ptm})$ are the baseline utility parameters that control the discrete choice of the

[1] Without loss of generality, all individuals can be assumed to participate in maintenance activities. On the other hand, an individual can participate in none, or one, or more of IH discretionary and 5 OH discretionary activity purposes (*p*) identified above. If (s)he chooses to participate in OH discretionary activities, (s)he can do so during one or more of the 6 time periods (*t*), and access the activities using one or more of the 2 travel modes (*m*). Thus, there is multiple discreteness in the choices across the activity purpose, activity timing, and travel mode dimensions.

alternative. For all alternatives except the first alternative, the γ terms (γ_2 and γ_{ptm}) allow for corner solutions (*i.e.,* the possibility of not choosing the alternative) as well as satiation effects (*i.e.*, diminishing marginal utility with increasing time investment).[2] There is no γ term corresponding to the first alternative (maintenance activity) as it is always chosen by all individuals.

Finally, let each of the 60 OH discretionary activity episode types (*ptm*) be defined (by its purpose-timing-mode (*ptm*) combination) such that an individual participates in no more than one episode of that type in a day. Consequently, if an individual chooses to undertake an activity episode type (*ptm*), it has to be at only one of the several destination alternatives (*l*) available to her/him.

Let the index for the activity destination (or location) be *l*, and let N_{ptm} be the set of destinations available for an activity episode type (*ptm*). Further, for each activity episode type (*ptm*), let ψ_{ptm} be defined as follows (Bhat et al., 2006):

$$\psi_{ptm} = \exp\left(\sum_{l \in N_{ptm}} \delta_{lptm} W_{lptm} \right), \tag{2}$$

where, W_{lptm} is the utility perceived by the individual for undertaking the OH discretionary activity episode of purpose *p*, during time period *t*, by traveling on mode *m* to location *l*, and δ_{lptm} is a dummy variable taking a value of 1 if the l^{th} location is chosen for that activity episode such that $\sum_{l \in N_{ptm}} (\delta_{lptm}) = 1$ (*i.e.*, only one location is chosen).

With the above definition of ψ_{ptm} and other terms described earlier, the individual is assumed to maximize the utility function $U(\boldsymbol{x})$ in Equation (1) subject to $x_1 + x_2 + \sum_{ptm} x_{ptm} = X$; $x_1 > 0,\ x_2 \geq 0,\ x_{ptm} \geq 0\ \forall ptm = 3,4,...62$. Since the individual maximizes $U(\boldsymbol{x})$ and can choose only one location for each activity episode *ptm* type, the functional form of $U(\boldsymbol{x})$ implies that the individual will consider the location that provides the maximum utility for each activity episode *ptm* type in the process of maximizing $U(\boldsymbol{x})$ (see Bhat et al., 2008). That is, $\sum_{l \in N_{ptm}} \delta_{lptm} W_{lptm} = \max_{l \in N_{ptm}} W_{lptm}$, or $\psi_{ptm} = \exp\left(\max_{l \in N_{ptm}} W_{lptm} \right)$ Thus, the individual's utility maximizing problem can be written as:

$$U(\boldsymbol{x}) = \{\psi_1 \ln x_1\} + \left\{ \gamma_2 \psi_2 \ln\left(\frac{x_2}{\gamma_2} + 1 \right) \right\} + \sum_{ptm} \left\{ \gamma_{ptm} \exp\left(\max_{l \in N_{ptm}} W_{lptm} \right) \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1 \right) \right\} \tag{3}$$

[2] To distinguish the satiation along OH discretionary activity purpose, activity timing, and travel mode dimensions (and to facilitate estimation), γ_{ptm} (*ptm* = 3,4,…,62) is parameterized as $\gamma_{ptm} = \gamma_p \times \gamma_t \times \gamma_m$, where γ_p, γ_t, γ_m are the estimated dimension-specific satiation parameters.

subject to $x_1 + x_2 + \sum_{ptm} x_{ptm} = X;\; x_1 > 0,\; x_2 \geq 0,\; x_{ptm} \geq 0\; \forall ptm.$

The analyst can solve for the optimal values of $x_1, x_2,$ and x_{ptm} by forming the Lagrangian and applying the Kuhn-Tucker (KT) conditions. Specifically, the following KT conditions can be formed (see Bhat, 2008):

$$H_2 = H_1 \;\; if \;\; x_2 > 0 \tag{4}$$

$$H_2 < H_1 \;\; if \;\; x_2 = 0$$

$$H_{ptm} = H_1 \;\; if \;\; x_{ptm} > 0$$

$$H_{ptm} < H_1 \;\; if \;\; x_{ptm} = 0$$

where,

$$H_1 = \ln(\psi_1) - \ln(x_1),$$

$$H_2 = \ln(\psi_2) - \ln\left(\frac{x_2}{\gamma_2} + 1\right), \text{ and}$$

$$H_{ptm} = \max_{l \in N_{ptm}} W_{lptm} - \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1\right)$$

2.2 Econometric Structure

To complete the model specification, let $\psi_1 = \exp(\beta' z_1 + \varepsilon_1)$ and $\psi_2 = \exp(\beta' z_2 + \varepsilon_2)$, where $\beta' z_1$ and $\beta' z_2$ are the observed baseline utility components of maintenance and IH discretionary activities, respectively, and ε_1 and ε_2 are the corresponding unobserved components assumed to be independent and identically Gumbel distributed. Further, to define ψ_{ptm}, we expand W_{lptm} as:

$$W_{lptm} = \beta' z_{ptm} + \phi' w_{lptm} + \eta_{lptm} \tag{5}$$

where, $\beta' z_{ptm}$ is the observed baseline utility corresponding to the activity purpose, timing, and mode of the OH discretionary activity episode *ptm*, $\phi' w_{lptm}$ is the observed utility corresponding to the potential location *l* for the activity episode, and η_{lptm} is the unobserved utility component associated with the location *l* of activity episode *ptm*. Similar to ε_1 and ε_2, the η_{lptm} terms are assumed to be independent and identically distributed (across different activity episode *ptm* types) Gumbel terms. Within each activity episode *ptm* type, however, all the error terms may share common unobserved attributes (specific to the activity episode *ptm* type) generating correlations among the η_{lptm} terms across all potential locations for the activity episode. Thus, for each activity episode *ptm* type, the following distribution of error terms may be used:

$$F(\eta_{1ptm}, \eta_{2ptm}, \ldots, \eta_{Lptm}) = \exp\left\{ -\left[e^{-\eta_{1ptm}/\theta_{ptm}} + e^{-\eta_{2ptm}/\theta_{ptm}} + \ldots + e^{-\eta_{Lptm}/\theta_{ptm}} \right]^{\theta_{ptm}} \right\} \tag{6}$$

where the θ_{ptm} is the dissimilarity parameter indicating the level of correlation among the η_{lptm} terms across all the potential locations for the activity episode *ptm* combination. Given this error distribution, using the properties of Gumbel distribution, H_{ptm} in Equation (4) can be expressed as:

$$\begin{aligned} H_{ptm} &= \max_{l \in N_{ptm}} \left\{ \beta' z_{ptm} + \phi' w_{lptm} + \eta_{lptm} \right\} - \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1 \right) \\ &= \beta' z_{ptm} + \theta_{ptm} \ln \sum_{l \in N_{ptm}} \exp\left(\frac{\phi' w_{lptm}}{\theta_{ptm}} \right) + \zeta_{ptm} - \ln\left(\frac{x_{ptm}}{\gamma_{ptm}} + 1 \right) \end{aligned} \tag{7}$$

where, ζ_{ptm} is a standard independent and identically distributed (across *ptm*) Gumbel error term. In this equation, $\ln \sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k} \right)$ constitutes the logsum term.

Next, following the MDCEV model derivations (see Bhat, 2008), the probability that the individual chooses the first Q out of K (=62) activity purpose-timing-mode alternatives (this may include maintenance as well as the IH discretionary activities without any timing and mode distinctions) for time investments $x_1^*, x_2^*, ..., x_Q^*$ may be written as:

$$P(x_1^*, x_2^*, ..., x_Q^* 0, 0, ..., 0) = \left[\prod_{k=1}^{Q} r_k \right] \left[\sum_{k=1}^{Q} \frac{1}{r_k} \right] \left[\frac{\prod_{k=1}^{Q} e^{V_k}}{\left(\sum_{h=1}^{K} e^{V_h} \right)^Q} \right] (Q-1)!, \tag{8}$$

where[3]

$r_1 = \left(\frac{1}{x_k^*} \right)$ and $r_k = \left(\frac{1}{x_k^* + \gamma_k} \right) \forall k > 1$

$V_1 = \beta' z_1 - \ln(x_1),$

$V_2 = \beta' z_2 - \ln\left(\frac{x_2}{\gamma_2} + 1 \right)$, and

$V_k = \beta' z_k + \theta_k \ln \sum_{l \in N_k} \left(\frac{\phi' w_{lk}}{\theta_k} \right) - \ln\left(\frac{x_k}{\gamma_k} + 1 \right); \forall k > 2$

The conditional probability that location *l* will be chosen for an activity episode purpose-timing-mode (*ptm*) combination *k*, given that $x_k^* > 0$, is given by:

$$P(l \mid x_k^* > 0;\; l \in N_k) = P\left[\phi' w_{lk} + \eta_{lk} > \phi' w_{l'k} + \eta_{l'k} \;\; \forall\; l' \neq l \right] \tag{9}$$

[3] Note that the notation for the subscripts of the choice alternatives has been changed to *k(=1,2,…62)* from *1,2,ptm(=3,4,…62)* for convenience.

Based on the multivariate Gumbel distribution function for the η_{lk} (or η_{lptm}) terms (l = 1,2,…, L) from Equation (6), the above probability expression can be computed using the following standard multinomial logit formula:

$$P(l \mid x_k^* > 0;\ \ l \in N_k) = \frac{\exp\left(\dfrac{\phi' w_{lk}}{\theta_k}\right)}{\sum_{l' \in N_k} \exp\left(\dfrac{\phi' w_{l'k}}{\theta_k}\right)} \tag{10}$$

Next, the unconditional probability that the individual spends x_1^* amount of time in daily maintenance activities, x_2^* amount of time in daily IH-discretionary activities, x_3^* amount of time in OH discretionary activity episode purpose-timing-mode (*ptm*) combination 3 (*i.e.*, k =3) at location a, x_4^* amount of time in OH discretionary activity episode purpose-timing-mode (*ptm*) combination 4 (*i.e.*, k =4) at location b, … and so on, may be written as:

$$\begin{aligned} &P(x_1^*,\ x_2^*,\ x_3^* \text{ at } a,\ x_4^* \text{ at } b,\ ...,\ x_Q^* \text{ at } q,\ 0,0,0,...0) \\ &= P(x_1^*, x_2^*, ...x_Q^*, 0,0,...0) \times P(a \mid x_3^* > 0) \times P(b \mid x_4^* > 0)...P(q \mid x_Q^* > 0) \end{aligned} \tag{11}$$

2.3 Sampling of Location Choice Alternatives

A practical issue with the proposed MDCEV-MNL model (as also with the deeply nested logit approach) is that, since there can be a large number of location choice alternatives at the single discrete choice level (and since multiple single discrete choice models may be invoked), the model estimation can be highly computation intensive. To reduce the computation time, the analyst can include only a smaller sample of the location choice alternatives (with the chosen alternative in the sample) during estimation. According to McFadden (1978), random sampling of alternatives will not compromise the consistency of the location choice model parameters as long as a simple multinomial logit modeling framework is maintained for the location choice as in Equation (10).[4] However, sampling the location choice alternatives warrants a correction to the log-sum term $\ln \sum_{l \in N_k} \exp\left(\dfrac{\phi' w_{lk}}{\theta_k}\right)$ used in the MDCEV component of the joint model (See Equation 7). This is because, in this term, the sum of exponentials of the utilities (scaled by the dissimilarity parameter) of all the location choice alternatives $\sum_{l \in N_k} \exp\left(\dfrac{\phi' w_{lk}}{\theta_k}\right)$ is not equal to the sum of exponentials of the utilities of a sample of those alternatives. This is corrected by

[4] The reader will note here that Equation (10) is derived from a nested extreme value error term distribution as in Equation (6). However, since this distribution assumes the same scale parameter for all location choice alternatives associated with the activity episode *ptm* type, the location choice parameters will be consistent. In essence, as long as the error distributions do not allow different scale parameters across the location choice alternatives associated with an activity episode *ptm* type (*i.e.*, to accommodate spatial correlations, etc.) and no random coefficients are estimated in the location choice model, one can use a random sample of location choice alternatives to consistently estimate the model parameters. See Bierlaire et al. (2008) for more details on sampling related issues with multi-dimensional choice models.

incorporating a scaling factor (π_k) that is equal to the total number of available location choice alternatives divided by the number of sampled alternatives. Since location choice alternatives are sampled randomly, and since the random sample varies across individuals and activity purpose-timing-mode (*ptm*) combinations, this scaling factor should help approximate the logsum term reasonably well. That is:

$$\ln\left(\pi_k \sum_{l \in \text{ a random sample of } N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right)\right) \approx \ln \sum_{l \in N_k} \exp\left(\frac{\phi' w_{lk}}{\theta_k}\right) \tag{12}$$

In this study, 30 location choice alternatives are randomly sampled from 1099 potential locations yielding, π_k = 36.63.

2.4 An Intuitive Behavioral Interpretation

The probability expression in Equation (11) is a combination of MDCEV and single discrete choice probabilities. Specifically, for each OH discretionary activity episode purpose-timing-mode (*ptm*) combination chosen by an individual, a single discrete choice model of location choice is invoked. The parameters ϕ and θ_k appear in both the MDCEV probability expression (Equation 8) as well as the standard discrete choice probability expression for the choice of activity location (Equation 10) to create jointness between the multiple discrete-continuous and single discrete choices. Further, the logsum term (see Equation 7) appearing in the MDCEV probability expression carries the accessibility of destinations (or potential locations) from the single discrete location choice model to the MDCEV model of time investment by activity purpose, timing, and travel mode. Thus, Equation (11) represents a unified and comprehensive model of activity-travel program generation that incorporates the influence of accessibility measures on activity time-use, timing, and mode choices.

The proposed two-level MDCEV-MNL model is an attractive alternative to the deeply nested logit modeling approach available in the literature, where accessibility measures have to propagate up to the activity generation level through multiple levels of a deeply nested logit model. Further, the MDCEV-MNL model provides a seamless way of incorporating time-use (and the impact of accessibility on time-use) into the framework. Specifically, the modeling framework explicitly accommodates the concept that individual’s activity time-use (*i.e.*, time allocation) decisions are important and influential components of their activity-travel decision-making (Bhat and Koppelman, 1999). On the other hand, the deeply nested logit approach does not explicitly incorporate activity time-allocation choices into the analysis framework in a straight forward manner. Another appealing feature is that the model recognizes the simultaneity of the activity time-use, timing, mode choice, and location choice decisions within a unified utility maximization framework.

3. DATA DESCRIPTION

The data set used in this paper is derived from 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 data includes information on: (1) Individual and household socio-demographics for over 15,000 households in the Bay Area, and

(2) All activity episodes (including activity type, start and end times of the activity, geo-referenced location of activity participation, and mode of travel to the activity) undertaken by the individuals in all surveyed households for a two-day period.

The travel survey records were augmented extensively with several secondary data items, including land-use characteristics, transportation network level-of-service data, and Census population and housing data. In addition, geo-referenced data on businesses, bicycle facilities, highways and local roads were used to derive spatial variables characterizing the activity-travel environment (ATE) in and around the household locations of the individuals in the data set. Details regarding the data preparation and augmentation processes can be found in Guo and Bhat (2004) and Pinjari et al., (2009).

As mentioned in the previous section, the activity choice dimensions modeled in this paper include activity type choice, activity time of day choice, travel mode choice, activity location (destination) choice, and activity time use allocation (duration). The MDCEV model component alternatives are formed as combinations of activity type, time of day, and travel mode while the duration of each activity episode constitutes the continuous dependent variable. Finally, the MNL module accommodates the activity location or destination choice. There are: (a) a maintenance activity type, (b) an in-home discretionary activity type, and (c) five out-of-home discretionary activity types, six time periods, and two travel modes, yielding a total of 62 possible MDCEV choice alternatives (2 + 5x6x2 = 62). It is to be noted that the activity timing and travel mode analysis is limited to the five out-of-home discretionary activity types.

In order to control for fundamental differences between workers and non-workers in their activity engagement patterns and choice processes, and in the interest of brevity, the analysis in this paper was restricted to the sample of 5,360 non-working individuals aged 16 years or above. Descriptive statistics for this sample of individuals are presented in Table 1. All 5,360 individuals participate in in-home maintenance for an average duration of nearly 11 hours. Forty percent engage in in-home discretionary activities for an average duration of about 5.5 hours. Note that the average durations are computed over those who actually participate in the activity type. A little over one-half of the sample participated in OH discretionary activities, for an average duration of about 2.5 hours. It is found that the automobile mode is the preferred and dominant mode of travel accounting for nearly 90 percent of all out-of-home discretionary activity engagement. Non-maintenance shopping shows a relatively high participation rate, but lower time allocation (regardless of mode), while activities such as meals, socializing, and recreation show lower participation rates but higher time allocation. Across the top of the table (in the grey shaded row), it is seen that only a very small percent of individuals participate in OH discretionary activities in the early morning, and the percentage steadily rises into the afternoon, and then shows a decline towards the night hours. Activities undertaken in the morning and early morning, however, show the longest average durations relative to those in the afternoon and evening, potentially indicating the effect of time constraints that might get tighter towards the latter half of the day. Overall, this table shows the interplay among the dimensions of activity-travel participation that merit a unified approach towards modeling these behavioral characteristics.

4. EMPIRICAL ANALYSIS

4.1 Model Specification And Estimation Results

Model estimation was performed using Gauss code written specifically to estimate the joint MDCEV-MNL model system. Although it would have been ideal to estimate a separate destination choice model for each of the 60 OH discretionary activity purpose-timing-mode (*ptm*) combination categories, for this initial effort, a single MNL location choice model was estimated for all discretionary activity *ptm* categories. However, extending the estimation process to incorporate 60 MNL models of destination choice is straightforward by specifying dimension-specific model coefficients; the model specification here is one in which all destination choice model coefficients are restricted to be identical across all activity purpose categories, timing categories, and mode categories. A variety of variables were included in the model specification including household and personal socio-economic and demographic variables, contextual variables such as day of week and season of the year, and a host of spatial variables characterizing the activity-travel environment (ATE) around the household locations, not to mention several transportation network level of service variables. The spatial ATE variables included density measures, activity opportunity and accessibility measures, and population and housing data for the neighborhood (traffic analysis zone). The ATE measures were considered at the level of the traffic analysis zone and at finer spatial resolutions, including within 0.25 mile, 1 mile, and 5 mile radii buffers of the household location (see Guo and Bhat, 2004 and Pinjari *et al*, 2009 for complete details).

In the current research effort, a comparison was made between the joint MDCEV-MNL model that integrates destination choice with activity choices and an independent MDCEV-MNL model that does not incorporate the log-sum parameters in the MDCEV component. The goodness of fit of the two models were compared using the Bayesian Information Criterion (BIC), which is given by the expression $-2\times\ln(L)+\textit{number of parameters}\times\ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence and Q is the number of observations. The model that results in the lower BIC value is the preferred model. The BIC value for the MDCEV-MNL model (with 103 model parameters) is,150514.2 which is substantially lower than that for the independent MDCEV-MNL model (152334.2 with 102 model parameters). Thus, the BIC clearly favors the MDCEV-MNL model of integrated activity choices and destination choice.

The discussion in this paper is limited to the results of the joint MDCEV-MNL model. The MDCEV component 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, activity timing and travel mode dimensions. Subsequently, any interaction effects of the variable over and above the uni-dimensional effects are identified. A blank entry corresponding to the effect of a variable indicates no significant effect of the variable on the integrated choice process. Further, the effects of variables on the baseline utilities have been constrained to be equal if coefficient equality could not be rejected based on statistical tests. Finally, t-statistics are presented in parentheses. The final specification of the MDCEV component of the model is presented in Tables 2. In the interest of brevity, and considering the large number of alternatives (62), tables showing estimates of baseline preference constants and satiation parameters are not furnished here.

Overall, the model results show indications as expected. Larger household sizes are associated with greater levels of participation in maintenance activities (in and out of home), while single persons are more prone to out-of-home socializing and recreation in the evening. The presence of very young kids motivates activity engagement in the prime period of the day as opposed to early mornings and late nights, although those with school age children are more restricted to pre- and post-school hours. The number of working adults contributes negatively to activity engagement in the middle of the day, presumably due to work constraints. Lower income individuals are more prone to in-home discretionary activities, while higher income individuals are prone to undertake out-of-home activities, consistent with expectations. Higher levels of car ownership contribute negatively to in-home activity participation and non-auto mode use.

Females are more likely to engage in volunteering and maintenance activities, particularly in the midday period, confirming the role of gender differences in activity engagement. Younger individuals are likely to socialize in the evening and night, while older individuals (65+ years) are more likely to volunteer and not undertake night activities. Those who are licensed to drive have a greater propensity for out-of-home activities, while the reverse is true for those physically disabled. Employed individuals engage less in maintenance activities and in-home discretionary activities, even on days that they do not work (this analysis was limited to non-working days for all 5,360 individuals, whether they are employed or not). Fridays are associated with greater out-of-home discretionary activity participation, and night time activities. On rainy days, it is less likely that individuals will eat out using non-auto modes. Population density contributes positively to out-of-home meals, shopping by non-auto mode, possibly because such areas are better served by transit and have better walk and bicycle access to destinations. Overall, the findings are consistent with expectations and consistent with those found earlier by Pinjari and Bhat (2009a).

The estimation results for the destination choice model are presented in Table 3. The destination choice model component was estimated with 30 randomly sampled choice alternatives for each location choice decision. The effects of transportation network level of service, built environment, and demographic interaction terms were represented in the final model specification. Auto travel times and costs decrease the utility associated with choosing a destination for any activity type. The presence of bicycle lanes, total employment, the size of the zone, and zonal household income positively impact destination choice for discretionary activities while retain and service employment, increasing fraction of land devoted to residential uses in the zone, and accessibility to passive and natural recreation contribute negatively to destination choice for the activity categories considered in this paper. The long list of interaction terms demonstrates how household and personal socio-economic and demographic characteristics play a key role in influencing destination choice for discretionary activities undertaken outside home. In the interest of brevity, a detailed explanation is not provided here, but suffice to say that all of the interaction terms included in the model specification are highly significant and indicate that household socio-economic and demographic characteristics serve to moderate or enhance the likelihood of choosing a certain type of destination for activity engagement. For example, females are more prone to choosing destinations with high density of eat-out centers, as are older people and higher income individuals. Those with kids and in larger households are less prone to choose zones with high household density as destinations, presumably because they prefer more open space and suburban locations to accommodate family activities.

The logsum parameters (θ_{ptm}) estimated for each activity purpose, timing, and travel mode combination were not statistically different from unity. In the final model estimation, all logsum parameters were restricted equal to one. This implies the absence of common unobserved factors across all location choice alternatives specific to an activity type, timing, and mode combination. Note that this finding does not imply independence between the MDCEV and MNL model components; rather the logsum variables tie the two model components together, where as the logsum parameters represent only the presence (or absence) of correlated unobserved factors across destination choice alternatives for each activity type, timing, and mode combination category.

4.2 Policy Simulation

The major objective of this paper was to develop a unified model of activity-travel and location choices and time use that would allow one to examine the influence of level of service measures and activity-travel environment (ATE) attributes on these choice dimensions in an integrated manner. To demonstrate the capabilities of the model system presented in this paper, the model was used to examine the impacts of the following scenarios on activity and time use behavior:

- Doubling travel cost across all time periods
- Doubling travel cost during peak periods
- Doubling travel cost for auto mode
- Doubling travel time across all time periods
- Doubling travel time during peak periods
- Doubling travel time by auto mode

Logsum variables computed using the activity destination choice MNL model were used as explanatory variables in the MDCEV model to predict individual's participation in and time allocation to activities by activity purpose, timing, and mode. For each policy scenario, logsum variables were computed for all 60 OH discretionary activity purpose, timing, and mode combinations (for use in the base case prediction), and then updated for the specific timing or travel mode categories for which the policy applied (for the policy case prediction). The prediction using MDCEV was carried out for all individuals in the sample using 1000 replications of the error term draws for each individual. Additional details about the forecasting procedure using the MDCEV model are provided in Pinjari and Bhat (2009b).

The forecasts under alternative scenarios are presented in Table 4. Specifically, the influence of each policy is reported as an aggregate percent change in the amount of time invested in maintenance activities, in-home discretionary activities, and out-of-home discretionary activities by purpose, time of day, and mode (relative to the base case).

In general, the results provide indications along expected lines. Increases in travel cost lead to reduced out-of-home activity engagement and slight increases in in-home activity engagement. Increases in travel cost during the peak period impact volunteer, eat-meal, and recreation activities more than others, and reduce peak period activity engagement while increasing off-peak activity engagement. Increases in auto travel costs and times reduce the use of auto mode for activity engagement and contribute to enhanced mode shares for non-auto modes. In general, travel time increases appear to have larger impacts than travel costs, suggesting that individuals are more time-sensitive when making activity-travel choices. In terms of the modal impact, it appears that all day travel cost or time increases have a greater impact than a time-specific peak-period travel cost or time increase. It appears that individuals are more likely to respond to price and time signals that cover an entire day as opposed to those that are narrower in the time band of influence. Overall, the policy simulation results clearly show that the model is effective in capturing the responses of individuals to system changes in a unifying framework.

5. CONCLUSIONS

This study aims to present a comprehensive unified model system of activity-travel choices that is consistent with microeconomic utility maximization theory of behavior. The activity-travel choice dimensions analyzed in this paper include activity type choice, time of day choice, mode choice, destination choice, and activity time allocation or duration. All discrete choices, except for activity destination choice, and the continuous choice dimension of activity duration are modeled simultaneously using the multiple discrete continuous extreme value (MDCEV) model form while the destination choice is modeled using a classic multinomial logit model (MNL) component. The model components are tied together within a utility maximization-consistent framework using logsum variables that reflect the accessibility of destinations for each activity type, timing, and mode combination. Model estimation results and the policy simulation analysis showed that the joint model system has merit, offers behaviorally intuitive interpretation, and offers a goodness of fit statistically superior to that offered by an independent model system that treats various choice dimensions separately and sequentially. The model specifications included built environment and transportation network level of service attributes demonstrating the impact of these variables on activity-travel dimensions. The model system is presented for a non-worker sample drawn from the 2000 San Francisco Bay Area Travel Survey (BATS). One of the key empirical findings of this analysis is that the built environment and transportation network level of service attributes of the destinations significantly impact activity time use allocation, an aspect that is often overlooked in the literature.

The model form adopted in this paper has key implications for activity-travel demand model development. It appears that the findings reported here support the notion that individuals make several activity-travel choices jointly as a "bundle", calling for the simultaneous modeling of various choice dimensions in a unifying framework. Activity-travel model systems that purport to simulate the behavior of agents along the time axis may benefit from the adoption of model forms that are able to simultaneously predict multiple choice dimensions as a "bundle". Ignoring to do so may yield erroneous policy scenario predictions.

The current study may be enhanced further by estimating dimension-specific (*i.e.*, activity purpose-, timing-, and mode-specific) coefficients for transportation network level of service measures and activity-travel environment attributes in the location choice models. In addition, one needs to note that the policy forecasts provided by the MDCEV model are potentially restrictive in that the total time allocation (budget constraint) is assumed constant across all policy scenarios (there is simply a reallocation of time across activity categories, but maintaining total time expenditure for all activity categories considered constant). Overcoming this limitation is another direction for future research.

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Table 1 Descriptive Statistics of Activity participation and Time-Use by Activity Purpose, Activity Timing and Travel mode[5]

		ACTIVITY TIMING					
		Early Morning (3am-7am)	Morning (7am-9am)	Late Morning (9am-12pm)	Afternoon (12pm-4pm)	Evening (4pm-7pm)	Night (7pm-3am)
ACTIVITY PURPOSE and TRAVEL MODE	Number (%) of non-workers participating, and mean duration of participation among those participating	63 (2.3%)[6] 140 min	382 (13.9%) 169 min	1131 (41.1%) 121 min	1257 (45.7%) 97 min	720 (26.2%) 103 min	371 (13.5%) 111 min
Maintenance	5360 (100%) 651 min	--	--	--	--	--	--
IH Discretionary	2133 (39.8%) 341 min	--	--	--	--	--	--
OH Discretionary	2752 (51.3%) 163 min	--	--	--	--	--	--
OH Discretionary Auto mode	2473 (89.9%) 158 min						
Volunteering	396 (14.4%)[7] 149 min	4 (1.0%)[8]	81 (20.5%)	137 (34.6%)	89 (22.5%)	72 (18.2%)	63 (15.9%)
Socializing	508 (18.5%) 128 min	6 (1.2%)	20 (3.9%)	125 (24.6%)	159 (31.3%)	97 (19.1%)	77 (15.2%)
Meals	809 (29.4%) 115 min	13 (1.6%)	90 (11.1%)	206 (25.5%)	270 (33.4%)	223 (27.6%)	84 (10.4%)
Non-Maintenance Shopping	1092 (39.7%) 60 min	4 (0.4%)	46 (4.2%)	372 (34.1%)	571 (52.3%)	175 (16.0%)	53 (4.9%)
Recreation	7 38 (26.8%) 145 min	33 (4.5 %)	116 (15.7%)	256 (34.7%)	200 (27.1%)	115 (15.6%)	88 (11.9%)
OH Discretionary Non Auto mode	432 (15.7%) 134 min						
Volunteering	37 (1.3%) 170 min	2 (5.4%)	9 (24.3%)	10 (27.0%)	8 (21.6%)	3 (8.1%)	6 (16.2%)
Socializing	72 (2.6%) 140 min	0 (0.0%)	3 (4.2%)	19 (4.2%)	27 (37.5%)	21 (29.2%)	4 (5.6%)
Meals	135 (4.9%) 119 min	1 (0.7%)	9 (6.7%)	35 (25.9%)	54 (40.0%)	25 (18.5%)	18 (13.3%)
Non-Maintenance Shopping	132 (4.8%) 59 min	0 (0.0%)	4 (3.0%)	50 (37.9%)	62 (47.0%)	12 (9.1%)	6 (4.5%)
Recreation	131 (4.8%) 136 min	1 (0.8%)	14 (10.7%)	52 (39.7%)	33 (25.2%)	32 (24.4%)	6 (4.6%)

[5] The reader will note here that the average time investments reported in this table are for only those who participated in the corresponding activity purpose or for those who participated in OH discretionary activities during the corresponding time period. Also, the activity participation percentages across all activity purposes (or across all time periods, or modes) may sum to more than 100% because of multiple discreteness (*i.e.*, participation in multiple activity purposes and/or during multiple time periods and/or travel by multiple modes over a day). For example, a non-worker can undertake both OH recreation and OH meal activities on a day.

[6] Percentages in this row are out of the 2752 non-workers who participated in at least one OH discretionary activity during the day.

[7] Percentages in this column, from this row onward, are out of the 2473 non-workers who traveled by auto mode for at least one OH discretionary activity during the day.

[8] Percentages from this row and column onward (within this block of rows) are based on total number of non-workers participating in row activity purpose [(4/396)×100=1.0%].

Table 2 The MDCEV Model Results: Baseline Parameter Estimates

	Household (HH) Socio-demographics								
	HH size	Single member HH	Kids of age <5 yrs present	Kids of age 5-15 yrs present	Number of kids of age <15 yrs	# of adults in HH who worked on the day	HH annual income < 45k	HH annual income >100k	# of vehicles in HH
‘Activity Purpose’ Dimension									
IH and OH Maintenance	0.071 (3.74)	-	-	-	-	-	-	-	-
IH Discretionary	-	-	-	-	-	-	0.168 (2.92)	-	-0.061 (-1.89)
OH Volunteering	-	-	-	-	-	-	-	-	-
OH Socializing	-	0.420 (3.73)	-	-	-	-	-	0.169 (3.61)	-
OH Recreation	-	-	-	-	-	-	-	0.169 (3.61)	-
OH Meals	-	-	-	-	-	-	-	0.169 (3.61)	-
OH Non-Maintenance Shopping	-	-	-	-	-	-	-	0.169 (3.61)	-
‘Activity Timing’ Dimension									
Early Morning	-	-	-	-	-	-	-	-	-
Morning	-	-	0.125 (1.77)	0.297 (2.10)	-	-	-	-	-
Late Morning	-	-	0.125 (1.77)	-	-	-0.170 (-4.43)	-	-	-
Afternoon	-	-	0.125 (1.77)	-	-	-0.170 (-4.43)	-	-	-
Evening	-	-	0.125 (1.77)	0.428 (3.88)	-	-	-	-	-
Night	-	-	-	-	-	-	-	-	-
‘Travel Mode’ Dimension									
Auto mode	-	-	-	-	-	-	-	-	-
Non-auto mode	-	-	-	-	-	-	-	-	-1.190 (-31.90)
Interactions									
OH Recreation – Evening	-	0.363 (3.53)	-	-	-	-	-	-	-
OH Recreation – Non-auto	-	-	-	-	-	-	-	0.463 (2.11)	-
OH Meals - Non-auto	-	-	-	-	0.154 (1.17)	-	-	-	-
OH Meals - Non-auto - Evening	-	-	-	-	-0.535 (-1.36)	-	-	-	-

Table 2 (Continued) The MDCEV Model Results: Baseline Parameter Estimates

	Individual Socio-demographics						Contextual			ATE attributes			
	Female	**Age < 30 yrs**	**Age > 65 yrs**	**Licensed to drive**	**Physically disabled**	**Employed**	**Friday**	**Fall**	**Rain**	**Retail employment**	**Population density**	**Total employment density**	**Density of highways**
‘Activity Purpose’ Dimension													
IH and OH Maintenance	0.315 (7.29)	-	-	-	-	-0.173 (-3.59)	-	-	-	-	-	-	-
IH Discretionary	-	-	-	-	-	-0.1263 (-1.98)	-	-0.105 (-1.98)	-	-	-	-	-
OH Volunteering	0.350 (3.46)	-	0.617 (6.51)	0.743 (9.46)	-0.249 (-3.09)	-	-	-	-	-	-	-	-
OH Socializing	-	0.467 (2.70)	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
OH Recreation	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.357 (4.14)	-	-	-	-	-	-
OH Meals	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
OH Non-Maintenance Shopping	-	-	-	0.743 (9.46)	-0.249 (-3.09)	-	0.242 (4.31)	-	-	-	-	-	-
‘Activity Timing’ Dimension													
Early Morning	-	-	-	-	-	-	-	-	-	-	-	-	-
Morning	-	-	-	-	-	-	-	-	-	-	-	-	-
Late Morning	0.286 (5.10)	-	-	-	-	-	-	-	-	-	-	-	-
Afternoon	0.286 (5.10)	-	-	-	-	-	-	-	-	-	-	-	-
Evening	-	0.308 (1.85)	-	-	-	-	-	-	-	-	-	-	-
Night	-	0.739 (4.78)	-0.482 (-3.70)	-	-	-	0.404 (3.23)	-	-	-	-	-	-
‘Travel Mode’ Dimension													
Auto mode	-	-	-	-	-	-	-	-	-	-	-	-	-
Non-auto mode	-0.220 (-2.92)	-	-	-	-	-	-	-	-	-	-	-	-
‘Interactions’													
OH Non-Maintenance Shopping – Afternoon	-	-	-	-	-	-	-	-	-	-0.001 (-2.59)	-	-	-
OH activity Non-auto - Afternoon (except shopping)	-	-	-	-	-	0.369 (1.91)	-	-	-	-	-	-	-
OH Meals - Non-auto	-	-	-	-	-	-	-	-	-0.263 (-0.85)	-	-	-	-
OH Meals, shopping -Non-auto	-	-	-	-	-	-	-	-	-	-	0.016 (5.43)	-	-
OH Recreation - Non-auto	-	-	-	-	-	-	-	-	-	-	-	0.006 (0.75)	-
OH Social, meals - Non-auto	-	-	-	-	-	-	-	-	-	-	-	-	-0.069 (-0.88)

Table 3 MNL Component (Location Choice) Model Estimation Results

Variable	Coefficient	t-stat
LOS Measures		
Auto peak travel time	-0.012	-11.82
Auto peak travel cost	-0.056	-2.59
ATE Attributes		
Density of bicycle lanes	0.129	7.75
Retail employment	-0.005	-5.70
Service employment	-0.005	-4.47
Logarithm of Total employment	0.405	29.06
Fraction of residential land-use	-2.272	-41.69
Logarithm of zonal area	0.056	5.44
Mean zonal household income	0.007	9.19
Accessibility to passive and natural recreation	-0.364	-2.92
Interaction with socio-demographics		
Density of bicycle lanes * age/100	-0.110	-4.84
Density of bicycle lanes * Continuous income x 10^{-5}	0.042	5.46
Density of bicycle lanes * household vehicles	0.025	4.94
Density of eat-out centers * female	0.003	3.26
Density of eat-out centers * Continuous income x 10^{-5}	0.010	13.31
Density of eat-out centers * age/100	0.027	32.64
Density of eat-out centers * household size	0.014	28.96
Density of eat-out centers * Own household	0.002	2.17
Logarithm of household population * age/100	0.102	6.42
Logarithm of household population * household vehicles	0.011	3.32
Household density * No. of kids < 15yrs	-0.006	-1.32
Household density * household size	-0.001	-0.36
Household density * household vehicles	0.009	3.41
Accessibility to employment * household size	-0.003	-6.25
Accessibility to employment * Own household	0.008	15.38

Table 4 Policy Simulation Results

Alternatives	**Activity Purpose**							**Activity Timing**							**Travel Mode**	
Scenario details	Maintenance	IH Discretionary	OH Volunteer	OH Social	OH Meals	OH Shopping	OH Recreation	Early Morning	Morning	Late Morning	Afternoon	Evening	Night	Auto	Non-auto
Travel cost measure increased by 100% for all time periods	0.01	0.02	-0.99	-1.00	-0.84	-0.91	-0.93	-0.92	-0.90	-0.92	-0.96	-0.92	-0.87	-1.00	-0.75
Travel cost measure increased by 100% for peak periods	0.00	0.00	-0.58	-0.05	-0.46	0.07	-0.29	1.34	-3.89	1.30	1.26	-3.93	1.34	-0.30	-0.19
Travel cost measure increased by 100% for auto mode	0.01	0.01	-1.16	-1.21	-0.27	-0.31	-0.83	-0.77	-0.75	-0.69	-0.64	-0.68	-0.76	-2.10	2.48
Travel time measure increased by 100% for all time periods	0.04	0.06	-3.36	-3.40	-2.86	-3.09	-3.18	-3.11	-3.07	-3.13	-3.26	-3.13	-2.95	-3.39	-2.57
Travel time measure increased by 100% for peak periods	0.01	0.02	-1.88	-0.15	-1.53	0.22	-0.95	4.41	-12.70	4.22	4.12	-12.83	4.37	-0.99	-0.64
Travel time measure increased by 100% for auto mode	0.03	0.04	-3.85	-3.99	-0.95	-1.05	-2.73	-2.54	-2.51	-2.30	-2.12	-2.27	-2.54	-7.03	8.34