A Comprehensive Activity-Travel Pattern Modeling System for Non-Workers with Empirical Focus on the Organization of Activity Episodes

Chandra Bhat and Rajul Misra
Department of Civil Engineering
University of Texas at Austin
ECJ 6.806, Austin, Texas 78712
Tel: (512) 471-4535, Fax: (512) 475-8744
E-mail addresses: bhat@mail.utexas.edu, misra@ieminc.com

ABSTRACT

This paper proposes a comprehensive continuous-time framework for representation and analysis of the activity-travel choices of non-workers. The paper also presents econometric formulations for components of the comprehensive framework that focus on the overall organization of activities (including number and type of activities, and activity sequencing) in the non-worker's daily activity-travel pattern. The paper concludes with an empirical analysis using activity-travel data from the 1990 San Francisco Bay Area travel diary survey. A companion paper being prepared by the authors discusses the econometric formulations and associated empirical results for components of the overall framework that address the temporal and spatial attributes of the daily activity-travel pattern.

1. Introduction

The activity-based approach to travel demand analysis views travel as a derived demand; derived from the need to pursue activities distributed over space and time. The conceptual appeal of this approach originates from the realization that the need and desire to participate in activities is more basic than the travel that some of these participations may entail. By placing primary emphasis on activity participation and focusing on sequences or patterns of activity behavior (using the whole day or longer periods of time as the unit of analysis), such an approach can address congestion-management issues through an examination of how people modify their activity participations (see Jones *et al*., 1990). The activity-based approach is also better suited to respond to the increased information demands placed on travel models by the 1990 Clean Air Act Amendments (CAAAs) (the reader is referred to Bhat and Koppelman, 1999a for a detailed review of the activity approach to travel analysis).

In the activity-based research literature, there has been extensive examination and analysis of worker activity travel patterns (for example, see Bhat and Singh, 2000; Hamed and Mannering, 1993; Damm, 1980; Strathman *et al*., 1994). The primary motivation for the focus on worker activity choices is the significant effect of commute travel behavior on peak traffic congestion and mobile source emissions. In contrast to the substantial literature on worker activity analysis, relatively little research has focused on studying the activity-travel behavior of non-workers. On the other hand, analysis of the activity-travel behavior of non-workers provides important input for transportation planning. A large proportion of non-workers include children or retired individuals who may have special mobility and accessibility requirements. Another important non-working group comprises homemakers who, while exhibiting high levels of mobility like workers, have rather flexible schedules due to the absence of temporal fixities (unlike commute trips for workers). The underlying factors influencing the travel-related decisions of these non-workers are likely to be quite different from those of workers (see Bianco and Lawson, 1996).

Some previous studies in the literature have developed analysis frameworks that may be applied to non-worker activity-travel analysis. These studies have made important contributions by recognizing complex inter-linkages among activity decisions. But most of these studies do not model the temporal dimension (except possibly for departure time categorized broadly into a.m. peak, p.m. peak, mid-day, and other), and/or require the *a priori* designation of activities as "primary" and "secondary" or “fixed” and “flexible” (see Ben-Akiva and Bowman, 1995 or Kitamura and Fujii, 1998). Some other studies of activity scheduling consider the generation of activity episodes and their attributes (such as number of activities, type of activities, duration of activities, location of activities, *etc.*) as exogenous inputs and emphasize the temporal sequencing of activity participations. Thus, these studies limit their attention only to certain aspects of the entire activity-travel pattern of individuals. Examples of scheduling models in the literature include CARLA (Clarke 1986), STARCHILD (Recker *et al.*, 1986a, 1986b), SCHEDULER (Garling *et al*., 1989), SMASH (Ettema *et al.*, 1993) and AMOS (Kitamura *et al.*, 1996). The reader is referred to Bhat and Koppelman (1999b) for a detailed review of these and other studies.

The purpose of this paper is to propose a comprehensive framework for the analysis of non-worker daily activity-travel patterns that a) considers all relevant activity-travel attributes of the non-worker pattern, b) models both the generation as well as scheduling of activity episodes, c) considers time as an all-encompassing continuous entity in analysis, and d) does not require the *a priori* designation of activity episodes as fixed or flexible, or primary or secondary.

The rest of this paper is structured as follows. The next section develops a representation and analysis framework of the daily activity-travel pattern of non-workers, which comprises seven model components. Section 3 provides econometric details of the first three of the seven model components that focus on the overall organization of activities (including number and type of activities, and activity sequencing) in the daily activity-travel pattern. The econometric structure of the remaining four model components, corresponding to the temporal and spatial attributes of the activity-travel pattern, is the focus of another paper being prepared by the authors. Section 4 presents empirical results using activity-travel diary data obtained from the San Francisco Bay area. The final section concludes the paper.

2. REPRESENTATION AND ANALYSIS FRAMEWORK

2.1. Activity-Travel Pattern Representation

We consider household and individual socio-demographics as exogenous determinants of the activity-travel pattern behavior of non-workers. The activity-travel environment is also considered as an exogenous input. The activity-travel environment comprises both the transportation system (*i.e.,* the network configuration of roads and the transit system) and the land-use environment (the location of opportunities for activity participation). Conditional on socio-demographics and the activity-travel environment, individuals make medium-term decisions (in combination with other individuals in their household) regarding their employment status, residence (type of residence, location, *etc.*), and car ownership. We consider these medium-term decisions as being exogenous to the determination of the daily activity-travel pattern (the medium-term activity-travel decisions may be modeled separately prior to the modeling of the daily activity-travel pattern, see Bhat and Koppelman, 1993). Finally, we assume 3 a.m. to be the start of the day and will assume that all individuals are at home during the start of the day.

A non-worker's activity-travel pattern comprises several out-of-home activity episodes (or “stops”) of different types interspersed with in-home activity stays (we will use the term “stops” to refer to out-of-home activity episodes in the rest of this paper). The chain of stops between two in-home activity episodes will be referred to as a tour.

The characterization of a non-worker's daily activity-travel pattern is accomplished by identifying a number of different attributes within the pattern. The attributes may be classified based on the level of representation they are associated with: that is, whether they are associated with the entire daily pattern, a tour in the day, or an episode. *Pattern level attributes* include whether or not the individual makes any stops during the day, the number of stops of each activity type if the individual leaves home during the day, and the sequencing of all episodes (both stops and in-home episodes). The only *tour-level attribute* is the travel mode for the tour. *Episode-level* attributes include the episode duration, travel time to episode from previous episode (except for the first home-stay episode), and the location of out-of-home episodes (*i.e.*, stops).

2.2. Analysis Framework

The analysis of the activity travel pattern of non-workers entails the modeling of each of the attributes identified in the activity-travel representation. The joint modeling of all the attributes is infeasible because of the large number of attributes and the large number of possible choice alternatives for each attribute. There is a need to develop an analytic framework to model the representation that is feasible to implement from a practical standpoint.

Our analysis approach is based on modeling the pattern-level attributes first, followed by the tour-level attribute of mode choice, and finally the episode-level attributes. We adopt such an analysis framework because the decisions regarding pattern-level attributes are driven by the basic activity needs of the individual (and the household of which the individual is a part). Consequently, and consistent with the derived demand philosophy of the activity-based approach, we consider the pattern-level decisions to be at the highest level of the analysis hierarchy. On the other hand, decisions regarding the episode-level attributes tend to be driven primarily by scheduling convenience, short-term temporal constraints, and travel conditions. Consequently, these attributes are relegated to the lowest level of the analysis hierarchy. The tour-level attribute of travel mode choice is positioned at the intermediate level of the analysis hierarchy since it affects the attributes of all out of-home episodes within the tour.

The *Pattern level attributes* are modeled using a system of three model components (Figure 1). The first model component, which takes the form of a bivariate binary-ordered response probit formulation, jointly models the decision to make at least one stop (versus staying at home for the entire day) and the decision of the number of stops if the individual leaves home during the day. The second model component, which uses a multinomial logit formulation for stop type, partitions the total number of stops (determined in the first model component) into number of stops by each out-of-home activity type. The final model component, which has a multinomial logit form with a pattern string as the unit of analysis, models the number of in-home episodes in an individual's activity travel pattern along with the entire sequence of all episodes (in-home and out-of-home) in the individual's activity pattern, given the number of stops by type in the pattern.

Figure 2 presents an overview of the four remaining model components used to analyze the tour- and episode-level attributes. The tour travel mode is modeled using a discrete choice formulation. The episode-level attributes include the activity duration of the episode, the travel time to the episode from previous episode, and the location of each out-of-home episode. Since the duration of the first home-stay episode is likely to be different from other subsequent home-stay episodes because of life-style and sleeping habits, this first home-stay duration is modeled separately using a hazard model. The reader will also note that travel time to this first home-stay episode is undefined since the individual is at home at the beginning of the day. Next, the travel time to the episode from previous episode and activity duration of the episode for all episodes other than the first home-stay episode are modeled jointly. Finally, the spatial location of each out-of-home episode (stop) is modeled using a disaggregate spatial destination choice model.

In this paper, we focus on the first three components associated with the pattern-level attributes (Figure 1). The remaining four components in Figure 2, associated with the tour and episode-level attributes, are the focus of another paper being prepared by the authors.

3. MATHEMATICAL FORMULATION

This section presents the model structure of each of the three pattern-level model components in Figure 1. All model estimations are undertaken using a full-information maximum likelihood procedure with the GAUSS matrix programming language.

3.1. Stop Occurrence/Number of Stops (SOC-NOS) Sub-Model

This model component analyzes individuals' participation in at least one stop (*i.e.*, out-of-home activity episode) during the day and the total number of stops undertaken (if non-zero). In the following presentation, we will use the index i to represent the ith individual (i=1,2,...,I), and the index k to represent the number of stops (k=1,2,...,K). The equation system is then as follows:

$$y_i^* = \beta' x_i - \varepsilon_i,\ \varepsilon_i \sim \mathrm{N}(0,1),\ y_i = 1 \text{ if } y_i^* > 0 \text{ and } y_i = 0 \text{ if } y_i^* \leq 0 \tag{1}$$

$$s_i^* = \gamma' z_i + \nu_i,\ \nu_i \sim \mathrm{N}(0,1),\ s_i = k \text{ if } \psi_{k-1} \leq s_i^* < \psi_k,\ s_i \text{ observed only if } y_i = 1,\ \psi_0 = -\infty,\ \psi_K = +\infty,$$

where y_i^* is the latent propensity of the ith individual to participate in one or more stops during the day, y_i represents the actual observed choice of whether or not the individual leaves home during the day (y_i=1 if individual leaves home and y_i=0 if the individual stays at home all day), ε_i is an error term assumed to be normal with a location parameter of zero and variance of one (the latter is an innocuous normalization), s_i^* is the latent propensity of the ith individual to make stops should she or he leave home, s_i is the actual number of stops made by the individual if s/he leaves home (s_i=1,2,…,K) and ν_i is a normally distributed error term parameter with a location parameter of zero and variance of one (the latter is again an innocuous normalization). s_i is characterized by the stop-making propensity s_i^* and the threshold bounds (the ψ's) in the usual ordered-response fashion. x_i and z_i are column vectors of exogenous variables affecting the decision to leave home and the decision of the number of stops, respectively. As structured, x_i includes a constant, while z_i does not include a constant. β and γ are corresponding column vectors of parameters to be estimated, along with the (K-1) threshold parameters in the ordered-response equation.

The decision of whether or not to leave home is separated from the number of stops if the person chooses to leave home because the behavioral underpinnings influencing the two decisions may be quite different; an individual may have a high propensity to leave home to shop because of her/his household characteristics, but those same household characteristics may not necessarily imply a high propensity to pursue several stops thereafter. Using a single ordered-response model to model both the decision of whether or not to leave home and the number of stops would tie the two decisions very tightly and restrictively.

If the two unobserved error components ε_i and ν_i are assumed to be independent of each other, the estimation of the first equation may be undertaken using a binary choice model and the estimation of the second using the standard ordered-response structure. However, just as tying these two decisions tightly may not be realistic, considering these two decisions to be independent of each other (after controlling for the effect of observed exogenous determinants) may not be appropriate either. Thus, a dynamic, out-going person maybe more likely to leave home during the day and may also undertake a high number of stops. Since the dynamic, outgoing, nature of the individual is likely to be unobserved, this would imply a negative correlation between the error terms ε_i and v_i in the context of the equation structure in (1). Similarly, there may be unobserved factors that might cause a positive correlation between the error terms. Such a positive covariance term implies that individuals who are more likely to stay at home make more number of stops if they go out on the survey day. This observation may just indicate significant day-to-day variation in the number of stops performed by individuals, *i.e.*, individuals who make more stops tend to organize their activity-travel patterns such that they perform a large number of out-of-home activities on some days and focus on the in-home tasks on other days. In either case, ignoring the correlation and estimating the two equations separately will result in inconsistent parameter estimates due to classic econometric sample selection bias (see Maddala, 1983). To incorporate the effect of such sample selection, we introduce a correlation ρ between the standard normal stochastic error terms in the binary and ordered response models. The relevant probabilities may then be written as:

$$\begin{aligned} &P(y_i = 0) = 1 - \Phi(\beta' x_i) \\ &P(y_i = 1, s_i = \mathrm{k}) = \Phi_2(\beta' x_i, -\gamma' \mathrm{z}_i + \psi_k, \rho) - \Phi_2(\beta' x_i, -\gamma' \mathrm{z}_i + \psi_{k-1}, \rho) \text{ for } k = (1,2,3,...,K), \end{aligned} \tag{2}$$

where $\Phi_2(.)$ represents the bivariate standard normal distribution function. Defining a set of dummy variables M_{ik} (i=1,2,…,I; k=1,2,…,K) such that M_{ik} =1 if individual i makes k stops and M_{ik} =0 otherwise, the log likelihood function for the estimation of the parameters in the model takes the form shown below:

$$L = \sum_{i=1}^{I}\left((1-y_i)\log P(y_i = 0) + \sum_{k=1}^{K} M_{ik}\log P(y_i = 1, s_i = k).\right) \tag{3}$$

3.2. Stop Type (STYPE) Model

This second model component determines the number of stops of each activity type undertaken by a non-worker given the total number of daily stops. The model is relevant only for individuals who leave home and make one or more stops during the day.

Let s_{it} represent the total number of stops of activity type t made by non-worker i (t=1,2,…,T; $\sum_{t=1}^{T} s_{it} = s_i$). Also, let the probability that activity type t will be pursued in any given stop be R_{it} for individual i. We assume a multinomial logit structure that associates this probability to a relevant column vector w_i of exogenous variables for non-worker i:

$$R_{it} = \frac{e^{\eta_t' w_i}}{\sum_{j=1}^{T} e^{\eta_j' w_j}} \ . \tag{4}$$

The estimation of the parameter vector η_t requires a relationship between the probability of stops being pursued for each activity type t (R_{it}) and the observed combination of the individual's allocation of stops among the activity type categories. To develop such a relationship, we assume that each individual follows a zero-order process in assigning stops to activity type categories. That is, we assume that in the generation of stops by activity type, participation level in one activity type is independent of participation level in other activity types (after controlling for exogenous variable effects included in the vector w_i). Then, the probability of non-worker i making k_1 stops of activity type 1, k_2 stops of activity type 2,....,k_T stops of activity type T, given that the individual makes k total stops (k =1,2,…,K), can be expressed as:

$$P\left(s_{i1} = k_1, s_{i2} = k_2, \ldots, s_{iT} = k_T \middle| s_i = k, k > 0\right) = G_{i,k_1k_2\ldots k_T} = \frac{k!}{\prod_t k_t!}\prod_t R_{it}^{\,k_t} \tag{5}$$

Next, define a set of dummy variables: $\delta_{i,k_1k_2\ldots k_T} = 1$ if $s_{i1} = k_1,\ s_{i2} = k_2, \ldots, s_{iT} = k_T$, 0 otherwise $(k_1 + k_2 + \ldots + k_T = k)$. Then the log-likelihood function for estimating the η_t parameter vectors (t =1,2,…,T) can be written as (see Bhat *et al*., 1999):

$$L_2 = \sum_{i=1}^{I} \left[\sum_t k_t \ln R_{it} \right] \tag{6}$$

3.3. Activity-Sequencing (ASEQ) Model

This model determines the sequence of activity episodes pursued by an individual, given the number of stops by activity type pursued by the individual. Consider an individual who makes a total of k stops, of which k_1 stops are of activity type 1, k_2 stops are of activity type 2, …, and k_T stops are of activity type T (we are suppressing the notation i for individuals in the following presentation). The individual's daily activity-travel pattern can be represented by a pattern string of these out-of-home activity episodes, interspersed with in-home episodes.

Let the set of all feasible pattern-strings for the individual be denoted by ϑ. This feasible pattern-string choice set comprises all the valid permutations (*i.e.*, all permutations that do not contain two consecutive in-home episodes) of k_1 stops of activity type 1, k_2 stops of activity type 2,…,k_T stops of activity type T, and each possible value r of intermediate in-home episodes (r = 0, 1, 2,…,R, where $R = k$-1). The first and last episodes of each (and all) possible pattern-strings correspond to an in-home activity episode (by definition) and are not labeled as intermediate in-home episodes.

There are three dimensions that, when taken together, characterize any pattern string: a) the number of intermediate in-home episodes r (that immediately determines the number of tours made by the individual), b) the number of stops between two consecutive in-home episodes (that is, the number of stops made in each tour), and c) the sequencing of episodes by activity type.

Our proposed activity-sequencing (ASEQ) model analyzes all of these three dimensions jointly. However, for presentation simplicity, we focus on each of these three dimensions individually in the next three sections. In Section 3.3.4, we discuss the overall estimation of the model.

3.3.1 Number of Intermediate In-Home Episodes

Consider a single member of the feasible choice set of pattern strings and label this as g (g = 1, 2,…,G, where G represents the number of members in ϑ). Define a binary variable A_g^r = 1 if the pattern g has r intermediate in-home episodes and A_g^r = 0 otherwise (r = 0, 1, 2,…,k-1). Next, let the deterministic utility assigned to making r intermediate in-home episodes be $\alpha_r = \eta_r^{'} f$, where f is a column vector of relevant individual exogenous variables affecting the number of intermediate in-home episodes and η_r is a column vector of the corresponding parameters to be estimated (η_0 = 0 for identification). The deterministic utility attributable to pattern g due only to the number of intermediate in-home episodes in g is then given as:

$$\vartheta_g = \sum_{r=0}^{s-1} A_g{}^r \alpha_r \ . \tag{7}$$

3.3.2 Distribution of Stops among Tours

The number of tours h in the activity-travel pattern of the non-worker is related to the number of intermediate in-home episodes r by $h = r$+1. We now examine the distribution of the total number of stops (irrespective of activity type) among tours. To do so, consider the number of stops in the last tour as the base category (the reader will note that the number of stops in the last tour is immediately determined from the stops in each of the previous tours for a given number of total stops).

We first consider a simple case where the individual performs three stops, all of the same type J. Let H represent an in-home episode. The number of intermediate in-home episodes r can take the values 0, 1, or 2. The corresponding set of feasible activity-travel pattern-strings has four members as follows:

$$\begin{array}{ll} H - J - J - J - H & \text{(for } r = 0\text{)} \\ H - J - H - J - J - H & \text{(for } r = 1\text{)} \\ H - J - J - H - J - H & \text{(for } r = 1\text{)} \\ H - J - H - J - H - J - H & \text{(for } r = 2\text{)} \end{array} \tag{8}$$

We observe in this example that for the cases $r = 0$ and $r = 2$, the number of intermediate in-home episodes directly yields a unique activity-travel pattern-string. However, if the number of intermediate in-home episodes is 1, there are two feasible pattern-strings that differ only in the number of stops assigned to each tour. The first pattern-string ($H - J - H - J - J - H$) has one stop in the first tour and two stops in the second tour. The second pattern-string ($H - J - J - H - J - H$) has a reverse structure with two stops in the first tour and one stop in the second tour. We may distinguish between these patterns by assigning a utility value for making two stops in the first tour relative to one stop in the first tour (by definition, a tour has to have at least one stop). More specifically, we can consider the second tour (*i.e.*, the last tour in this example) as the base and model the number of stops in the first tour. This may be achieved by normalizing the utility of one and two stops in the last tour (in the current example, the second tour) to zero, and normalizing the utility of one stop in the first tour also to zero (these are innocuous normalizations necessary for identification).

More generally, define dummy variables $D_h^q = 1$ if there are q stops in tour h, and 0 otherwise. Also, let the utility of assigning q stops to the h^{th} tour be γ_h^q ($\gamma_{r+1}^q = 0$ for all q and $\gamma_h^1 = 0$ for all h for identification). Then the deterministic utility component associated with the distribution of stops among tours for pattern-string g is given as $\omega_g = \sum_{h \in B_g} \sum_q D_h^q \gamma_h^q$, where B_g is the set of all tours in pattern-string g. Of course, γ_h^q can be specified to be a function of individual-related attributes.

3.3.3 Activity Type of Each Out-of-Home Episode

The final aspect of sequencing is the activity type of each stop in the pattern string. To model the activity type sequence, we consider the activity pattern-string as a first-order Markov chain. Since the first episode of the activity pattern-string is pre-determined (*i.e.,* an in-home episode), all the subsequent episodes can be modeled if the transition probabilities between activity pairs are known. Although the assumption of first-order Markov state-dependence implies that each activity episode in the pattern-string depends only on the episode immediately preceding it, due to the propagation of conditional probabilities in a Markov chain, the effects of all activity episodes are also taken into account (see Kitamura and Kermanshah, 1984 a & b for a more detailed discussion on this).

We again begin with a simple case where the individual performs only two stops, represented by J_1 and J_2 corresponding to activity types 1 and 2, respectively. In this particular simple case, the number of intermediate in-home stops immediately determines the allocation of stops to tours. The feasible activity-travel pattern-strings may be written as follows:

$$\begin{array}{ll} H - J_1 - J_2 - H & \text{(for } r = 0) \\ H - J_2 - J_1 - H & \text{(for } r = 0) \\ H - J_1 - H - J_2 - H & \text{(for } r = 1) \\ H - J_2 - H - J_1 - H & \text{(for } r = 1) \end{array} \tag{9}$$

Let λ_{mn} be the deterministic utility derived from performing episode of activity type n immediately after an episode of activity type m. If we represent the in-home activity type as 0, the Markov utilities (π's) for the four activity pattern-strings above are given as:

$$
\begin{aligned}
&\pi_{[H-J_1-J_2-H]} = \lambda_{01} + \lambda_{12} + \lambda_{20} \\
&\pi_{[H-J_2-J_1-H]} = \lambda_{02} + \lambda_{21} + \lambda_{10} \\
&\pi_{[H-J_1-H-J_2-H]} = \lambda_{01} + \lambda_{10} + \lambda_{02} + \lambda_{20} \\
&\pi_{[H-J_2-H-J_1-H]} = \lambda_{02} + \lambda_{20} + \lambda_{01} + \lambda_{10}
\end{aligned} \tag{10}
$$

The transition matrix (containing the Markov parameters as its elements) is not symmetric. Hence, for example, λ_{12} is different from λ_{21}. We also observe that the Markov utilities for the last two pattern-strings are exactly the same. This is because the two pattern-strings contain the same activity pairs and the only difference is in terms of the temporal occurrence of the activities in the two pattern-strings. These temporal effects can be taken into account by providing additional utility components if the activity occurs at a particular time in the activity-travel pattern. Hence, if Δ_1 is the additional utility derived by performing activity type 1 as the first stop of the day (relative to performing activity type 2 as the first stop), the third pattern string would have this additional term making it possible to distinguish between the last two pattern-strings.

Consider now the Markovian utility component in general form for a pattern-string g from the feasible choice set ϑ of a non-worker. Let the activity pattern-string g be represented by ($a_1, a_2, ..., a_e, ... a_E$), where a_e represents the activity type of episode e (a_e can take one of the following values; 1,2,…,T,T+1; where the first T values correspond to the activity type of out-of-home episodes and the last one corresponds to in-home activity). Let $\delta_n(a_e)$ be a binary variable that takes value 1 if the activity type of episode e is n (n = 1,…,T+1), and 0 otherwise. The Markov utility derived from the pattern-string can be written as:

$$
\pi_g = \sum_{e=2}^{E} \left[\sum_{m=1}^{T+1} \sum_{n=1}^{T+1} \delta_m(a_{e-1}) \delta_n(a_e) \lambda_{mn} \right] + \sum_{n=1}^{T} \delta_n(a_2) \Delta_n \tag{11}
$$

The first term extracts the appropriate utilities for each activity pairing in the pattern string. The second term adds an additional utility term specific to the choice of the activity type of the second episode. This second component accommodates a differential Markov effect for the first home to stop type pairings compared to corresponding pairings that occur later on in the sequence. We adopt such a structure because descriptive analysis by Kitamura and Kermanshah (1994b) and by Misra and Bhat (2000) suggest that the transition probabilities for the first home-to-stop pairings are different from those for corresponding pairings occurring later on, but that there is no substantial differences in transitions beyond the first set of pairings (note that *n* cannot be equal to *T*+1 in the second component since the second episode needs to be an out-of-home stop; also the last out-of-home stop type *T* is considered as the base in the utility formulation of this component, $\Delta_T = 0$).

3.3.4 Overall Model Estimation

The total deterministic utility derived by choosing a particular pattern-string *g* is the sum of the three utility components (presented in sections 3.3.1, 3.3.2, and 3.3.3) and is given by $\tilde{\theta}_g = \nu_g + \omega_g + \pi_g$. We next add a random Gumbel error component that is assumed to be independent and identically distributed across all pattern strings for an individual. The assumption of an IID error term across pattern strings implies that there are no unobserved correlations across strings, and leads to the Independence from Irrelevant Alternatives (IIA) property. This assumption is useful in the estimation procedure. Empirical tests discussed in the next section do not reject this assumption.

The probability of choice of pattern-string *g* by a non-worker from her/his feasible choice set is then given by:

$$\tilde{P}_g = \frac{e^{\tilde{\theta}_g}}{\sum_{g' \in \vartheta} e^{\tilde{\theta}_{g'}}} \quad . \tag{12}$$

The usual maximum likelihood function procedure can be used to estimate the relevant parameters in the discrete choice model of equation (12). However, the use of a pattern-string as the unit of analysis poses problems in the generation of all the possible pattern strings for a given number of stops by activity type. For example, if an individual pursues 2 stops of each of four possible activity types, the total number of stops undertaken is 8. These 8 stops can be undertaken in a minimum of 1 tour (the case where all the stops are undertaken in the same tour) and a maximum of 8 tours (the case where each stop is undertaken in a separate tour). The total number of feasible pattern-strings (*i.e.*, all the pattern strings without two consecutive in-home episodes) for the case of 8 stops can be shown to be 12,249,720 (a generic formula for calculating this number, given total number of out-of-home stops, is available from the authors). It is clear that the number of alternatives in an individual's feasible choice set can be very high. To resolve this situation, we utilize the independence from irrelevant alternatives (IIA) property of the multinomial logit formulation (on which the ASEQ model is based). The IIA property implies that elimination of irrelevant alternatives from the choice set does not have any effect on the probability of choice of a given alternative in the choice set. We can hence devise a choice set generation process (CSGP) that is based on a random sampling of the alternative pattern-strings.

The CSGP randomly selects a fixed pre-specified number of alternative feasible pattern-strings corresponding to each possible value of number of intermediate in-home episodes (which is based on the total number of out-of-home activities performed) for an individual. Adequate care is taken to ensure that the pattern-string actually chosen by the individual forms a part of the feasible set. Pattern-strings are chosen for each value of the number of intermediate in-home episodes to ensure adequate representation of alternatives in the computation of the utility associated with the number of intermediate in-home episodes. Details of this generation process are available in Misra (1999).

4. EMPIRICAL RESULTS

We now present the results of estimation of the three models formulated in the previous section using the 1990 activity-travel data obtained from the San Francisco Bay Area. This activity-travel survey was conducted for the Metropolitan Transportation Commission (MTC) by E.H. White and Company, Nelson/Nygaard and Phase III Research of Northern California. The survey collected one-weekday activity-travel data for 21,278 individuals in 9,359 sampled households. Of the 21,278 individuals for whom the activity-travel data was collected, 8,112 were not employed. Among these non-workers, approximately half were students. Since the activity-travel behavior of students is usually built around their school schedule, students' activity-travel behavior may be analyzed in a manner similar to that for workers. Hence, in this paper, we focus on the activity-travel behavior of non-workers who are not students. Dropping the full and part time students from the 8,112 non-workers left 4,328 non-student non-workers in the data set (for the sake of presentation simplicity, we will refer to these non-student non-workers simply as non-workers).

Among the 4,328 non-workers, 2,864 individuals pursued at least one out-of-home activity while the remaining 1,464 individuals stayed at home all day. After detailed consistency checks to screen out invalid non-worker activity-travel patterns and missing socio-demographic information, 2,048 individual records remained from the original 2,864 (81.25%) individuals who pursued at least one out-of-home activity (see Misra, 1999 for details of the consistency/screening checks). A random sample of 1,047 individuals was then drawn from the

1,464 individuals who stayed at home all day and these individuals were added to the 2,048 screened individual records with at least one out-of-home activity. This procedure ensures that the ratio of individuals with no activity and individuals with one or more out-of-home activities in the raw data is maintained in the final sample. The final sample, thus, comprises 3,095 individuals.

4.1. Stop Occurrence and Number of Stops (SOC-NOS) Model

Table 1 presents the model estimation results for the propensity to make one or more stops during the day (stop occurrence) and the propensity to make stops should a person leave home (number of stops). Three sets of variables are included: household socio-demographics, household race, and individual socio-demographics. Household location variables were also introduced in our specifications to proxy the effect of locational differences in accessibility to activity opportunities (household location was classified into one of six area types; Central Business District (CBD) core, CBD area, urban business, urban, suburban, and rural; based on the population and employment densities of the traffic zone of residence of the household). However, these variables were not statistically significant.

Among household socio-demographics, the results indicate that non-workers in households with a large number of employed individuals are likely to stay at home the whole day, suggesting a higher degree of responsibility for household tasks for such individuals. On the other hand, individuals in couple and single member households, and individuals in high-income households, are likely to pursue stops away from home. Interestingly, however, these variables do not impact the propensity to make stops once a person decides to leave home. The determinants of the propensity to make stops once a person leaves home include the number of young children (between 5 and 11 years old) and the number of individuals over 65 years. The effects of these two variables are intuitive. The presence of young children is likely to lead to increased participation in maintenance and serve child activities, while non-workers in households with many old individuals are likely to make fewer stops due to in-home care for, and mobility challenges of, the elderly.

The household race variables do not have an impact on the propensity to leave home during the day, though Caucasians tend to make more stops than other races conditional on the decision to leave home.

Within the category of individual socio-demographics, the results show that a) individuals with a driver license have a higher probability to undertake an out-of-home activity episode and to pursue many stops due to their higher mobility, b) physically challenged individuals are unlikely to venture out-of-home, and c) women are observed to have a higher propensity to pursue stops, though they are no more likely than men to leave home during the day. These results are similar to those obtained in a number of earlier studies (see Bianco and Lawson, 1996 and Bhat, 1997).

The joint modeling of the decision to go out of home and the number of stops is necessitated by the potential presence of correlation in unobserved elements affecting the two decisions. The last row of Table 1 shows a highly statistically significant correlation between the error components ε_i and ν_i in equation (1). As indicated earlier, the positive correlation parameter implies that unobserved factors that increase the propensity to leave home to participate in activities also act to decrease stop-making propensity.

The threshold parameters (see note 1 under Table 1) represent the points on the continuous propensity scale that identify the bounds for each discrete number of total stops, and do not have any behavioral significance.

4.2. Stop Type (STYPE) Model

Table 2 presents estimation results corresponding to the four out-of-home activity types modeled in this study: serve-passenger, personal-business, shopping, and recreation. The three columns in Table 2 with parameters represent estimates of the relative propensity of the non-worker to allocate a stop (from a pre-determined total number of stops) to a particular activity type compared to the serve-passenger activity type (which is considered as the base activity type).

Within the class of household socio-demographic variables, the highly significant negative parameters on the nuclear family household variable and the “number of children” variables, along with their relative magnitudes across activity types, suggest that non-workers in nuclear households with young children are primarily involved in serving the needs of the children (*i.e.*, in serve-passenger activities).

Household race has a significant effect on the type of activity performed, with non-Caucasians more likely to participate in a serve-passenger activity and less likely to participate in the other activity types.

Among the variables associated with individual socio-demographics, the results show that a) individuals with a driving license have a higher probability to undertake serve-passenger stops (this is simply a manifestation of the fact that a driving license is a requirement for serve passenger activity), b) women have a higher propensity to participate in shopping and serve passenger activity compared to recreational and personal business activity (presumably a reflection of the continuing trend of women to be primarily responsible for household maintenance activities and for dropping off/picking up children from day-care (see Mensah, 1995), and c) older individuals are less likely to participate in a serve-passenger activity.

As in the case of the number of stops model in the previous section, we introduced location variables to proxy the effect of locational differences in accessibility to different activity types. But these variables were not statistically significant for any of the purposes.

4.3. Activity-Sequencing Model

The estimation results of the ASEQ model are presented in four sub-sections corresponding to the number of intermediate in-home episodes (which gives the number of tours in the pattern-string), number of stops in each tour, Markov state dependence parameters, and the differential Markov effects corresponding to the first stop of the day. The fifth sub-section discusses data fit measures of the activity sequencing model and presents a test for the IIA assumption among activity pattern strings.

4.3.1. Number of Intermediate In-home Episodes

For ease in interpretation, Table 3 presents the estimated parameters for this part of the model in terms of the number of tours (which is one more than the number of intermediate in-home episodes) undertaken by the non-worker.

The number of tours made by an individual is likely to be influenced by both the overall participation levels (*i.e.*, number of stops) in each activity type, as well as the attributes of the individual and the household of which s/he is a part. Thus, we use both these kinds of exogenous variables in the model.

The effect of the activity participation variables indicates that the tendency to chain activities is strongly related to the number of serve-passenger stops and personal business stops undertaken by the individual during the day; individuals making many such stops are likely to have fewer tours. This is perhaps because individuals participating in many activities are likely to have a more purposeful organization pattern for their activities (see Strathman *et al*., 1994 for a similar result in the context of worker activity patterns).

The effects of the household socio-demographic variables suggest a decrease in activity chaining propensity (*i.e.*, more # of tours) for individuals in nuclear family households and households with several vehicles. The latter effect may reflect the lower prevalence of car allocation arrangements in households with many cars; thus, individuals in these households may not require the level of efficiency in the organization of their out-of-home activity episodes as do non-workers in households with few cars.

Household race does not impact activity-chaining propensity. The only individual socio-demographic variable that has a statistically significant impact on activity chaining is the female dummy variable; the effect of this variable suggests that women have a greater tendency to link activities (see Lockwood and Demetsky, 1994 for a similar result).

To summarize, both activity participation by type and household/individual factors affect activity-chaining propensity.

4.3.2. Number of Stops in each Tour

Table 4 presents the estimates of the parameters for the number of stops in each tour. The last tour undertaken by an individual is taken as the base. We neglect the differential allocation of number of stops in the second or higher intermediate tours and also combine the effect of five or more stops in a tour because of small sample sizes.

The results in Table 4 show positive and statistically significant parameters on the constants for each number of stops and for non-last tours. As explained in section 3.2, this implies that individuals are likely to participate in a higher number of stops in earlier tours compared to the last tour of the day. We also observe, in general, that the parameter estimates for each number of stops is higher for the second and subsequent intermediate tours than for the first suggesting that individuals make more stops in intermediate tours than in the first or last tours of the day. Interestingly, neither overall daily activity participation levels nor socio-demographic variables appear to influence the assignment of stops among tours.

4.3.3 Markov State Dependence Parameter Estimates

Table 5 presents the estimation results of the Markov state-dependence parameters, which represent the propensity of the individual to perform a particular activity type in the next episode, if he/she performs a particular activity type in the current episode. We considered the effect of individual socio-demographics on sequencing behavior by parameterizing the state-dependence parameters as a function of individual attributes. However, these effects were not statistically significant. This finding suggests that there is little systematic variation across individuals in the sequencing of activities.

The results in Table 5 indicate that if the non-worker is currently at home, he/she is most likely to perform a serve-passenger activity as the first out-of-home activity. The next most likely activity at the beginning of a tour is a recreation or personal business activity, with shopping being the least likely to occur first in a tour. This is intuitive since shopping stops are usually pursued toward the end of a tour, and followed by a return home (especially if the shopping is for the purchase of perishable/frozen grocery items).

If the non-worker is currently engaged in a serve-passenger activity, he/she is equally likely to either participate in another activity or return home immediately after completing the current activity. A personal-business activity, on the other hand, is most likely to be followed by either a serve-passenger activity or a shopping activity episode. If the current activity is shopping, then the individual is likely to pursue a serve-passenger activity or another shopping activity next, and unlikely to pursue a personal business activity. The individual is equally likely to either return home or participate in a recreation activity after completing the shopping activity.

Finally, an examination of the state-dependence parameters corresponding to recreation activity indicates that a recreation activity is likely to be followed by another recreation activity or a serve-passenger activity. Personal-business, shopping, and return home are all equally likely to follow a recreation activity episode.

4.3.4. Differential Markov Effects for First Stop of the Day

We observe that the Markov differential parameters (Table 6) corresponding to both serve-passenger and personal-business activities are statistically significant and have similar magnitudes. Interpreting these parameters in conjunction with the state-dependence parameters corresponding to the current activity being "at-home" (see Table 5) indicates that a serve-passenger activity is most likely to be the first activity in a non-worker's daily activity-travel pattern, as well as the first stop in any subsequent tour in the pattern. Furthermore, the positive differential parameter for the personal-business activity indicates that a personal-business activity is more likely to be the first stop of the day compared to shopping or recreation; however, it is not more likely than recreation to be the first stop of subsequent tours.

An estimate of the transition probabilities from one activity type to the other may be computed from the state dependence parameters in Tables 5 and 6, if it is assumed that only the state dependence parameters affect the utility of the overall activity sequence. The resulting transition probability estimates are provided in Table 7, and reflect the discussion above. However, this table more clearly indicates the asymmetry in transitions. For example, it is very likely that the first stop from home in a tour is a serve-passenger activity, as can be observed by the relatively high transition rates from home to serve-passenger activity; however, the next stop after a serve-passenger activity is equally likely to be any activity, as can be noted from the equal transition probabilities after a serve-passenger activity. Such asymmetry in transitions provide valuable information regarding the sequencing of activity types in a tour. In particular, the pattern of asymmetries in transition probabilities in the table suggest that if a passenger serve or personal business activity is pursued by the individual, they are likely to be pursued as the first stops in a chain. In addition, if other shopping and recreational stops are pursued, these are pursued later on in the tour (see Kitamura and Kermanshah, 1984a, for similar results).

4.3.5. Overall Measure of Fit and Test of the IIA Assumption

The bottom of Table 7 shows the log-likelihood at convergence for the ASEQ model, and the log-likelihood with only the constants in the number of tours and assignment of stops to tours sub-components of the ASEQ model (this latter log-likelihood corresponds to a market share model for tours and assignment of stops to tours, with no state-dependence in sequencing of activity types). A log-likelihood ratio test clearly rejects the hypothesis that activity chaining is independent of number of stops made by the individual and the socio-demographic attributes of the individual, and that there is no state-dependence in activity sequencing.

One of the important features of the logit structure of the ASEQ model is the independence from irrelevant alternatives (IIA) property. This property was used to develop a choice set generation process (CSGP) during the estimation of the model to achieve computational efficiency. We performed the Hausman and McFadden (1984) test (see Ben-Akiva and Lerman, 1985 for a description) to determine the validity of this assumption. For this test, a restricted version (corresponding to a sample size of 5 for each value of number of intermediate in-home episodes, *i.e.*, a maximum possible sample space of 25 elements for a particular individual corresponding to a maximum of 5 intermediate in-home episodes) and an unrestricted version (corresponding to a sample size of 15 for each value of the number of intermediate in-home episodes, *i.e.*, a maximum possible sample space of 75 elements for a particular individual) of the ASEQ model were tested. The analysis yielded a Hausman and McFadden statistic of 38.1 with 32 degrees of freedom, which is less than the critical χ^2 statistic value of 45.91. Thus, the test does not reject the IIA assumption for the ASEQ model for this data set.

5. CONCLUSION

This paper contributes to the non-worker activity-travel pattern literature by proposing a comprehensive continuous-time framework for representation and analysis of the activity-travel choices of non-workers. The activity-travel pattern comprises a series of stops of different activity types interspersed with in-home episodes. The activity-travel attributes used to represent the activity-travel pattern of the non-worker are classified under three broad categories: pattern level, tour level, and episode level. The proposed analysis framework comprises a series of seven econometric model components.

This paper presents the detailed mathematical description of the first three model components corresponding to the organization of activities in the non-worker's activity-travel pattern. The mathematical description is followed by results of the estimation of the three model components using data obtained from the 1990 San Francisco Bay Area activity-travel diary survey. We discuss these results and their implications briefly in the next three sections.

5.1. Stop Occurrence and Number of Stops

The important results from the stop occurrence and number of stops analysis are as follows: a) Non-workers in households with several employed individuals are less likely to leave home during the day, b) Individuals in single-member and couple households, and in high income-earning households, are more likely to venture out of home to participate in activities, c) Caucasians, women, individuals with a driving license, and individuals in households with small children are highly mobile, d) Physically challenged individuals are less likely to leave their home than other individuals.

The above results suggest that the stop-making patterns of the population may see substantial changes in the next few decades due to changing socio-demographics. In particular, stop occurrence and number of stops may decrease over time, due to higher employment levels, and fewer Caucasian households (U.S. Bureau of Census, 1998; 1999). However, stop-making may increase because of fewer nuclear family households, and more single and couple families (see U.S. Bureau of Census, 1996). The actual impact will depend on the magnitude of changes in the different socio-demographic attributes of the population. The model in the current paper can reflect these socio-demographic changes and assess the impact on overall stop-making due to non-workers. An important finding for planning is that physically-challenged individuals are not very likely to leave home. This may reflect "unfriendly" urban design and transportation planning for such individuals; at the least, it suggests the need for a more systematic effort to examine the rhythms of such individuals, and to design facilities which may be compatible with the needs and challenges that such individuals face.

5.2. Number of Stops by Type

The model component for number of stops by activity type also indicates the significant impact of socio-demographic attributes. Important results from this analysis include the following: a) Nuclear family households and other types of households with children make fewer shopping, recreational and personal business trips than other households, though they make more serve-passenger stops, b) Caucasian households make more shopping and recreational stops, and fewer serve-passenger stops, c) Older individuals make more personal business, shopping, and recreational stops, and fewer serve-passenger stops, while the reverse is true for women compared to men. Overall, the results imply that the demand for shopping and recreational facilities is likely to increase in the future due to the fewer number of households with children and also because of the rapidly growing age of the population. From a broader societal standpoint, the higher shopping/recreational demands of the growing number of older (yet physically active) individuals suggests a need for targeted investments to provide more opportunities for recreational pursuits, especially in retirement communities.

5.3. Activity Sequencing

Several informative results are obtained from the activity sequencing analysis, including the following: a) Serve-passenger activity, if it is pursued, is most likely to be the first activity of the day and the first activity of any tour, b) Personal business activities are also more likely to be undertaken as the first activity of the day relative to shopping and recreational activities, c) Shopping and recreational activities are quite often “sandwiched” between serve-passenger activities for individuals who undertake paired serve-passenger trips. These tendencies in sequencing may reflect a strategy of pursuing spatially and temporally fixed activities (serve-passenger and personal business) at the beginning of tours, and pursuing more flexible activities (shopping and recreation) toward the end of tours.

Two additional overall results can be drawn from this paper. First, the location of the household does not appear to impact stop-making of non-workers. That is, spatial factors of accessibility to activity opportunities do not influence participation in activity stops. This suggests that activity generation is primarily determined by the activity needs of the individual (as part of her/his household), not by the activity environment. Another perspective is that individuals and households locate themselves in areas that provide accessibility to activity opportunities that are compatible with their mobility needs, and this manifests itself in the form of lack of effect of accessibility on stop-making. This issue needs to be explored in much more depth, and reinforces the need for an integrated land use-activity based travel demand modeling approach to urban planning. Second, it is interesting to note that while socio-demographics play a very important role in influencing stop occurrence, stop-making, and activity chaining behavior, they do not influence the sequencing of activities. Thus, activity sequencing appears to be primarily determined by the type of activities in which an individual participates, and not by variations in individual/household characteristics. Of course, these results may be specific to the empirical context of the current paper. In this regard, application and analysis of non-worker activity-travel patterns using data from other metropolitan regions would be a useful direction for future research.

REFERENCES

Ben-Akiva, M.E. and S.R. Lerman (1985). Discrete Choice Analysis: Theory and Application to Travel Demand. The MIT Press, Cambridge.

Ben-Akiva, M.E. and J.L. Bowman (1995). Activity-based disaggregate travel demand model system with daily activity schedules. Paper presented at the EIRASS Conference on Activity-Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, The Netherlands.

Bhat, C.R. (1997). Work travel mode choice and number of non-work commute stops. Transportation Research, 31B, 1, 41-54.

Bhat, C.R. and F.S. Koppelman (1993). A conceptual framework of individual activity program generation. Transportation Research, 27A, 6, 433-446.

Bhat, C.R. and F.S. Koppelman (1999a). A retrospective and prospective survey of time-use research. Transportation, 26, 2, 119-139.

Bhat, C.R. and F.S. Koppelman (1999b). Activity-based modeling of travel demand, in The Handbook of Transportation Science, 35-61, edited by Randolph Hall, Kluwer Academic Publishers, Norwell, Massachusetts.

Bhat, C.R. and S.K. Singh (2000). A comprehensive daily activity-travel generation model system for workers. Transportation Research, 34A, 1, 1-22.

Bhat, C.R., J.P. Carini and R. Misra (1999). On modeling the generation and organization of household activity stops. Proceedings of the 1999 Annual Transportation Research Board Meeting, Washington, D.C.

Bianco, M.J. and C. Lawson (1996). Trip-chaining, childcare and personal safety: critical issues in women's travel behavior. Presented at the Second National Conference on Women's Travel Issues, Baltimore, Maryland, October 24-26.

Clarke, M.I. (1986). Activity modeling – a research tool or a practical planning technique?, in Behavioral Research for Transport Policy, 3-15, VNU Science Press, Utrecht, The Netherlands.

Damm, D. (1980). Interdependencies in activity behavior. Transportation Research Record, 750, 33-40.

Ettema, D., A.W.J. Borgers and H.J.P. Timmermans (1993). Simulation model of activity-scheduling behavior. Transportation Research Record, 1413, 1-11.

Garling, T., K. Brannas, J. Garvil, R.G. Golledge, S. Gopal, E. Holm and E. Lindberg (1989). Household activity scheduling, in Transport Policy, Management & Technology Towards 2001: Selected Proceedings of the Fifth World Conference on Transport Research, Vol. IV, 235-248, Western Periodicals, Ventura, California.

Hamed, M.M. and F.L. Mannering (1993). Modeling travelers' postwork activity involvement: toward a new methodology. Transportation Science, 27, 4, 381-394.

Hausman, J. and D. McFadden (1984). Specification tests for the multinomial logit model. Econometrica, 52, 1219-1240.

Jones, P.M., F.S. Koppelman, and J.P. Orfeuil (1990). Activity analysis: state of the art and future directions, in Developments in Dynamic and Activity-Based Approaches to Travel Analysis, pp. 34-55, Gower, Aldershot, England.

Kitamura, R. and M. Kermanshah (1984a). Identifying time and history dependencies of activity choice. Transportation Research Record, 944, 22-30.

Kitamura, R. and M. Kermanshah (1984b). Sequential model of interdependent activity and destination choices. Transportation Research Record, 987, 81-89.

Kitamura, R., E.I. Pas, C.V. Lula, T.K. Lawton, and P.E. Benson (1996). The sequenced activity mobility simulator (SAMS): and integrated approach to modeling transportation, land use and air quality. Transportation, 23, 267-291.

Kitamura, R. and S. Fujii (1998). Two computational process models of activity-travel behavior, in T. Garling, T. Laitila and K. Westin (eds.) Theoretical Foundations of Travel Choice Modeling, Oxford, Elsevier Science, 251-279.

Lockwood, P.B. and M.J. Demetsky (1994). Nonwork travel – a study of changing behavior. Presented at the 73rd annual meeting of the Transportation Research Board, Washington, D.C., January.

Maddala, G.S. (1983). Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge.

Mensah, J. (1995). Journey to work and job characteristics of the urban poor: a gender analysis of a survey data from Edmonton, Alberta. Transportation, 22, 1-19.

Misra, R. (1999). Toward a comprehensive representation and analysis framework for non-worker activity-travel pattern modeling. Doctoral Dissertation, Department of Civil Engineering, University of Texas, Austin, TX, unpublished.

Misra, R. and C.R. Bhat (2000). Activity-travel patterns of non-workers in the San Francisco Bay area: an exploratory analysis. Forthcoming, Transportation Research Record.

Recker, W.W., M.G. McNally and G.S. Root (1986a). A model of complex travel behavior: part i. Theoretical development. Transportation Research, 20A, 307-318.

Recker, W.W., M.G. McNally and G.S. Root (1986b). A model of complex travel behavior: part ii. An operational model. Transportation Research, 20A, 319-330.

Strathman, J.G., K.J. Dueker and J.S. Davis (1994). Effects of household structure and selected travel characteristics on trip chaining. Transportation, 21, 23-45.

U.S. Bureau of Census (1996). Projected Number of Families with Children under 18 Years by Type: 1995 to 2010. Population Division, Population Projections Branch, www.census.gov/population/www/projections/nathh.html.

U.S. Bureau of Census (1998). Inter-racial Tables. Population Division, Racial Statistics Branch, www.census.gov/population/www/socdemo/interace.html.

U.S. Bureau of Census (1999). Working at Home. Population Division, Journey to Work and Migration Statistics Branch, www.census.gov/population/www/socdemo/workathome/wkhtab1.html

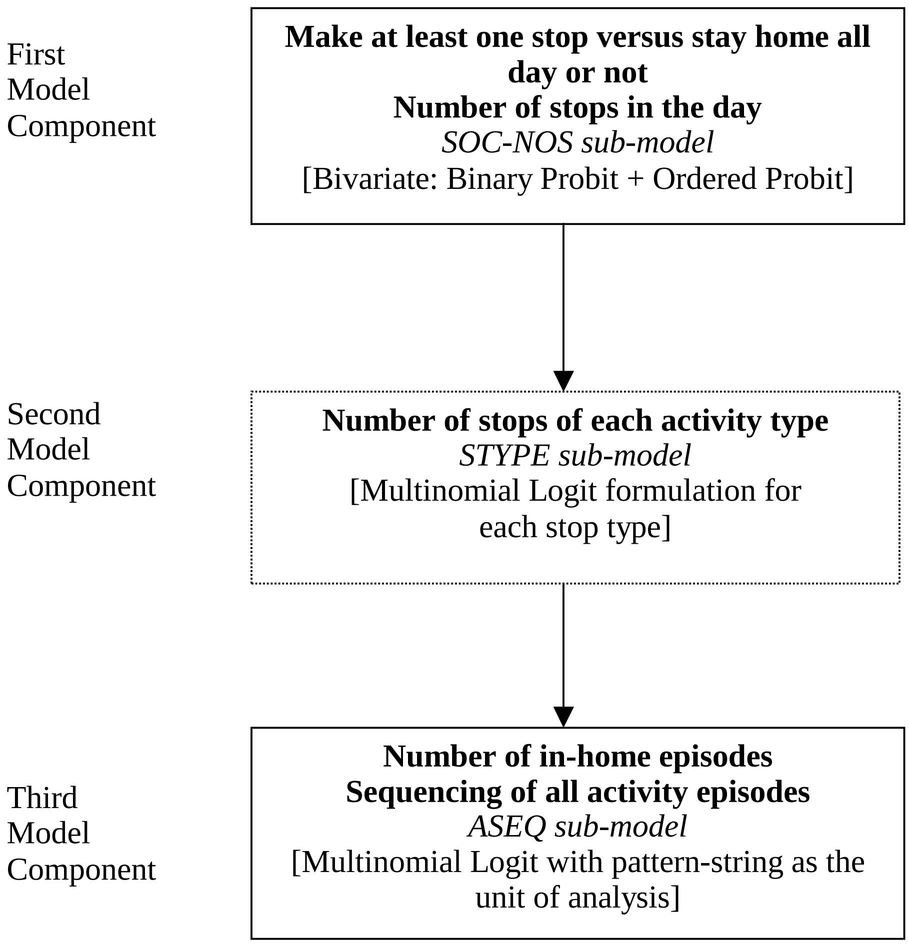

Figure 1. Modeling Framework for Pattern Level Attributes

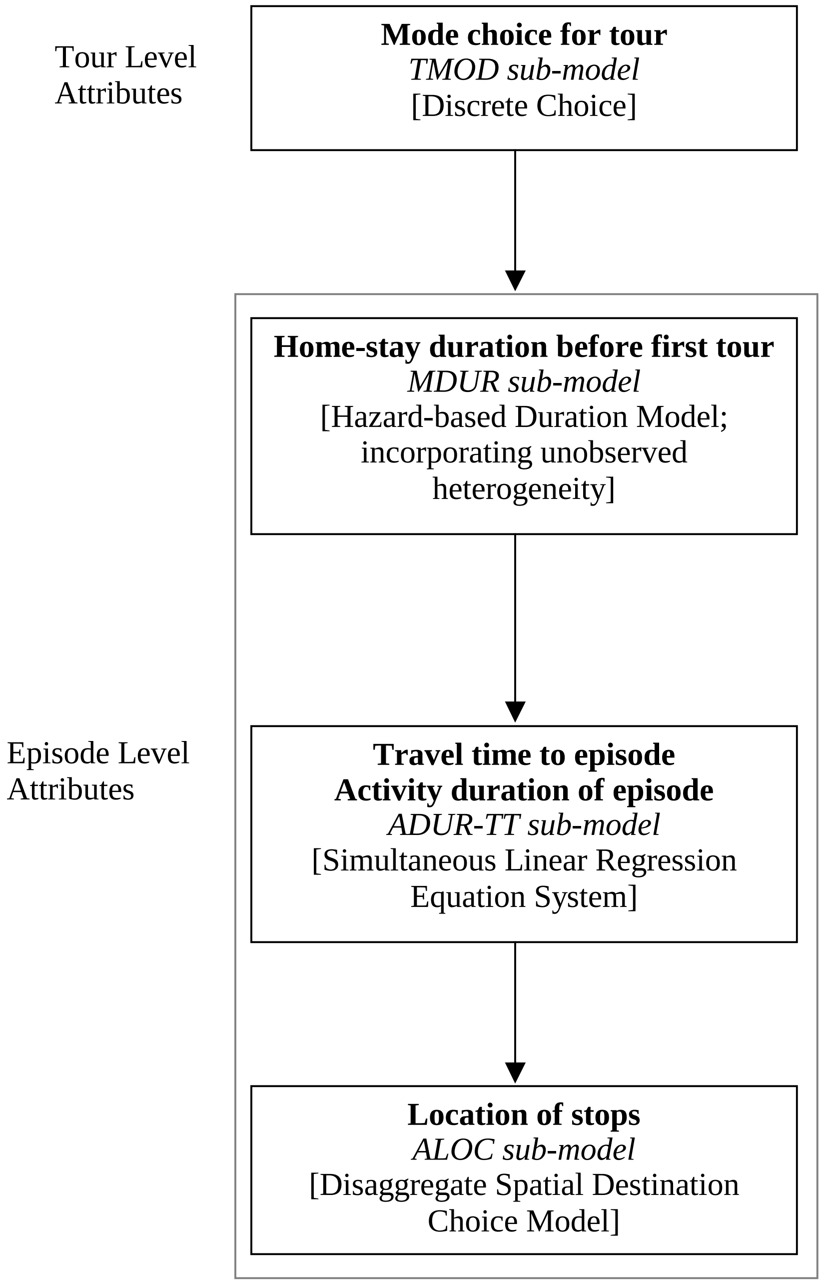

Figure 2. Modeling Framework for Tour Level and Episode Level Attributes

Table 1. SOC-NOS model estimation results: Parameters on explanatory variables

Explanatory Variables	Stop Occurrence		Number of Stops	
	Estimates	**Est./s.e.**	**Estimates**	**Est./s.e.**
Constant	-0.045	*-0.519*	-	-
Household Socio-demographics				
Number of Employed Individuals in HH	-0.133	*-3.633*	-	-
Couple	0.114	*2.113*	-	-
Single Member family	0.146	*2.244*	-	-
Household Income ('000 $)	0.004	*4.898*	-	-
Number of Children between 5 & 11 years	-	-	0.198	*4.538*
Number of Individuals over 65 years old	-	-	-0.069	*-2.633*
Household Race				
Caucasian	-	-	0.209	*3.781*
Individual Socio-demographics				
Driver	0.476	*7.978*	0.276	*2.755*
Physically challenged	-0.250	*-2.848*	-	-
Sex (Female = 1)	-	-	0.128	*2.880*
Rho (Correlation Coefficient)	Parameter Estim: +0.741; t-static: +7.163			

Notes: 1) The ordered-response threshold parameters (and their t-statistics) for the number of stops model are as follows from the first threshold to the last: -0.135 (-0.927), 0.424 (2.483), 0.842 (4.240), 1.170 (5.172), 1.535 (5.857) and 1.848 (6.201).

2) The log-likelihood at convergence for the model is –5163.844. The log-likelihood with only the constant in the stop occurrence model and with only the thresholds in the number of stops model is –5319.841.

Table 2. STYPE model estimation results: Parameters on explanatory variables
[Base = Serve-passenger Activity]

Variable Name	Personal-business		Shopping		Recreation	
	Estimates	**Est./s.e.**	**Estimates**	**Est./s.e.**	**Estimates**	**Est./s.e.**
Constant	1.648	*5.157*	1.756	*5.750*	1.516	*4.607*
Household Socio-demographics						
Nuclear family household	-0.757	*-6.252*	-0.647	*-5.436*	-0.694	*-5.577*
Number of Children between 5 and 11	-0.709	*-7.853*	-0.763	*-8.640*	-0.624	*-6.864*
Number of Children between 12 and 16	-0.309	*-2.795*	-0.399	*-3.597*	-	-
Household Race (Caucasian race is base)						
Non-Caucasians	-0.249	*-2.274*	-	-	-	-
Individual Socio-demographics						
Driver	-1.183	*-5.105*	-1.376	*-6.023*	-1.245	*-5.283*
Sex (Female = 1)	-0.234	*-3.173*	-	-	-0.376	*-4.696*
Age	0.013	*3.500*	0.012	*3.271*	0.011	*3.243*
Log-likelihood (preferred model)	-6503.300					
Log-likelihood (market-share model)	-6773.842					
Number of cases	2048					

Table 3. ASEQ model estimation results: Number of tours
[Base = No Intermediate In-Home Episode (*i.e.* One tour)]

Variable Name	2 tours		3 tours		> 3 tours	
	Estimates	**Est./s.e.**	**Estimates**	**Est./s.e.**	**Estimates**	**Est./s.e.**
Constant	-0.145	*-0.980*	-0.127	*-0.499*	-0.766	*-1.626*
Activity Participation Variables						
Number of stops for Pass. Serve and PB	-0.204	*-3.312*	-0.366	*-4.192*	-0.463	*-3.515*
Household Socio-Demographics						
Nuclear Family	0.322	*2.045*	0.669	*2.949*	1.229	*3.427*
Number of Vehicles in HH	0.181	*3.121*	0.181	*3.121*	0.181	*3.121*
Individual and Household Characteristics						
Sex (Female = 1)	-0.229	*-1.656*	-0.289	*-1.338*	-0.206	*-0.549*

Table 4. ASEQ model estimation results: Number of stops in each tour
[Bases = Last tour undertaken by the individual; and Number of stops = 1]

Tour Number	Variable Name	Number of Stops							
		2 stops		3 stops		4 stops		≥ 5 stops	
		Estimates	**Est./s.e.**	**Estimates**	**Est./s.e.**	**Estimates**	**Est./s.e.**	**Estimates**	**Est./s.e.**
1	Constant	0.181	*1.65*	0.940	*6.094*	1.045	*4.215*	2.231	*7.180*
≥ 2	Constant	0.553	*3.35*	0.979	*3.265*	1.926	*4.378*	2.893	*3.232*

Table 5. ASEQ model estimation results: First order Markov state dependence effects [Base = In-home Activity Episode]

Current Activity	Next Activity	Estimates	Est./s.e.
At-Home (Recreation activity is base)	Passenger-serve Personal-business Shopping	1.222 - -0.504	*7.319* - *-4.239*
Serve-passenger	Non-Home	-	-
Personal-business	Passenger-serve Personal-business Shopping Recreation	0.738 - 0.522 -	*3.007* - *3.978* -
Shopping	Passenger-serve Personal-business Shopping Recreation	0.634 -0.446 0.568 -	*2.677* *-3.417* *4.156* -
Recreation	Passenger-serve Personal-business Shopping Recreation	1.256 - - 0.582	*5.323* - - *4.182*

Table 6. ASEQ model estimation results: Differential effects of first stop of day [Base = Recreation Activity]

Activity	Estimates	Est./s.e.
Serve-passenger	0.526	*3.349*
Personal-business	0.438	*4.527*
Shopping	-	-

Table 7. ASEQ model estimation results: Transition probabilities corresponding to Markov state dependence parameters

Current Activity	Next Activity	Probability
At-Home (For first tour of the day)	Serve-passenger	0.647
	Personal-business	0.173
	Shopping	0.069
	Recreation	0.112
At-Home (For 2^{nd} and subsequent tours)	Serve-passenger	0.566
	Personal-business	0.166
	Shopping	0.102
	Recreation	0.166
Serve-passenger	Serve-passenger	0.200
	Personal-business	0.200
	Shopping	0.200
	Recreation	0.200
	At-Home	0.200
Personal-business	Serve-passenger	0.309
	Personal-business	0.148
	Shopping	0.248
	Recreation	0.148
	At-Home	0.148
Shopping	Serve-passenger	0.299
	Personal-business	0.101
	Shopping	0.280
	Recreation	0.160
	At-Home	0.160
Recreation	Passenger-serve	0.423
	Personal-business	0.121
	Shopping	0.121
	Recreation	0.215
	At-Home	0.121
Log-likelihood (preferred model)	-2422.026	
Log-likelihood (market share model)	-2643.087	
Number of cases	2048	

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