A Mixed Multinomial Logit Model Analysis of Weekend Recreational Episode Type Choice

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ABSTRACT

This paper presents a model for the type of recreational activity episodes that individuals pursue during the weekend. The choice set characterizing the type of recreational episode includes in-home, out-of-home, and pure recreational episodes (pure recreation refers to recreation trips pursued for the sole purpose of the recreational value obtained from the trip, such as walking, bicycling, and joy driving). The paper estimates a mixed multinomial logit formulation using the 2000 San Francisco Bay Area Travel Survey. The effects of household and individual sociodemographics, land-use and density variables, and episode participation attributes are examined. Inter-individual and intra-individual variation in unobserved determinants of episode type choice are also analyzed. Finally, the implications of the results for land-use and transportation planning are identified.

Keywords: Weekend activity-pattern, recreational activity, mixed logit, activity-based travel modeling

1. INTRODUCTION

Activity-based travel analysis has received substantial attention in the past three decades and has matured in the last few years (see Bhat and Koppelman, 1999 and Pendyala and Goulias, 2002). In particular, several operational frameworks within the activity-based analysis paradigm have been proposed, and a few large metropolitan planning organizations (MPOs) in the country are even implementing these frameworks (see Waddell *et al.*, 2002).

The activity-based approach to travel demand analysis views travel as a demand derived from the need to pursue activities distributed in space (see Jones *et al*., 1993 or Axhausen and Garling, 1992). While there has been considerable work in the activity analysis field in the past, there are certain areas within this field that have received lesser attention than others. This research effort attempts to contribute to the activity analysis field in these relatively lesser-researched areas. The next few sections highlight the salient aspects of the current research effort.

1.1 Focus on Weekend Activity and Travel

The activity-based analysis efforts to date have predominantly focused on weekday activity and travel. However, weekend travel has been increasing over time and constitutes approximately 26% of total trips, according to the 1995 Nationwide Personal Transportation Survey Results (Federal Highway Administration and Bureau of Transportation Statistics, 1995). In addition, weekend travel characteristics tend to be quite different from weekday travel. In particular, the peak travel periods occur during the midday rather than during the early morning or late afternoons. Also, trip distances are larger, and transit shares are lower during the weekend. The net result is that air quality emissions violations for ozone are extending to weekend days in many metropolitan areas.

In the current paper, the focus is on analyzing weekend activities and travel, rather than weekday activities and travel.

1.2 In-Home versus Out-of-Home Activity Substitution

In almost all activity-based frameworks thus far, the focus has been on out-of-home activity episodes and travel. In-home activity episodes are not adequately analyzed in these frameworks. In-home and out-of-home activity episodes have quite different implications for travel; an in-home episode does not involve travel (for a person already at home), while an out-of-home episode requires travel. Thus, the in-home/out-of-home participation decision has an impact on the generation and spatial distribution of trips (see Yamamoto and Kitamura, 1999; Bhat and Koppelman, 1999). Understanding this substitution is important, particularly at a time when opportunities for shopping and entertainment at home are burgeoning because of the increased accessibility of households to computers and theatre quality home entertainment systems (see Bhat *et al.*, 2003).

One of the impediments to a detailed analysis of in-home and out-of-home substitution has been the (un)availability of data on in-home activities. Most surveys do not collect data on in-home activities. In this research, we use a recent survey that has collected data on in-home activity episodes to model the substitution between in-home and out-of-home activity episodes.

1.3 Work versus Nonwork Activity Modeling

Most existing activity-based travel analysis studies have examined the activity-travel patterns associated with the work commute and/or weekday worker activity-travel patterns (for example, see Bhat and Singh, 2000; Hamed and Mannering, 1993; Strathman *et al.*, 1994; Mahmassani, *et al.,* 1997; Pendyala *et al*., 2002). One of the major motivations for the focus on weekday 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 weekday worker activity analysis, relatively little research has examined the activity-travel behavior of nonworkers on weekdays or of nonwork activities of all individuals over the weekend (but see Bowman and Ben Akiva, 2000; Kitamura and Fujii, 1998; Arentze and Timmermans, 2002; and Bhat and Misra, 2001 for studies that include the activity-travel behavior of nonworkers on weekdays).

In this study, the focus is on nonwork activities of individuals over the weekend. More specifically, the emphasis is on recreational activity episodes (including exercising and entertainment) within the context of weekend nonwork activities. Trips to such out-of-home recreational activity episodes constitute about 23% of all trips over the weekends according to the 1995 Nationwide Personal Transportation Survey. The NPTS data also indicate that the average recreational trip length is around 13 miles, over twice the length of an average shopping trip. Further, Yai *et al.* (1995) point out that the total recreational vehicle kilometers per day over the weekends is much higher than the total daily commute vehicle kilometers on weekdays. Clearly, an analysis of recreational activity participation is important to predict changes in, and manage, weekend traffic levels.

1.4 Consideration of Pure Recreational Activity Episodes

Recreational activity episodes can be trips pursued for the sole purpose of the recreational value obtained from the trip. We will label such recreational trips as pure recreational activity episodes. Examples include walking, jogging, riding a bike, and joy driving. These episodes do not have any specific destination and generally begin and end at home without any stop in-between. Such pure recreational activity episodes have not received much (if any) attention in previous activity analyses. Specifically, almost all earlier studies have focused only on out-of-home recreational episodes pursued at a specific out-of-home destination. As indicated by Schwartz *et al.* (2001), the behavior governing participation in pure recreational activity episodes is likely to be quite different from those underlying participation in out-of-home recreational episodes. Further, with limited time to participate in recreational activities, there may be substitution between out-of-home recreational episodes and pure recreational episodes in addition to substitution between these two episode types and in-home recreational episodes.

1.5 Summary and Focus of Current Research

The literature in the area of activity-based travel modeling, and travel demand modeling in general, has primarily focused on weekday travel, out-of-home activities, worker activity-travel patterns, and travel for the purpose of participating in an activity at the end of the travel. In contrast, the current study examines weekend activity and travel participation, in-home as well as out-of-home activities, worker and non-worker activity-travel patterns, and travel episodes that themselves generate utilitarian value to individuals. The focus is specifically on urban recreational activity episodes in this paper.

As indicated by Pozsgay and Bhat (2001), the literature on intra-urban recreational activity episodes and trips is rather sparse. Most earlier studies on recreational travel have been undertaken in the recreational, tourism, and land economics fields, and these studies have focused on long-distance inter-urban trips (see, for example, Train, 1998; Morey *et al.*, 1991; Yai *et al.*, 1995; Kozak and Rimmington, 2000; Kemperman *et al*., 2002). Some recent studies have examined various dimensions of out-of-home intra-urban recreational activity episodes. For example, Pozsgay and Bhat (2001) examined location choice of out-of-home urban recreational activity episodes, while Hunt and Patterson (1996) and Steed and Bhat (2000) have analyzed departure time for out-of-home recreational activity episodes. However, these studies are focused on weekdays and do not consider in-home episodes or pure recreational activity episodes.

The studies by Bhat and Misra (1999) and Yamomoto and Kitamura (1999) are closer in spirit to the current study. Both these studies examine the allocation of time to discretionary activities between weekend days and weekdays and explicitly model the substitution between total durations spent in in-home versus out-of-home recreational activities. Our study, however, may be distinguished from these two earlier studies in two respects. First, we focus on participation in individual recreational activity episodes during the weekend as opposed to total time duration spent within each of the four categories defined by the combination of in-home/out-of-home and weekday/weekend activities. Second, our study includes pure recreational activity episodes in the analysis.

The data source used in the current analysis is the 2000 San Francisco Bay Area Activity-Travel Survey (BATS). The BATS data is a time-use survey and is ideally suited for the analysis in this paper because it collects information on in-home as well as out-of-home activity episodes. Further, the BATS survey elicited information on all activities for a two-day period from participating households, including weekend days. This provides a substantial number of weekend episodes for analysis.

The rest of this paper is structured as follows. The next section provides details of the model structure used in our analysis. Section 3 discusses model estimation issues. Section 4 describes the data sources and sample formation procedures. Section 5 presents the results of the empirical analysis. Finally, Section 6 summarizes the important findings from the research and discusses the implications for land-use and transportation planning.

2. THE MODEL STRUCTURE

In this paper, we formulate a mixed multinomial-logit (or MMNL) model of weekend recreational activity for the choice among three episode types: in-home, out-of-home, and pure recreation. The formulation accommodates heterogeneity (*i.e.*, differences in behavior) across individuals due to both observed and unobserved individual attributes. Correlation in common unobserved factors influencing the choice of episode types are also considered (for example, unobserved attributes such as a dynamic and outgoing personality may increase the utilities of both out-of-home episode choice and pure recreation episode choice). The choice probabilities in the MMNL structure do not have a closed-form expression. However, recent advances in simulation techniques to approximate integrals facilitate the application of the MMNL structure (see Bhat, 2001; 2003)[1].

[1] The episode type model in this paper is estimated using repeated recreational episode type choices of individuals. It is important to note that such repeated choice data is needed to accommodate unobserved variations in intrinsic preferences for each episode type across individuals.

In the tradition of utility-maximization models, the utility U_{qit} that an individual q (q=1,2,…,Q) associates with an alternative i (i=1,2,…,I) on choice occasion t (t=1,2,…,T_q) may be written as:

$$U_{qit} = \alpha_{qi} + \theta' x_{qit} + \varepsilon_{qit}\,, \tag{1}$$

where α_{qi} is a scalar utility term representing individual q's intrinsic preference for alternative i; x_{qit} is a column vector of observed variables affecting the utility of individual q for alternative i at the t^{th} choice occasion. θ is a corresponding column vector of coefficients, and ε_{qit} is an unobserved random term that represents the idiosyncratic effect of omitted variables that are not individual-specific but choice occasion-specific. ε_{qit} is assumed to be independent of α_{qi} and x_{qit}.

Equation (1) represents the micro-level utility model for episode type choice. We now allow the scalar utility term α_{qi} to vary across individuals in a higher-level macro-model:

$$\alpha_{qi} = (\delta' + \gamma_q')\, y_i\,, \tag{2}$$

where δ is a (I x 1)-column vector with the i^{th} element representing the "average" (across individuals) effect of unobserved variables on the utility associated with alternative i. γ_q is a (I x 1)-column vector with its i^{th} element capturing individual q's differential preference for alternative i compared to the "average" preference across all individuals for alternative i, and y_i is a (I x 1)-column vector of 1's and 0's with a 1 in row i and 0 in other rows. The reader will note that the individual-specific γ_q vector allows unobserved heterogeneity across individuals in the intrinsic preference for each alternative.

Next, the error term ε_{qit} may be partitioned into two components, ζ_{qit} and $\mu' z_{qit}$. The first component, ζ_{qit}, is assumed to be independently and identically standard Gumbel distributed across alternatives and choice occasions. The second component in the error term, $\mu' z_{qit}$, induces heteroscedasticity and correlation across unobserved utility components of the alternatives at any choice occasion *t*. z_{qit} is specified to be a column vector of dimension *M* with each row representing a group *m* (*m*=1,2,...,*M*) of alternatives sharing common unobserved components. The row(s) corresponding to the group(s) of which *i* is a member take(s) a value of one and other rows take a value of zero. The vector μ (of dimension *M*) may be specified to have independent elements, each element having a variance component σ_m^2. The result of this specification is a covariance of σ_m^2 among alternatives in group *m*, and heteroscedasticity across the groups of alternatives.

Defining $\beta = (\delta', \theta')'$, $w_{qit} = (y_i', x_{qit}')'$, and using Equation (2) and the error components specification for ε_{qit} discussed above, Equation (1) may be rewritten as:

$$U_{qit} = \beta' w_{qit} + \gamma_q' y_i + \mu' z_{qit} + \zeta_{qit}\,. \tag{3}$$

The coefficient vector γ_q in the above equation is individual-specific. Let the distribution of the variation of the γ_q vector across individuals (*i.e.*, the distribution of unobserved preference heterogeneity) be multivariate normal, so that γ_q is a realization of a random multivariate normally distributed variable $\tilde{\gamma}$. Let ω be a vector of true parameters characterizing the mean and variance-covariance matrix of $\tilde{\gamma}$. Further, let σ be a parameter vector characterizing the variance-covariance matrix of the multivariate normal distribution of μ.

Conditional on $\tilde{\gamma}$ and μ, the probability that individual q will choose alternative i at the t^{th} choice occasion can be written in the usual multinomial logit form (see McFadden, 1978):

$$P_{qit} \mid (\tilde{\gamma},\mu) = \frac{e^{\beta' w_{qit} + \tilde{\gamma}' y_i + \mu' z_{qit}}}{\sum_{j=1}^{I} e^{\beta' w_{qjt} + \tilde{\gamma}' y_j + \mu' z_{qjt}}} \,. \tag{4}$$

The unconditional probability can be subsequently obtained as:

$$P_{qit} = \int_{\tilde{\gamma}=-\infty}^{\infty} \int_{\mu=-\infty}^{+\infty} \frac{e^{\beta' w_{qit} + \tilde{\gamma} y_i + \mu' z_{qit}}}{\sum_{j=1}^{I} e^{\beta' w_{qjt} + \tilde{\gamma} y_j + \mu' z_{qjt}}} dF(\mu \mid \sigma) dF(\tilde{\gamma} \mid \omega), \tag{5}$$

where F is the multivariate cumulative normal distribution. The reader will note that the dimensionality in the integration above is dependent on the number of elements in the μ and γ_q vectors.

3. MODEL ESTIMATION

The parameters to be estimated in the model of Equation (5) are the β, σ, and ω vectors. To develop the likelihood function for parameter estimation, we need the probability of each sample individual's set of observed recreational episode type choices. Conditional on $\tilde{\gamma}$, the likelihood function for individual q's observed set of choices is:

$$L_q(\beta,\sigma,\tilde{\gamma}) = \prod_{t=1}^{T_q} \left[\int_{\mu=-\infty}^{+\infty} \left\{ \prod_{i=1}^{I} \left[P_{qit}(\beta,\tilde{\gamma},\mu) \right]^{M_{qit}} \right\} f(\mu \mid \sigma) d\mu \right], \tag{6}$$

where M_{qit} is a dummy variable taking the value of 1 if the q^{th} individual chooses the i^{th} alternative in the t^{th} occasion and 0 otherwise. The unconditional likelihood function for individual q's observed set of choices is:

$$L_q(\beta,\sigma,\omega) = \int_{\tilde{\gamma}=-\infty}^{+\infty} L_q(\beta,\sigma,\tilde{\gamma}) f(\tilde{\gamma} \mid \omega) d\tilde{\gamma}$$

$$= \int_{\tilde{\gamma}=-\infty}^{+\infty} \left\{ \prod_{t=1}^{T_q} \left[\int_{\mu=-\infty}^{+\infty} \left\{ \prod_{i=1}^{I} \left[P_{qit}(\beta,\tilde{\gamma},\mu) \right]^{M_{qit}} \right\} f(\mu \mid \sigma) d\mu \right] \right\} f(\tilde{\gamma} \mid \omega) d\tilde{\gamma} \; . \quad (7)$$

The log-likelihood function is $\mathcal{L}(\beta,\sigma,\omega) = \Sigma_q \ln L_q(\beta,\sigma,\omega)$.

We apply quasi-Monte Carlo simulation techniques to approximate the integrals in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across all individuals with respect to β, σ, and ω. The procedure to simulate each individual's likelihood function, $L_q(\beta,\sigma,\omega)$, is as follows: (a) For a given value of the parameter vector ω, draw a particular realization of $\tilde{\gamma}$ from its distribution, (b) For a given value of the σ vector, draw several sets of realizations of μ from its distribution, each set corresponding to a choice occasion of the individual, (c) compute the probability of the chosen alternative for each choice occasion for given values of the β vector (*i.e.*, the likelihood function of that choice occasion) at that choice occasion's set of μ realizations, and for the current $\tilde{\gamma}$ realization, (d) Average the likelihood functions across the various realizations of μ for each choice occasion, (e) Compute the individual likelihood function as the product of the averaged likelihood functions across all choice occasions of the individual, (f) Repeat steps a through e several times with fresh realizations of $\tilde{\gamma}$ and new sets of draws of μ, and (g) Compute the average across all individual likelihood function evaluations. Mathematically, the individual likelihood function is approximated as:

$$SL_q(\beta,\sigma,\omega) = \frac{1}{D} \sum_{d=1}^{D} \left[\prod_{t=1}^{T_q} \left\{ \frac{1}{G} \sum_{g_d=1}^{g_d=G} \left(\prod_{i=1}^{I} \left[P_{qit}(\beta,\mu^{g_d} \mid \sigma, \tilde{\gamma}^d \mid \omega) \right]^{M_{qit}} \right) \right\} \right], \quad (8)$$

where $SL_q(\beta,\sigma,\omega)$ is the simulated likelihood function for the q^{th} individual's set of episode type choices given the parameter vectors β, ω, and σ, $\tilde{\gamma}^d \mid \omega$ is the d^{th} draw (d=1,2,...,D) from $f(\tilde{\gamma} \mid \omega)$, $\mu^{g_d} \mid \sigma$ is the $g_d{}^{\text{th}}$ draw (g_d =1,2,...,G) from $f(\mu \mid \sigma)$ at the d^{th} draw of $\tilde{\gamma}$, and other variables are as defined earlier. $SL_q(\beta,\sigma,\omega)$ is an unbiased estimator of the actual likelihood function $L_q(\beta,\sigma,\omega)$. Its variance decreases as D and G increase. It also has the appealing properties of being smooth (*i.e.*, twice differentiable) and being strictly positive for any realization of the draws (see McFadden and Train, 2000).

The simulated log-likelihood function is constructed as:

$$S\mathcal{L}(\beta,\sigma,\omega) = \sum_q \ln[SL_q(\beta,\sigma,\omega)]. \tag{9}$$

The parameter vectors β, ω, and σ are estimated as the values that maximize the above simulated function. Under rather weak regularity conditions, the maximum (log) simulated likelihood (MSL) estimator is consistent, asymptotically efficient, and asymptotically normal (see Hajivassiliou and Ruud, 1994 and Lee, 1992).

In the current paper, we use the Halton sequence to draw realizations for $\tilde{\gamma}$ and μ from their population normal distributions. Details of the Halton sequence and the procedure to generate this sequence are available in Bhat (2003). Bhat (2003) has demonstrated that the Halton simulation method out-performs the traditional pseudo-Monte Carlo (PMC) methods for mixed logit model estimation.

The estimations and computations in the paper were carried out using the GAUSS programming language on a personal computer. Gradients of the log simulated likelihood function with respect to the parameters were coded.

4. DATA SOURCES AND SAMPLE FORMATION

4.1 Data Sources

The primary data source used for this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS). This survey was designed and administered by MORPACE International, Inc. for the Bay Area Metropolitan Transportation Commission. The survey collected detailed information on all activity and travel episodes for a two-day period from members of 15,064 households residing in the Bay Area (see MORPACE International, Inc. 2002, for details of survey sampling and administration procedures). The information collected for activity episodes included the start and end time of participation, type of activity, and location of participation (*i.e.*, in-home or out-of-home, and if out-of-home, the actual geographic location). The information gathered on travel episodes included information on travel mode used, number of other individuals in the vehicle for non-transit and non-motorized modes, costs incurred, and the start and end time of the trip. In addition to activity and travel episode information, the survey also collected individual and household sociodemographic information, employment-related characteristics, and internet use at home.

A secondary data source used in the analysis is a zonal-level land-use and demographic file obtained from the Metropolitan Transportation Commission. The land-use file provides the following information for each traffic analysis zone (TAZ): (a) zonal land area and acreage in residential, commercial/industrial, and open space land-use purposes, (b) number of detached (single family) and non-detached (duplex, apartments, *etc*.) housing units, (c) total employment and employment disaggregated by agricultural/manufacturing, retail and service sectors, (d) total zonal population, and the income and age distribution of the population, and (e) the area type of the zone (*i.e.*, whether the zone can be characterized as a core CBD zone, a CBD zone, an urban business zone, an urban zone, a suburban zone, or a rural zone). These data provided information to examine the effect of land-use and demographic characteristics of the residence zone on recreational episode-type choice of individuals.

4.2 Sample Formation

The process of developing the sample for analysis involved several steps. First, only individuals who were 16 years or older were considered so that the analysis could be focused on the subgroup of the population who are relatively independent in their decision-making and mobility.[2] Second, weekend activity and travel episodes were selected from the larger activity survey file. Third, activity episodes identified by respondents as recreational episodes (including hobbies, exercise, TV and entertainment) were selected and categorized as in-home or out-of-home episodes. Fourth, travel episodes that began and ended at home without any stop in-between were selected, labeled as pure recreation episodes, and added to the file containing in-home and out-of-home recreational activity episodes. Fifth, the zone-level land-use and demographic characteristics were appended to each recreational episode based on the zone of residence of the individual. Finally, several screening and consistency checks were undertaken, including eliminating episode observations with missing data on location and time-of-day, and missing individual and household demographics.

The final sample for analysis includes 3,493 weekend recreational activity episodes of 2,390 individuals. The number of episodes per individual varies from 1 to 10 with an average of

[2] While it is possible that teenagers under the age of 16 may also be independent in their decision-making and mobility, the factors affecting young teenagers' choices among alternative forms of recreation are likely to be quite different from those of individuals over 16 years. Besides, the lack of driving alone as a mobility option is likely to impact recreational decisions. Clearly, it would be interesting to examine recreational choices of individuals younger than 16 years too, but this is beyond the scope of the current paper (note, however, that the influence of recreational needs and desires of children younger than 16 years on the recreational activity participation decisions of adults in the household is considered indirectly in the current analysis through the use of children-specific variables).

1.46 episodes. The dependent variable in the analysis is the choice of the type of recreational activity episode pursued over the weekend. This choice is characterized by three alternatives: in-home episode, out-of-home episode, or pure recreational episode.

The overall distribution of recreational activity episodes among the three episode categories is as follows: 45% in-home, 39% out-of-home, and 16% pure recreational. The distribution on Saturdays is 42% in-home, 41% out-of-home, and 17% pure recreational. The corresponding percentages for Sundays are 48%, 36%, and 16%, respectively. These numbers indicate a higher percentage level of participation in in-home recreation and a lower percentage level of participation in out-of-home recreation on Sundays relative to Saturdays. This is quite reasonable, since Sundays serve as a transition day between the weekend and the workweek, and many individuals use it as an in-home “rest” day. However, it is interesting to note that the level of pure recreation is about the same on both weekend days.

Table 1 provides the split among episode types by time of day for each weekend day. The results indicate that individuals are (a) more likely to participate in in-home activity episodes (compared to out-of-home and pure recreation episodes) in the evening relative to other time periods, (b) more likely to pursue out-of-home episodes in the afternoon relative to other time periods, and (c) more likely to undertake pure recreational episodes in the morning relative to other time periods. A comparison of the figures for Saturday and Sunday indicate that the split between the three activity episodes is about the same on both days in the afternoon. However, individuals are more likely to participate in out-of-home activities in the morning and evening of Saturdays than in the morning and evening of Sundays. This suggests a trend to start out-of-home recreational episodes earlier in the mornings and pursue out-of-home episodes later into the evening on Saturdays compared to Sundays.

5. EMPIRICAL ANALYSIS

5.1 Variable Specification

Several types of variables were considered in the weekend recreational activity episode type choice model. These included household sociodemographics, individual sociodemographics and employment characteristics, land-use mix and density variables, and episode participation occasion variables.

The household sociodemographic characteristics considered in the specifications included household size, presence and number of children, number of household vehicles, number of bicycles in the household, number of telephones, household income, availability of e-mail and web access, family type (*i.e.*, whether the individual belongs to a nuclear, couple, single person, single parent, returning young adult, or roommate family arrangement), and dwelling type (*i.e.*, whether the individual lives in a single family detached unit, duplex unit, multifamily unit, or other type of housing units).

The individual sociodemographics and employment variables explored in the specifications included gender, age, ethnicity, student status, license holding to drive, presence of physical disability, employment status, number of days of work, flexibility in work hours, and number of jobs held.

The zonal land-use mix and density variables included a land-use mix diversity variable, fractions of detached and non-detached dwelling units, area type variables classifying zones into one of 6 categories (core central business districts, central business districts, urban business, urban, suburban, and rural), and residential density and employment density variables. The first of these variables, the land-use mix diversity variable, is computed as a fraction between 0 and 1. Zones with a value closer to one have a richer land-use mix than zones with a value closer to zero. Three categories of land-uses are considered in the computation of the mix diversity variable: acres in residential use (*r*), acres in commercial/industrial use (*c*), and acres in other land-uses (*o*). The actual form of the land-use mix diversity variable is:

$$\text{Land-use mix diversity} = 1 - \left\{ \frac{\left|\frac{r}{T} - \frac{1}{3}\right| + \left|\frac{c}{T} - \frac{1}{3}\right| + \left|\frac{o}{T} - \frac{1}{3}\right|}{(4/3)} \right\}, \qquad (10)$$

where $T = r + c + o$. The functional form assigns the value of zero to zones in which land-use is focused in only one category, and assigns a value of 1 to zones in which land-use is equally split among the three land-use categories.

Finally, the episode participation occasion variables capture the time-of-day, day of weekend, and season of year effects. As indicated earlier in Table 1, time-of-day is represented by partitioning the day into morning (3a.m. – noon), afternoon (noon – 5p.m.), and evening (5p.m. – 3a.m.) periods. The day of weekend effect is captured by defining a dummy variable for Sunday. Seasonality effects are considered by defining dummy variables for each month of the year.

The final model specification was developed through a systematic process of adding groups of different variables to the market share model (*i.e.*, the constants only model) and eliminating statistically insignificant variables. Also, variables were combined when their effects on the model were not statistically different. This process was guided by intuitive consideration and parsimony in the representation of variable effects.

5.2 Empirical Results

5.2.1 Normalization Considerations and Error-Component Specification

The episode type preference constants and the effect of all other variables in the recreational episode type choice model are included using the in-home category as the base. In our analysis, we considered several error components specifications, but the one that provided the best statistical result included a single error component specific to the out-of-home and pure recreation categories. This result is quite intuitive, since it indicates the presence of common unobserved factors (such as outgoing nature and preference for active living) impacting recreational participation away from home.

5.2.2. Overall Measures of Fit

The log-likelihood value at convergence of the final mixed multinomial logit (MMNL) specification is –3020.6. The log-likelihood value of the market share model is –3569.4 and the log-likelihood value of a simple multinomial logit (MNL) model is –3265.2. The likelihood ratio test value for comparing the MMNL model with the MNL model is 489, which is substantially greater than the critical chi-square value with three degrees of freedom. The three additional parameters estimated in the MMNL model, relative to the MNL model, include the standard deviation of the distribution of intrinsic preference for out-of-home and pure recreation episodes across individuals (*i.e.*, the two preference heterogeneity terms), and the correlation in unobserved factors affecting the utilities of pure recreation and out-of-home episode types. Thus, the test between the MMNL and MNL model very strongly rejects the absence of preference heterogeneity and unobserved correlation between the utilities of pure recreation and out-of-home episode types.

5.2.3 Variable Effects

The final specification results of the recreational episode type choice model are presented in Table 2. In the following sections, we discuss the effect of variables by variable category. The observed variables are included with the coefficient on in-home episode type considered as the base (*i.e.*, the coefficient on in-home activity is arbitrarily normalized to zero). In instances where only one alternative appears for a variable, the excluded alternative, along with the in-home episode type, forms the base.

An important note is in order here. Some of the independent variables used in the current analysis may actually be endogenous to (or co-determined with) the choice of recreational episode type choice. This is particularly the case with the land-use and density variables; it is possible, if not very likely, that individuals and households self-select themselves into neighborhoods based on their recreational episode type participation desires. For example, individuals who like to run around the neighborhood (*i.e.*, participate in pure recreation) may choose to locate in areas where there are clear pedestrian paths. If so, and if this self-selection effect is ignored, the result is an overestimate of the true causal effect of pedestrian walkways on the choice of pure recreational episodes. A method to disentangle the self-selection effect from the true causal effect of land-use and density variables is to jointly model residential location choice and recreational episode type choice. This is an important direction for future research. The discussion of the variable effects below should be viewed with caution because of the above self-selection issue.

<u>5.2.3.1 Household Sociodemographics</u> Among the household sociodemographic variables (see Table 2), the effect of the number of adults indicates that individuals in households with several

adults are less likely to pursue out-of-home and pure recreational episodes compared to individuals in households with few adult members. This may be a reflection of the increased opportunity for joint in-home recreational participation in households with many adults, such as watching a movie at home. Further, out-of-home or pure recreation can also serve as a social outlet for individuals living alone or with few other adult members, while such social interaction needs are satisfied within the household when there are many adults.

The presence of children in the household increases the likelihood of participation in out-of-home and pure recreation episodes, especially in the latter category. This is perhaps a result of the outdoor recreational pursuits of children (such as participation in youth soccer and baseball leagues), and round-the-block family walks and bicycle trips with children (see Mallett and McGuckin, 2000 for a similar result).

The next household attribute is the number of bicycles in the household. As the number of bicycles increases in an individual's household, he or she is more likely to pursue out-of-home and pure recreational episodes. This is quite reasonable. Households who own more bicycles may be more outdoor-oriented by nature, and owning bicycles also provides an additional means to participate in outdoor recreation.

The effects of other household attributes are also intuitive. Specifically, (a) individuals in higher income households have a high propensity to participate in out-of-home recreation (but are not any more likely than individuals in low income households to participate in pure recreation), (b) single parents are unlikely to participate in pure recreational episodes compared to adults in other family types, perhaps due to the higher time constraints of single parents, and (c) duplex unit dwellers are more likely than individuals in other dwelling units to participate in outdoor recreation. This last result may be related to the neo-urbanist claim that more variegated frontages and porches encourage an active lifestyle (almost all the non-duplex units correspond to detached single-family units, which are set farther from the street and may not contribute to a socially vibrant environment).

5.2.3.2 Individual Sociodemographics and Employment Characteristics Several individual characteristics were tested in the model, but only those related to age, vehicle license holding, employment, and ethnicity appeared in the final specification. The results indicate that older individuals are less likely to participate in out-of-home recreational episodes compared to younger individuals. In addition to the linear effect presented in the table, non-linear spline effects of age were also explored. However, the non-linear effects did not improve data fit significantly. Additionally, an approach that assigned individuals to discrete age categories was also examined, but did not provide better results than the linear age specification.

The availability of a license to drive has a positive effect on participation in out-of-home activity episodes. This can be attributed to the greater mobility to reach out-of-home recreational activity centers. Similarly, employed individuals have a higher propensity to participate in out-of-home recreation over the weekend than do unemployed individuals, perhaps due to a release of built-up, but suppressed (due to time constraints), desire for out-of-home recreation during the course of the workweek. On the other hand, the results indicate that African-Americans are less likely to pursue out-of-home recreation relative to other races (primarily, Caucasian). This finding is similar to those of previous works in the area of recreational activity participation (see Misra and Bhat, 2000 and Mallett and McGuckin, 2000).

5.2.3.3 Land-Use and Density Variables Among the various land-use and density variables that we considered, only two had a marginally significant effect on recreational episode type choice. These correspond to zonal employment density and zonal land-use mix diversity.

The effect of employment density of the residential zone shows that densely-employed zones are more conducive to out-of-home and pure recreational episodes, possibly because of "pedestrian-oriented" and "bicycle-friendly" urban forms associated with high density development. In addition, higher density is likely to be correlated with better accessibility to recreational activity centers.

The direction of influence of the land-use mix density variable is not intuitive. The result suggests a lower propensity to participate in outdoor recreation (relative to in-home recreation) for households located in zones with a more diverse land-use mix. It is quite likely that this result is associated with the geographic resolution used in computing land-use mix. A better measure would be one that uses a finer resolution (than the zonal level) to compute land-use mix diversity. Future research should also consider more detailed urban form characteristics of the built environment (such as heights and setbacks of buildings, size and location of recreational facilities, building aesthetics and design features, and degree of interconnectivity of the street and walkway systems in the neighborhood).

5.2.3.4 Episode Participation Occasion Variables The time of day of participation in recreational activity episodes is an important determinant of the type of episode chosen for participation. Specifically, individuals are less likely to participate in pure recreational episodes in the afternoon than in the morning, and even more less likely to participate in the evening compared to the morning period. The "loading" of pure recreational episodes in the early morning period may be a consequence of conducive weather conditions in the morning as well as a desire to complete pure recreational activities before other expected and unexpected schedule considerations set in during the course of the day.

The day of the weekend is represented by a dummy variable for Sunday. The coefficient on this variable indicates that individuals are less likely to pursue outdoor recreational episodes (relative to in-home episodes) on Sunday compared to Saturday. As indicated earlier, this result is quite reasonable, since Sunday serves as a transition day for preparing for the next workweek.

Finally, the month of year variables indicate a lower likelihood to participate in out-of-home activity in February and March compared to other months of the year. In addition, the months of March and October appear to be periods of relatively low pure recreational activity compared to other months of the year. Further exploration of these seasonality effects to better understand the differential seasonal patterns is an area for future research.

5.2.4 Unobserved Heterogeneity and Unobserved Correlation

The unobserved preference heterogeneity terms are presented toward the bottom of Table 2 and are highly significant from a statistical standpoint. This indicates substantial variation across individuals in the overall preference for out-of-home and pure recreational episodes relative to in-home episodes. Similarly, there is also significant covariance in unobserved factors affecting the utilities of out-of-home and recreational episode categories at each choice occasion.

The variances of the unobserved preference heterogeneity terms and the unobserved correlation terms provide important information regarding the fractions of variation in utility explained by observed variables and by unobserved factors. To see this, consider Equation (3) for the case when i corresponds to the out-of-home episode type or the pure recreation episode type. Since the in-home episode category is the base with a systematic utility of zero, one can write the difference between the utilities for the out-of-home episode/pure recreational episode type and the in-home episode type as follows:

$$U_{qit} - U_{q,in-\text{home},t} = U^*_{qit} = \beta' w_{qit} + \gamma'_q y_i + \mu' z_i + \xi_{qit} \text{ , where } \xi_{qit} = (\zeta_{qit} - \zeta_{q,in-\text{home},t}) \, . \quad (11)$$

ξ_{qit} is standard logistically distributed, since the difference of two standard extreme value terms is logistic. Thus, $Var(\xi_{qit}) = \pi^2 / 3$.

The variance of the relative utilities of the out-of-home and pure recreational episode types across all choice occasions can now be obtained as:

$$Var(U_{qit}{}^*) = Var(\beta' w_{qit}) + \left\{ Var(\gamma'_q y_i) + Var(\mu' z_i) + \frac{\pi^2}{3} \right\}, \quad (12)$$

where $Var(\beta' w_{qit})$ represents the variance due to observed factors characterizing each choice occasion. The second term in parenthesis represents the variance due to unobserved heterogeneity. This second term can be further partitioned into inter-individual unobserved heterogeneity $[Var(\gamma'_q y_i)]$ and intra-individual unobserved heterogeneity $[Var(\mu' z_i) + (\pi^2 / 3)]$. Finally, the intra-individual unobserved heterogeneity terms can be further partitioned into the variance due to common unobserved factors influencing the utility of both out-of-home and pure recreational episode types at each choice occasion $[Var(\mu' z_i)]$ and the variance due to other unobserved factors $(\pi^2 / 3)$.

The percentage of variation in the relative utility for out-of-home and pure recreation episodes explained by each of the different variance components can be computed from the estimates of β and the estimated variances of the many error components. These percentages are presented in Table 3. The percentage of variation captured by observed and unobserved factors is indicated first. Next, within unobserved heterogeneity, the percentage of variation captured by inter- and intra- individual heterogeneity is presented. Thus, the number associated with inter-individual heterogeneity in Table 3 indicates the percentage of unobserved heterogeneity captured by inter-individual heterogeneity. Finally, the intra-individual heterogeneity component is partitioned into its two components. Several important observations may be drawn from this table. First, the utility variation captured by observed factors is of the order of 20-25% of total utility variations. This is quite reasonable, although it also suggests room for improvement in specifications through the inclusion of variables such as microform urban measures and detailed characteristics of the built environment. Second, 33-43% of the utility variation due to unobserved factors may be attributed to unobserved individual-specific factors. The higher percentage of inter-individual unobserved heterogeneity for pure recreation episodes compared to out-of-home episodes suggests higher variation in overall preferences across individuals for pure recreation compared to out-of-home recreation. That is, there is more disparity across individuals in the propensity to participate in pure recreation episodes than in the propensity to participate in out-of-home recreation episodes. Third, the intra-individual unobserved variation in the utility is higher than inter-individual unobserved variation. Fourth, the breakdown of intra-individual unobserved heterogeneity into its components suggests that unobserved factors common to both out-of-home and pure recreation episodes comprise about 25% of the total utility variation due to unobserved factors within an individual.

5.2.6 Elasticity Effects of Exogenous Variables

The parameters on the exogenous variables in Table 2 do not directly provide the magnitude of the effects of variables in the choice probabilities of each episode type. To address this issue, we compute the aggregate-level "elasticity effects" of variables.

The aggregate-level elasticity effect of a continuous exogenous variable x (such as age or income) on the expected share of each episode type $(\overline{P}_i)$ may be computed from the choice probability expression in Equation (5) as:

$$\eta_x^{\overline{P}_i} = \frac{\sum_q \sum_t \left[\int_{\tilde{\gamma}=-\infty}^{\infty} \int_{\mu=-\infty}^{\infty} \left(P_{qit} \mid \tilde{\gamma}, \mu\right) \left[\beta_i - \sum_j \left(P_{qjt} \mid \tilde{\gamma}, \mu\right) \beta_j \right] dF(\mu \mid \sigma) dF(\tilde{\gamma} \mid \omega) \right] x_{qt}}{\sum_q \sum_t \left[\int_{\tilde{\gamma}=-\infty}^{\infty} \int_{\mu=-\infty}^{\infty} \left(P_{qit} \mid \tilde{\gamma}, \mu\right) dF(\mu \mid \sigma)\, dF(\tilde{\gamma} \mid \omega) \right]}, \tag{13}$$

where β_i is the coefficient specific to alternative i, and x_{qt} is the value of the continuous variable for individual q during her or his t^{th} episode.

To compute an aggregate-level "elasticity" of an ordinal exogenous variable (such as the number of working adults in the household), we increase the value of the ordinal variable by 1 unit for each household and obtain the relative change in expected aggregate shares. Thus, the "elasticities" for the ordinal exogenous variables can be viewed as the relative change in expected aggregate shares due to an increase of 1 unit in the ordinal variable across all households.

Finally, to compute an aggregate-level "elasticity" of a dummy exogenous variable (such as urban residential location of a household), we change the value of the variable to one for the subsample of observations for which the variable takes a value of zero and to zero for the subsample of observations for which the variable takes a value of one. We then sum the shifts in expected aggregate shares in the two subsamples after reversing the sign of the shifts in the second subsample and compute an effective proportional change in expected aggregate shares in the entire sample due to a change in the dummy variable from 0 to 1.

The elasticity effects are presented in Table 4 by variable category. As can be observed from the table, the most important determinants of episode type choice include household income, age of individual, license holding, ethnicity (whether the individual is African-American or not), and the time of day and month of year of episode participation.

6. CONCLUSIONS

This paper presents a model for the type of recreational activity episodes that individuals pursue during the weekend. The choice set characterizing the type of recreational episode includes in-home, out-of-home, and pure recreational episodes. The focus on the type of weekend recreational episodes is motivated by (a) the growing number of recreation episodes in urban areas, (b) an interest in examining substitution effects between in-home and out-of-home activities, and (c) a desire to examine the determinants of participation in pure recreational episodes that contribute to active living.

The paper uses a mixed multinomial logit formulation that accommodates (a) common individual-specific unobserved factors that affect repeated choices of the same individual and (b) incorporates common unobserved factors affecting the utilities of out-of-home and pure recreational episodes. The mixed multinomial logit model is estimated using a maximum simulated likelihood method that employs Halton draws.

The empirical analysis in the paper is based on the 2000 San Francisco Bay Area Travel Survey. A variety of variables were considered in the model specifications, including household demographics, individual demographics and employment characteristics, land-use mix and density variables, and episode participation occasion variables. Important findings from our analysis are as follows:

1. Individuals in households with several other adults have a high propensity to participate in in-home recreation; on the other hand, individuals in households with children and with

bicycles and individuals who live in duplex dwelling units, are likely to prefer outdoor recreation (including out-of-home and pure recreation).

2. Individuals in high-income households are more likely than individuals in low-income households to participate in out-of-home recreation; however, there is no difference in the propensity to participate in pure recreation due to household income.
3. Single parents are less likely to participate in pure recreation than other individuals. Older individuals and African-Americans are less likely to participate in out-of-home recreation than younger individuals and non-African-Americans, respectively; on the other hand, employed individuals and individuals who hold a driver's license have a high propensity to pursue out-of-home recreation over the weekend.
4. Land-use and density variables do not have a substantial impact on weekend recreation episode type choice. This result may be associated with the rather aggregate nature of land-use and density variables used in the current research.
5. Individuals prefer to participate in pure recreational episodes in the morning and prefer to pursue in-home recreation on Sundays. Individuals participate less in out-of-home recreation during the months of February and March and less in pure recreation during the months of March and October.
6. There is significant intra-individual as well as inter-individual variation due to unobserved factors affecting weekend recreation episode type choice; also, unobserved factors that increase the likelihood of participation in out-of-home recreation also increase the propensity for participation in pure recreation.

The above results have implications for land-use, transportation, and air quality planning. Specifically, the results indicate that sociodemographic and employment-related attributes have a substantial impact on an individual's choice of type of recreational participation. These impacts are important at a time when demographics and employment characteristics are changing rather rapidly. For example, the structure of the household is changing rapidly with an increase in households with no children (the number of households with no children under 18 years is projected to increase from 53% to about 60% in the next decade; see U.S. Census Bureau, 1996). The results of our analysis suggest a decrease in outdoor recreation because of such an increase in households with no children.

The finding that individuals with low-income, African-Americans, and older individuals participate less in out-of-home recreation may be an indication of the lack of adequate recreational centers around low-income neighborhoods, African-American neighborhoods, and retirement communities. Targeting such neighborhoods for the construction of recreational facilities, or for information campaigns on currently available facilities, might therefore need to be a goal of land-use and transportation planning in the next decade.

Our empirical analysis also suggests that a reason for increased weekend travel may be the displacement of weekday out-of-home recreation to weekend out-of-home recreation due to an increase in employed individuals who find it difficult to pursue non-work activities during the workweek. As the number of workers in the population increases (see U.S. Census Bureau, 1999), this displacement of out-of-home recreation to the weekends is likely to become larger, leading to more weekend travel in the future.

From a broader societal standpoint, the analysis results indicate that single parents are not likely to pursue pure recreational episodes such as exercising, walking, and playing outdoor games (see also Misra and Bhat, 2000 for a similar result). This may be a reflection of the substantial time constraints on such individuals and suggests that population health concerns might warrant societal policies that provide more flexible time at work for single parents. Further, the provision of relatively inexpensive and “round-the-day” mixed recreational and child-care facilities may also contribute to a more active recreational lifestyle of single parents.

To summarize, the current model can be used to assess the impacts of changing demographics and employment patterns, for land-use planning and transportation policy analysis, and to examine broader societal issues such as active living. The study, to our knowledge, represents the first examination of weekend recreational episodes in an urban context, including in-home and pure recreational episodes. One can envision the current effort as being part of a larger analysis framework that generates the total number of weekend recreational episodes, then splits this into in-home, out-of-home, and pure recreational episodes using the model in this research, and subsequently models the modal, duration, location, and chaining-related dimensions of each of the episodes.

Several extensions of the current work may be identified. First, there is a need to assemble and accommodate more disaggregate measures of urban form and the built environment in the analysis. Second, the mathematical structure of the current model can be extended to consider episode type choice <u>jointly</u> with the modal, duration, and location dimensions of population. Third, one can examine the episode type choices of individuals in a household simultaneously to identify joint episode participations, as well as to explicitly consider the interactions among household measures. Fourth, extension of the work to consider recreational participation as an element of a larger weekend activity-based travel model system is important to consider interactions between recreational episodes and episodes of other activity purposes. Finally, accommodating the issue of self-selection into neighborhoods based on recreational activity type participation desires is an important avenue for future work to better quantify the true causal effects of land-use and urban form variables on recreational episode type choice.

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LIST OF TABLES

TABLE 1 Distribution of Episode Type by Time of Day [a]

Episode Type	Saturday			Sunday		
	Morning	Afternoon	Evening	Morning	Afternoon	Evening
In-home	27[b]	36	61	37	37	70
Out-of-home	47	51	29	39	50	20
Pure recreation	26	13	10	24	13	10

[a] The times of day are defined as follows: Morning (3a.m. – Noon), Afternoon (Noon – 5pm), and Evening (5pm – 3a.m.)

[b] The numbers in the cells represent column percentages (the sum of the figures in each column is 100%). Thus 27% of all recreational episodes pursued on Saturday morning are in-home episodes.

TABLE 2 Effect of Variables on Propensity to Participate in Each Episode Type [a]

Explanatory Variable	Out-of-Home		Pure Recreation	
	Parameter	t-statistic	Parameter	t-statistic
Constant	0.0865	0.158	-0.8040	-2.058
Household Sociodemographics				
Number of adults (≥ 16 years)	-0.3478	-2.924	-0.3478	-2.924
Presence of children (< 16 years)	0.3579	1.927	0.6770	2.573
Number of bicycles	0.1674	3.266	0.1674	3.266
Annual income (in 10,000 dollars)	0.6455	3.823	-	-
Single parent	-	-	-1.2310	-1.804
Duplex dwelling unit	0.6104	1.686	0.6104	1.686
Individual Sociodemographics and Employment Characteristics				
Age (divided by 100)	-0.2100	-3.745	-	-
Driver's license	1.4966	3.693	-	-
Employed	0.3512	1.895	-	-
African-American	-1.1647	-2.202	-	-
Land-Use and Density Variables				
Employment density	0.0177	1.484	0.0177	1.484
Diversity in land-use mix	-0.6221	-1.741	-0.6221	-1.741
Episode Participation Occasion Variables				
Afternoon (morning is base)	-	-	-1.6984	-6.635
Evening (morning is base)	-2.2184	-10.216	-2.9041	-9.847
Sunday	-0.5465	-3.704	-0.5465	-3.704
February	-1.7222	-2.266	-	-
March	-0.3886	-1.630	-0.6865	-1.863
October	-	-	-1.4836	-2.666
Standard deviations of unobserved individual heterogeneity specific to…				
Out-of-home episode type	2.1286	10.507	-	-
Pure recreation episode type	-	-	3.2278	10.937
Unobserved covariance between out-of-home and pure recreation episode types	1.0600 (2.468)			

Note: [a] The in-home episode type is the base for all variables.

TABLE 3 Percentage of Utility Variation Explained by Observed and Unobserved Factors

Heterogeneity Source	**Percentage of total utility variation explained by each heterogeneity source for…**	
	Out-of-home recreation	Pure recreation
Observed heterogeneity	25	21
Unobserved heterogeneity	75	79
Inter-individual	*33*	*43*
Intra-individual	*67*	*57*
Related to common factors affecting out-of-home and pure recreation utilities	24	24
Other	76	76

TABLE 4 Elasticity Effects of Variables

Variable	In-Home	Out-of-Home	Pure Recreation
Household Sociodemographics			
Number of adults (≥ 16 years)	0.044	-0.033	-0.011
Presence of children (< 16 years)	-0.056	0.026	0.030
Number of bicycles	-0.021	0.016	0.005
Annual Income (in 10,000 dollars)	-0.120	0.161	-0.100
Single Parent	0.032	0.025	-0.057
Duplex dwelling unit	-0.075	0.056	0.018
Individual Sociodemographics and Employment Characteristics			
Age (divided by 100)	0.200	-0.267	0.161
Driver's license	-0.126	0.159	-0.032
Employed	-0.032	0.040	-0.008
African-American	0.105	-0.132	0.027
Land-Use and Density Variables			
Employment density	-0.016	0.013	0.012
Diversity in land-use mix	0.066	-0.053	-0.051
Episode Participation Occasion Variables			
Afternoon (morning is base)	0.045	0.033	-0.079
Evening (morning is base)	0.309	-0.213	-0.096
Sunday	0.068	-0.051	-0.017
February	0.149	-0.187	0.038
March	0.058	-0.031	-0.027
October	0.038	0.030	-0.068