On Distinguishing Between Physically Active and Physically Passive Episodes and Between Travel and Activity Episodes: An Analysis of Weekend Recreational Participation in the San Francisco Bay Area

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ABSTRACT

This paper examines the out-of-home recreational episode participation of individuals over the weekend, with a specific focus on analyzing the determinants of participation in physically active versus physically passive pursuits and travel versus activity episodes (travel episodes correspond to recreational pursuits without any specific out-of-home location, such as walking, bicycling around the block, and joy-riding in a car, while activity episodes are pursued at a fixed out-of-home location, such as playing soccer at the soccer field and swimming at an aquatics center). The above disaggregation of recreational episodes facilitates the better analysis and modeling of activity-travel attributes, such as travel mode, episode duration, time-of-day of participation and location of participation. From a broader societal standpoint, the disaggregation of recreational episodes provides important information to encourage active participatory recreational pursuits, which can serve to relieve mental stress, improve the physical health of the population, and contribute to a socially vibrant society through increased interactions among individuals.

The paper employs a mixed multinomial logit formulation for examining out-of-home recreational episode type participation using the 2000 San Francisco Bay area travel survey. A variety of variables, including individual and household sociodemographics, location attributes, and day of week and seasonal effects, are considered in the model specification. Individual-specific unobserved factors affecting the propensity to participate in different types of recreational episodes are also accommodated.

Keywords: recreational activity, weekend activity-travel patterns, mixed multinomial logit, physical activity, activity-based travel analysis.

1. INTRODUCTION

Most existing activity-based travel analysis studies have examined 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 on peak period 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 the nonwork activities of individuals over the weekend. The emphasis on weekend activity participation behavior is motivated by the fact that the person trip rates during the weekend day are only marginally lower than those during the weekday. For example, a study using data from the New York metropolitan area indicates that the number of person trips per household is 8.02 on weekend days compared to 8.87 on weekdays (see Parsons Brinckerhoff Quade and Douglas, 2000), while another study using data from the San Francisco Bay area indicates that the number of person trips per person is 3.01 on weekend days compared to 3.40 on weekdays (see Lockwood *et al.*, 2003). Further, the average trip distances are larger on weekends relative to weekdays (7 to 8 miles per weekend trip compared to 7.1 miles per weekday trip in the New York metropolitan area, and 8.57 miles per weekday trip compared to 8.70 miles per weekend day trip in the San Francisco Bay area). The net result is that the person miles of travel are about the same on weekend days and weekdays. Thus, weekend activities and their associated travel warrant careful attention and analysis for both transportation congestion alleviation and reductions in mobile source emissions.

Within the category of weekend activities, the specific focus of this paper is on out-of-home social-recreational episodes. We will refer to such episodes as recreational episodes in the rest of this paper. Recreational episodes comprise about 41% of all out-of-home episodes over the weekend (as obtained from the San Francisco Bay area data) and are associated with an average trip length of about 13 miles (which is about twice the average length to shopping episodes). Thus, recreational episodes contribute substantially to both the number of episodes and the vehicle miles of travel over the weekend.

1.1 Weekend Recreational Activity Episodes: A Typology for Analysis

There are many different dimensions characterizing weekend recreational activity episodes, including the number of recreational episodes, the type of recreational episodes, the location of participation, the travel mode and time-of-day of participation, and chaining of recreational episodes with other recreational and non-recreational episodes. One possible analysis structure to examine these dimensions would be to model the total number of recreational activity episodes first (possibly along with the number of episodes for other activity episodes; see Bhat and Srinivasan, 2003 for such an analysis), followed by a model that determines the type of each recreational episode generated, and finally a series of models for the location, mode, time-of-day, duration, and position of the episode in the overall weekend day activity sequence. In such an analysis structure, the type of recreational activity is a very important dimension, since it would affect the location, mode, time-of-day, duration, and chaining propensity of the episode. For example, a recreational participation at the beach will likely have a very different set of characteristics than a visit to the movies. Because of this critical nature of the type of recreational activity pursued in each episode, the focus of the current analysis will be on the specific activity type dimension of weekend recreational episodes.

Of course, the issue that arises immediately is what resolution (or level of disaggregation) should be used in defining recreational activity types? One approach is to use very disaggregate types, such as going to the movies, playing softball, running, walking around the neighborhood, going to a coffee shop, sunning on the beach, visiting a friend, and the like[1]. The problem with this disaggregate taxonomy is that there will be too many recreational categories and the sample size for each category will become too thin to be able to empirically estimate a recreational type choice model (and, more importantly, to estimate location, mode, time-of-day, duration, and chaining models accommodating the very disaggregate typology). A second approach, and the one used in the current research, is to cluster types into a few aggregate categories that are likely to have quite different underlying behavioral mechanisms and preferences driving activity-travel choices. Specifically, in this study, we group recreational episodes into one of four categories based on whether the episode is (1) a physically active one or a physically passive one and (2) a travel episode without a specific destination (for example, running around the neighborhood, a bicycle trip starting and ending at home, a car ride starting and ending at home, *etc.*) or an activity episode pursued at a specific out-of-home location that requires travel as a means to get to the location. The specific activity episode types classified as physically active include those pursued at 23 location types, including aerobics class, aquatics center, bike trail, bowling alley, ice rink, batting cages, yacht club, and indoor recreational sports (see Appendix A for a complete

[1] The Bay area survey asked respondents to characterize the location at which they participated in out-of-home episodes (for example, shopping mall, health club, movie theatre, beach, *etc*.), and this information can be used to determine the specific activity type.

listing). For travel episodes, an episode is defined as an active one if it involves the use of a non-motorized mode.

1.2 Basis for Recreational Episode Typology

The basis of the four-group classification of recreational episodes may be motivated by the differences in the activity-travel dimensions associated with the episode types. Table 1a provides the travel mode distribution for each of the four types of recreational episodes. As can be observed, the travel modes for physically active travel episodes are (by definition) walk or bicycle, while the modes for physically passive travel are motorized. The modal distributions for physically active and physically passive activity episodes are similar to each other, though there is a slightly higher usage of the non-motorized travel modes for the physically active activity episodes. Table 1b provides the time of day distributions for the four types of recreational episodes. This table reveals clear differences in the temporal distribution across the episode types. A higher fraction of physically active travel episodes are pursued in the early morning period than for other episode types. On the other hand, a relatively low percentage of physically active activity episodes are pursued in the early morning period; that is, if individuals decide to participate in physically active activity episodes (such as swimming at a sports center or skiing at a lake), they are more likely to participate later in the morning. The two physically passive episode categories (last two columns in Table 1b) are loaded toward the latter parts of the day. This is to be expected, since the evenings are a more convenient and relaxed time for passive activities such as visiting friends and family, eating out in a social setting, and going to the movies.

In addition to the differences in the travel mode and time-of-day dimensions among the four episode types, there are also differences in the travel time to episode and episode duration dimensions. The travel time to episode is, by definition, not defined (or zero) for travel episodes. The travel time to physically active activity episodes is shorter than for physically passive activity episodes (the mean for the former is 21 minutes, while the mean for the latter is 28 minutes). The episode durations are also much higher for the physically passive episode types relative to the physically active episode categories (the mean durations for physically passive travel episodes and physically passive activity episodes are 134 minutes and 158 minutes, respectively, compared to about 60 minutes for both the physically active episode categories).

Clearly, there are substantial differences in the activity-travel dimensions characterizing the four recreation episode type categories identified in this study. Besides, the underlying motivations and factors affecting participation in the four category types are likely to be rather different. All these considerations point to the need to distinguish between the four episode types for travel demand forecasting.

In addition to the travel demand modeling-related benefit of the four-group classification of recreational episodes, the identification of individual and locational attributes that impact the propensity to participate in (physically) active episodes can provide important information for encouraging active participatory recreation pursuit, and promoting a healthier population.

1.3 Brief Literature Review and Structure of Paper

There have been very few studies focusing on intra-urban recreational episodes in the literature. Most earlier studies have examined recreational pursuits requiring long distance inter-urban travel (see Train, 1998; Moray *et al.*, 1991; Yai *et al.*, 1995; Kozak and Rimmington, 2000;

Kemperman *et al.*, 2002). The studies examining the activity-travel dimensions of intra-urban recreational episodes have focused on weekdays and have considered all recreational episodes as a single aggregate category (see Pozsgay and Bhat, 2001; Hunt and Patterson, 1996; and Steed and Bhat, 2000). The one closest to this study is the work of Bhat and Gossen (2004), who also examine weekend recreational episodes. However, their focus is more on in-home versus out-of-home pursuits and they do not consider if an activity is physically active or physically passive.

The rest of this paper is structured as follows. The next section provides details of the model used in our analysis, including structure, model identification, and estimation issues. Section 3 describes the data source and sample formation procedures. Section 4 presents the results of the empirical analysis. Finally, Section 5 summarizes the important findings from the research.

2. THE MODEL

2.1 Structure

In this paper, we formulate a mixed multinomial logit (or MMNL) model of weekend recreational activity for the choice among four types of out-of-home recreational episodes: (1) Physically active recreational travel, (2) Physically active recreational activity, (3) Physically passive recreational travel, and (4) Physically passive recreational activity[2]. The model formulation accommodates heterogeneity (*i.e.*, differences in behavior) across individuals due to both observed and unobserved individual attributes. In addition, the formulation also considers individual-specific unobserved attributes that may make an individual more pre-disposed toward physically active (or passive) pursuits and/or more likely to participate in recreational travel (or

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[2] An important point to note here is that intra-household interactions in weekend recreational activity participation, such as joint participation of multiple individuals in a recreational activity, are not explicitly modeled here. This is an area for future research.

activity) pursuits. Thus, an individual who maintains an active lifestyle and is health-conscious is likely to associate a higher than average utility (in her/his peer group) for both physically active recreational travel and physically active recreational activities, while a person predisposed to a physically inactive lifestyle will assign a higher preference for physically passive recreational travel and physically passive recreational activities. Similarly, an individual may prefer pursuing recreation at specific locations (working out at a gym or going to the cinema) or may prefer recreational travel (jogging around the neighborhood or going for a joyride in the car). The net result of such unobserved individual factors is an increase in sensitivity between pairs of recreational episode types among the four alternatives listed earlier. It is important to note that this competition structure operates at the individual level and not at the choice occasion level (there can be multiple choice occasions from the same individual). Consequently, one cannot use cross-sectional GEV structures such as the cross-nested logit of Vovsha (1997) or the paired generalized nested logit model of Wen and Koppelman (2001). A "panel" mixed multinomial logit model from repeated choice data is the appropriate structure.

In the following presentation of the model structure, we will use the index q for individuals (q = 1, 2, …, Q), l for whether an episode is physically active (l = 1) or physically passive (l = 2), m for whether an episode corresponds to travel (m = 1) or an activity (m = 2), and t for choice occasion (t = 1, 2, …, T_q). For generality in notation, we will assume that l can take one of L values (l = 1, 2, …, L; L = 2 in the setting of the current paper) and that m can take one of M values (m = 1, 2, …, M; M = 2 in the current paper).

Let the utility U_{qmlt} that an individual q associates with the alternative {l, m} on choice occasion t be written as follows:

$$U_{qlmt} = (\alpha_{lm} + \lambda'_q v_{lm}) + \beta'_{lm} x_{qt} + \varepsilon_{qlmt}, \tag{1}$$

where α_{lm} represents the "average" (across individuals) effect of unobserved variables on the utility associated with alternative {*l*, *m*}, λ_q is a $[(L*M)\times 1]$- column vector with its *lm*^th^ element capturing individual *q*'s differential preference for alternative {*l*, *m*} compared to the "average" preference for alternative {*l*, *m*} across all her/his peer individuals, v_{lm} is also a $[(L\times M)\times 1]$- column vector with a 1 in row $(l\times m)$ and 0 elsewhere, β_{lm} is a $(K\times 1)$ - column vector of coefficients to be estimated for alternative {*l*, *m*}, x_{qt} is a $(K\times 1)$ - column vector of independent variables specific to individual *q* and choice occasion *t* (there are no independent variables associated with the alternatives in the context of the current paper), and ε_{qlmt} is a choice-occasion specific idiosyncratic random error term assumed to be identically and independently standard Gumbel distributed (across alternative choice occasions and individuals).

Next, the component $\lambda'_q v_{lm}$ in Equation (1) that represents individual *q*'s differential preference for alternative {*l*, *m*} can be partitioned into three components: (1) a component that represents individual *q*'s differential preference along the *l* dimension ($\mu'_q z_l$; z_l is a $(Z\times 1)$- column vector of dummy variables with a 1 in row *l* and zero otherwise), (2) a component that represents individual *q*'s differential preference along the *m* dimension ($\eta'_q s_m$; s_m is a $(M\times 1)$- column vector of dummy variables with a 1 in row *m* and zero elsewhere), and (3) a remaining component that represents individual *q*'s generic differential preference for the alternative {*l*, *m*} ($\gamma'_q y_{lm}$; y_{lm} is identical to v_{lm}). The μ_q, η_q, and γ_q vectors are appropriately dimensioned vectors that are not observed to the analyst. A natural assumption is to consider the elements of these vectors to be independent realizations from normal population distributions; $\mu_{ql}\sim N(0,\sigma^2)$, $\eta_{qm}\sim N(0,\theta^2)$, and $\gamma_{qlm}\sim N(0,\Delta^2_{lm})$. The result of this specification is a covariance across alternatives with the same value of l for individual q at each of q's choice occasions: $\mathrm{Cov}(U_{qlmt}, U_{qlm^*t}) = \sigma^2$; $m \neq m^*$. Similarly, there is also a covariance across alternatives with the same value of m for individual q at each of her/his choice occasions: $\mathrm{Cov}(U_{qlmt}, U_{ql^*mt}) = \theta^2$; $l \neq l^*$.

For given values of the vectors μ_q, η_q, and γ_q, the probability that individual q will choose alternative $\{l, m\}$ at the t^{th} choice occasion can be written in the usual multinomial logit form (McFadden, 1978):

$$P_{qlmt} \mid \mu_q, \eta_q, \gamma_q = \frac{e^{\alpha_{lm} + \beta'_{lm} x_{qt} + \mu'_q z_l + \eta'_q s_m + \gamma'_q y_{lm}}}{\sum_g \sum_h e^{\alpha_{gh} + \beta'_{gh} x_{qt} + \mu'_q z_g + \eta'_q s_h + \gamma'_q y_{gh}}} \tag{2}$$

The unconditional probability can then be computed as

$$P_{qlmt} = \int_{\mu_q} \int_{\eta_q} \int_{\gamma_q} (P_{qlmt} \mid \mu_q, \eta_q, \gamma_q) dF(\mu_q \mid \sigma) dF(\eta_q \mid \theta) dF(\gamma_q \mid \Delta_{lm}) \tag{3}$$

where F is the multivariate cumulative normal distribution. The expression above involves an $\left[L + M + (L \times M)\right]$-dimensional integral.

2.2 Model Identification Issues

Discrete choice models require identification restrictions because it is only the utility differences that matter and also because of the latent nature of the utility function. These considerations lead to the usual location normalization of (a) one of the alternative-specific constants to zero and (b) one of the alternative-specific coefficients of each variable to zero (that is, α_{lm} = 0 and β_{lm} = 0 for one alternative). Further, the scale of utility is normalized by standardizing the gumbel-distributed error term ε_{qlmt} in the multinomial logit model. These normalizations are maintained in the mixed logit model (though an infinite set of restrictions can also be imposed to achieve identification). The question then is whether or not Δ_{lm} is theoretically identified for each alternative {*l*, *m*}, and if σ and θ are identified. A straightforward way to address this question is by examining the covariance matrix of utility differences (see Walker, 2002). To do so, we write out the specific form of the four-alternative model structure under consideration in this paper (*l* = 1, 2 and *m* = 1, 2) for a particular individual *q* (say *q* = 1). Without loss of generality, we consider only two choice occasions for the individual *q* in the following analysis (*t* = 1, 2). The utility for each of the four alternatives is written in the form of U_{qmlt} as earlier. The random terms μ_{ql}, η_{qm}, and γ_{qlm} are written in terms of standard normal variables δ_{ql}, ξ_{qm}, and ζ_{qlm}, respectively, as $\mu_{ql} = \sigma\delta_{ql}$, $\eta_{qm} = \theta\xi_{qm}$, and $\gamma_{qlm} = \Delta_{lm}\zeta_{qlm}$.

The utility functions, their differences taken with respect to the fourth alternative, and the covariance matrix of the utility differences are provided in Figure 1 (only the lower triangle of the covariance matrix is presented for convenience). The covariance matrix clearly shows that the four independent variance terms associated with pure individual heterogeneity (Δ^2_{lm} for *l* = 1, 2 and *m* = 1, 2), as well σ^2 and θ^2, are theoretically identified. The identification of all these parameters is possible because of the covariance among the choice occasions from the same individual (there are six independent equations from the covariance matrix from which to identify the six variance parameters).

2.3 Model Estimation

The parameters to be estimated in the model of Equation (2) are the α_{lm} scalar and β_{lm} vectors for each {*l*, *m*} combination (except a base alterative), and the following variance terms: σ, θ, and Δ_{lm} for each $\{l, m\}$ combination. Let α be a vector of α_{lm} elements, and let Δ be a vector of Δ_{lm} elements. Also, let β be a vector that stacks all the β_{lm} 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 μ_q, η_q, and γ_q, the likelihood function for individual q's observed set of choices is:

$$L_q(\alpha, \beta) \mid (\mu_q, \eta_q, \gamma_q) = \prod_{t=1}^{T_q} \left[\prod_{(l,m)} \left\{ P_{qlmt}(\alpha, \beta) \mid \mu_q, \eta_q, \gamma_q \right\}^{M_{qlmt}} \right], \tag{4}$$

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

$$L_q(\alpha, \beta, \sigma, \theta, \Delta) = \int_{\mu_q} \int_{\eta_q} \int_{\gamma_q} \left[L_q(\alpha, \beta) \mid \mu_q, \eta_q, \gamma_q \right] \, dF(\mu_q \mid \sigma) \; dF(\eta_q \mid \theta) \; dF(\gamma_q \mid \Delta) \tag{5}$$

The log-likelihood function is $\ell(\alpha, \beta, \sigma, \theta, \Delta) = \sum_q \ln L_q(\alpha, \beta, \sigma, \theta, \Delta)$.

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 α, β, σ, θ, and Δ. Under rather weak regularity conditions, the maximum (log) simulated likelihood (MSL) estimator is consistent, asymptotically efficient, and asymptotically normal (see Hajivassiliou and Ruud, 1994; Lee, 1992; McFadden and Train, 2000).

In the current paper, we use the Halton sequence to draw realizations for μ_q, η_q, and γ_q 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.

3. DATA SOURCES AND SAMPLE FORMATION

3.1 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 information on all activity and travel episodes undertaken by individuals from over 15,000 households in the Bay Area for a two-day period (see MORPACE International Inc., 2002 for details on survey, sampling, and administration procedures). The information collected on activity episodes included the type of activity (based on a 17-category classification system), start and end times of activity participation, and the geographic location of activity participation. Travel episodes were characterized by the mode used, and the start and end times of travel. For all out-of-home activity episodes, additional information on the name of the activity participation location (for example, Jewish community center, Riverpark plaza, *etc.*) and the type of location (such as religious place or shopping mall) were collected. Furthermore, data on individual and household socio-demographics, individual employment-related characteristics, household auto ownership, and internet access and usage were also obtained.

A secondary data source obtained from the Metropolitan Transportation Commission provided zonal-level land-use and demographics data for each of the Traffic Analysis Zones (TAZ). The data obtained from this source included: (1) area by land-use purpose, (2) number of housing units, (3) employment levels by sector, (4) zonal population, income and age distribution of the population, and (5) area type of the zone (core CBD, other CBD, urban, suburban, or rural). This information was used to study the impact of the characteristics of the residence zone on out-of-home recreational episode type choice.

3.2 Sample Formation

The process of generating the sample for analysis involved several steps. First, only individuals 16 years or older were considered to focus the analysis on the subgroup of the population who exercise a choice over the kind of recreational episode to participate in. Second, all weekend out-of-home activity episodes were selected from the original survey data. Third, weekend travel episodes that began and ended at home without any stops in-between (for example, walking or bicycling around the neighborhood) were identified, labeled as "recreational travel" and appended to the file from Step 2. Fourth, social-recreational episodes (including meals, hobbies and exercising, conversation and visiting family/friends, relaxing/resting, and recreation travel) were selected from the larger file of all out-of-home episodes for the analysis. Fifth, the social/recreational episodes were categorized into one of four types based on whether or not the episode involved physically active pursuits (as opposed to physically passive pursuits) and whether or not the episode was a travel episode (as opposed to an activity episode). The distinction between physically active and inactive recreational episodes for activity episodes was based on the location type of out-of-home activity participation. The location type was recorded as string variables in the BATS survey. About 10,000 distinct location types are present, and these were manually recoded into 450 categories for the analysis. The location type categories considered as being associated with physically active recreation are listed in Appendix A. The distinction between physically active and inactive recreational episodes for travel episodes was based on whether or not a non-motorized mode was used for the recreational travel. Sixth, data on individual, household, and zonal (residence zone) characteristics were appropriately cleaned and added. Finally, several screening and consistency checks were performed and records with missing or inconsistent data were eliminated.

The final sample for analysis includes 3,232 out-of-home weekend recreational episodes of 2,341 individuals. The number of episodes per individual varies from 1 to 7 with an average of 1.38 episodes. The dependent variable in the analysis is the choice of the type of recreational episode pursued over the weekend. This choice is characterized by four alternatives: Physically active travel (PAT) episodes, (2) Physically active activity (PAA) episodes, (3) Physically passive travel (PPT) episodes, and (4) Physically passive activity (PPA) episodes.

The distribution of recreational episodes among the four episode categories is as follows: 6.3% PAT, 14.1% PAA, 9.8% PPT, and 69.8% PPA. These numbers indicate the clear dominance of physically passive activities pursued at an out-of-home location. The distribution on Saturdays is 5.1% PAT, 14.3% PAA, 10.4% PPT, and 70.1% PPA, while the corresponding percentages for Sunday are 8% PAT, 13.9% PAA, 8.8% PPT and 69.3% PPA. Overall, there appears to be little difference in the types of out-of-home recreational episodes individuals participated in on Saturdays and Sundays, except perhaps for a slightly higher likelihood of participating in PAT episodes on Sundays relative to Saturdays.

4. EMPIRICAL ANALYSIS

4.1 Variable Specification

Several types of variables were considered in the empirical analysis. These included individual demographics, household demographics, location variables, and day of week/seasonal effects.

The individual demographic 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 household sociodemographic characteristics considered in the specifications included household income, household structure (household size and family type of household), presence and number of children, number of household vehicles, number of bicycles in the household, number of telephones, household income, 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 location variables included a land-use mix diversity variable, fractions of detached and non-detached dwelling units, area type variables classifying zones into one of 4 categories (central business districts, urban, suburban, and rural), residential density and employment density variables, and residential county-specific 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 on this land-use diversity variable have a richer land-use mix than zones with a value closer to zero (see Bhat and Gossen, 2004 for the development of this measure).

Finally, the day of week/seasonal variables capture the day of weekend (Saturday or Sunday), and season of year effects (fall, winter, spring, or summer).

The final model specification was developed through a systematic process of adding variables to the market share model (*i.e.*, the constants only model) and evaluating the improvement of fit using well-known statistical measures. Another consideration in the specification was to ensure a reasonable number of observations in each categorical independent variable category for each choice alternative. Specifically, since the number of PAT and PPT episodes are a very small fraction in the sample, we conducted extensive descriptive analyses to examine the number of observations available in each dependent variable-independent variable category combination. As an example, the fraction of overall recreational episodes in the sample contributed by African Americans is 2% and by Hispanic individuals is 5%. These low shares translate to only a handful of episodes from these individuals in the PAT, PAA, and PPT categories, rendering it meaningless to explore the effect of African American and Hispanic race on recreational episode type choice. Of course, the overall specification process was also guided by intuitive and efficiency considerations.

4.2 Overall Measures of Fit

The log-likelihood value at convergence of the final mixed multinomial logit (MMNL) specification is –2680.6. The log-likelihood value of the market share model is –3017 and the log-likelihood value of a simple multinomial logit (MNL) model is –2940. The likelihood ratio test value for comparing the MMNL model with the MNL model is 519, which is substantially greater than the critical chi-square value with six degrees of freedom. The six additional parameters estimated in the MMNL model relative to the MNL model include the standard deviation of the distribution of intrinsic preference for each of the four episode categories across individuals (*i.e.*, the four preference heterogeneity terms), and the individual-level covariances in unobserved factors affecting the utilities of (1) PAT and PAA episode categories, (2) PPT and PPA episode categories, (3) PAT and PPT episode categories, and (4) PAA and PPA episode categories. The first two covariances are generated by common unobserved terms with variance σ along the physically active versus physically passive dimension and the second two covariances are generated by common unobserved terms with variances θ along the travel versus activity dimension (see Figure 1b). The likelihood ratio test between the MMNL and

MNL model very strongly rejects the absence of individual-level preference heterogeneity and unobserved correlation.

Another intuitive way to compare the performance of the multinomial logit and mixed multinomial logit models is to compute the average probability of correct prediction:

$$\bar{r} = Q^{-1}\sum_{q}\sum_{\{l,m\}}\sum_{t} M_{qlmt}\hat{P}_{qlmt} \;, \tag{6}$$

where $\hat{P}_{qlmt}$ is the estimated probability of individual q selecting alternative $\{l, m\}$ at the t^{th} choice occasion. The values of this statistic are 0.435 for the multinomial logit and 0.538 for the mixed logit model, again reflecting the superior fit of the mixed multinomial logit model.

4.3 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.

4.3.1 Individual Sociodemographics

Several individual characteristics were tested in the model, but only those related to age, employment, and sex of the individual appeared in the final specification. The results indicate that young adults (16-17 years of age) are less likely to participate in physically active recreational episodes and travel-related recreation compared to older adults. This suggests that the younger generation of adults do not have a very physically active recreational lifestyle, and are likely to participate in recreation at specific out-of-home locations. Overall, these young adults are most likely to participate in physically passive activities (such as going to the movies or visiting a friend) and most unlikely to participate in physically active travel (such as walking or bicycling around the neighborhood). On the other hand, the coefficients on the "age greater than 65 years" variable indicates that senior adults are most likely to participate in physically active travel recreation compared to other recreation categories. Several other age categories were also considered, but were not statistically significant.

The influence of employment on recreational episode type choice is included by distinguishing between full-time, part-time, and not employed adults. The results suggest that adults employed full-time are less likely to participate in travel-oriented recreational episodes relative to other adults, but are more likely to participate in physically active pursuits at out-of-home locations (such as going to the gym, park, *etc.*). The latter result may be reflecting a higher level of health-consciousness and a more active lifestyle of adults employed full-time.

Finally, in the class of individual sociodemographics, the effect of the "female" dummy variable shows that women are less likely than men to pursue physically passive travel episodes such as joy-riding.

4.3.2 Effect of Household Demographics

In the category of household demographics, the effect of household income is included as a linear effect (non-linear effects were also considered, but did not improve data fit). The sign of the variable on income indicates that individuals in high income households are unlikely to pursue physically active travel episodes for recreation.

The effects of number of cars and presence of bicycles in a household are intuitive. Individuals in households with many cars are unlikely to pursue physically active recreational pursuits, while those in households with bicycles are very likely to pursue physically active recreation and unlikely to participate in physically passive travel episodes. This is presumably a reflection of the higher propensity to bicycle around the neighborhood for exercise and/or use the bicycle for utilitarian travel such as going to the park or to the soccer field. However, the causal direction of these effects should be viewed with caution. For example, individuals predisposed to an active lifestyle may be the ones who own bicycles; thus, it could be that the presence of the bicycle itself is not the causal factor for engaging in physically active pursuits.

Household structure also has an impact on recreational episode type choice. The results indicate that adults in couple households are more likely to pursue physically active travel episodes relative to adults in other non-nuclear family households. On the other hand, adults in couple households are least likely to participate in physically passive travel episodes. The effect of “nuclear family” shows that adults in nuclear families (*i.e.*, families with small children) are most likely to pursue physically active recreation and travel episodes. This may be the result of joint participation of adults and children in physically active and travel recreation, such as playing in the park and walking/bicycling around the neighborhood (note that the coefficient on the nuclear family variable for physically active travel episodes is 0.2555 + 0.7772 = 1.0327).

4.3.3 Effect of Residential Location

Interestingly, the analysis results indicate that none of the residential location variables (including zonal population density, land-use mix density, area type, and the county-specific variables) have a statistically significant impact on recreational episode type choice. The coefficient on the “rural residence” variable indicates a small positive effect on the propensity for travel-related recreational episodes. This variable was statistically significant in the multinomial logit model, but dropped to insignificance in the MMNL model.

A potential reason for the insignificance of the location effects, in addition to the genuine possibility of lack of location effects, is the geographic resolution used in computing the residential location attributes. All of the location attributes are computed at the zonal level, and there may be substantial variation in the attributes within a zone.

4.3.4 Effect of Day of Week/Season Effects

The results indicate the significantly higher propensity to participate in physically active travel episodes on Sundays compared to Saturdays (this result was also observed when descriptively examining the sample in Section 3.2). The only seasonal effect appears to be the higher inclination to participate in physically passive travel recreation in the winter season, though there is no clear behavioral interpretation for this result.

4.4 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 each of the recreational episode type categories. The variation in utility across individuals for the physically passive travel (PPT) category is, in particular, very large, suggesting the wide diversity in intrinsic preferences for participation in PPT episodes.

The standard deviation of the error terms that capture correlation in individual-specific unobserved factors for physically active and physically passive pursuits is highly significant. This reveals that individuals having a higher than normal propensity to participate in physically active travel are also likely to have a higher than normal propensity to participate in physically active activities at a fixed out-of-home location. The same holds for the preference for physically passive pursuits. The variation that captures correlation in individual-specific unobserved factors for activity versus travel pursuits is only marginally significant.

4.5 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 income) on the expected share of each episode type $(\overline{P}_i)$ may be computed from the choice probability expression in Equation (2) as:

$$\eta_x^{\overline{P}_{lm}} = \frac{\sum_q \sum_t \left[\int\limits_{\mu_q} \int\limits_{\eta_q} \int\limits_{\gamma_q} \left(P_{qlmt} \mid \mu_q, \eta_q, \gamma_q\right) \left[\beta_{lm} - \sum_{gh} \left(P_{qght} \mid \mu_q, \eta_q, \gamma_q\right) \beta_{gh} \right] dF(\mu_q \mid \sigma) dF(\eta_q \mid \theta) dF(\gamma_q \mid \Delta) \right] x_{qt}}{\sum_q \sum_t \left[\int\limits_{\mu_q} \int\limits_{\eta_q} \int\limits_{\gamma_q} \left(P_{qlmt} \mid \mu_q, \eta_q, \gamma_q\right) dF(\mu_q \mid \sigma) dF(\eta_q \mid \theta) dF(\gamma_q \mid \Delta) \right]}, \qquad (7)$$

where β_{lm} is the coefficient specific to alternative $\{l, m\}$ 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 3 by variable category. As can be observed from the table, the most important determinants of episode type choice include age of individual, household income, and household structure.

5. CONCLUSIONS

This paper examines the recreational episode participation of individuals over the weekend. The focus on weekend activities is motivated by the sizable contribution of weekend travel to total weekly travel, as well as by the very limited analysis of weekend activity-travel patterns in the literature. Within the context of weekend activity-travel patterns, the specific focus is on the physically active versus physically passive dimension and the activity versus travel dimension of recreational activity episode participation. This disaggregation of the broad recreational activity purpose facilitates the better analysis and modeling of activity travel dimensions such as travel mode, duration, time-of-day of participation, and location of participation. At a broader societal level, a good understanding of participation in physically active recreation can help identify demographic groups who do not participate much in physically active pursuits and can identify urban form/location attributes that foster such pursuits. This information, in turn, can help in the design of effective information campaigns and policy measures to foster an active lifestyle in the population.

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 individual-specific unobserved factors affecting the utilities of the various alternatives. 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 individual demographics, household demographics, location attributes, and day of week/seasonal effects. There are several important findings from our study. First, individuals employed full-time have a higher propensity to participate in physically active pursuits at an out-of-home location and a lower propensity to participate in physically active travel-related recreational episodes. Also, young adults (16-17 years) are less inclined to participate in physically active recreation. Second, individuals with several cars in their households are unlikely to participate in physically active recreational pursuits. On the other hand, individuals with bicycles in their households have a high propensity to participate in physically active pursuits. Third, location effects (density of development, land-use mix, area type, *etc*.) do not appear to directly impact recreational activity type participation. However, this result may be a consequence of the use of rather aggregate spatial units (*i.e.*, zones) as the basis for computing the location attributes. The development and use of location variables at a finer spatial resolution is an important area for future research. It should also be noted that, while the location attributes do not have a direct impact on recreational episode type choice, these variables are likely to have an indirect impact through their effect on car ownership and bicycle ownership levels. Fourth, there are no substantial season of the year effects on out-of-home recreational episode type choice. This points to the stability of preferences for physically active/passive and activity/travel recreational across seasons. Fifth, there is very substantial variation in intrinsic preferences for the nature of recreational episode pursuits across individuals.

The current research effort may be viewed as one component of a larger weekend activity-travel pattern forecasting system that first predicts the total number of weekend out-of-home recreational activity episodes along with the total number of weekend out-of-home episodes of other activity purposes, then disaggregates the out-of-home recreational activity episodes using the model developed in the current paper, and subsequently analyzes the location, mode, time-of-day, duration, and chaining dimensions of recreational episodes. The value of the current modeling effort is that it provides a segmentation tool to distinguish between recreational episodes with substantially different activity and travel attributes.

The most important results of the study, from a land-use and transportation policy standpoint, are the important effects of car ownership and bicycle ownership on physically active recreational pursuits. Earlier studies have already established that a higher number of cars in a household leads to increased trip-making, more drive alone travel, the decoupling of activities from activity chains, and increased trip lengths (see, for example, Agyemang-Duah and Hall, 1997, Misra and Bhat, 2000, and Pozsgay and Bhat, 2001). The current study suggests that car ownership also has an impact on the level of physical activity. Thus, land-use and transportation policies (such as better land-use mixing, improved transit service, and higher car purchase costs and gas taxes) that reduce car dependency and increase car costs, and eventually reduce car ownership and increase non-motorized mode ownership, constitute not only an important way to alleviate traffic congestion, but also to foster physically active recreational pursuits.

Finally, the results of this paper emphasize the important and dominant effect of sociodemographics on out-of-home recreational episode type choice. Specifically, the age of the individual, household income, and household structure are the three most important determinants of the type of out-of-home recreational episodes pursued by individuals. This information can be used to target appropriate sub-populations in an effort to encourage non-motorized travel and physically active pursuits. For instance, our results indicate that young adults (16-17 years of age) are unlikely to use non-motorized forms for travel-related recreation and are not inclined to pursue physically active recreation. Thus, an effective policy would be to target informational campaigns promoting non-motorized travel and an active lifestyle toward these young adults in the population and the parents of these young adults. There is also a broader implication of the strong effects of sociodemographics. In particular, the application of the model for forecasting requires spatial-temporal forecasts of age, household structure, income, car ownership, and employment. This need for extensive sociodemographic forecasting is sometimes inappropriately perceived as a “weakness” of disaggregate activity-travel model systems. The more appropriate conclusion to be drawn from the results is that sociodemographic forecasting must be given substantially more attention today, both because of the changing face of the population as well as because of the substantial impacts that these changes will have on future activity and travel patterns.

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APPENDIX A

Location type categories considered as physically active social/recreational activities

1. Aerobics
2. Aquatics Center
3. Archery
4. Ballet Class
5. Batting Cages
6. Bike Trail
7. Bowling
8. Camp
9. Convention Center
10. Field
11. Fitness Class/Center
12. Ice Rink
13. Indoor Recreation/Sports
14. Karate/Martial Arts Classes
15. Park/Community Garden
16. Pool/Swim Center
17. Running/Walking
18. Skating/Skiing
19. Soccer
20. Swimming Lessons
21. Tennis
22. Yacht club
23. YMCA/ Youth Club

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1st choice occasion

$$\begin{aligned}
U_{1111} &= (\alpha_{11}+\beta'_{11}x_{11}) + \sigma\delta_{11} + \theta\xi_{11} + \Delta_{11}\zeta_{111} + \varepsilon_{1111} \\
U_{1121} &= (\alpha_{12}+\beta'_{12}x_{12}) + \sigma\delta_{11} + \theta\xi_{12} + \Delta_{12}\zeta_{112} + \varepsilon_{1121} \\
U_{1211} &= (\alpha_{21}+\beta'_{21}x_{21}) + \sigma\delta_{12} + \theta\xi_{11} + \Delta_{21}\zeta_{121} + \varepsilon_{1211} \\
U_{1221} &= \sigma\delta_{12} + \theta\xi_{12} + \Delta_{22}\zeta_{122} + \varepsilon_{1221}
\end{aligned}$$

2nd choice occasion

$$\begin{aligned}
U_{1112} &= (\alpha_{11}+\beta'_{11}x_{11}) + \sigma\delta_{11} + \theta\xi_{11} + \Delta_{11}\zeta_{111} + \varepsilon_{1112} \\
U_{1122} &= (\alpha_{12}+\beta'_{12}x_{12}) + \sigma\delta_{11} + \theta\xi_{12} + \Delta_{12}\zeta_{112} + \varepsilon_{1122} \\
U_{1212} &= (\alpha_{21}+\beta'_{21}x_{21}) + \sigma\delta_{12} + \theta\xi_{11} + \Delta_{21}\zeta_{121} + \varepsilon_{1212} \\
U_{1222} &= \sigma\delta_{12} + \theta\xi_{12} + \Delta_{22}\zeta_{122} + \varepsilon_{1222}
\end{aligned}$$

FIGURE 1a Utility equations.

1st choice occasion

$$\begin{aligned}
U_{1111}-U_{1221} &= (\alpha_{11}+\beta'_{11}x_{11}) + \sigma\delta_{11} - \sigma\delta_{12} + \theta\xi_{11} - \theta\xi_{12} + \Delta_{11}\zeta_{111} - \Delta_{22}\zeta_{122} + (\varepsilon_{1111}-\varepsilon_{1221}) \\
U_{1121}-U_{1221} &= (\alpha_{12}+\beta'_{12}x_{12}) + \sigma\delta_{11} - \sigma\delta_{12} + \Delta_{12}\zeta_{112} - \Delta_{22}\zeta_{122} + (\varepsilon_{1121}-\varepsilon_{1221}) \\
U_{1211}-U_{1221} &= (\alpha_{21}+\beta'_{21}x_{21}) + \theta\xi_{11} - \theta\xi_{12} + \Delta_{21}\zeta_{121} - \Delta_{22}\zeta_{122} + (\varepsilon_{1211}-\varepsilon_{1221})
\end{aligned}$$

2nd choice occasion

$$\begin{aligned}
U_{1112}-U_{1222} &= (\alpha_{11}+\beta'_{11}x_{11}) + \sigma\delta_{11} - \sigma\delta_{12} + \theta\xi_{11} - \theta\xi_{12} + \Delta_{11}\zeta_{111} - \Delta_{22}\zeta_{122} + (\varepsilon_{1112}-\varepsilon_{1222}) \\
U_{1122}-U_{1222} &= (\alpha_{12}+\beta'_{12}x_{12}) + \sigma\delta_{11} - \sigma\delta_{12} + \Delta_{12}\zeta_{112} - \Delta_{22}\zeta_{122} + (\varepsilon_{1122}-\varepsilon_{1222}) \\
U_{1212}-U_{1222} &= (\alpha_{21}+\beta'_{21}x_{21}) + \theta\xi_{11} - \theta\xi_{12} + \Delta_{21}\zeta_{121} - \Delta_{22}\zeta_{122} + (\varepsilon_{1212}-\varepsilon_{1222})
\end{aligned}$$

FIGURE 1b Utility difference equations (with respect to fourth alternative).

$$Cov(\Delta\upsilon) = \left[\begin{array}{ccc|ccc}
2\sigma^2+2\theta^2+\Delta_{11}^2+\Delta_{22}^2+2h^2 & & & & & \\
2\sigma^2+\Delta_{22}^2+h^2 & 2\sigma^2+\theta^2+\Delta_{12}^2+\Delta_{22}^2+2h^2 & & & & \\
2\theta^2+\Delta_{22}^2+h^2 & \Delta_{22}^2+h^2 & 2\theta^2+\Delta_{21}^2+\Delta_{22}^2+2h^2 & & & \\
\hline
2\sigma^2+2\theta^2+\Delta_{11}^2+\Delta_{22}^2 & & & 2\sigma^2+2\theta^2+\Delta_{11}^2+\Delta_{22}^2+2h^2 & & \\
2\sigma^2+\Delta_{22}^2 & 2\sigma^2+\theta^2+\Delta_{12}^2+\Delta_{22}^2 & & 2\sigma^2+\Delta_{22}^2+h^2 & 2\sigma^2+\theta^2+\Delta_{12}^2+\Delta_{22}^2+2h^2 & \\
2\theta^2+\Delta_{22}^2 & \Delta_{22}^2 & 2\theta^2+\Delta_{21}^2+\Delta_{22}^2 & 2\theta^2+\Delta_{22}^2+h^2 & \Delta_{22}^2+h^2 & 2\theta^2+\Delta_{21}^2+\Delta_{22}^2+2h^2
\end{array}\right]$$

Note: h = $\pi^2/6$

FIGURE 1c Covariance matrix of utility differences.

TABLE 1a Travel Mode Distribution of Episode Type Categories

Mode	Modal distribution for			
	Physically active travel	Physically active activity	Physically passive travel	Physically passive activity
Bicycle	10	2	0	1
Walk	90	10	0	8
Motorized vehicle	0	88	100	91
Total	100%	100%	100%	100%

TABLE 1b Time of Day Distribution of Episode Type Categories

Time of Day	Time of day distribution for			
	Physically active travel	Physically active activity	Physically passive travel	Physically passive activity
3 a.m. – 8 a.m.	21	8	10	3
8 a.m. – 12 noon	35	38	31	25
12 noon – 4 p.m.	19	37	22	33
4 p.m. – 8 p.m.	20	16	27	30
8 p.m. – 3 a.m.	5	1	10	9
Total	100%	100%	100%	100%

TABLE 2 Mixed Multinomial Model Results for Recreational Episode Type Participation Propensity

Explanatory Variable	Parameter	t-statistic
Constants		
Physically active travel	-3.4356	-9.14
Physically active activity	-1.9921	-9.65
Physically passive travel	-6.9530	-8.27
Individual sociodemographics		
Age 16 or 17 years		
Physically active	-0.4642	-1.29
Travel	-0.5944	-0.93
Age greater than 65 years		
Physically active travel	0.8710	2.90
Full-time employed		
Physically active travel	-0.7457	-3.12
Physically active activity	0.4383	3.21
Physically passive travel	-0.5503	-1.41
Female		
Physically passive travel	-0.5715	-1.53
Household sociodemographics		
Annual household income (divided by 100,000)		
Physically active travel	-0.7762	-3.23
Number of cars		
Physically active	-0.1945	-3.00
Presence of bicycles		
Physically active	0.0892	2.36
Physically passive travel	-0.4950	-3.95
Couple		
Physically active travel	0.8199	3.34
Physically passive travel	-1.1766	-2.62
Nuclear family		
Physically active	0.2555	1.81
Travel	0.7772	2.97
Residential Location		
Rural		
Travel	0.3125	0.87
Day of week/season effects		
Sunday		
Physically active travel	0.6658	3.31
Winter		
Physically passive travel	1.6882	2.42
Spring		
Travel	0.1194	0.61
Standard deviations of unobserved individual heterogeneity specific to…		
Physically active travel	0.5560	1.98
Physically active activity	0.8105	3.15
Physically passive travel	5.6406	10.12
Physically passive activity	0.5978	3.10
Standard deviation of error terms generating covariance between:		
Physically active travel and physically active activity/physically passive travel and physically passive activity	1.3895	9.26
Physically active travel and physically passive travel/physically active activity and physically passive activity	0.1505	1.16

TABLE 3 Elasticity Effect of Variables

Variable	Physically active travel	Physically active activity	Physically passive travel	Physically passive activity
Individual sociodemographics				
Age 16 or 17 years	-0.038	-0.031	-0.010	0.079
Age greater than 65 years	0.045	-0.008	-0.003	-0.035
Full-time employed	-0.040	0.053	-0.013	-0.001
Female	0.002	0.002	-0.014	0.010
Household sociodemographics				
Annual household income	-0.040	0.032	0.021	0.029
Number of cars	-0.007	-0.018	0.001	0.024
Presence of bicycles	0.005	0.011	-0.012	-0.004
Couple	0.043	-0.003	-0.030	-0.010
Nuclear family	0.046	0.016	0.014	-0.076
Location variables				
Rural	0.015	-0.002	-0.001	-0.011
Day of week/season effects				
Sunday	0.028	-0.005	-0.002	-0.022
Winter	-0.005	-0.007	0.048	-0.035
Spring	0.005	-0.001	0.003	-0.006