MODELING THE SPATIAL AND TEMPORAL DIMENSIONS OF RECREATIONAL ACTIVITY PARTICIPATION WITH A FOCUS ON PHYSICAL ACTIVITIES

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ABSTRACT

This study presents a unified framework to understand the weekday recreational activity participation time-use of adults, with an emphasis on the time expended in physically active recreation pursuits by location and by time-of-day. Such an analysis is important for a better understanding of how individuals incorporate physical activity into their daily activities on a typical weekday, and can inform the development of effective policy interventions to facilitate physical activity, in addition to contributing more generally to activity-based travel modeling. The methodology employed here is the multiple discrete continuous extreme value (MDCEV) model, which provides a unified framework to explicitly and endogenously examine recreation time use by type, location, and timing. The data for the empirical analysis is drawn from the 2000 Bay Area Travel Survey (BATS), supplemented with other secondary sources that provide information on physical environment variables. To our knowledge, this is the first study to jointly address the issues of 'where', 'when' and 'how much' individuals choose to participate in 'what type of recreational activity'.

The results provide important insights regarding the effects of individual demographics, work-related characteristics, household demographics, and physical environment variables on the propensity to invest time in physical activity, and the associated spatial and temporal choices of physical activity participation. These results and their implications are presented and examined.

Keywords: Adult's recreational activity, physical activity, activity time use, urban form, activity location, activity timing, multiple discrete continuous models.

1. INTRODUCTION

1.1 Background

There has been a dramatic increase in the prevalence of obesity among adults in the U.S. In particular, adult obesity rates have doubled in the past couple of decades (Center for Disease Control (CDC), 2009a). Data from the U.S. National Health and Nutritional Examination Survey (NHANES) indicate that, as of 2006, 33.3% of adult men and 35.3% of adult women may be classified as obese (CDC, 2009b). Unfortunately, obesity is positively associated with significant health problems, including diabetes, hypertension, cardiovascular diseases, strokes, some forms of cancer, sleep apnea and anxiety (Swallen *et al.*, 2005 and WHO, 2006). Such health-related issues, in addition to causing emotional distress, have serious economic impacts on individuals and households, and the U.S. health care system as a whole (USDHHS, 2001). According to a CDC report (CDC, 2009b), diseases associated with obesity accounted for 27% of the increase in medical costs from 1987 to 2001, and obesity health care costs reached $117 billion in 2001.

Over the last two decades, several research studies have examined the factors that affect obesity levels. Among other things, these studies have found clear evidence that obesity is strongly correlated with physical inactivity (see, for instance, Haskell *et al.*, 2007, and Steinbeck, 2008). Struber (2004) indicated that the "prevalence of obesity is more closely related to decreases in energy expenditure (perhaps creating a chronic energy imbalance), than to increases in energy intake, strongly implicating physical inactivity in the etiology of obesity" (see also Sparling *et al.*, 2000 and Westerterp, 2003). In addition to influencing obesity, physical inactivity is a primary risk factor for the onset of several diseases such as coronary heart disease and colon cancer, and it is an important contributing factor to mental health diseases such as depression and anxiety (see Struber, 2004 and USDHHS, 2008). On the other hand, physical activity increases cardiovascular fitness, enhances agility and strength, and improves mental health (CDC, 2006 and USDHHS, 2008).

Despite the adverse impacts of physical inactivity (and the health benefits of physical activity), sedentary (or physically inactive) lifestyles are quite prevalent among adults in the U.S. In particular, according to the 2007 Behavioral Risk Factor Surveillance System (BRFSS) survey, almost half of U.S. adults do not engage in recommended levels of physical activity, and almost one-third of U.S. adults are physically inactive.[1] It is not surprising, therefore, that there is now a reasonably large body of literature on examining the factors affecting the physical activity behavior of individuals, with the end-objective of using these insights to design intervention strategies to promote physically active lifestyles. However, most of these earlier studies focus on examining attributes influencing the level and/or intensity of physical activity participation, such as whether an individual participates in physical activity and/or the amount of time expended in physical activity (for example, see Collins *et al*., 2007, Cohen *et al*., 2007, Salmon *et al*., 2007, Bhat and Sener, 2009, and Srinivasan and Bhat, 2008). There has been relatively little attention on the temporal and spatial context of the physical activity participations, that is, on the "when" and "where" of physical activity participation.[2] On the other hand, an understanding of the temporal and spatial contexts of physical activity participation can provide important insights to design customized physically active lifestyle promotion strategies at different locations (such as in-home versus a gym) and times of the day to target specific demographic groups.

Of course, an examination of recreational activity participation in general is also important from a transportation perspective. Out-of-home (OH) recreational activity episode participation comprises a substantial share of total OH non-work activity episode participation on a typical weekday. For instance, Lockwood *et al.* (2005) examined data from San Francisco, and observed that about 20% of all non-work activity episodes during a typical workday are associated with physically inactive or physically active recreation. The share contributed by OH recreation episodes to total OH non-work episodes was only next to the share contributed by serve passenger episodes. Further, Lockwood *et al.* also found that, among all non-work episodes, recreation episodes entailed the longest travel distances, and generated the highest person miles of travel and vehicle miles of travel. In addition to the sheer volume of episode participation and travel mileage attributable to OH recreational activity participation, there is quite substantial joint activity participation and joint travel associated with OH recreational

[1] The current adult physical activity guidelines call for at least 150 minutes a week of moderate-level physical activity (such as brisk walking, bicycling, water aerobics) or 75 minutes a week of vigorous-level physical activity (such as jogging, running, mountain climbing, bicycling uphill) (USDHHS, 2008).

[2] As indicated by Dunton *et al.* (2008), this situation is, at least in part, due to the way data has been collected for analysis in several earlier physical activity studies. For instance, several studies focus on a single location setting (such as parks or playgrounds) for physical activity observation (see, for example, Reynolds *et al.*, 2007) and/or use long-term retrospective self-reports of participation and extent of participation in physical activities (see, for example, Mowen *et al.*, 2007). These studies do not consider the possible range of physical activity locations and detailed time-of-day context information.

activity episodes, especially between children and adults within a household (see, for instance, Gliebe and Koppelman, 2002 and Kato and Matsumoto, 2009). Thus, from an activity-based travel demand perspective, a study of participation and time-use in OH recreational episodes, as well as the spatial and temporal dimensions of these episode participations, is important. In doing so, one needs to distinguish between OH physically active and physically inactive episodes, since the temporal and spatial contexts of these two types of episodes (such as time of day, spatial location, travel, and duration of time investment) tend to be very different (Lockwood *et al.*, 2005). In addition, out-of-home recreation episodes also need to be distinguished from in-home episodes, since the former entail travel while the latter do not. Besides, there may be substitution between in-home, OH physically inactive, and OH physically active recreational participations (Bhat and Gossen, 2004).

1.2 The Current Paper

In the current paper, we use an activity diary survey to model adults' overall recreational activity participation on weekdays, with an emphasis on the time expended in physically active recreation by location and by time-of-day. In terms of location, we have no way to differentiate between physically inactive and physically active recreational pursuits in-home, because, as discussed later in the data section, the only way in the data to identify if a recreational episode is physically active or not is based on the location type classification of the out-of-home activity episode (such as bowling alley, gymnasium, shopping mall, or movie theatre). Thus, we use a composite in-home recreation category. However, for out-of-home recreation pursuits, we are able to distinguish between physically inactive and physically active episodes. In the current analysis, we retain out-of-home physically inactive recreation as a single category, but categorize the time invested in out-of-home physically active recreation in one of three location categories: (1) Fitness center/health club/gymnasiums (or simply "club" for brevity), (2) In and around residential neighborhood (such as walking/biking/running around one's residence without any specific destination for activity participation; we will refer to this location as "neighborhood"), and (3) Park/outdoor recreational area ("outdoors" for brevity). Further, the time invested in out-of-home physically active recreation is categorized temporally in one of the following four time periods of the weekday: (1) AM peak (6:01 AM – 9 AM), (2) Midday (9:01 AM – 4 PM), (3) PM peak (4:01 PM – 7 PM), and 4) Night (7:01 PM – 6 AM). Overall, the total recreation time for each individual is categorized into 14 activity type-location-time of day alternatives, corresponding to in-home recreation, out-of-home physically inactive recreation, and the 12 out-of-home physically active recreation categories based on combinations of the three location categories and four time-of-day periods. [3]

From a methodological standpoint, the model formulation used in the current analysis is the multiple discrete continuous extreme value (MDCEV) model developed by Bhat (2005, 2008). This model is capable of predicting the discrete choice participation in, and the continuous choice of the time allocated to, each of the 14 activity type-location-time of day alternatives described above. The MDCEV model is ideally suited for the current analysis due to its utility-theoretic formulation.[4] It uses a non-linear, additive, utility structure that is based on diminishing marginal utility (or satiation effects) with increasing participation duration in any of the 14 alternatives.

The empirical analysis incorporates an extensive set of explanatory variables, including individual/household demographics and physical environment variables. While there is a huge body of literature on physical activity participation examining the first category of factors, there has been relatively scant attention on the physical environment determinants of physical activity, even though physical environment characteristics can significantly facilitate or constrain individuals' engagement in physical activity (see Duncan *et al.*, 2005, Papas *et al.*, 2007, and Bhat and Sener, 2009). The activity survey data used in the current study provide information on the residential location of individuals, which is used to develop measures of the physical environment variables in the family's neighborhood. The physical environment variables include (a) activity day and seasonal characteristics, (b) transportation system attributes, (c) built environment measures, and (d) residential neighborhood demographics (more on the variable specifications later).

The rest of the paper is structured as follows. The next section provides an overview of the model structure employed in the paper. Section 3 presents the data source, and discusses the sample formation procedure as well as important descriptive statistics of the sample. Section 4 presents the results of the empirical analysis. Finally, Section 5 concludes the paper with

[3] The particular emphasis on physically active recreation in this paper is because of the obvious confluence of interest in this kind of recreation from both a public health perspective as well as a transportation perspective.

[4] A utility-theoretic formulation, as used here, is one that derives its theoretical basis from microeconomic utility concepts of consumer choice.

discussion of the results and the potential implications for intervention strategies aimed at promoting recreational physical activity.

2. MODEL STRUCTURE

In this section, we present an overview of the MDCEV model structure, which is used to examine adults' recreational activity participation, and time investment, in each activity type-location-timing combination alternative (for ease in presentation, we will refer to the activity type-location-timing combination alternatives simply as activity alternatives in the rest of this paper). The reader is referred to Bhat (2005) and Bhat (2008) for the intricate details of the model structure.

2.1 Basic Structure

Let t_k be the time invested in activity alternative k (k = 1, 2, …, K), where K = 14 in the current empirical analysis. Consider the following additive, non-linear, functional form to represent the utility accrued by an individual through the weekday time investment vector $\boldsymbol{t} = \{t_1,\ t_2, \ldots,\ t_K\}$ in various activity alternatives (the index for the individual is suppressed in the following presentation):[5]

$$U(\boldsymbol{t}) = \sum_{k=1}^{K} \frac{1}{\alpha_k} \exp(\beta' z_k + \varepsilon_k)\left\{(t_k + 1)^{\alpha_k} - 1\right\} \tag{1}$$

z_k is a vector of exogenous determinants (including a constant) specific to alternative k. The term $\exp(\beta' z_k + \varepsilon_k)$ represents the random marginal utility of one unit of time investment in alternative k at the point of zero time investment for the alternative. This can be observed by computing the partial derivative of the utility function $U(\boldsymbol{t})$ with respect to t_k and computing this marginal utility at $t_k = 0$ (*i.e.*, $\partial U(\boldsymbol{t})/\partial t_k\big|_{t_k=0}$). Thus, $\exp(\beta' z_k + \varepsilon_k)$ controls the discrete choice participation decision in alternative k. We will refer to this term as the baseline preference for alternative k. α_k $(\alpha_k \leq 1)$ is a satiation parameter whose role is to reduce the marginal utility with increasing consumption of alternative k. When α_k = 1 for all k, this represents the case of

[5] Several other additive, non-linear, utility forms, as proposed by Bhat (2008), were also considered. However, the one provided below was the best form in the empirical analysis of the current paper.

absence of satiation effects. Lower values of α_k imply higher satiation (or lower time investment) for a given level of baseline preference. The constraint that $(\alpha_k \le 1)$ for k = 1, 2, …, K is maintained by reparameterizing α_k as $[1-\exp(\lambda_k)]$, where λ_k is a scalar to be estimated.

From the analyst's perspective, individuals are maximizing random utility $U(\boldsymbol{t})$ on each weekday subject to the activity time budget constraint that $\sum_k t_k = T$, where T is the total weekday time available for adults to participate in recreation activity.[6]

Assuming that the error terms ε_k (k = 1, 2, …, K) are independent and identically distributed across alternatives with a type-1 extreme value distribution, the probability that the adult allocates time to the first M of the K alternatives (for duration t_1^* in the first alternative, t_2^* in the second, … t_M^* in the M^{th} alternative) is (see Bhat, 2008):

$$P\left(t_1^*, t_2^*,\ t_3^*,\ \ldots,\ t_M^*,\ 0,\ 0,\ \ldots,\ 0\right) = \left[\prod_{i=1}^{M} c_i\right]\left[\sum_{i=1}^{M} \frac{1}{c_i}\right]\left[\frac{\prod_{i=1}^{M} e^{V_i}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right](M-1)! \tag{2}$$

where $c_i = \left(\dfrac{1-\alpha_i}{t_i^*+1}\right)$ for i = 1, 2, …, M.

2.2 Mixed MDCEV Structure and Estimation

The structure discussed thus far does not consider correlations among the error terms of the alternatives in the specification of the baseline preference. On the other hand, it is possible that such correlations exist. For instance, some adults may have a general predisposition (due to factors unobserved to the analyst) to participate in out-of-home pursuits, which can be reflected by an error-component specific to the baseline preferences of all the alternatives except the in-home recreation alternative. Alternatively, or in addition, some adults may have a predisposition to participate in physically active recreation at a certain activity location type such as a club or at a certain time of day such as the PM peak. The former effect can be accommodated through an

[6] We focus only on individuals who undertake some amount of recreation activity during the sampled weekday (*i.e.*, we only consider individuals for whom $T > 0$). Since recreation activity includes in-home recreation, out-of-home physically inactive recreation, as well as out-of-home physically active recreation, a very large fraction of individuals in our sample actually do have $T > 0$.

error component specific to the baseline preferences of all physically active alternatives that include the club location (that is, an error component common to club-AM peak, club-Midday, club-PM peak, and club-night), while the latter effect may be captured through an error component specific to the baseline preferences of all physical active alternatives that include the PM-peak time of day (that is, an error component common to club-PM peak, neighborhood-PM peak, and outdoors-PM peak). Of course, the above examples are simply illustrative, and one can also test for several other patterns of error components. Such patterns of error components can be accommodated by defining appropriate dummy variables in the z_k vector to capture the desired error correlations, and considering the corresponding β coefficients in the baseline preference of the MDCEV component as draws from a multivariate normal distribution. In general notation, let the vector β be drawn from $\boldsymbol{\phi}(\beta)$. Then the probability of the observed time investment (t_1^*, t_2^*, $\ldots t_M^*$, 0, 0, …0) for the adult can be written as:

$$P(t_1^*, t_2^*, \ldots t_M^*, 0,0,0..0) = \int_{\beta} P(t_1^*, t_2^*, .. t_M^*, 0,0,..0 \mid \beta) \boldsymbol{\phi}(\beta) d\beta \,, \tag{3}$$

where $P(t_1^*, t_2^*, \ldots, t_M^*, 0,0,\ldots 0 \mid \beta)$ has the same form as in Equation (2).

The parameters to be estimated in Equation (3) include the mean vector and variance matrix of the β vector, and the λ_k scalars (k = 1, 2, …, K) that determine the satiation parameters α_k. The likelihood function (3) includes a multivariate integral whose dimensionality is based on the number of error components in β. The parameters are estimated using a maximum simulated likelihood approach using Halton draws (see Bhat, 2003).

3. DATA SOURCE AND SAMPLE DESCRIPTION

3.1 The Data

3.1.1 The Primary Data Source

The primary source of data is the 2000 San Francisco Bay Area Travel Survey (BATS), which was designed and administered by MORPACE International, Inc. for the Bay Area Metropolitan Transportation Commission (see MORPACE International Inc., 2002). The survey collected detailed information on individual and household socio-demographic and employment-related characteristics from about 15,000 households in the Bay Area. The survey also collected information on all activity and travel episodes undertaken by individuals of the sampled households over a two-day period. The information collected on activity episodes included the type of activity (based on a 17-category classification system), the name of the activity participation location (for example, Jewish community center, Riverpark plaza, *etc.*), the type of participation location (such as in-home, health center, or amusement park), and start and end times of activity participation.

The out of-home physically active activity episodes were identified based on the activity type and the type of participation location at which the episode is pursued, as reported in the survey.[7] The type of out-of-home participation location was then used to determine the activity location alternatives. For instance, an out-of-home physically active recreational activity episode such as walking/running/bicycling around the neighborhood without any specific destination is labeled as being a "neighborhood" recreational activity. Furthermore, the start and end times of each activity participation episode were used to identify the activity episode timing (that is, activity episode time of day) as well as the activity episode duration dimensions.

3.1.2 The Secondary Data Source

In addition to the 2000 BATS survey data set, several other secondary data sets were used to obtain physical environment variables (particularly transportation system attributes, built environment characteristics, and residential neighborhood demographics) that may influence the physical activity participation, activity location, and activity timing/duration behavior of adults. All these variables were computed at the level of the residential traffic analysis zone (TAZ) of each household.[8] The secondary data sources included land-use/demographic coverage data, the 2000 Census of population and household summary files, a Geographic Information System (GIS) layer of bicycle facilities, a GIS layer of highways and local roadways, and GIS layers of businesses. Among the secondary data sets identified above, the land-use/demographic coverage data, LOS data, and the GIS layer of bicycle facilities were obtained from the Metropolitan Transportation Commission (MTC). The GIS layers of highways and local roadways were

[7] A physically active episode requires regular bodily movement during the episode, while a physically passive episode involves maintaining a sedentary and stable position for the duration of the episode. For example, swimming or walking around the neighborhood would be a physically active episode, while going to a movie is a physically passive episode.

[8] Due to privacy considerations, the point coordinates of each household's residence are not available; only the TAZ of residence of each household is available.

obtained from the 2000 Census Tiger Files. The GIS layers of businesses were obtained from the InfoUSA business directory.

Among the physical environment variables, the zonal-level transportation system and built environment measures constructed from secondary data sources were as follows:

1. *Transportation system attributes*, including highway density (miles of highway facilities per square mile), local roadway density (miles of roadway density per square mile), bikeway density (miles of bikeway facilities per square mile), street block density (number of street blocks per square mile), non-motorized distance between zones (*i.e.*, the distance in miles along walk and bicycle paths between zones), and transit availability. The non-motorized distance between zones was used to develop an accessibility measure by non-motorized modes, computed as the number of zones (a proxy for activity opportunities) within "x" non-motorized mode miles of the adult's residence zone. Several variables with different thresholds for "x" were formulated and tested.
2. *Land use structure variables*, including housing type measures (fractions of single family, multiple family, duplex and other dwelling units), land-use composition measures (fractions of zonal area in residential, commercial, and other land-uses), and a land-use mix diversity index computed as a fraction based on land-use composition measures with values 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; see Bhat and Guo, 2007 for a detailed explanation on the formulation of this index).
3. *Regional accessibility measures,* which include Hansen-type (Fotheringham, 1983) employment, shopping, and recreational accessibility indices that are computed separately for the drive and transit modes.
4. *Activity opportunity variables*, characterizing the composition of zones in terms of the intensity or the density of various types of activity centers. The typology used for activity centers includes five categories: (a) maintenance centers, such as grocery stores, gas stations, food stores, car wash, automotive businesses, banks, medical facilities, (b) physically active recreation centers, such as fitness centers, sports centers, dance and yoga studios, (c) physically passive recreational centers, such as theatres, amusement centers, and arcades, (d) natural recreational centers such as parks and gardens, and (e) restaurants and eat-out places.

The residential neighborhood demographics constructed from secondary data sources were as follows:

1. *Zonal population size and employment/population density measures*, including total population, number of housing units, population density, household density, and employment density by several employment categories, as well as dummy variables indicating whether the area corresponds to a central business district (CBD), urban area, suburban area, or rural area.
2. *Zonal ethnic composition measures*, constructed as fractions of Caucasian, African-American, Hispanic, Asian and other ethnic populations for each zone.
3. *Zonal demographics and housing cost variables*, including average household size, median household income, and median housing cost in each zone.

3.2 Sample Description

3.2.1 Sample Formation

The final sample generation process involved several steps. First, only individuals aged 16 years or older were considered in the analysis. Second, one weekday of the survey was selected for each adult, since the focus of the current analysis is exclusively on weekdays. Third, all activity episodes in which adults participated were categorized by purpose and only the recreational activity episodes were chosen for this study. Fourth, all recreational activity episodes were categorized as in-home or out-of-home, according to the location of the activity episode participation. Fifth, each out-of-home recreational activity episode was categorized as physically active or physically inactive based on definitions presented earlier (see Section 3.1). Sixth, each out-of-home physically active recreational episode was classified into one of three location categories (club, neighborhood, and outdoors) and into one of four time periods of the day (AM peak -- 6:01 AM – 9 AM, Midday -- 9:01 AM – 4 PM, PM peak -- 4:01 PM – 7 PM, and night -- 7:01 PM – 6 AM. Finally, the time investments across all episodes in the day within each activity alternative were aggregated to obtain the total daily time investments in each of 14 activity alternatives (in-home recreation, out-of-home physically inactive recreation, and the 12 out-of-home physically active recreation categories based on location and time-of-day). The participation decisions, and the daily time investments, in these 14 alternatives constitute the dependent variables for the MDCEV model.

3.2.2 Sample Characteristics

The final estimation sample includes 4448 individuals residing in nine Counties of the San Francisco Bay Area (Alameda, Contra Costa, San Francisco, San Mateo, Santa Clara, Solano, Napa, Sonoma and Marin). Table 1 presents the descriptive statistics of recreational activity participation for the sample. The first row of the table indicates that about 51% of individuals in the sample participated in in-home recreation (IHR), with a mean weekday duration across individuals who participate in IHR being quite high at 221 minutes (about 3 hours and 40 minutes). The last two main columns present the split between solo participations (*i.e.*, participation in only the row activity alternative) and multiple activity alternative participations (*i.e.*, participation in the row activity alternative and other activity alternatives). Thus, the results indicate that 77% of those who participate in IHR do not participate in any other recreation activity alternative during the weekday, while 23% of those who participate in IHR also participate in one or more of the remaining activity alternatives. The second and third rows of the table provide the corresponding figures for out-of-home physically inactive recreation (PIR) and out-of-home physically active recreation (PAR). In the third row, the figures for PAR represent a composite category, which is further broken down by location and time-of-day in subsequent rows (as we discuss later). The results of the second and third rows reveal a slightly higher participation rate in PAR (34%) than in PIR (30.7%), though the mean time investment in PIR among those participating in PIR is higher than the mean time investment in PAR among those participating in PAR (117 minutes versus 100 minutes). Interestingly, the last two columns of the table indicate that about 71% of individuals who participate in PIR do not participate in IHR or PAR, while an almost identical percentage of individuals who participate in PAR do not participate in IHR or PIR.

The remaining rows in Table 1 provide more details of the PAR participation by location and time-of-day.[9] The results indicate that the highest percentage of participation in PAR in terms of location is at a club, followed by participation in one's neighborhood. From a temporal standpoint, the highest PAR participation is in the midday period, while the lowest is in the night (note, however, that the length of time windows varies across the time-of-day periods; thus, from

[9] The sum of the entries for the number of individuals participating in PAR alternatives across activity locations is greater than 1512 (the total number of individuals participating in PAR) because some individuals may participate in PAR at multiple locations in the same day. The same is true for the number of individuals participating in PAR alternatives across times-of-day because some individuals may participate in PAR during multiple time periods of the weekday.

the perspective of PAR participation per time unit, there is higher PAR participation in the AM peak and PM peak periods than at other times of the day). As we will see later, an important variable determining temporal patterns of PAR participation is employment, with unemployed individuals more likely than those employed to participate in the midday period. The mean duration of PAR participation is highest when pursued outdoors, and shortest when pursued in/around the residential neighborhood. In terms of time-of-day, the mean duration of PAR participation shows little variation across the day-time temporal periods (AM peak, midday, and PM peak), though the mean duration is shorter for PAR participation in the night relative to the day-time periods. The last two main columns corresponding to the PAR alternatives reveal that those who pursue PAR in their neighborhoods are also most likely to participate in other PAR alternatives or IHR or PIR, while those participating in PAR at clubs are the least likely to participate in other PAR alternatives or IHR or PIR. Also, note that a significant proportion of individuals participate in multiple alternatives among the 14 recreational alternatives considered in the current paper, as should be clear from the entries in the final column of Table 1, highlighting the need for, and appropriateness of, the MDCEV model for the current analysis.

Table 1 only shows the aggregate distribution of participation in PAR separately along each of the location and time-of-day dimensions. On the other hand, in the current paper, we focus on the interactions of location and time-of-day for PAR activities. In Table 2, we present the participation levels in PAR by location and time-of-day. The first two number columns (for locations) and the first number row (for time-of-day) provide the one-dimensional participation statistics, while the rest of the table presents the descriptive statistics for each combination alternative. For instance, the first number in the combination part of the table indicates that 134 individuals participate in PAR at a club during the AM peak period. This corresponds to 20.2% of all adults participating in PAR at a club, and 33.8% of all adults participating in PAR during the AM peak period of the weekday (note that the percentages for each row (column) across activity locations (times-of-day) can sum to more than 100% due to multiple discreteness; for instance an adult can go to a club for weight-training during the AM peak period and then play tennis at a club with a friend in the night period. In general, the results in Table 2 show that the midday period is the most likely one for pursuing PAR at a club or outdoors, while the AM peak period is the most likely time-of-day for pursuing PAR in and around one's neighborhood. Also, the most frequent PAR location during each time-of-day is as follows: AM peak – in/around one's neighborhood, midday – club, PM peak – club, and night – club.

4. MODEL RESULTS

4.1 Variable Specification

Several different variables within the two broad variable categories of individual/household factors and physical environment correlates were considered in our model specification. The individual/household factors included individual demographics (age, sex, race, driver's license holding, physical disability status, *etc.*), work-related characteristics (employment status, hours of week, work schedule, and work flexibility, *etc.*), and household demographics (number of children, family structure, number of vehicles, *etc*.). The physical environment factors included activity day and seasonal characteristics, transportation system attributes, built environment characteristics and residential neighborhood demographics (see Section 3.2 for details on the latter three sets of variables).

The final variable specification was based on a systematic process of eliminating variables found to be statistically insignificant, intuitive considerations, parsimony in specification, and results from earlier studies. Several different variable specifications, functional forms of variables as well as interaction variables were examined. The specification includes some variables that are not highly statistically significant, because of their intuitive effects and potential to guide future research efforts in the field. In addition to alternative variable specifications, we also considered several error-component structures to generate correlation in the unobserved error terms of the baseline utilities of the 14 alternatives. But the only one that turned out to be statistically significant was a common error component across alternatives that included the "neighborhood" location.

4.2 Estimation Results

The final specification results of the mixed MDCEV model are provided in Tables 3 and 4. Table 3 presents the results of the parameter estimates corresponding to the baseline preference utility (the β parameter vector in Equation 1), while Table 4 presents the results of the implied satiation parameters (obtained by estimating λ_k and then obtaining the corresponding α_k parameter and its standard error). A '-' entry in Table 3 under a particular activity alternative for a particular variable implies that this variable is omitted from the utility specification for that alternative (that is, the alternative constitutes a base alternative about which the impact of the variable on other alternatives should be interpreted). Also, note that, for dummy exogenous variables, it is implicit that the omitted dummy variable category (or categories) serves (serve) as the baseline reference.

The results for the baseline preference specification for the in-home recreation (IHR) and the out-of-home physically inactive recreation (PIR) alternatives are presented in the first two rows. For the out-of-home physically active recreation (PAR) alternative, the effect of each variable is first identified separately along the location and time-of-day dimensions. The final row panel of the table identifies any interaction effects of each variable on the PAR baseline utility for each location-time of day combination alternative over and above the one-dimensional location/time-of-day effects.[10]

4.2.1 Individual Demographics

Among individual demographics, the gender-related effects indicate that women are more likely than men to participate in weekday PIR activities and PAR activities (regardless of location, and particularly in the AM and PM peak periods) than in IHR activity (except for outdoor PAR activities in the night). The higher participation level of women in PIR activities is consistent with the findings from several earlier studies indicating that women are more involved with arts/crafts shows, concerts, museums and related "high-culture" activities (see Srinivasan and Bhat, 2006 and Nakai, 2009). The higher PAR participation of women relative to men is not consistent with those of several earlier studies that suggest higher physical activity levels among men than among women (see, for example, Azevedo *et al.*, 2007, and Trolano, 2008). Of course, one should keep in mind that the measure of physical activity in our study is the duration of time spent in physical activity on a single weekday as self-reported in a general activity survey, while several earlier studies have considered time expended in physical activity over longer stretches of time (such as a week or a longer period of time) using focused physical activity surveys or objective measurements of physical activity. A careful comparative analysis of the time-unit used to measure physical activity, the metric used for physical activity measurement, and the

[10] To conserve on space, we do not present the baseline preference constants in Table 3. These constants do not have any substantive interpretations.

methods employed to obtain physical activity information would be beneficial, and should be a research priority for the future.

The age effects indicate the lower baseline preference of individuals less than 30 years of age (compared to their older peers) to participate in PAR activities in/around residences, regardless of time-of-day (note the -0.91 coefficient for “neighborhood”, which is higher in magnitude than even the positive coefficients on the PM peak and night time periods). The same is true for participation in PAR outdoors in the AM peak and midday periods, though young adults are more likely than their older peers to participate in PAR outdoors during the PM peak (the net effect on the baseline utility for the PAR outdoor-PM peak alternative is $-0.42+0.73=+0.31$). Also, the results indicate that young adults have a much higher preference than their older peers to participate in PAR at clubs in the PM peak and night periods. Similar results of lower preference for participation in PAR in neighborhoods (except in the PM peak period) and higher preference for PAR participation at clubs during the PM peak can be observed for those in the 30-49 years age group relative to the “50 years or more” age group category, though the effects are less pronounced than for the youngest age group. Dunton *et al.* (2008) found similar results of age-based preferences for PAR location. In general, the tendency among younger individuals to pursue PAR at clubs and of older individuals to pursue PAR in neighborhoods may be a reflection of generational differences. Since clubs were not very common or well dispersed until the 1980’s and 1990’s, older generations of adults are probably used to engaging in physical activities outside of clubs. Therefore, these individuals may simply perceive no need or reason for exercising at a club. On the other hand, younger adults are likely to be more familiar with the physical activity options available at clubs and may also view club-based PAR as a social activity. Caspersen *et al.* (2000) also notes that strengthening exercises, which may be particularly facilitated by the use of machines available at a club, dramatically declines with age, which may explain the lower PAR participation of older adults at clubs. However, it is still not clear whether older individuals, in general, do not partake in strengthening exercises as often as their younger peers and therefore do not go to clubs, or simply do not go to clubs and therefore partake less in strengthening exercises.

The physical disability status of individuals is a strong deterrent factor for both PIR and PAR activities. In particular, the results show that physically disabled adults are more likely to participate in in-home recreation (see also Pinjari and Bhat, 2009). Also, these individuals are particularly not likely to participate in PAR activities during peak hours, perhaps because they would rather avoid dense traffic conditions.

The remaining individual demographic effects indicate the lower preference of full-time students to participate in PAR during the AM peak period relative to other time periods, presumably because of school-time constraints. This result might also be a reflection of a typical "shifted day" that an adult student adopts, with a late start to the day and with activities stretching into the late night hours. Finally, adults with a driver's license are less likely (relative to adults without a driver's license) to participate in PAR in their neighborhood. This result is to be expected, because individuals with a driver's license have an increased opportunity to drive to physical activity locations outside their neighborhood.

4.2.2 Work-Related Characteristics

The effects of work-related characteristics are quite intuitive. First, employed adults have a higher propensity than those unemployed to participate in PAR at a club rather than participating at PAR at other locations. Perhaps, employed individuals tend to attend gym facilities at or within close proximity of their employment locations. They are also likely to find the showering and locker facilities at clubs to be convenient. Second, employed adults (relative to non-employed adults) have a lower baseline utility preference to partake in physical activities during the AM peak and midday periods than in other time periods of the weekday. This clearly reflects the employed individual's perceived or real obligation to work during the traditional workday hours (that is, 8 AM to 5 PM). Third, the interaction effect in the bottom panel of the table indicates the particular inclination of employed individuals to participate in PAR at a club during the PM peak period, perhaps, in part, reflecting an activity chaining effect on the way back home from work. Finally, the work flexibility variable effects indicate a progressively higher baseline propensity of individuals with increasing flexibility to pursue PAR at clubs, though workers with flexibility are less likely to pursue PAR during the mid-day period. Overall, the work-related effects suggest that effective policy interventions to encourage PAR among workers would provide club facilities in/around work centers, since employed adults appear to be predisposed to exercise in clubs if such an option is conveniently available from a spatial and temporal standpoint.

4.2.3 Household Demographics

Among the household demographics, the nuclear family variable indicates a lower propensity of adults in nuclear families (relative to adults in other families such as single parent families and families with no children) to participate in in-home recreation compared to out-of-home recreation, perhaps a reflection in nuclear families of the increased opportunities for one or both parents to pursue joint out-of-home recreation with children (see also Bhat and Lockwood, 2004 and Sener *et al.*, 2009 for similar results). These results are reinforced by the age-specific effects of children, which suggest that the presence of young children (aged 0-4) in the household increases PAR during the midday, especially outdoors (at parks). On the other hand, adults with older children (aged 5-15) are likely to avoid participation in physical activity during the peak time periods compared to other time periods of the day. This is presumably because of the responsibilities of adults associated with preparing school-age children for school and/or transporting them to/from school.

As continually underscored in the literature (see, for instance, TRB, 2005), individuals living in low income households (those with an annual income less than $35,000) have a higher propensity than those in middle or high income households to engage in in-home recreation (IHR) activities relative to out-of-home recreation (PIR or PAR), perhaps due to financial constraints. The implication is that individuals in low income households participate less than those in middle-to-high income households even in physically active recreation (PAR) activities in their immediate neighborhoods. Since PAR in neighborhoods should not have substantial financial implications to individual families, this result is another indication that the quality of the environment in which low income households reside appears to have an impact on PAR. As stated by Bennett *et al*. (2007), "residing in a neighborhood that is perceived to be unsafe at night is a barrier to regular physical activity among individuals, especially women, living in urban low-income housing. Feeling unsafe may also diminish confidence in the ability to be more physically active." The income-related effects also point to the higher propensity of high income households to participate in PAR at clubs, probably due to financial ability.

Individuals from households owning one or more vehicles have a higher propensity to engage in physically inactive recreation (PIR) activities relative to individuals from households with no vehicles, according to the results in Table 3. Individuals with more vehicles in their household are also more likely to participate in PAR recreation during the AM peak, especially outdoors. However, the results also reveal a lower propensity among individuals with more household vehicles to pursue PAR during the PM peak in their neighborhoods or outdoors, though there is no statistically significant difference based on vehicle ownership in PAR participation in the PM peak at clubs (note that the effective impact of vehicle ownership on the baseline utility for the club/PM peak alternative is $-0.29+0.30 \approx 0$). These vehicle-based effects need to be examined more carefully in future studies. Finally, in the class of household demographics, bicycle ownership is a significant motivator for increased PAR in/around an individual's neighborhood.

4.2.4 Physical Environment Variables

The seasonality effects within the group of physical environment variables reveal the increased tendency to stay put at home for recreation activities during the winter season, and a higher predisposition to participate in outdoor PAR activities during the summer season (see also, Tucker and Gilliland, 2007, Sener and Bhat, 2007, and Pivarnik *et al.*, 2003 for such seasonal effects). These results suggest a need to target physical activity promotion campaigns during the winters toward ways to increase in-home physical activity, and/or on providing accessible and inexpensive indoor club facilities.

In the category of transportation system attributes/built environment characteristics, very few variables turned out to be statistically significant, suggesting that, in general, participation in PAR may be more of a lifestyle choice than related to the availability of spatial opportunities for PAR participation. However, the density of bikeway has the expected positive influence on PAR in the neighborhood when interacted with bicycle ownership in the household. This result has also been documented in some earlier studies (see, for instance, Pinjari *et al.*, 2009 and Cervero and Duncan, 2003).[11] Furthermore, accessibility to physical activity centers in the residence zone of an individual has clear positive impacts on PAR at clubs (see Norman *et al.*, 2006 and Duncan *et al.*, 2005 for similar results).

With respect to zonal demographics, the results indicate the higher participation of Caucasian Americans in PAR activities (regardless of location and time-of-day) compared to

[11] One has to be cautious though about the causal direction of this result – it is certainly possible that individuals who are more PAR-oriented may own more bicycles and locate themselves in residential neighborhoods with good bicycle facilities (see Pinjari *et al.*, 2008 for a study that accounts for such self-selection effects).

other races. This result is consistent with several previous studies (see Gordon-Larsen *et al.*, 2005 and 2006). Research studies aimed at better understanding the reasons for these race-based differences in PAR participation may help in the design of targeted PAR promotion campaigns. Finally, individuals residing in zones with a high mean household income are more likely to participate in PAR activities at clubs.

4.2.5 Satiation Parameters

The satiation parameter estimates in Table 4 are the implied α_k estimates in Equation 1. The t-statistics of the α_k parameters are computed for the hypothesis that $\alpha_k = 1$, which corresponds to no satiation effects (α_k values close to 1 indicate low satiation, while α_k values farther away from 1 indicate high satiation). Clearly, the results reject the null hypothesis of no satiation effects in recreational activity participation. Across the activity alternatives, the satiation effect for IHR activity is the lowest, which is consistent with the high rate of participation and high mean duration of participation in IHR (see Table 1). At the other end of the spectrum, the satiation is highest for outdoor PAR activities in the night, reflecting the very low participation rate and mean duration of participation in this alternative. In fact, the implied α_k parameter for this alternative consistently came out to be close to 0, and so is fixed at 0 in the estimation. Among the alternatives other than the outdoor-night alternative, the results show that PAR pursued in/around residential neighborhoods have higher satiation levels compared to PAR pursued at clubs and outdoor parks/recreational areas. This is consistent with the low mean duration of PAR in neighborhoods compared to other PAR locations (see Table 1).

4.2.6 Error Components

The final specification included only one error component specific to the “neighborhood” location. This error component has a standard deviation of 1.07 with t-statistics of 8.96, indicating the existence of common unobserved factors that predispose adults to participate in physical activity in/around their neighborhood regardless of time-of-day.

4.2.7 Likelihood-Based Measures of Fit

The log-likelihood value at convergence of the final mixed MDCEV model is -20811.1. The corresponding value for the model with only the constants in the baseline preference and the satiation parameters is -21096.2. The likelihood ratio test for testing the presence of exogenous variable effects on baseline preference and error components is 570.2, which is substantially larger than the critical chi-square value with 45 degrees of freedom at any reasonable level of significance. This clearly indicates the value of the model estimated in this paper to predict adults' recreational activity time use by location and time-of-day based on individual demographics, work-related characteristics, household demographics, and physical environment variables.

5. CONCLUSIONS AND IMPLICATIONS

Over the last couple of decades, there has been a decrease in physical activity levels in the U.S. population, with a concomitant increase in the rates of obesity and overweight among adults and children. In this regard, the main objective of the current study was to propose and apply a modeling framework to examine individuals' time-use in in-home recreation (IHR), out-of-home physically inactive recreation (PIR), and out-of-home physically active recreation (PAR). The study places particular emphasis on studying the location and time-of-day of PAR participation to inform the development of effective policy interventions to facilitate physical activity. The methodology employed is the multiple discrete continuous extreme value (MDCEV) model, which provides a unified framework to explicitly and endogenously examine recreation time use by type, location, and timing. The data for the empirical analysis is drawn from the 2000 Bay Area Travel Survey (BATS), supplemented with other secondary sources that provide information on physical environment variables.

The empirical results provide several insights for the design of targeted interventions to promote physical activity. First, young adults are more likely to participate in PAR at clubs during the PM peak periods, while older adults are more likely to participate in PAR in and around their neighborhoods during non-PM peak time periods. Thus, interventions aimed at promoting PAR among young adults would benefit from promoting club-related opportunities and offering special classes (such as yoga, pilates, aerobics, weight-training, *etc.*) at these clubs during the PM peak period. On the other hand, residential areas with a high fraction of middle-aged to senior adults would benefit from a well-planned network of pedestrian and bicycle pathways that are conducive to PAR in/around neighborhoods. Second, employed adults have a high preference to partake in PAR at clubs during the PM peak period (4 PM – 7 PM), suggesting that employers can play a role in promoting PAR among their employees by providing fitness center facilities at the work place and/or providing subsidies for club membership at fitness centers within close proximity to the work place. Further, staggering work hours to an early start and an early end to the work day (say, for example, a 7 AM – 4 PM schedule rather than a 8 AM – 5 PM schedule) may provide beneficial results by providing more time in the afternoon (and before dinner time) to invest in PAR. Third, as in several earlier studies, our study also points to the lower PAR among adults in low income households and those residing in neighborhoods with a high fraction of non-Caucasians. While the reasons for these results need to be explored further in future studies, the results suggest a need for targeted campaigns to increase awareness about physical activity benefits in neighborhoods with a significant fraction of low-income households and/or non-Caucasian households. Further, it is important to pursue efforts to evaluate current facilities for PAR, and invest in improved facilities and PAR opportunities, in low income and/or non-Caucasian neighborhoods. This is an issue that needs top priority, especially because there is evidence from earlier research (see Davison *et al.*, 2003, Trost *et al.*, 2003, and Davis *et al.*, 2007, Sener *et al.*, 2009) that children explicitly model their parents' physical activity participation.[12] This finding in the literature, combined with the decreasing share of the Caucasian population in the U.S. and the increasing share of the non-Caucasian population, implies that there could be a "ripple" effect in physical inactivity levels over the next few generations of the U.S. population, unless quick and immediate steps are taken to "nip physical inactivity in the bud" among adults in the U.S. population in general, and in non-Caucasian adults in particular. Fourth, interventions targeted toward year-round physical activities should benefit from promoting home-based physical activity in the winters, given the tendency to pursue recreational activities at home during the cold season. Finally, and not withstanding residential self-selection issues, our results suggest the

[12] While the relative contributions of various mechanisms of the positive association between parents' PAR and their children's PAR is still being debated (*i.e.*, whether this is based on genetics, direct modeling (*i.e.*, parents' own physical activity involvement effects on children's physical activity levels), provision of time and money resources to support children's activities, rewarding desirable behaviors and punishing//ignoring undesirable behaviors, parents' own attitudes and beliefs about the importance of physical activity, and adopting authoritative parenting procedures to encourage children's physical activity), that direct modeling does play a role in this association is not in question.

positive PAR benefits of improved bicycle facilities and clubs in/around residences. These built environment effects do point to the need for the design of near term, feasible, and effective urban form strategies that promote compact and mixed land-use designs with good bicycling facilities.

In addition to the implications of the research results for public health policies, the model developed in the paper can be used as part of activity-based travel frameworks for forecasting purposes. For example, in the Comprehensive Econometric Microsimulator for Daily Activity-travel Patterns (CEMDAP; see Pinjari *et al.*, 2006), one of the modules of the activity generation stage corresponds to the prediction of recreational activity participations of individuals. The model in this paper can readily be integrated for this purpose. Further, and as noted earlier, the underlying motivation and behavior of recreational activity participation as well as the travel for recreational activities are quite different than that of other activity purposes. Therefore, activity-based travel demand forecasting tools would significantly benefit from incorporating the spatial and temporal contexts of recreational activity participation as identified in the proposed model.

Overall, this paper indicates the important effects of individual demographics, work-related characteristics, household demographics and physical environment variables on the propensity to invest time in physical activity, and the associated spatial and temporal choices of physical activity participation. The paper also underscores the importance of examining the spatial and temporal contexts of physical activity participation for informed physical activity promotion and activity-based travel analysis. The field would benefit from additional research on the contexts characterizing individual recreational physical activity participations, rather than focusing solely on the intensity (in terms of frequency, duration, and/or level of effort) of recreational physical activity within a given time period.

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Table 1. Descriptive Statistics of Recreational Activity Participation

Type of Recreational Activity (4448 adults in total)	Total number (and %) of individuals participating		Mean duration of participation among those who participate in the activity (mins)	Number of individuals, and % of total number, who participate….			
				Only in activity category		In the activity category and other activity categories	
	#	%		#	%	#	%
In-home recreation **(IHR)**	2266	50.9	221	1745	77.0	521	23.0
Out-of-home physically inactive recreation **(PIR)**	1367	30.7	117	971	71.0	396	29.0
Out-of-home physically active recreation **(PAR)**	1512	34.0	100	1075	71.1	437	28.9
Location							
Club	663	14.9	96	484	73.0	179	27.0
Neighborhood	475	10.7	61	280	58.9	195	41.1
Outdoors	411	9.2	142	285	69.3	126	30.7
Time-of-day							
AM peak	397	8.9	100	228	57.4	169	42.6
Midday	561	12.6	101	373	66.5	188	33.5
PM peak	387	8.7	90	262	67.7	125	32.3
Night	256	5.8	78	165	64.5	91	35.5

Table 2. Distribution of Participation in Physical Recreational Activities by Location and Time-of-day

	# of individuals	%	AM peak		Midday		PM peak		Night	
			#	%	#	%	#	%	#	%
			397	26.3[*]	561	37.1	387	25.6	256	16.9
Club	663	43.8[†]	134	20.2[‡]	245	37.0	173	26.1	117	17.6
				33.8[ς]		43.7		44.7		45.7
Neighborhood	475	31.4	181	38.1	141	29.7	104	21.9	95	20.0
				45.6		25.1		26.9		37.1
Outdoors	411	27.2	82	20.0	185	45.0	110	26.8	47	11.4
				20.7		33.0		28.4		18.4

[*] and [†] Percentages are based on the number of individuals who participate in at least one (out-of-home) physical recreational activity during the survey day; *i.e.*, out of 1512 individuals.

[‡] Percentages are based on total number of individuals participating in row activity type [(134/663) × 100 = 20.2%].

[ς] Percentages are based on total number of individuals participating in column activity type [(134/397) × 100 = 33.8%].

Table 3. The Mixed MDCEV Model Results: Baseline Parameter Estimates

	Individual Demographics												Work-Related Characteristics					
	Female		**Age**				**Physically disabled**		**Full time student**		**Driver license**		**Employed**		**Work-schedule flexibility**			
			Less than 30 years		**30 - 49 years**										**Partially flexible**		**Fully flexible**	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
In-home recreation **(IHR)**	-	-	-	-	-	-	0.48	3.05	-	-	-	-	-	-	-	-	-	-
Out-of-home physically inactive recreation **(PIR)**	0.37	5.27	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Out-of-home physically active recreation **(PAR)**																		
Location																		
Club	0.27	2.79	-	-	-	-	-	-	-	-	-	-	0.49	3.52	0.22	1.68	0.32	2.58
Neighborhood	0.22	1.80	-0.91	-4.59	-0.26	-2.02	-	-	-	-	-0.55	-2.39	-	-	-	-	-	-
Outdoors	0.15	2.91	-0.42	-3.01	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Time-of-day																		
AM peak	0.19	1.58	-	-	-	-	-0.58	-1.84	-1.17	-2.97	-	-	-0.71	-6.01	-	-	-	-
Midday	-	-	-	-	-	-	-	-	-	-	-	-	-0.74	-5.74	-0.52	-3.00	-0.35	-2.28
PM peak	0.17	1.42	0.73	4.18	0.57	4.00	-0.58	-1.84	-	-	-	-	-	-	-	-	-	-
Night	-	-	0.40	2.88	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Location / time-of-day																		
Club / PM peak	-	-	-	-	-	-	-	-	-	-	-	-	0.71`	2.48	-	-	-	-
Neighborhood / PM peak	-	-	-	-	-0.48	-1.83	-	-	-	-	-	-	-	-	-	-	-	-
Outdoors / Midday	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outdoors / Night	-0.15	-2.23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 3 (Continued.) The Mixed MDCEV Model Results: Baseline Parameter Estimates

	Household Demographics													
	Nuclear family		**Presence of kids**				**Household Income**				**Number of vehicles**		**Number of bicycles**	
			Aged 0-4		**Aged 5-15**		**Less than 35K**		**Greater than 90K**					
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
In-home recreation **(IHR)**	-0.22	-2.86	-	-	-	-	0.31	4.45	-	-	-	-	-	-
Out-of-home physically inactive recreation **(PIR)**	-	-	-	-	-	-	-	-	-	-	0.15	4.00	-	-
Out-of-home physically active recreation **(PAR)**														
Location														
Club	-	-	-	-	-	-	-	-	0.46	5.09	-	-	-	-
Neighborhood	-	-	-	-	-	-	-	-	-	-	-	-	0.07	1.80
Outdoors	-	-	-	-	-	-	-	-	-	-	0.05	1.97	-	-
Time-of-day														
AM peak	-	-	-	-	-0.36	-3.28	-	-	-	-	0.15	3.04	-	-
Midday	-	-	0.48	3.00	-	-	-	-	-	-	-	-	-	-
PM peak	-	-	-	-	-0.36	-3.28	-	-	-	-	-0.29	-3.41	-	-
Night	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Location / time-of-day														
Club / PM peak	-	-	-	-	-	-	-	-	-	-	0.30	2.48	-	-
Neighborhood / PM peak	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Outdoors / Midday	-	-	0.40	1.66	-	-	-	-	-	-	-	-	-	-
Outdoors / Night	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 3 (Continued.) The Mixed MDCEV Model Results: Baseline Parameter Estimates

	Physical Environment Variables											
	Seasonal Characteristics				***Transportation System Attributes/Built Environment Characteristics***				***Zonal Demographics***			
	Winter		**Sumer**		**Accessibility to physical activity centers**		**'Bikeway density' interacted with 'number of bicycles in the household'**		**Fraction of Caucasian American population**		**Mean household income**	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
In-home recreation **(IHR)**	0.22	2.53	-	-	-	-	-	-	-0.16	-1.45	-	-
Out-of-home physically inactive recreation **(PIR)**	-	-	-	-	-	-	-	-	-0.16	-1.45	-	-
Out-of-home physically active recreation **(PAR)**												
Location												
Club	-	-	-	-	2.44	2.75	-	-	-	-	0.01	2.41
Neighborhood	-	-	-	-	-	-	0.02	2.95	-	-	-	-
Outdoors	-	-	0.17	3.82	-	-	-	-	-	-	-	-
Time-of-day												
AM peak	-	-	-	-	-	-	-	-	-	-	-	-
Midday	-	-	-	-	-	-	-	-	-	-	-	-
PM peak	-	-	-	-	-	-	-	-	-	-	-	-
Night	-	-	-	-	-	-	-	-	-	-	-	-
Location / time-of-day												
Club / PM peak	-	-	-	-	-	-	-	-	-	-	-	-
Neighborhood / PM peak	-	-	-	-	-	-	-	-	-	-	-	-
Outdoors / Midday	-	-	-	-	-	-	-	-	-	-	-	-
Outdoors / Night	-	-	-	-	-	-	-	-	-	-	-	-

Table 4. The Mixed MDCEV Model Results: Satiation Parameters - α_k Estimates

Activity type	Activity location		Activity time-of-day	α_k Parameters	t-statistic*
Both physically inactive and active	In-home		-	0.989	3.69
Physically inactive	Out-of-home		-	0.930	15.75
Physically active	Out-of-home	Club	AM peak	0.949	4.66
			Midday	0.956	5.74
			PM peak	0.960	4.61
			Night	0.957	4.15
		Neighborhood	AM peak	0.876	8.37
			Midday	0.883	7.08
			PM peak	0.885	6.16
			Night	0.871	6.35
		Outdoors	AM peak	0.940	4.34
			Midday	0.947	5.67
			PM peak	0.965	3.37
			Night	0	Fixed

*The t-statistic is computed for the null hypothesis $\alpha_k = 1$.