A Joint Model for the Perfect and Imperfect Substitute Goods Case: Application to Activity Time-Use Decisions

Chandra R. Bhat
The University of Texas at Austin
Department of Civil, Architectural & Environmental Engineering
1 University Station C1761, Austin, Texas 78712-0278
Tel: 512-471-4535, Fax: 512-475-8744
Email: bhat@mail.utexas.edu

Sivaramakrishnan Srinivasan
University of Florida
Dept of Civil and Coastal Engineering
365 Weil Hall, PO Box 116580, Gainesville, FL 32611-6580
Tel: 352-392-9537, Fax: (352) 392-3394
Email: siva@ce.ufl.edu

Sudeshna Sen
The University of Texas at Austin
Department of Civil, Architectural & Environmental Engineering
1 University Station C1761, Austin, Texas 78712-0278
Tel: 512-471-4535, Fax: 512-475-8744
Email: ssen@mail.utexas.edu

ABSTRACT

This paper formulates a model for the joint analysis of the imperfect and perfect substitute goods case. That is, it enables the modeling of choice situations where consumers choose multiple alternatives at the same time from a certain set of alternatives, but also choose only one alternative from among a subset of alternatives. For example, in the context of time-use in leisure activity, individuals may participate in combinations of social, out-of-home recreation, and out-of-home non-maintenance shopping pursuits. These three activity types are imperfect substitutes in that they serve different functional needs of individuals and households. However, if an individual participates in out-of-home recreation, s/he may participate in only one of physically passive activities (for example, going to the movies), partially physically active activities (going to the beach or participating in spectator sports), or physically active activities (for example, working out at a gym) during a given time period (such as a weekday or a weekend day). To our knowledge, this paper is the first to consider a unified utility-maximizing framework for the analysis of such a joint imperfect-perfect substitute goods case in the economic literature.

The model formulated in the paper is applied to the time-use decisions of individuals. Specifically, individual time-use in maintenance and leisure activities are modeled as a function of demographic variables, urban environment attributes, and day of week/season effects. The results from the model can be used to examine time use choices across different segments of the population (for example, male vs. female, young vs. old, *etc.*), as well as to assess the potential impact of urban form policies on individual time use decisions.

1. INTRODUCTION

There are several choice situations that are characterized by the choice of multiple alternatives simultaneously. An example of such a choice situation is activity type choice, where an individual may decide to participate in multiple kinds of maintenance and leisure activities within a given time period. Such multiple discrete situations may be modeled using the traditional single discrete choice models by identifying all combinations or bundles of the "elemental" alternatives (activity types in the example above), and treating each bundle as a "composite" alternative (the term "single discrete choice" is used to refer to the case where a decision-maker chooses only one alternative from a set of alternatives). A problem with this approach is that the number of composite alternatives increases rapidly with the number of elemental alternatives. Specifically, if J is the number of elemental alternatives, the total number of composite alternatives is ($2^J - 1$). As an example, with 10 different activity types, the total number of all bundled alternatives is 1023.

Another approach to analyze multiple discrete situations is to use the multivariate probit (logit) methods of Manchanda *et al.* (1999), Baltas (2004), Edwards and Allenby (2003), and Bhat and Srinivasan (2005). In these multivariate methods, the multiple discreteness is handled through statistical methods that generate correlation between univariate utility maximizing models for single discreteness. While interesting, this second approach is more of a statistical "stitching" of univariate models rather than being fundamentally derived from a rigorous underlying utility maximization model for multiple discreteness. The resulting multivariate models also do not collapse to the standard discrete choice models when all individuals choose one and only one alternative at each choice occasion.

In both the approaches discussed above to handle multiple discreteness, there is no recognition that individuals choose multiple alternatives to satisfy different functional or variety seeking needs (such as wanting to relax at home as well as participate in out-of-home recreation). Thus, the approaches fail to incorporate the diminishing marginal returns (*i.e.*, satiation) in participating in a single type of activity, which is the fundamental driving force for individuals choosing to participate in multiple activity types. Finally, in both the approaches above, it is very cumbersome, even if conceptually feasible, to include a continuous choice into the model (for example, modeling the different activity purposes of participation as well as the duration of participation in each activity purpose).

A simple and parsimonious econometric approach to handle multiple discreteness was formulated by Bhat (2005) based on the use of a non-linear utility structure with a multiplicative log-extreme value error term. The non-linear utility structure used in Bhat's approach was employed originally by Kim *et al.* (2002) as a specific satiation-based formulation within the broader Kuhn-Tucker multiple-discrete economic model of consumer demand proposed by Wales and Woodland (1983).[1] Bhat's model, labeled the multiple discrete-continuous extreme value (MDCEV) model, is analytically tractable in the probability expressions and is very practical even for situations with a large number of discrete consumption alternatives, unlike the models of Wales and Woodland and Kim *et al.* In fact, the MDCEV model represents the multinomial logit (MNL) form-equivalent for multiple discrete-continuous choice analysis and collapses exactly to the MNL in the case that each (and every) decision-maker chooses only one alternative. Extensions of the MDCEV model to accommodate unobserved heteroscedasticity

[1] The reader is referred to von Haefen and Phaneuf (2005) for a recent review of Kuhn-Tucker demand system approaches. We would like to thank an anonymous reviewer for bringing our attention to the work by von Haefen and colleagues.

and error correlation among alternatives is straightforward, and is similar to the movement from the MNL model to the MMNL model in the standard discrete choice literature.

The MDCEV model and its mixed extensions are suited for the case when the alternatives are imperfect substitutes, as recognized by the use of a non-linear utility that accommodates a diminishing marginal utility as the consumption of any alternative increases. Thus, in the context of time-use in many different kinds of leisure activity purposes, the time investment in all the consumed leisure activity purposes is such that the marginal utilities are the same across purposes at the optimal time allocations. Also, for an activity purpose in which no time is invested, the marginal utility for that activity purpose at zero time investment is less than the marginal utility at the consumed times of other purposes (Bhat, 2005). However, there are many instances where the real choice situation is characterized by a combination of imperfect and perfect substitutes (perfect substitutes correspond to the case where consumers prefer to select only one discrete alternative at any choice occasion; see Hanemann, 1984). For example, individuals may participate in a combination of grocery shopping, other non-maintenance shopping (shopping for clothes, shoes, furniture, *etc.*), and recreational pursuits. These three alternatives are imperfect substitutes in that they serve different functional needs of households and individuals. However, within the group of recreational activity, there may be multiple kinds of more specific sub-activity types. There are many different ways of classifying recreational pursuits, as discussed by Mokhtarian *et al.* (2005). But assume that the recreational pursuits are classified based on the level of associated physical activity as (1) physically passive (for example, going to the movies, attending a concert, *etc*.), (2) partially physically active (such as going to the beach or participating in spectator sports), and (3) physically active (working out at a gym or playing soccer). In any given day, an individual, if s/he chooses to participate in recreation, may participate in only one of these recreational activity categories. The MDCEV model, as formulated in Bhat (2005), needs to be modified to handle such a combination of a multiple discrete-continuous choice among alternatives, as well as a single choice of one sub-alternative within one or more of the alternatives.

In this paper, we extend Bhat's model for the imperfect substitute goods case to include a nested structure that facilitates the joint analysis of the imperfect and perfect substitute goods case. This is achieved by using a satiation-based utility structure across the imperfect substitutes, but a simple standard discrete choice-based linear utility structure within perfect substitutes. To our knowledge, this is the first consideration of such a unified utility-maximizing framework for joint imperfect-perfect substitute goods analysis in the economic literature. As discussed earlier, previous studies of the imperfect substitute goods case include Wales and Woodland (1983), Kim *et al.* (2002), and Bhat (2005), while previous studies of the perfect substitute goods case include Hausman (1980), Dubin and McFadden (1984), Hanemann (1984), Mannering and Winston (1985), Train (1986), Chiang (1991), Chintagunta (1993), and Arora *et al.* (1998).

The formulation of the joint model is developed in the context of time-use among several different activity types on a weekend day. Such an analysis is central to the activity-based approach to travel demand modeling, as discussed by Bhat and Koppelman (1999), Pendyala and Goulias (2002), Arentze and Timmermans (2004), and Ye *et al.* (2004). To be sure, several earlier studies have also used a utility-maximization structure to examine individuals' time-use in the past. These include Munshi (1993), Kitamura *et al.* (1996), Yamamoto and Kitamura (1999), Bhat and Misra (1999), Meloni *et al.* (2004), Ettema (2005), and Bhat (2005). The current effort generalizes these earlier efforts by formulating a flexible and easy-to-estimate model even with a large number of activity types. In addition to considering both imperfect and perfect substitutes, the paper differs from earlier time-use analysis studies in several ways. First, the current effort considers time-use in both maintenance-related as well as leisure activities by considering maintenance-related activity as an "outside" good in the consumer demand analysis. Thus, the overall time invested in leisure activities is endogenous in the modeling analysis. Second, we use a 13-category classification of leisure activities compared to the relatively coarse 2-5 category classification used in earlier studies. Third, the analysis distinguishes out-of-home recreational time-use based on the level of physical activity, as well as differentiates between time use in pure recreation travel episodes without a specific destination (for example, running/bicycling around the neighborhood or taking a car ride) and recreational activity episodes pursued at a specific out-of-home location that requires travel as a means to get to the location. As discussed by Bhat and Lockwood (2004), the underlying motivations and factors affecting participation in these different kinds of recreation are not the same, which points to the need to distinguish among these recreational activity types for travel demand forecasting. In addition, differentiating among the types of recreational activity pursuits can provide important information for encouraging physically active lifestyles, and promoting a healthier population. Fourth, several urban form and street network measures are computed in the current analysis at different spatial resolutions around a household to examine the impacts of the physical environment on time-use patterns.

The rest of this paper is organized as follows. The next section develops the utility structure and the econometric framework for the joint model of perfect and imperfect substitutes. Section 3 discusses the data sources and the sample formation procedure. This section also provides important descriptive statistics of the sample. Section 4 presents the empirical results. Section 5 demonstrates the application of the model. Section 6 concludes the paper.

2. UTILITY STRUCTURE

Consider, without loss of generality, that the first activity purpose corresponds to maintenance activities (grocery shopping, household chores, personal business, medical appointments, *etc.*). As one would expect, all individuals spend some time on maintenance activities over the weekend day. Let there also be (J-1) different leisure activity purposes that an individual can potentially allocate time to (we suppress the index for the individual in the following presentation). Let t_j be the time spent in activity purpose j (j = 1, 2, …, J). We specify the utility accrued to an individual as the sum of the utilities obtained from investing time in each activity purpose. Specifically, we define utility over the J purposes as:

$$U = \psi(x_1)t_1^{\alpha_1} + \sum_{j=2}^{J}\psi(x_j)(t_j + 1)^{\alpha_j} \ , \tag{1}$$

where $\psi(x_j)$ is the baseline utility for time invested in activity purpose j, and the α_j's (j = 1, 2, …, J) are parameters. Note that ψ is a function of observed characteristics, x_j, associated with purpose j. A translational parameter of 1 is added to t_j for j=2, 3…, J in the utility function to allow corner solutions for these activity purposes (*i.e.*, to allow the possibility that the individual does not participate in one or more of these activity purposes; see Kim *et al.*, 2002 and Bhat, 2005). There is no such translation parameter for the first activity purpose because all individuals allocate some time to activity purpose 1 (by definition). α_j influences the rate of diminishing marginal utility of investing time in activity purpose j. The function in Equation (1) is a valid utility function if $\psi(x_j) > 0$ and $0 < \alpha_j \leq 1$ for all j.

The utility form of Equation (1) is able to accommodate a wide variety of time allocation situations based on the values of $\psi(x_j)$ and α_j. A high value of $\psi(x_1)$ and a value of α_1 close to 1 implies a high baseline preference and low satiation for maintenance activity. This represents the situation where the individual allocates almost all his/her time to maintenance activity and little to no participation in leisure activities. On the other hand, about equal values of $\psi(x_j)$ and small values of α_j across the various purposes *j* represents the situation where the individual invests time in almost all activity purposes (*i.e.* a "variety-seeking" individual). More generally, the utility form allows a variety of situations characterizing an individual's underlying behavioral mechanism with respect to time allocation to activity purpose *j*, including (a) low baseline preference and high satiation (low ψ_j and low α_j), (b) high baseline preference and high satiation (high ψ_j and low α_j), (c) low baseline preference and low satiation (low ψ_j and high α_j), and (d) high baseline preference and low satiation (high ψ_j and high α_j).

2.1 Random Utility Model

As in Kim *et al.* (2002) and Bhat (2005), we introduce a multiplicative random element to the baseline utility as follows:

$$\psi(x_j, \varepsilon_j) = \psi(x_j) \cdot e^{\varepsilon_j}, \tag{2}$$

where ε_j captures idiosyncratic (unobserved) characteristics that impact the baseline utility for purpose *j*. The exponential form e^{ε_j} for the introduction of random utility guarantees the positivity of the baseline utility as long as $\psi(x_j) > 0$. To ensure this latter condition, we further parameterize $\psi(x_j)$ as $\exp(\beta' x_j)$, which then leads to the following form for the baseline random utility:

$$\psi(x_j, \varepsilon_j) = \exp(\beta' x_j + \varepsilon_j). \tag{3}$$

The x_j vector in the above equation includes a constant term reflecting the generic preference in the population toward purpose *j*. The overall random utility function then takes the following form:

$$\tilde{U} = [\exp(\beta' x_1 + \varepsilon_1)] t_1^{\alpha_1} + \sum_{j=2}^{J} [\exp(\beta' x_j + \varepsilon_j)](t_j + 1)^{\alpha_j} \tag{4}$$

From the analyst's perspective, the individual is maximizing random utility ($\tilde{U}$) subject to the time budget constraint that $\sum_{j=1}^{J} t_j = T$, where T is the time available for allocation among the J activity purposes.

2.2 Accommodating Perfectly Substitutable Subpurposes within Each Purpose *j*

The development thus far is similar to Bhat (2005). However, now we consider the case where an activity purpose *j* may be more finely classified into one of several subpurposes. For example as indicated earlier, the out-of-home recreation activity purpose can be one of several types: physically passive recreation, partially physically active recreation, or physically active recreation. An individual may participate only in one of these types of out-of-home recreation (OHR) during a certain time period (such as a day), if there is any participation in OHR at all. To handle such situations, partition the leisure activity purpose j $(j \geq 2)$ into two categories: (1) those that are not more finely classified $(j \notin B)$ and (2) those that are more finely classified $(j \in B)$. Then, we rewrite the utility form as:

$$\begin{aligned} \tilde{U} = {} & [\exp(\beta' x_1 + \varepsilon_1)] t_1^{\alpha_1} + \sum_{j \notin B} [\exp(\beta' x_j + \varepsilon_j)](t_j + 1)^{\alpha_j} \\ & + \sum_{j \in B} \left[\exp\left(\max_{l \in N_j} \{W_{lj}\} \right) \right] (t_j + 1)^{\alpha_j}, \end{aligned} \tag{5}$$

where N_j is the set of subpurposes l within activity purpose j $(j \in B)$, and the random utility of the activity subpurpose l within purpose j is written as:

$$W_{lj} = \beta' x_j + \gamma' z_{lj} + \eta_{jl}. \tag{6}$$

In the above expression, $\beta' x_j$ is the overall observed utility component of activity purpose j, z_{lj} is an exogenous variable vector influencing the utility of subpurpose l within activity purpose j $(j \in B)$, γ is a corresponding coefficient vector to be estimated, and η_{jl} is an unobserved error component specific to subpurpose l of purpose j $(j \in B)$.

The Lagrangian function for maximizing random utility $(\tilde{U})$ in Equation (5) subject to the time budget constraint is:

$$‹ = \tilde{U} - \lambda \left[\sum_{j=1}^{J} t_j - T \right], \tag{7}$$

where λ is the Lagrangian multiplier associated with the time constraint. The Kuhn-Tucker (*K-T*) first order conditions for the optimal time allocations (the t_j^* values) can then be shown to be given by (see discussion in Bhat, 2005):

$$\left.\begin{array}{l} H_j = H_1 \text{ if } t_j^* > 0 \\ H_j < H_1 \text{ if } t_j^* = 0 \end{array}\right\} (j = 2,3,...K), \tag{8}$$

where

$$\begin{aligned} H_1 &= \beta' x_1 + \ln \alpha_1 + (\alpha_1 - 1) \ln t_1^* + \varepsilon_1, \\ H_j &= \beta' x_j + \ln \alpha_j + (\alpha_j - 1) \ln(t_j^* + 1) + \varepsilon_j \text{ if } j \notin B, j \geq 2, \\ &= \underset{l \in N_j}{Max} \{ \beta' x_j + \gamma' z_{lj} + \eta_{jl} \} + \ln \alpha_j + (\alpha_j - 1) \ln(t_j^* + 1) \text{ if } j \in B, j \geq 2. \end{aligned} \tag{9}$$

The satiation parameter, α_j, in the expressions above needs to be bounded between 0 and 1, as discussed earlier. To enforce this condition, we parameterize α_j as $1/[1 + \exp(-\delta_j)]$.

Further, to allow the satiation parameters to vary across individuals, we write $\delta_j = \tau'_j y_j$, where y_j is a vector of individual characteristics impacting satiation for the *j*th alternative, and τ_j is a corresponding vector of parameters. Also, note that, in Equation (9), a constant cannot be identified in the $\beta' x_j$ term for one of the *J* alternatives (because only the difference in the H_j from H_1 matters). Similarly, individual-specific variables are introduced in the H_j's for (*J*-1) alternatives, with the remaining alternative serving as the base.

2.3 Econometric Model

The assumptions about the ε_j terms and the η_{jl} terms complete the econometric specification: different assumptions lead to different model structures. In the remainder of this section, we identify structures with varying levels of flexibility, all of which are also easy to estimate.

2.3.1 Basic Structure

The simplest structure is obtained by assuming that the ε_j terms $(j = 1 \text{ and } j \notin B)$ and the η_{jl} terms $(j \in B)$ are identically standard extreme value distributed. Further, we write the error term η_{jl} as $\eta_{jl} = \lambda_j + \lambda_{jl}$, where λ_j is a common unobserved utility component shared by all subpurpose alternatives within activity purpose *j*. λ_{jl} is an extreme value term distributed identically with scale parameter θ_j $(0 < \theta_j \leq 1 \; \forall \; j \in B)$. The λ_{jl} terms are independent of one another and of the λ_j and ε_j terms.

With the above assumptions and using the properties of the extreme value distribution, we can simplify the expression for H_j for $j \in B$ as:

$$
\begin{aligned}
H_j &= \beta' x_j + \lambda_j + \underset{l \in N_j}{Max}\{\gamma' z_{lj} + \lambda_{jl}\} + \ln \alpha_j + (\alpha_j - 1)\ln(t_j^* + 1) \\
&= \beta' x_j + \theta_j \ln \sum_{l \in N_j} \exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right) + \ln \alpha_j + (\alpha_j - 1)\ln(t_j^* + 1) + \varepsilon_j \, ,
\end{aligned}
\tag{10}
$$

where ε_j $(j \in B)$ is also now standard extreme value distributed. Then, following the derivation of the MDCEV model in Bhat (2005), the marginal probability that the individual participates in the first M of the K activity purposes ($M \geq 1$) for durations $t_1^*, t_2^*, \ldots t_M^*$ may be written as:

$$
P(t_1^*, t_2^*, \ldots t_M^*, 0, 0, 0, \ldots, 0) = \left[\prod_{j=1}^{M} r_j\right]\left[\sum_{j=1}^{M} \frac{1}{r_j}\right]\left[\frac{\prod_{j=1}^{M} e^{V_j}}{\left(\sum_{j=1}^{K} e^{V_j}\right)^M}\right](M-1)!\, ,
\tag{11}
$$

where

$$
r_j = \left(\frac{1-\alpha_j}{t_j^* + 1}\right) \text{ and}
$$

$$
\begin{aligned}
V_1 &= \beta' x_1 + \ln \alpha_1 + (\alpha_1 - 1)\ln t_1^*, \\
V_j &= \beta' x_j + \ln \alpha_j + (\alpha_j - 1)\ln(t_j^* + 1) \text{ if } j \notin B, j \geq 2, \\
&= \beta' x_j + \theta_j \ln \sum_{l \in N_j} \exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right) + \ln \alpha_j + (\alpha_j - 1)\ln(t_j^* + 1), \text{if } j \in B, j \geq 2.
\end{aligned}
\tag{12}
$$

The conditional probability that subpurpose l will be participated in for an amount of time $t_j^* (l \in N_j, j \in B)$, given that $t_j^* > 0$, may be obtained from Equation (6) as:

$$
P(l \mid t_j^* > 0; l \in N_j) = \frac{\exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right)}{\sum_{g \in N_j} \exp\left(\frac{\gamma' z_{gj}}{\theta_j}\right)}
\tag{13}
$$

Next, let j=2, 3, …S ($S \leq M$-1) be the activity purposes that the individual participates in that are more finely classified into subpurposes and let j=S+1, S+2,…M be activity purposes that the individual participates in that are not further categorized into subpurposes. Then, the unconditional probability that the individual chooses to participate in subpurpose a of activity purpose 2 for duration t_{2a}^*, subpurpose b of activity purpose 3 for t_{3b}^*, … subpurpose s of activity purpose S for t_{Ss}^*, and for durations $t_{S+1}^*, t_{S+2}^* ... t_M^*$ in the other activity purposes may be written as:

$$\begin{aligned} &P(t_1^*, t_{2a}^*, t_{3b}^* ... t_{Ss}^*, t_{S+1}^*, t_{S+2}^* ... t_M^*, 0,0...0) \\ &= P(t_1^*, t_2^*, ... t_M^*, 0,0,...0) \times P(a \mid t_2^* > 0) \times P(b \mid t_3^* > 0) \times ... \times P(s \mid t_S^* > 0) \end{aligned} \tag{14}$$

There are two points to note in the expression above. First, the parameters γ and $\theta_j \, (j \in B)$ appear in both the MDCEV probability expression $P(t_1^*, t_2^*, \ldots t_M^*, 0,0,\ldots 0)$ as well as the standard discrete choice probability expression for the choice of subpurpose within the corresponding purpose j. This creates the jointness in the multiple discrete and single discrete choices. Second, if $\theta_j = 1$ for all $j \in B$, the joint model collapses to a restricted version of the MDCEV model with a total number of $J + \sum_{j \in B} A_j$ alternatives, where A_j is the number of alternatives in N_j. This can be easily observed from Equation (11) and Equation (14) by noting that the $\sum_{l \in N_j} \exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right)$ terms in the denominators of the single discrete choice models for activity subpurposes within each (and all) purposes $j \in B$ cancel with identical terms occurring in the $\prod_{j=1}^{M} e^{V_j}$ expression in the MDCEV probability expression of Equation (11) under the condition that $\theta_j = 1$. The restriction in the resulting MDCEV model is that the satiation parameter is equal across those "new" alternatives in the expanded MDCEV choice set that are subpurposes within the alternatives in the original MDCEV model. This restriction is to be expected, because different satiation parameters for the subpurpose alternatives would imply "imperfect" substitution, which cannot be allowed since only one subpurpose is chosen within each activity purpose.

2.3.2. GEV Structure for Single Discrete Choice

The basic structure discussed in the previous section adopted a multinomial logit (MNL) specification for the choice of subpurpose within each activity purpose $j \in B$. The MNL is saddled with the independence from irrelevant alternatives (IIA) property, which implies a restrictive equal cross-elasticity competition structure. To relax the IIA restriction, one can adopt a more general GEV specification for the single discrete choice models within each activity purpose $j \in B$. Specifically, rather than assuming that the λ_{jl} terms are independent across subpurposes l within activity purpose j ($j \in B$), one can impose a more general correlation structure as follows:

$$F_j(\lambda_{ji}, \lambda_{j2}, \ldots \lambda_{jL}) = \exp[-G_j(e^{-\lambda_{j1}}, e^{-\lambda_{j2}}, \ldots e^{-\lambda_{jL}})], \tag{15}$$

where G_j is a non-negative, homogeneous, function such that $G_j() \to +\infty$ when any of the arguments goes to $+\infty$, and the cross-partial derivatives are negative for odd cross-partials and positive for even cross-partials. Then, by McFadden's (1978) proof, the single discrete choice probabilities in Equation (13) take the following closed-form solution:

$$P(l \mid t_j^* > 0; l \in N_j) = \frac{e^{\gamma' z_{lj}} \cdot G_{lj}(e^{\gamma' z_{1j}}, e^{\gamma' z_{2j}}, \ldots e^{\gamma' z_{Lj}})}{\dfrac{1}{\theta_j} \times G_j(e^{\gamma' z_{1j}}, e^{\gamma' z_{2j}}, \ldots e^{\gamma' z_{Lj}})}, \tag{16}$$

where θ_j is the scale parameter of $\lambda_{j1}, \lambda_{j2} \ldots \lambda_{jL}$ and G_{lj} is the derivative of the function G_j with respect to its lth argument. Accordingly, the term that enters into the V_j expression in Equation (12) in the MDCEV model is $\theta_j \ln G_j (e^{\gamma' z_{j1}}, e^{\gamma' z_{j2}}, \ldots e^{\gamma' z_{jL}})$ instead of $\theta_j \ln \sum_{l \in N_j} \exp(\gamma' z_{jl} / \theta_j)$.

The G_j functions and the probability expressions for the single discrete choice in the joint model for some special cases are provided in Table 1. Two points to note from this table. First, the expressions in the table are similar to the traditional single discrete choice models, except for the additional scale parameter θ_j which determines the correlation due to common unobserved elements across all alternatives $l \in N_j$. Second, different GEV structures can be used for different alternatives *j* of the MDCEV model. Thus, the joint model of imperfect and perfect substitutes goods can combine the MDCEV model with many different types of GEV models simultaneously within a single unifying modeling framework.

2.3.3. Mixed Joint Model

The analyst can incorporate heteroscedasticity and/or error correlation in the multiple discrete-continuous component of the joint model or in the single discrete choice component of the joint model using a mixing distribution (see Bhat, 2005; Bhat, 2003). Alternatively, the analyst can also incorporate random coefficients in one or both components of the joint model using a mixing distribution. In all these cases, the formulation entails developing the conditional (on the random parameters) joint probability function, which takes the form of Equation (14). The unconditional probability is then obtained by integrating over the mixing distribution of the random parameters.

2.4 Model Estimation

The joint model can be estimated in a straightforward manner using the maximum likelihood inference approach. The likelihood function for any particular individual is given by Equation (14) for the basic model structure. The parameters to be estimated in the basic model structure include the β vector, the τ_j vector for each alternative *j* (embedded in the scalar α_j within V_j), the θ_j scalars for each alternative $j \in B$, and the γ vector. The parameters to be estimated in the GEV structure and the mixed joint structure include additional parameters from the GEV correlation structure and the mixing distribution.

3. DATA SOURCES AND SAMPLE INFORMATION

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 16 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.

In addition to the 2000 BATS data, several other secondary sources were used to derive measures associated with the urban and transportation environment in which the survey respondents undertake their activities and travel. The MTC provided, for each of the Traffic Analysis Zones (TAZ), data on (1) area coverage by land-use purpose, (2) number of housing units by dwelling type, (3) employment levels by sector, (4) population, income and age distribution of the population, and (5) area type of the zone. The MTC also provided zone-to-zone travel level of service (LOS) data that included inter-zonal distances, as well as peak and off-peak travel times and costs. The land-use/demographic and LOS files were used to characterize the urban environment and develop measures of accessibility to activity opportunities, as discussed in the next section. Another data source obtained from MTC was a GIS line layer describing all existing bicycle facilities in the Bay Area region. It included class 1 facilities (separate paths for cyclists and pedestrians), class 2 facilities (painted lanes solely for cyclists), and class 3 facilities (signed routes on shared roads). A final source of data was the Census 2000 TIGER files, from which two GIS line layers were extracted for the Bay Area region: one is the highway network (including interstate, toll, national, state and county highways) and the other is the local roadways network (including local, neighborhood, and rural roads).

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 clearly exercise a choice in their time-use. Second, we selected weekend day activity episodes 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 "pure recreation", and appended to the file from the second step. Fourth, all activity episodes were classified as in-home or out-of-home based on the location of participation. Fifth, the out-of-home shopping episodes were classified as maintenance or non-maintenance. This distinction was based on the location type of out-of-home activity participation, which was provided by respondents in the form of an open-ended response. About 10,000 distinct location types were reported in the survey, and they were manually recoded into 450 categories for analysis. The location types categorized as maintenance shopping included "dry cleaners/laundry services", "fruit stand", "grocery", and "gas station". Sixth, the following activity purposes were aggregated into a single maintenance activity purpose category: (1) in-home meals, (2) in-home and out-of-home personal household chores and personal care, (3) in-home and out-of-home personal business (barber/beauty shop, banking, *etc.*), (4) out-of-home maintenance shopping, and (5) out-of-home medical appointments. At the end of this sixth step, there were 11 non-work and non-school activity type categories: (1) maintenance, (2) in-home relaxation, (3) in-home recreation (hobbies, TV, *etc.*), (4) non-work internet use (which was mostly in-home and which we will refer to as internet use), (5) in-home social, (6) out-of-home social, (7) out-of-home meals, (8) out-of-home non-maintenance shopping (which we will refer to simply as out-of-home shopping), (9) out-of-home volunteer (including civic and religious activities), (10) out-of-home recreation (hobbies, exercise, *etc.*), and (11) pure recreation. Next, in the seventh step, we disaggregated the out-of-home recreation episodes into three types based on whether or not the episode involved physically passive pursuits, partially physically active pursuits, or physically active pursuits. This classification was based on the location type of the out-of-home recreational episode (note that we are unable to break down the in-home recreation episodes in a similar fashion). Eighth, pure recreation episodes were also categorized as physically active (if they involved the use of a non-motorized mode) or physically passive (if they involved a motorized mode for joy-riding). Next, the total time invested during the weekend day in each of the non-work activity purposes listed above was computed based on appropriate time aggregation across individual episodes within each category. During this process, we also computed the work duration on the weekend day to serve as an independent variable in the analysis of non-work time use. In addition, a careful analysis was undertaken to differentiate between imperfect substitutes and perfect substitutes across activity types. This analysis reflected the following: (a) individuals participate in either in-home or out-of-home social activities, but not both, (b) individuals participate in only one of the three types of out-of-home recreation (physically passive, partially physically active, and physically active), and (c) individuals participate in either active or passive pure recreation, but not both. Accordingly, we developed the two-level representation for the joint multiple discrete-continuous and single discrete analysis shown in Figure 1, where the higher level corresponds to the MDCEV model and the lower level reflects subpurposes within three of the MDCEV alternatives. Next, data on individual and household characteristics were appended to the data. Finally, a number of urban environment accessibility measures around each individual's residence were extracted from the land-use/demographic and LOS files, as discussed in the next section.

3.3 Urban Environment and Accessibility Variables

A number of urban environment variables characterizing the zone of residence of each individual were extracted/computed from the MTC zonal land-use/demographic file. These included (1) land-use composition measures (percentages of residential, commercial/industrial, and other categories), (2) fractions of single family and multi-family dwelling units, (3) residential density and employment density variables, and (4) area type variables classifying zones into one of 6 categories (core central business district, central business district, urban businesses, urban, suburban, and rural).

Two types of index measures were also computed from the zonal land-use/demographic file and the zonal LOS file. The first index variable, the land-use diversity variable, is computed as a fraction between 0 and 1. Values closer to one imply a richer land-use mix than values closer to zero. Three categories of land-uses are considered in the computation of the mix diversity variable: acres in residential use (*r*), acres in commercial/industrial use (*c*), and acres in other land uses (*o*). The actual form of the land-use mix diversity variable is:

$$\text{Land-use mix diversity} = 1 - \left\{ \frac{\left|\frac{r}{L} - \frac{1}{3}\right| + \left|\frac{c}{L} - \frac{1}{3}\right| + \left|\frac{o}{L} - \frac{1}{3}\right|}{(4/3)} \right\}, \qquad (17)$$

where $L = r + c + o$. The functional form assigns the value of zero if land-use is focused in only one category, and assigns a value of 1 if land-use is equally split among the three land-use categories. The second type of index measure corresponds to accessibility measures, which are of the Hansen type. We develop two accessibility measures, one each for shopping and recreation. These measures are computed as follows:

$$A_i^{shop} = \left(\sum_{j=1}^{N} R_j / d_{ij} \right) / N \text{ and } A_i^{rec} = \left(\sum_{j=1}^{N} V_j / d_{ij} \right) / N, \qquad (18)$$

where A_i^{shop} and A_i^{rec} denote the shopping and recreation accessibility indices, respectively, for TAZ *i*; R_j and V_j are the number of retail employees and vacant land acreage, respectively, in TAZ *j*; d_{ij} is the distance between zones *i* and *j*; and *N* is the total number of TAZs.

The urban environment variables and the land-use mix diversity variables discussed above were computed not only at the zonal level, but also at higher levels of geographic resolution. Specifically, these variables were computed for 0.25 mile, 1 mile, and 5 mile radii around the residence of each individual in the sample. This latter approach of using circular areas is not only of higher spatial resolution than a zone, but is likely to provide better measures of a household's immediate neighborhood (see Guo and Bhat, 2004). The procedure to compute the variables for circular areas around zones was based on assuming that the zonal level variables follow a uniform distribution within each zone, so that the zonal data can be disaggregate uniformly in space within the zone. Subsequently, the disaggregated data were projected onto and re-aggregated over the circular buffers around the geo-coded residences of each household to produce the appropriate circular unit measures. The motivation to compute the urban environment variables for different radii around a residence was to endogenously determine the spatial extent of the influence of such variables on individual time-use decisions during model estimation. Finally, the bikeway network GIS layer from MTC, and the highway network and local road network GIS layers from the census 2000 Tiger files, were projected onto the circular units of 0.25 mile, 1 mile, and 5 mile radii around each household's residence to obtain the total length of bikeways, highways, and local roads within each circular unit for each household.

3.4 Descriptive Time-Use Statistics in Sample

The final sample for analysis includes the weekend day time-use information of 6000 individuals. Table 2 provides descriptive statistics of participation in each of the activity purposes in the higher level multiple discrete-continuous component of the joint model. The second and third columns of the table indicate the frequency (percentage) of individuals participating in each activity type and the mean duration of participation among those who participate, respectively. Several observations may be made from the statistics in these two columns. First, all individuals, of course, participate in maintenance activity over the weekend, as can be observed from the first row of the second column. Second, among the leisure activity purposes, individuals participate most in out-of-home meals and out-of-home shopping (see second column of Table 2). Interestingly, these two leisure activity purposes also are among those with the shortest mean duration of participation (as can be observed from the third column in Table 2). This suggests a high baseline preference, and a high satiation, for out-of-home meals and out-of-home shopping activities within the group of leisure activities. Third, a reasonable percentage of individuals participate in in-home relaxing, in-home recreation, social, and out-of-home recreation, and the mean duration of participation in these activities is quite high. This implies a higher baseline preference for these four activity types compared to internet use, out-of-home volunteer activities, and pure recreation, as well as low satiation for these four activity categories compared to all other leisure activity purposes. Fourth, the internet use and pure recreation activity purposes have the lowest baseline preference among all activities; however, while pure recreation has high satiation effects (*i.e.*, low duration of participation), the internet use purpose has a relatively low satiation effect (*i.e.*, high duration of participation). The last two columns in Table 2 indicate the split between solo participations (*i.e.*, individual participation in only one activity type or a corner solution) and multiple activity participations (*i.e.*, individual participation in multiple activity types or interior solutions) for each activity type. Thus, the number for the maintenance activity type indicates that, of the 6000 individuals in the sample, 1145 (or 19%) participated only in maintenance activity during the day and 4855 (or 81%) participated in maintenance activity along with participation in one or more leisure activity types during the day. The results clearly indicate that, among the leisure activity purposes, individuals tend to participate in internet use, social, out-of-home meals, and in-home relaxing activities more often in conjunction with participation in other activity types during the day. This may be because individual observed and unobserved factors that increase participation in these activities also increase participation in other activity types or because of high satiation rate for one or more of these activities. The model in the paper accommodates both possibilities and can disentangle the two alternative effects.

Table 3 provides information on the distribution of the number of leisure activity purposes that individuals participate in, and the most common type of leisure activity purpose combinations. As can be observed, only about 19% of individuals participate exclusively in maintenance activities (this corresponds to the number of leisure activity purposes being equal to zero). Clearly, this result indicates that a traditional single discrete choice model is not adequate, and that a multiple discrete-continuous model is warranted. A majority of the individuals participate in 1 or 2 leisure activity types in addition to maintenance activity, though a significant fraction (about 22%) participate in 3 or more leisure activity purposes. The most common activity purpose combinations in each category of number of leisure activity purposes is provided in the final column of Table 3 (this column does not include the maintenance activity type for presentation ease, since all individuals participate in maintenance activity). The table shows that, among individuals who participated in maintenance activity and one other activity type, the most common leisure purposes are out-of-home shopping, in-home recreation, and out-of-home recreation. Among individuals participating in two or more leisure activity types, frequent combinations include out-of-home recreation, out-of-home shopping and out-of-home meals.

The splits in the lower-level single discrete choice models of Figure 1 are as follows: (1) For social activity, in-home social (19%) and out-of-home social (81%), (2) For out-of-home recreation activity, physically passive recreation (58%), partially physically active recreation (28%), and physically active recreation (14%), (3) For pure recreation, passive pure recreation (54%) and active pure recreation (46%).

4. EMPIRICAL ANALYSIS

4.1 Variables Considered

Several types of variables were considered in the discretionary time-use model. These included household sociodemographics (household size, presence and number of children, number of household vehicles, number of bicycles in the household, household income, family structure, and dwelling type), household location attributes (discussed in Section 3.3), individual demographics and employment characteristics (age, license holding to drive, student status, employment status, number of days of work, internet use, and ethnicity), and day of week (Saturday or Sunday) and season of year (fall, winter, spring, or summer).

4.2 Empirical Results

4.2.1 Error-Component Specification

In our analysis, we considered several error component specifications in the MDCEV part of the joint model to introduce correlation in the utilities of the nine leisure activity types. The best statistical result included the following error components: (1) an error component to accommodate correlation between the in-home leisure activities (in-home relaxation, in-home recreation, and the predominantly in-home internet use category), (2) one error component to accommodate correlation between the out-of-home leisure activities (out-of-home meals, out-of-home shopping, out-of-home volunteering, out-of-home recreation and pure recreation), and (3) an error component to accommodate correlation between the recreation activity categories (in-home relaxing, in-home recreation, out-of-home recreation, and pure recreation).

We also considered both a multinomial logit (MNL) and ordered generalized extreme value (OGEV) for the single discrete choice model among physically passive, partially physically active, and physically active recreation within the group of out-of-home recreation activity. The OGEV model allows adjacent alternatives (*i.e.*, the passive and partially active alternatives, and the partially active and active alternatives) to share unobserved factors. However, our analysis indicated that the MNL structure was statistically as good as the OGEV structure, and so a simple MNL structure was adopted.

4.2.2. Variable Effects

The effects of exogenous variables at the multiple discrete-continuous level and at the single discrete choice level are estimated jointly, along with the satiation and error-component parameters at the multiple discrete-continuous level, and the logsum parameters (*i.e.*, the θ_j

parameters). In this section, we discuss the variable effects separately in the multiple discrete-continuous level and at the simple discrete-choice level for ease in presentation. It is important to note that the variables in the single discrete choice model affect the baseline utility of the corresponding multiple discrete-continuous alternative through the logsum variable, $\ln \sum_{j \in N_j} \exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right)$.

4.2.2.1 MDCEV Model

The final specification results of the MDCEV component of the leisure time-use model are presented in Table 4. The maintenance activity purpose serves as the base category for all variables (and, thus, this purpose does not appear in the table as a column). In addition, a "-" for a variable for an alternative implies that the alternative also constitutes the base category for the variable.

Household Sociodemographics Among the household sociodemographic variables, the effect of the number of active and senior adults indicates that individuals in households with several adults have a high baseline preference for internet use and a low preference for out-of-home meals. Further, individuals in households with several active adults have a high baseline preference for in-home recreation (perhaps due to joint participation in such in-home recreation activities as watching a movie or a television show; see Bhat and Misra, 1999 for similar results using data from the Netherlands), while individuals in households with several senior adults have a high baseline preference for voluntary activities.

The impact of the household structure variables indicate the high baseline preference of individuals in nuclear family households for out-of-home volunteer, out-of-home recreation, and pure recreational pursuits, perhaps due to a stronger need to have a change from caring for children in-home and the propensity to participate with young children in outdoor pursuits. Individuals in nuclear and returning young adult families have a low preference for internet use, while single parent and single person families have a high preference for internet use. Finally, individuals in single parent and single person families have a high baseline preference for recreational and social pursuits.

The next household attribute is the number of bicycles in the household. As the number of bicycles in an individual's household increases, the individual is more likely to pursue out-of-home recreational activity. This is quite reasonable. Households who own more bicycles may be more outdoor-oriented by nature, and owning bicycles also provides an additional means to participate in outdoor recreation. The results also show that high bicycle ownership reduces the propensity to participate in in-home recreation and social activities, while high motorized vehicle ownership reduces participation in internet use. Also, the effect of the presence of internet access at home on internet use shows a positive effect. This is intuitive, especially because most individuals are in-home when accessing the internet over the weekends.

Finally, among the set of household sociodemographics, the results indicate that individuals in low income households have a higher baseline preference for in-home relaxation and in-home recreation than those in high income households, while those in high income households are more likely to participate in out-of-home shopping and out-of-home recreation. These results are consistent with the higher consumption potential of goods and out-of-home recreation facilities for individuals in high income earning households.

Household Location Variables An examination of the impact of household location variables indicates that, in general, individuals residing in central business district and urban zones are more likely to participate in leisure activities relative to individuals residing in suburban and rural zones (perhaps due to better accessibility to leisure activity opportunities in the more urbanized areas). Further, individuals residing in households with a high service employment within a 0.25 mile radius of their households have a high baseline preference for out-of-home meals, while individuals in households with high retail employment within a 5 mile radius have a high baseline preference for out-of-home shopping. These effects, again, are measuring the availability of opportunities for participation. However, the spatial extent for perceiving opportunity availability is more expansive for shopping relative to meals.

The effect of the land-use mix diversity variable suggests a higher (lower) propensity to participate in out-of-home shopping (out-of-home recreation) activities among individuals residing in households with a diverse land-use around 0.25 mile radius of their households. The negative effect of the fraction of single family households within a 0.25 mile radius on out-of-home recreational participation, and the negative impact of the population within a 1 mile radius on volunteer activities, are statistically significant, though not immediately intuitive (these effects need further exploration). Finally, among the household location variables, the length of bicycle lanes within a 1 mile radius of a household is associated with increased participation of individuals in pure recreation pursuits, as one would expect.

An important issue is in order here regarding the interpretation of the effect of household location variables. In the current analysis, household residential location is considered as an exogenous choice in the modeling of activity time-use. However, it is conceivable (if not quite likely) that households choose their location of residence based on their time-use desires, in which case the location effects are really correlations and not causal effects. Accommodating this self selection of households into neighborhoods is an important issue for future research.

Individual Sociodemographics and Employment Characteristics The results indicate that older individuals (>30 years) are, in general, less likely to participate in leisure activities than younger individuals ($\leq$29 years), a result also found by Yamamoto and Kitamura (1999). The availability of a license to drive has a positive effect on participation in out-of-home leisure activity pursuits, which may be attributed to the greater mobility to reach out-of-home activity centers.

Employed individuals have a higher propensity to participate in out-of-home shopping and recreation activity over the weekend than do unemployed individual, perhaps because of temporal constraints to access shopping and recreation activity centers and pursue such activities during the course of the work week. The impact of whether an individual worked on the weekend day and the duration of work need to be considered together. The results indicate that individuals who work over the weekend day are generally more likely to participate in leisure activity purposes compared to weekend non-workers. This is particularly true for in-home relaxation, in-home recreation, and out-of-home meals. However, weekend workers who work for more than 2.5-4 hours are less likely than weekend non-workers to participate in social, out-of-home shopping, and out-of-home recreational pursuits.

Other results associated with individual sociodemographics are as follows. Physically challenged individuals are less likely to participate in out-of-home leisure pursuits due to mobility constraints. Men are more unlikely than women to participate in out-of-home shopping, and volunteer activities, but more likely to participate in all other non-social leisure pursuits.

The effect of the race variables show that Caucasian-Americans, in general, are more likely than non-Caucasian-Americans to participate in all types of leisure activity pursuits. This is not the case only for social activities, out-of-home shopping, and pure recreation pursuits.

Day of Week and Seasonal Effects The results for the day of week effects shows a higher level of preference for in-home leisure activities and lower level of preference for out-of-home leisure on Sundays relative to Saturdays. This is reasonable since Sundays serve as a transition day between the weekend and the work week, and many individuals use it as an in-home "rest" day (see Lockwood *et al.*, 2005). The positive sign on "Sunday" for volunteer activities is intuitive since volunteer activities include religious activities. The seasonal effects are, rather surprisingly, not very important in determining activity participation.

Baseline Preference Constants All the baseline preference constants are negative, indicating the high baseline preference for the outside good (*i.e.*, maintenance activity). Among the leisure activities purposes, the high negative constants for internet use, out-of-home volunteer, and pure recreation activities are consistent with the low levels of participation in these purposes, as discussed in Section 3.2.

4.2.2.2 Single Discrete Choice Models for In-Home Out-of-Home Social Activity

Table 5 provides the results for the binary logit model of the choice of participation between in-home and out-of-home social activity, conditional on participation in social activity. The base category is "in-home social", and the parameters shown are specific to the "out-of-home social" category.

Household Sociodemographic Variables The results reveal that individuals in households with several other adults, and who are in nuclear families, are less likely to participate in out-of-home social activities (compared to in-home social activities). This is perhaps because individuals with other adults/children in the household have less of a need to socialize externally. Also, individuals in households with many vehicles (motorized or non-motorized) are more likely to pursue out-of-home social activities, presumably due to fewer mobility constraints.

Individual Sociodemographic and Employment Variables The age variables indicate that individuals in the mid-age range (30-65 years) are more likely to pursue out-of-home social activities than young individuals ($\leq$ 29 years) and old individuals (>65 years). Weekend workers are less likely than weekend non-workers to pursue out-of-home social activities, potentially due to the time overhead in pursuing out-of-home social activities. Physically challenged individuals are less likely to pursue out-of-home social activities due to mobility constraints. Finally, African-Americans are less likely to participate in out-of home social (and more likely to participate in in-home social) activities than other races.

Day of Week and Season of Year Individuals are less likely to participate in out-of-home social activities on Sundays (presumably due to Sundays being a transitional "rest" day at home before the new work week) and in the fall season.

4.2.2.3. Single Discrete Choice Model for Out-of-Home Recreation

The three choice alternatives under the out-of-home recreation activity purpose are physically passive recreation (base category), partially physically active recreation, and physically active recreation. Table 6 presents the results. None of the household sociodemographic variables turned out to be statistically significant, and so these variables do not appear in the table.

Household Location Variables The only household location variable appearing in the final specification is the diversity of land-use mix within 0.25 miles radius of the household. The sign on this variable shows that a diverse land-use mix is the immediate vicinity of a household is associated with increased participation in physically active recreation (however, the caveat that this may be a correlation effect rather than a causal effect applies).

Individual Sociodemographic and Employment Variables The results in Table 6 suggest that younger individuals ($\leq$29 years of age) are more disposed than other individuals to participate in passive recreation. This is an issue that would be of concern from a societal health standpoint, and suggests the need for informational campaigns on the health benefits of physical activity targeted toward young adults. Weekend workers are less likely to participate in partially active recreation compared to passive and active recreational pursuits, while the reverse is true for men.

Day of Week and Season of Year Individuals are more likely to participate in partially active recreation on Sundays (compared to Saturday) and less likely to participate in physically active recreation in the winter (compared to other seasons).

4.2.2.4. Single Discrete Choice Model for Pure Recreation Activity

The binary logit model results of the choice of participation between physically passive and physically active pure recreation are provided in Table 7. The results are self-explanatory. The effects of all variables are marginally significant.

4.2.3. Satiation Parameters

The satiation parameter, α_j, for each activity type *j* is parameterized as $1/[1+\exp(-\delta_j)]$, where $\delta_j = \tau'_j y_j$, where y_j is a vector of individual characteristics impacting satiation for the j^{th} alternative. This parameterization allows α_j to vary across individuals and still be bounded between 0 and 1. In our empirical analysis, no statistically significant variation was found in the α_j parameters based on the above characteristics for all activity purposes except maintenance and in-home relaxation.

Table 8 provides the estimated values of α_j and the t-statistics with respect to the null hypothesis of α_j=1 (note that standard discrete choice models assume α_j=1). Several important observations may be drawn from the table. First, all the satiation parameters are very significantly different from 1, thereby rejecting the linear utility structure employed in standard discrete choice models. That is, there are clear satiation effects in maintenance and leisure time-use decisions. Second, the satiation effect is very high for maintenance activity compared to leisure activities. While this is not readily apparent from the sample statistics in Table 2 (where the mean duration of participation in maintenance activities is high), the reason for this high satiation for maintenance is that the baseline preference is very high for maintenance activity relative to the leisure purposes (because all individuals participate in maintenance activity). Compared to the disparity in the participation rates between the maintenance category and the leisure categories, the disparity in duration between these categories is much smaller. The MDCEV model recognizes this by decreasing the utility for maintenance activity rapidly with time investment in maintenance activity. Third, the satiation effect for maintenance activity is highest for non-nuclear families during the Spring and Fall seasons. Fourth, within the group of leisure activity purposes, the highest satiation levels are for out-of-home meals and out-of-home shopping, while the lowest are for in-home relaxation and in-home recreation.

4.2.4. Logsum Parameters

The logsum parameters correspond to the $\theta_j\,(j \in B)$ parameters, and form the link between the single discrete choice and the MDCEV components of the joint model. There are three logsum parameters: (1) the social activity logsum parameter is estimated to be 0.4154 (the t-statistic for the test that the parameter is different from 1 is 4.51), (2) the out-of-home recreation activity logsum parameter is not significantly lesser than 1 and is constrained to 1, and (3) the pure recreation logsum parameter is estimated to be 0.3962 (the t-statistic for the test that the parameter is different from 1 is 2.82). The logsum parameter estimates indicate the presence of common unobserved attributes that affect the utilities of (1) in-home and out-of-home social pursuits, and (2) physically active and physically passive pure recreation.

4.2.5. Random Error Components

The error components introduced in the baseline preference function (see Section 4.2.1) generate covariance in unobserved factors across activity types. The results are as follows: (1)

the standard deviation of the in-home error component is 0.8339 (t-statistic of 14.352), indicating individual specific unobserved components (such as inertial tendencies and preference for privacy at home) that predispose individuals to in-home activity pursuits, (2) the standard deviation of the out-of-home error component is 0.2151 (t-statistic of 2.459), indicating individual-specific unobserved components related to a general affinity for out-of-home pursuits, and (3) the standard deviation of the recreation error component is 0.4588 (t-statistic of 7.143). Clearly, all the error components are statistically significant and indicate the need for the mixed version of the joint model.

4.2.6. Overall Likelihood-Based Measures of Fit

The log-likelihood value at convergence of the final joint model is -88300. The corresponding value for the model with only the constants in the MDCEV and single discrete choice components, the satiation parameters, and unit logsum parameters is -89188. The likelihood ratio test for testing the presence of exogenous variable effects, logsum effects, and the error components is 1776, which is substantially larger than the critical chi-square value with 145 degrees of freedom at any reasonable level of significance. This clearly indicates variations in the baseline preferences for the discretionary activity types based on household demographics/location variables, individual demographics/employment attributes, and day of week/seasonal effects, as well as similarity effects among alternatives.

5. DEMONSTRATION OF MODEL APPLICATION

The model estimated in this paper can be used to determine the change in time use patterns due to changes in independent variables over time. This is particularly important because of changing demographic, employment-related and race-related trends in the population. The model can also assess the impact of land-use and urban form policies on time-use.

The prediction method to assess the changes in time-use patterns in response to changes in relevant exogenous variables is based on a three step procedure. In the first step, the time investments in the activity purposes defined in the MDCEV component of Figure 1 are obtained by solving the following constrained optimization problem (in the expression below, we use the index q for individuals):

$$\text{Max}\,\tilde{U}_q = \int_{\mu_q=-\infty}^{\infty}\int_{\varepsilon_{q1}=-\infty}^{\infty}\int_{\varepsilon_{q2}=-\infty}^{\infty}\cdots\int_{\varepsilon_{qJ}=-\infty}^{\infty}[\exp(\beta' x_{q1}+\varepsilon_{q1})]t_{q1}^{\alpha_1}+\sum_{j\notin B}[\exp(\beta' x_{qj}+\mu_q' z_j+\varepsilon_{qj})](t_{qj}+1)^{\alpha_j}$$
$$+\sum_{j\in B}\left[\exp\left(\beta' x_{qj}+\theta_j \ln\sum_{l\in N_{qj}}\exp\left[\frac{\gamma' z_{qlj}}{\theta_j}\right]+\mu_q' z_j+\varepsilon_{qj}\right)\right]dG(\varepsilon_{q1})dG(\varepsilon_{q2})...dG(\varepsilon_{qJ})dF(\mu_q\,|\,\sigma),$$

subject to $\sum_{J} t_{qj}=T_q,\ t_{qj}\geq 0$ for all j, (19)

where G is the standard cumulative Gumbel distribution, F is the multivariate normal distribution function, $\mu_q' z_j$ constitutes the mechanism to generate correlation across the unobserved utility components of the alternatives, and other quantities are as defined earlier in the paper.[2]

In the second step, the probabilities of each subpurpose l being chosen in the single discrete components of Figure 1 are computed based on Equation (13).

In the final step, the time duration of investment for each individual q in subpurpose l of activity purpose j $(j\in B)$ is computed as:

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[2] z_j is specified to be a column vector of dimension H with each row representing a group h (h = 1, 2, …, H) of alternatives sharing common unobserved components. The row(s) corresponding to the group(s) of which j is a member take(s) a value of one and other rows take a value of zero. The vector μ (of dimension H) is specified to have independent normally distributed elements, each element having a variance component σ_h^2. The result of this specification is a covariance of σ_h^2 among alternatives in group h. σ is a parameter vector characterizing the variance-covariance matrix of μ_q.

$t_{qlj} = P_{qlj} \times t_{qj}$,

where P_{qlj} is the predicted probability that individual q participates in subpurpose l of activity purpose j $(j \in B)$ as obtained from the second step, and t_{qj} is the predicted time investment of individual q in activity purpose j $(j \in B)$ as obtained from the first step. For purpose j with no further classification into subpurposes $(j \notin B)$, t_{qj} is obtained directly in the first step.

In this paper, we demonstrate the application of the model by studying the effect of increasing the land-use mix diversity and the length of bikeways around households. Specifically, we increase the land-use mix diversity index within a 0.25 mile radius of individual's residences by 25% (except that the resulting variable is capped at 1.00) and similarly also increase the length of bikeways within a 1 mile radius of individual's residences by 25%. These changes are applied to each individual in the sample. The predicted aggregate time use patterns after and before these changes are estimated, and percentage changes from the baseline estimates are obtained.[3] The effect of the changes on aggregate time-use patterns is measured along two dimensions: (1) Percentage change in the number of individuals participating in each activity purpose and subpurpose, and (2) net percentage change in the duration of participation in each activity purpose and subpurpose across all individuals.

Table 9 presents the results. The table does not show the effect of the change in the land-use diversity index and the length of bikeways on the maintenance, in-home relaxation, in-home recreation, internet use, in-home social, out-of-home social, out-of-home meals, and out-of-home volunteer activity purposes because these changes are lesser than 0.5% along both dimensions of change. Further, the table has a '-' entry for the pure recreation purpose categories for the land-

[3] A change in land use mix diversity and length of bikeways may also lead to changes in other determinant variables of time-use. For example, an increase in the length of bikeways can potentially increase bicycle ownership, which then can impact time-use patterns (as discussed in Section 4.2.2.1). However, we do not consider these indirect impacts in the current demonstration.

use mix diversity variable, and a '-' entry for the out-of-home shopping and recreation purpose categories for the length of bikeways variable because these changes were also less than 0.5%.

Several important observations may be drawn from the table. First, in response to an increase in land-use mix diversity, there is about a 5% increase in the number of individuals participating in out-of-home shopping (see first row under the land-use mix diversity variable). This is, of course, a result of the positive effect of land-use mix diversity on the baseline preference for out-of-home shopping (see Section 4.2.2.1 under "Household Location Variables"). Second, there is an overall decrease in the number of individuals participating in the out-of-home recreation subpurposes, because of the negative effect of the land-use mix diversity variable on the baseline preference of the out-of-home recreation purpose in the MDCEV model. However, the decrease is lowest for the physically active subpurpose because, among the out-of-home recreation subpurposes, there is an inclination to participate more in physically active recreation compared to the other two subpurposes in response to an increase in land-use mix diversity (see Section 4.2.2.3). Third, the second row under the land-use mix diversity variable change effect shows that there is an increase of about 4.6% in the mean time of participation in out-of-home shopping. There is a drop of about 5.5% in the mean time of participation in the physically passive and partially physically active subpurposes. However, there is an increase in the mean time of participation in the physically active subpurpose (due to the shifting of time spent earlier on physically passive or partially physically active pursuits to physically active recreation pursuits). Fourth, similar conclusions may be drawn for the case when there is an increase in the length of bikeways. Note, however, that the percentage change in the number of individuals participating in physically passive and physically active pure recreation is the same (and equal to the percentage change of individuals participating in pure recreation as a whole) because the “length of bikeways” variable appears only in the MDCEV component of the joint model. The percentage change in the mean durations of participation in physically passive pure recreation is higher than the mean duration of participation in physically active pursuits because the probability of choice of physically passive pursuits is higher than that of physically active pursuits for individuals with a long duration of participation in pure recreation.

Overall, our results indicate rather small (and inelastic) changes in time-use patterns due to changes in urban environment characteristics. That is, it appears that our ability to influence time-use patterns (for example, increasing the time spent in physically active pursuits to improve public health) by proactively altering the urban environment is rather limited. Thus, there is weak support for the neo-urbanist design view that the urban environment can impact activity patterns of individuals. Of course, our analysis does not consider potential self-selection effects in residential choice based on desired activity time-use patterns. However, the presence of such self-selection effects will likely only result in an even more weaker conclusion about the effect of the urban environment on time-use patterns.

6. CONCLUSION

This paper extends Bhat’s MDCEV model to include a nested structure that facilitates the joint analysis of the imperfect and perfect substitute goods case. This is achieved by using a satiation-based utility structure across the imperfect substitutes, but a simple standard discrete choice-based linear utility structure within perfect substitutes. To our knowledge, this is the first consideration of such a unified utility-maximizing framework for joint imperfect-perfect substitute goods analysis in the economic literature. The joint model is applied to analyze individual time-use in both maintenance and leisure activities using weekend day time-use data from the 2000 San Francisco Bay Area travel survey is used for the analysis.

Several potential explanatory variables are considered in the analysis, including demographic variables, household location variables, and day of week/season of year effects. Among the household location variables, a wide variety of land use, urban form and transportation network measures are considered. These include population, acreage, employment by sector, housing type, accessibility indices for activity opportunities by activity purpose, land-use mix diversity, length of bikeways, length of highways, and length of local roads. The household location variables are computed at the zonal level, as well as over concentric circles of 0.25 miles, 1 mile, and 5 mile radii around the household location. Examining the effects of household location variables at multiple geographic levels enables the endogenous determination of the spatial extent of the impacts of these variables.

The empirical results provide important insights into the determinants of time-use decisions of individuals. The results can be used to examine time use choices across different segments of the population (for example, male vs. female, young vs. old, *etc.*) as well as to assess the potential impact of urban form policies on individual time-use decisions.

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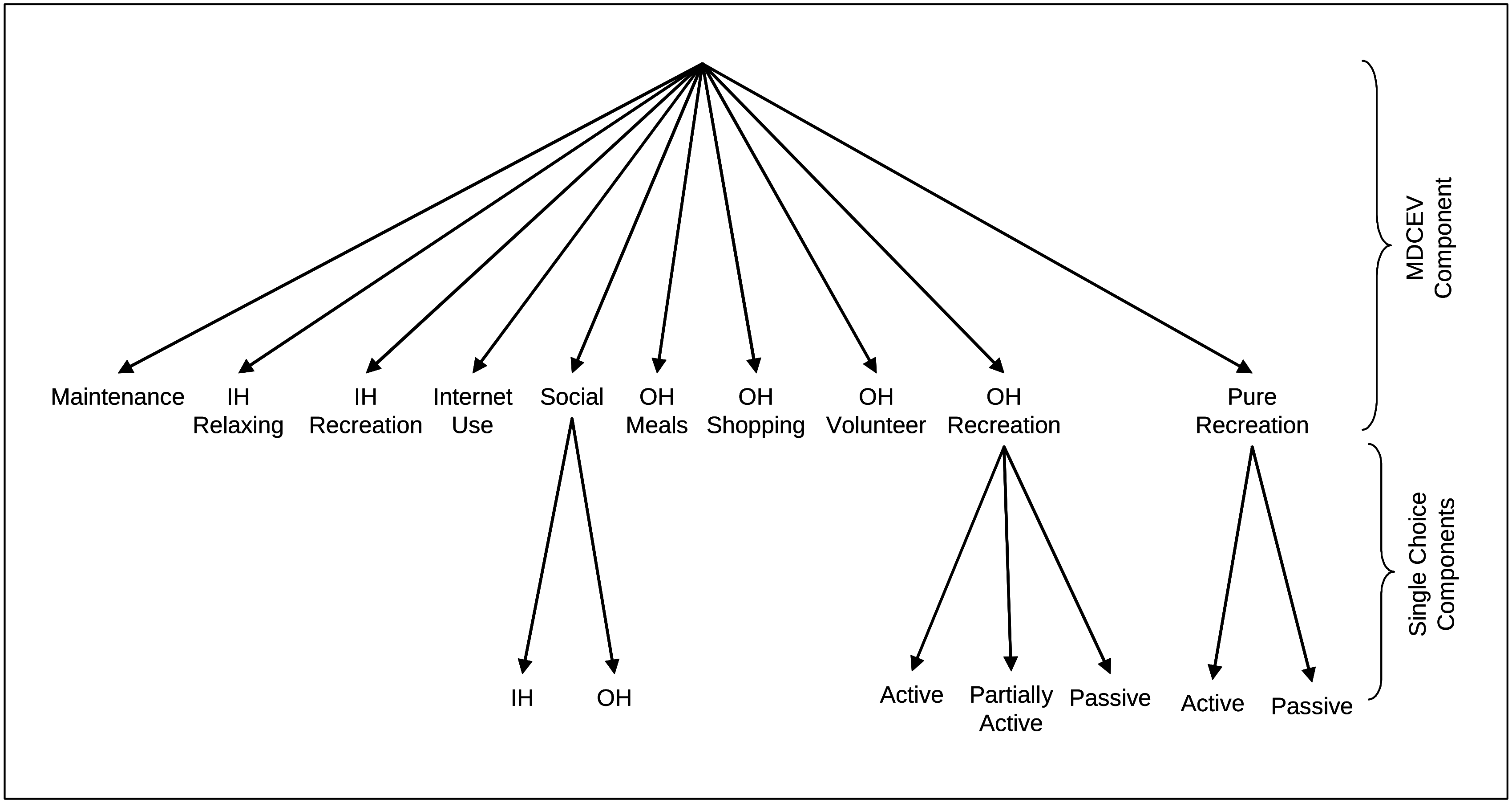

Figure 1. Modeling Framework

Table 1. Alternative GEV forms for Single Discrete Choice in Joint Model[4]

Single Discrete Choice Model Type	G_j function	$P(l \mid t_j^* > 0; l \in N_j)$	Comments
Multinomial Logit (MNL)	$\sum_{m \in N_j} \left[\exp(\gamma' z_{mj})\right]^{1/\theta_j}$	$\exp\left(\frac{\gamma' z_{lj}}{\theta_j}\right) \Big/ \sum_{m \in N_j} \exp\left(\frac{\gamma' z_{mj}}{\theta_j}\right)$	–
Nested Logit (NL)	$\sum_{k=1}^{K} \left\{ \sum_{m \in D_k} [\exp(\gamma' z_{mj})]^{1/\rho_k} \right\}^{\frac{\rho_k}{\theta_j}}$	$\frac{\exp\left(\frac{\gamma' z_{lj}}{\rho_k}\right)}{\sum_{m \in D_k} \exp\left(\frac{\gamma' z_{mj}}{\rho_k}\right)} X \frac{\left[\sum_{m \in D_k} \exp\left(\frac{\gamma' z_{mj}}{\rho_k}\right)\right]^{\frac{\rho_k}{\theta_j}}}{\sum_{f=1}^{K} \left[\sum_{m \in D_f} \exp\left(\frac{\gamma' z_{mj}}{\rho_f}\right)\right]^{\frac{\rho_f}{\theta_j}}}$	k is an index for nests D_k is the set of alternatives in nest k $l \in D_k$ ρ_k is the dissimilarity parameter for nest k $0 < \rho_k \le \theta_j \, \forall k$
Ordered Generalized Extreme value (OGEV)	$\sum_{k=1}^{K} \left\{ \frac{1}{2}\left[\exp(\gamma' z_{k-1,j})\right]^{1/\rho} + \frac{1}{2}\left[\exp(\gamma' z_{k,j})\right]^{1/\rho} \right\}^{\rho/\theta_j}$	$\frac{\exp\left(\frac{\gamma' z_{lj}}{\rho}\right) \left\{ \left[\exp\left(\frac{\gamma' z_{l-1,j}}{\rho}\right) + \exp\left(\frac{\gamma' z_{lj}}{\rho}\right)\right]^{\frac{\rho}{\theta_j}-1} + \left[\exp\left(\frac{\gamma' z_{lj}}{\rho}\right) + \exp\left(\frac{\gamma' z_{l+1,j}}{\rho}\right)\right]^{\frac{\rho}{\theta_j}-1} \right\}}{\sum_{k=1}^{K} \left[\exp\left(\frac{\gamma' z_{k-1,j}}{\rho}\right) + \exp\left(\frac{\gamma' z_{kj}}{\rho}\right)\right]^{\frac{\rho}{\theta_j}}}$	ρ is dissimilarity parameter that generates correlation between adjacent ordered alternatives $0 < \rho \le \theta_j$
Generalized Nested Logit	$\sum_{k=1}^{K} \left\{ \sum_{m \in D_k} \left[\alpha_{mk} \exp(\gamma' z_{mj})\right]^{1/\rho_k} \right\}^{\rho_k/\theta_j}$	$\sum_{k=1}^{K} \frac{\left[\alpha_{lk} \exp(\gamma' z_{lj})\right]^{1/\rho_k}}{\sum_{m \in D_k} \left[\alpha_{mk} \exp(\gamma' z_{mj})\right]^{1/\rho_k}} X \frac{\left[\sum_{m \in D_k} \left[\alpha_{mk} \exp(\gamma' z_{mj})\right]^{1/\rho_k}\right]^{\rho_k/\theta_j}}{\sum_{f=1}^{K} \left\{ \left[\sum_{m \in D_f} \left[\alpha_{mf} \exp(\gamma' z_{mj})\right]^{1/\rho_k}\right]^{\rho_k/\theta_j} \right\}}$	$\sum_k \alpha_{mk} = 1 \, \forall m$ D_k is a nest of alternatives ρ_k is dissimilarity parameter for nest k $0 < \rho_k \le \theta_j \, \forall k$

[4] In all cases, the term that enters V_j of the MDCEV part of the joint model is $\theta_j \ln G_j$.

Table 2: Descriptive Statistics of Activity Type Participation

Activity Type	Total number (%) of individuals participating	Mean duration of participation (mins)	Number of individuals (% of total number participating) who participate….	
			Only in activity type	In the activity type and other activity types
Maintenance-related time	6000 (100%)	488.47	1145 (19%)	4855 (81%)
In-home relaxing	1391 (23%)	254.17	244 (18%)	1147 (82%)
In-home recreation	1227 (20%)	280.00	274 (22%)	953 (78%)
Internet use	207 (3%)	165.73	25 (12%)	182 (88%)
Social (in-home and out-of-home)	1128 (19%)	195.29	193 (17%)	935 (83%)
Out-of-home meals	1680 (28%)	106.06	252 (15%)	1428 (85%)
Out-of-home shopping	1744 (29%)	80.67	347 (20%)	1397 (80%)
Out-of-home volunteer	635 (11%)	150.73	139 (22%)	496 (78%)
Out-of-home recreation (active, partially active, and passive)	1292 (22%)	190.90	273 (21%)	1019 (79%)
Pure recreation (active and passive)	374 (6%)	84.42	95 (25%)	279 (75%)
Total (one or more discretionary activity types)	4855 (81%)	338.72	1842 (38%)	3013 (62%)

Table 3: Number and Common Activity Purpose Combinations of Leisure Activities Undertaken by Individuals[5]

Number of Leisure Activity Purposes	Freq.	%	Common Activity Purpose Combinations
0	1145	19.08	N/A
1	1842	30.70	(1) OH shopping[6]
			(2) IH recreation[7]
			(3) OH recreation
2	1688	28.13	(1) OH shopping and OH meals
			(2) OH recreation and OH meals
			(3) OH recreation and OH shopping
3	915	15.25	(1) OH recreation, OH shopping, and OH meals
			(2) OH shopping, OH meals, Social
			(3) OH shopping, OH meals, IH relaxing
4	343	5.72	(1) OH recreation, OH shopping, OH meals, and IH relaxing
			(2) OH recreation, OH shopping, OH meals, and Social
			(3) OH recreation, OH shopping, OH meals, and IH recreation
5	59	0.98	(1) OH recreation, OH shopping, OH meals, Social, and IH recreation
			(2) OH recreation, OH shopping, OH meals, Social, and IH relaxing
			(3) OH volunteer, OH shopping, OH meals, Social, and IH relaxing
6	8	0.13	(1) OH recreation, OH volunteer, OH shopping, OH meals, Social, and Internet use
			(2) Pure recreation, OH recreation, OH volunteer, OH meals, Social and IH relaxing
			(3) OH recreation, OH volunteer, OH shopping, OH meals, Social, and IH relaxing
Total	6000	100.00	N/A

[5] All individuals participate in maintenance activity.
[6] OH – Out-of-home
[7] IH – In-home

Table 4. MDCEV Model Results

	In-home Relaxation	In-home Recreation	Internet Use	Social	Out-of-home Meals	Out-of-home Shopping	Out-of-home Volunteer	Out-of-home Recreation	Pure Recreation
Household Sociodemographics									
# of active adults	-	0.117(2.68)	0.550(5.71)	-	-0.154(-2.82)	-	-	-	-
# of senior adults	-	-	0.452(2.58)	-	-0.471(-6.34)	-	0.346(5.57)	-	-
Household Structure									
Nuclear family	-	-	-0.288(-1.38)	-	-	-	0.346(3.33)	0.298(3.61)	0.384(3.07)
Returning young adult family	-	-	-0.540(-1.70)	-	-	-	-	-	-
Single parent family	0.502(2.41)	0.495(1.99)	0.922(1.97)	0.384(1.91)	-	-	-	0.769(3.92)	-
Single person	-	0.249(2.31)	0.817(3.38)	0.243(2.63)	-0.218 (-2.19)	-	-	0.307(3.21)	-
Number of Vehicles									
Number of bicycles	-0.085(-3.80)	-0.048(-2.11)	-	-0.079(-2.64)	-	-	-	0.071(3.50)	-
Number of mot. vehicles	-	-	-0.375(-3.69)	-	-	-	-	-	-
Have internet access at home	-	-	2.560(5.38)	-	-	-	-	-	-
Annual Household Income dummy variables									
Medium annual income (35K-90K)	-0.178(-1.66)	-0.255(-2.26)	-	-	-	0.230(2.35)	-	0.229(1.89)	-
High annual income (>90K)	-0.185(-1.57)	-0.343 (-2.67)	-	-	-	0.196(1.87)	-	0.480(3.71)	-
Household Location Variables									
Zonal dummy variables									
CBD Zone	-	0.550(2.51)	-	-	-	-	-	0.251(1.19)	-
Urban Zone	-	-	0.774(1.91)	-	0.191(2.86)	-	-	-	-
Suburban Zone	-	-	0.754(1.94)	-	-	-	-	-	-
Rural Zone	-0.160(-1.16)	-	-	-	-	-	-	-	-
Neighborhood variables around household									
Service employment within 0.25 mi radius (in 10000s)	-	-	-	-	2.335(4.75)	-	-	-	-
Retail employment within 5 mi radius (in 10000s)	-	-	-	-	-	0.037(2.59)	-	-	-
Diversity in land-use mix in 0.25 mi radius	-	-	-	-	-	0.344(2.67)	-	-0.444(-2.59)	-
Fraction of single family hhlds within 0.25 mi radius	-	-	-	-	-	-	-	-0.499(-3.47)	-
Total population within 1 mi radius (in 10000s)	-	-	-	-	-	-	-0.080(-2.32)	-	-
Length of bicycle lanes within 1 mile (in 100,000 meters)	-	-	-	-	-	-	-	-	1.204(3.89)

Table 4 (continued). MDCEV Model Results

	In-home Relaxation	In-home Recreation	Internet Use	Social	Out-of-home Meals	Out-of-home Shopping	Out-of-home Volunteer	Out-of-home Recreation	Pure Recreation
Individual Sociodemographics and Employment Characteristics									
Age-related dummy variables									
Age less than or equal to 29 yrs	-	0.385(3.94)	0.569(2.86)	-	-	-	-	0.791(7.91)	-
Age between 30 – 49 yrs	-0.490(-5.19)	-	-	-0.701(-6.42)	-	-	-	-	-
Age between 50 – 65 yrs	-0.474(-4.63)	-	-	-0.889(-6.69)	-	-	-	-	-
Age > 65 yrs	-0.844(-6.70)	-	-	-1.043(-7.88)	-	-0.280(-2.84)	-	-	-
Driver's license	-	-	-	-	0.491(3.24)	0.455(2.97)	-	0.380(2.03)	-
Employment-related variables									
Employed	-	-	-	-	-	0.486(7.05)	-	0.349(4.50)	-0.182(-1.55)
Worked on weekend day?	0.778(4.59)	0.673(3.64)	-	0.374(1.86)	0.725(5.43)	0.384(2.71)	-	0.487 (2.59)	-
Duration of work on weekend day (in 100s of minutes)	-0.099(-2.54)	-0.080(-1.89)	-	-0.166(-3.53)	-0.109(-3.42)	-0.242(-6.54)	-	-0.198(-4.15)	-
Physically challenged	-	-	-	-	-0.308(-1.71)	-0.346(-1.94)	-	-0.433(-1.81)	-
Male	0.199(2.99)	0.371(5.13)	0.566(3.74)	-	0.157(2.91)	-0.231(-4.14)	-0.108(-1.25)	0.169(2.28)	0.270(2.35)
Race-related variables									
Caucasian – American	-	-	-	-	-	-	0.335(2.86)	0.223(2.78)	-
African – American	-	-	-	-	-0.541(-2.69)	-	-	-	-
Hispanic – American	-	-0.213 (-1.32)	-1.095(-2.03)	0.226(1.69)	-0.342(-2.52)	-	-	-	-
Asian – American	-0.335(-2.88)	-	-0.413(-1.57)	-	-	-	-	-	-
Other	-0.239(-1.46)	-0.222(-1.24)	-	0.211(0.137)	-0.273(-1.92)	-	-	-	-
Day of the Week and Seasonal Effects									
Sunday	0.136(2.04)	-	0.286(1.90)	-	-0.139(-2.58)	-0.308(-5.64)	1.430(14.46)	-0.262(-3.53)	-
Summer	-0.149(-1.95)	-	-	-	-	-	-	0.107(1.46)	-
Fall	-0.386(-4.62)	-	-	-	-	-	-	-0.164(-2.10)	-0.226(-1.80)
Baseline preference constants	-7.727(-38.4)	-8.963(-41.0)	-14.302(-21.3)	-8.444(-32.7)	-7.958(-30.9)	-8.533(-33.9)	-10.279(-46.0)	-9.771(-30.7)	-10.094(-40.4)

Table 5. Binary Logit Model Results for Social Activity [8]

Variable	Parameter	t-stat
Household Sociodemographics		
Number of active adults	-0.0631	-1.554
Nuclear family	-0.1545	-1.969
Number of motorized vehicles	0.0626	1.819
Number of bicycles	0.0420	1.537
Individual Sociodemographics and Employment Variables		
Age between 30 – 49 yrs	0.1325	1.531
Age between 50 – 65 yrs	0.1974	1.838
Worked on weekend day?	-0.1253	-1.198
Physically challenged	-0.4592	-2.560
African-American	-0.3962	-1.974
Day of the Week and Seasonal Effects		
Sunday	-0.1965	-3.130
Fall	-0.1250	-2.060

[8] The base category is in-home social activity. All parameters are specific to out-of-home social activity.

Table 6. Multinomial Logit Model Results for Out-of-Home Recreation[9]

Variable	Parameter	t-stat
Household Location Variables		
Diversity in land-use mix within 0.25 mile radius of household specific to physically active recreation	0.8726	1.965
Individual Sociodemographics and Employment Variables		
Age less than or equal to 29 yrs		
Specific to partially physically active recreation	-0.4826	-2.632
Specific to physically active recreation	-0.5803	-2.407
Worked on weekend day specific to partially physically active recreation	-1.0620	-4.075
Male specific to partially physically active recreation	0.2746	2.150
Day of the Week and Seasonal Effects		
Sunday specific to partially physically active recreation	0.1634	1.279
Winter specific to partially physically active recreation	-0.6345	-2.444

[9] The base category is physically passive out-of-home recreation.

Table 7. Binary Logit Model Results for Pure Recreation [10]

Variable	Parameter	t-stat
Household Sociodemographics		
Number of bicycles	0.0494	1.307
Household Location Variables		
Residence in central business district zone	0.8988	1.747
Total population within 1 mile radius	-0.0786	-1.649
Individual Sociodemographics and Employment Variables		
Age greater than 50 yrs	0.2986	1.681

[10] The base category is physically passive pure recreation. All parameters are specific to physically active pure recreation.

Table 8. Satiation Parameters

Activity Type	Parameter	t-statistic[11]
Maintenance		
Non-nuclear families in spring/fall	0.1186	78.12
Non-nuclear families in summer	0.1229	72.96
Non-nuclear families in winter	0.1318	65.19
Nuclear families in spring/fall	0.1282	68.73
Nuclear families in summer	0.1328	64.43
Nuclear families in winter	0.1423	57.82
In-home relaxation		
Winter, spring, and summer	0.8650	13.29
Fall	0.9023	5.47
In-home recreation	0.9114	10.67
Non-work internet use	0.8403	5.32
Social	0.8568	13.71
Out-of-home meals	0.7570	18.25
Out-of-home shopping	0.7187	18.33
Out-of-home volunteer	0.8568	7.72
Out-of-home recreation	0.8570	12.74
Pure recreation	0.7866	6.35

[11] The t-statistic is computed for the null hypothesis that the satiation parameter is equal to 1. Equivalently, the t-statistic is for the test that there are no satiation effects or that the utility structure is linear.

Table 9. Impact of Change in Urban Environment Variables

25% increase in…	Dimension of change	Activity Purpose and Subpurpose					
		Out-of-home shopping	Out-of-home recreation			Pure recreation	
			Physically passive	Partially physically active	Physically active	Physically passive	Physically active
Land-use mix diversity variable within 0.25 mile radius of residence	% change in number of people participating in activity purpose	5.09	-6.06	-5.13	-3.38	--	--
	Net % change in mean duration of participation in activity purpose	4.63	-5.77	-5.49	2.55	--	--
Length of bikeways within 1 mile of residence	% change in number of people participating in activity purpose	--	--	--	--	4.35	4.35
	Net % change in mean duration of participation in activity purpose	--	--	--	--	2.27	1.82