An Analysis of the Determinants of Children's Weekend Physical Activity Participation

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ABSTRACT

This paper examines the out-of-home, weekend, time-use patterns of children aged 5 through 17 years, with a specific emphasis on their physical activity participation. The impact of several types of factors, including individual and household demographics, neighborhood demographics, built environment characteristics, and activity day variables, on physical activity participation is analyzed using a joint nested multiple discrete-continuous extreme value-binary choice model. The sample for analysis is drawn from the 2000 San Francisco Bay Area Travel Survey. The model developed in the paper can be used to assess the impacts of changing demographics and built environment characteristics on children's physical activity levels.

1. INTRODUCTION

1.1 Background

Public health professionals have been increasingly emphasizing the need to promote physically active lifestyles in the United States. This is because several epidemiological research studies have now established a clear link between physical inactivity and public health problems. For instance, physical inactivity has been identified as an important risk factor for such chronic diseases as coronary heart disease, stroke, diabetes, some forms of cancer, and depression (see US Department of Health and Human Services, USDHHS, 1996; Center for Disease Control, CDC, 2005). Further, regular physical activity correlates with reduced symptoms of anxiety and depression, fewer physician visits, and reduced dependence on medications (see CDC, 2005).

While the benefits of regular physical activity, and the negative consequences of a physically inactive lifestyle, are well-established, about a quarter of the American adult population is completely inactive, and about a half of the adult population do not participate adequately in physical activity to accrue health benefits. Additionally, physical inactivity is not confined to adults. A recent CDC report suggests that about a third of teenagers do not engage in adequate physical activity for health, and that the high school physical education class participation rate has been steadily declining over the past decade (CDC, 2002).

The critical need to promote physical activity has led public health professionals to reach beyond their traditional domain of recreational physical activity to non-motorized transportation for utilitarian trips, an area that has received fairly substantial attention in the transportation field (utilitarian trips refer to trips to participate in an out-of-home activity episode at a specific destination). At the same time, urban/transportation planners are increasingly becoming aware of the need to better understand the individual and inter-personal/social determinants of non-motorized travel, as well as the recreational desires/activities of individuals. In fact, the activity-based analysis movement in transportation planning emphasizes time-use, and space/time interactions, in activity/travel participations within and between individuals (see Bhat *et al.*, 2004; Arentze and Timmermans, 2004). The net result of these developments has been the formulation of a synergistic research agenda to clearly and accurately understand the determinants of physical activity (including non-motorized travel) within the overall context of the time-use decisions of individuals (see Sallis *et al*, 2004; Handy *et al.*, 2002; Transportation Research Board and Institute of Medicine, 2005).

1.2   Research Objective and Motivation

The objective of this research is to examine the physical activity participation of children (aged 5 years through 17 years) within the broader context of their overall time-use. Our motivation to examine children's physical activity participation stems from four main considerations. <u>First</u>, from a transportation standpoint, an understanding of children's activity-travel patterns, and the inter-relationships between the activity-travel patterns of children and other members in the household, is an important precursor to developing a good overall activity-based travel modeling system for all individuals (see Bhat and Koppelman, 1999; Vovsha *et al.*, 2004). While this issue is well recognized, it has not been adequately addressed (see Kitamura, 1983; Hoefer *et al.*, 2001). <u>Second</u>, from a public health standpoint, physical activity in children has been linked to (a) healthier bones, muscles, and joints, (b) prevention and/or delay in the onset of high blood pressure problems, (c) an increase in self-esteem and a sense of social well-being, and (d) reduction in stress and depression/anxiety (see Pate *et al.*, 1995; USDHHS, 1996). Consequently, there is an incentive to examine the determinants of physical activity participation and time-use within the broader context of children's activity-travel choices. <u>Third</u>, there has been relatively little attention on understanding the physical activity patterns and time-use of children in a household as a function of the physical environment (land-use, transportation system, perceived safety, weather and season of year). Among the very few studies that consider the physical environment, the variables used to describe the land-use and transportation system are confined to access to recreational facilities and programs (see, for example, Garcia *et al.*, 1995; Gordon-Larsen *et al.*, 2000; Sallis *et al.*, 1993; Sallis *et al.*, 2000; and Zakarian *et al.*, 1994; Handy, 2004 is an exception). <u>Fourth</u>, our understanding of the trade-offs and potential substitution/complementary effects among three distinct components comprising physical activity – recreational physical activity (physical activity at a specific location), utilitarian non-motorized travel, and recreational non-motorized travel (physical activity in the form of running, walking, or bicycling, or other human-powered means of transportation without a specific destination in mind) – is limited. Besides, health is affected by total physical activity, which requires considering all of the three components above rather than one or two components (see Sallis et al., 2004, who make a similar point). On the other hand, no previous study that we are aware of in the field of children's physical activity behavior has examined all these three components of physical activity jointly. The studies in the public health field mostly focus on recreational physical activity and recreational non-motorized travel (but see Pucher and Dijkstra, 2003; DiGuiseppe *et al.*, 1998). In contrast, those in the urban planning/transportation field have focused on utilitarian non-motorized travel (see Environmental

Protection Agency, EPA, 2003, McMillan, 2002, Clifton, 2003, Black *et al.*, 2001, Martin-Diener and Sauter, 2005, Scottish Executive, 2002, and Zwerts and Wets, 2006).[1]

1.3   Overview of Current Research

The current research examines children's time-use decisions in five activity-travel categories: (1) Passive activity (physically inactive episodes pursued at a specific location), (2) Passive travel (motorized forms of travel, either to a specific destination for participation in an activity or for pure recreation purposes such as joy-riding), (3) Utilitarian active travel (non-motorized forms of travel to a specific destination for participation in an activity), (4) Recreational active activity (physically active recreational episodes pursued at a specific location such as a swimming pool or a gym), (5) Recreational active travel (non-motorized forms of travel without any specific destination, such as walking or running around the neighborhood). The model used in the current analysis extends the basic structure of the multiple discrete-continuous extreme value (MDCEV) model originally proposed by Bhat (2005). The formulation recognizes that children can (and generally will) participate in more than one of the five activity-travel categories listed above on any given day, based on their preferences and satiation levels for each activity-travel category and their overall time budgets. The preferences and satiation levels of individuals for each activity-travel category is modeled using a comprehensive framework that considers individual demographics and employment characteristics, household demographics, neighborhood demographics, land-use variables, transportation network attributes, and characteristics of the weekend day (weather conditions, season of year, and day of week). Further, the land-use and transportation network variables are measured in the immediate neighborhood of the individual's residence rather than using an arbitrarily defined zonal configuration.

The empirical analysis uses data from the 2000 San Francisco Bay Area Travel Survey (BATS) and several other secondary data sources. The analysis is confined to weekend days to limit the research scope, and also because individuals have more free time (time spent not eating or sleeping, and not in personal care, school, and child care) during the weekends compared to weekdays (see Shepard *et al.*, 1980 and Lockwood *et al.*, 2006). Finally, the analysis is also confined to out-of-home activity episodes and travel episodes, and does not include in-home activity episodes. This is because the BATS data does not provide adequate

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[1] An important point to be noted here is that there are other possible components comprising physical activity in children, such as free play and incidental physical activity. We do not explicitly consider these other components because they are difficult to identify in the survey used in the current analysis.

information to identify whether or not a recreational episode pursued in-home is an active one. Future research should include in-home activity episodes in the analysis to obtain a comprehensive understanding of activity-generation and physical activity participation determinants.

The rest of the paper is structured as follows. The next section provides an overview of the data and sample used in the analysis. Section 3 presents the model structure and the model estimation procedure. Section 4 discusses the empirical analysis. Section 5 applies the model estimated in the paper to examine the impact of built environment changes on children's physical activity patterns. Section 6 concludes the paper by highlighting the important findings from the research.

2.   DATA SOURCE AND SAMPLE FORMATION

2.1   Data Sources and Sample Formation

The main source of data for our analysis is the 2000 San Francisco Bay Area Travel Survey (BATS). The survey collected activity and travel information, for a two-day period, from individuals of over 15,000 households in the nine county Bay Area (see MORPACE International, Inc., 2002 for details on survey, sampling and administration procedures). The information collected in the survey for <u>each activity episode</u> included type of activity, start and end times of the activity, and the geographic location of the activity. Further, for each out-of-home activity episode, additional information on the name of the activity participation location (for example, Joan's Ballet Studio, Napa Hair Salon, *etc*.) and the type of location (such as bowling alley or shopping mall) were collected. The survey also collected socio-demographic data on the individual and the household, the date of each survey day, and the geocoded residential location. The information collected in the survey for <u>each travel episode</u> included the modes used, and start and end times of travel. The survey also collected socio-demographic data on the individual and the household, the date of each survey day, and the geocoded residential location. It should be noted that, for a child less than 15 years, a parent recorded and provided information on the activity/travel episodes and socio-demographic attributes of the child.[2]

In the current empirical analysis, the BATS activity/travel data was processed to include only the out-of-home weekend activity and travel episodes of individuals aged five through

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[2] Parents' reporting of the activity/travel participation of their young children less than 15years of age may introduce reporting biases that may be different from the self-reporting biases of children of 15 years or older. An examination of these reporting biases is beyond the scope of this paper.

seventeen years. Each activity episode was classified as a passive activity or a recreational active activity based on the location type of the out-of-home activity participation.[3] Each travel episode was classified as an active episode (if pursued by bicycling or walking) or a passive episode (if pursued by a motorized mode). Each active travel episode was further disaggregated into either a utilitarian active travel episode or a recreational active travel episode. A utilitarian active travel episode corresponds to a non-motorized travel episode that is followed by an activity episode whose location is not the same as the origin of the travel episode. On the other hand, a recreational active travel episode corresponds to a non-motorized travel episode that begins and ends at home without any stops in-between (for example, walking or bicycling around the neighborhood). Finally, the total time invested during the weekend day by each individual in passive activities, passive travel, utilitarian active travel, recreational active activity, and recreational active travel was calculated based on appropriate time aggregation across all the episodes of each type pursued by the individual.

In addition to the BATS data, several other data sources were used in the analysis. The Metropolitan Transportation Commission (MTC) provided zonal-level land-use and demographic information for each Transportation Analysis Zone (TAZ). This data source was used to obtain, within a one-mile radius of the individual's residence, the number of employees and percentage of employment by sector (retail, wholesale, service, manufacturing, agriculture, and other), and the percentage of land used for each of four specific purposes (residential, office, retail, and vacant). In addition, a land-use diversity index variable was computed as a fraction between 0 and 1 (see Bhat and Guo, 2005 for details of the formulation of such an index). MTC also provided a bicycle facility GIS layer which was used to calculate the number of miles of bikeway within one mile of the individual's residence.

Data was also extracted from the 2000 Census files for the analysis. The Census 2000 population and housing data summary file (SF1) provided census block and census block-group level information on the number and type of residential housing units, total population, and number of people by ethnicity. GIS procedures were used to compute the following neighborhood demographic variables and land-use variables within one mile of each individual's residence: total population, the percentages of non-Hispanic white, non-Hispanic black, Asian, Hispanic, and other ethnicity populations, and the percentage of single-family and multi-family

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[3] Due to space constraints, we are unable to provide a detailed description of this activity episode classification procedure. Interested readers may obtain the procedure from the authors. Of course, a limitation of our classification procedure is that it is solely based on the location type of activity participation, and does not consider any measure of the physical intensity level or nature (structured versus unstructured) of activity participation.

housing units within a one-mile radius of the individual's residence. Census 2000 TIGER files were used to calculate transportation network variables including the number of miles of highways and local roads, average block size, and number of street blocks, within one mile of an individual's residence.

Precipitation data was obtained from the National Climatic Data Center (NCDC) weather stations. Each residence in the sample was linked to the closest weather station using Euclidean distance measures. Total precipitation was extracted for each individual's survey day from his/her corresponding weather station.

Finally, the spatial distribution of businesses (by type), parks, schools, and churches was extracted from InfoUSA (InfoUSA, 2004). The business database was used to calculate the number of restaurants, food stores, religious organizations, automotive businesses, state, private, and national parks, recreational businesses, fitness and sports centers, and preschool through secondary schools within one mile of the individual's residence.

2.2 Descriptive Time-Use Statistics in Sample

The final sample used in the analysis includes the weekend time-use of 1104 children aged 5-17 years with at least one out-of-home activity participation. Each individual contributes only one weekend day, with 547 children providing information for a Saturday and 557 children providing information for a Sunday. In the overall sample, 32% of children participate in some form of physical activity during the weekend day, while the remaining 68% do not undertake physical activity (these numbers are consistent with those found in CDC, 2002 and CDC, 2003). Table 1 presents additional descriptive statistics characterizing participation in the five activity-travel categories. The second column in the table indicates the high percentage (95%) of individuals participating in some form of passive activity. In contrast, participation rates in the active activity-travel categories are rather low, varying from 3% in recreational active travel to 19% in utilitarian active travel. It is indeed interesting to note that the percentage of individuals participating in utilitarian active travel is about the same as the percentage of individuals participating in the active recreation categories of recreational active activity and recreational active travel. The statistics in Table 2 provide, perhaps for the first time in the literature, direct empirical evidence of the importance of considering both utilitarian active travel and active recreation in promoting physical activity among children.

The third column in Table 1 provides the mean duration of participation in each activity-travel category among those participating in the activity-travel category. As expected, the mean duration of participation in passive activities (accumulated over the entire weekend day) is about

5 hours, while the corresponding value is about 1.5 hours for passive travel. The model in this paper is able to appropriately consider activity-travel categories that may have about equal participation rates, but quite different mean durations of participation, as in the case of passive activity and passive travel. Among the remaining three active activity-travel categories, the table indicates that, in general, individuals participate longer in recreational active activity than the two active travel categories, and longer in recreational active travel than in utilitarian active travel. It is important to examine the trade-offs among the active activity-travel categories, since encouraging one form of active category (such as utilitarian active travel) may take away from participation in, and duration of participation in, the other active categories (such as recreational active travel).

The last two columns in Table 1 indicate the split between solo participations (*i.e.*, individual participation in only one activity-travel category) and multiple activity participations (*i.e.*, individual participation in multiple activity-travel categories) for each activity-travel category. Clearly, it is seldom that individuals participate in only one activity-travel category. The most common activity-travel categories participated together are passive activity and passive travel. A reasonable fraction of individuals also participate in one of these passive categories and utilitarian active travel or recreational active activity. Importantly, no individual participates in both recreational active activity and recreational active travel, indicating that these two activity-travel categories are perfect substitutes. That is, if an individual participates in active recreation, it is in the form of either activity episodes or travel episodes, but not in both these activity-travel categories. Accordingly, in the model formulation, we allow the possibility that individuals choose one or more of the activity-travel categories of (1) Passive travel, (2) Passive activity, (3) Utilitarian active travel, and (4) Active recreation (including both recreational active activity and recreational active travel). These four categories represent imperfect substitutes. But we also recognize the binary choice nature of the decision to participate in recreational active activity versus recreational active travel, subject to participation in active recreation[4].

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[4] From a strictly theoretical standpoint, the time investment in passive travel and/or utilitarian active travel must be positive if there is any time investment in passive activity or recreational active activity, but imposing this assumption is not practical within the MDCEV framework. However, the data used in estimation reflects this constraint, and thus the estimated model will assign very low probabilities for infeasible conditions.

3.   THE MODEL

3.1   Specification Structure

In this paper, we apply a multiple discrete-continuous extreme value (MDCEV) model derived from the primitives of utility theory to model time allocation among the four activity travel categories of passive activity, passive travel, utilitarian active travel, and active recreation. The MDCEV model was developed recently by Bhat (2005) and is ideally suited for time use modeling because it is based on the concept that individuals participate in multiple activity/travel purposes due to diminishing marginal returns from participation in any single purpose.

In the current application, we use an extension of the MDCEV model as discussed in Bhat *et al.* (2006) to (a) accommodate unobserved heteroscedasticity and error correlation across the utility functions of the four activity-travel categories (which allows the preferences for a subset of the categories to be influenced by common unobserved individual factors), and (b) accommodate the presence of the binary choice model within the active recreation category (which recognizes that individuals choose between participating in recreational active activity and recreational active travel, but not both, should they decide to pursue active recreation). At the same time, the utility of the recreational active activity and recreational active travel categories should influence the overall utility of active recreation in the MDCEV model. Accordingly, we use a model formulation that is appropriate for the nested model system shown in Figure 1.

3.2   Basic Model Structure

Let the utility that an individual *q* accrues from allocating time t_j to each of the four activity-travel categories identified in the upper level of Figure 1 be as follows:

$$U = \sum_{j=1}^{4} \psi(x_j)(t_j + 1)^{\alpha_j} \tag{1}$$

where $\psi(x_j)$ is the baseline utility for time invested in category *j*, and the α_j's are parameters (we suppress the index *q* for individuals in this presentation). Note that ψ is a function of observed characteristics, x_j, associated with category *j*. A translational parameter of 1 is added to t_j in the utility function to allow the possibility that the individual does not participate in one or more of these categories (see Kim *et al.*, 2002 and Bhat, 2005). α_j influences the rate

of diminishing marginal utility of investing time in activity purpose *j* for passive activity, passive travel, and active recreation. In the case of utilitarian active travel, α_j may be viewed as a statistical attenuation factor that controls the duration of time investment in this type of travel. This is because shorter or longer utilitarian travel times do not reflect mechanisms of satiation directly, but rather indicate the willingness to travel to access activity locations. For ease in presentation, we will, however, refer to α_j as a satiation parameter for all *j*. The reader will also note that 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 $\psi(x_j)$ and a value of α_j close to 1 implies a high baseline preference and low satiation (*i.e.*, high participation levels and high duration of participation) for the *j*th category. This represents the situation where the individual allocates almost all his/her time to the *j*th category and little to no participation in other 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-travel categories. More generally, the utility form allows a variety of situations characterizing an individual's underlying behavioral mechanism with respect to time allocation to category *j*.

The utility function in Equation (1) assumes deterministic baseline utilities $\psi(x_j)$. In reality, the analyst does not observe all the factors impacting the baseline utility that an individual associates with each activity *j*. Accordingly, and as in Kim *et al.* (2002) and Bhat (2005), we introduce a multiplicative random element to the baseline utility of the first three alternatives in the upper level of Figure 1 as follows:

$$\psi(x_j, \varepsilon_j) = \exp(\beta' x_j + \varepsilon_j), \text{ for } j = 1, 2, 3, \tag{2}$$

where ε_j is a standard Gumbel error term that captures idiosyncratic (unobserved) characteristics that impact the baseline utility for purpose *j* (*j* = 1, 2, 3). An exponential parameterization is used to guarantee the positivity of the baseline utility.

For the fourth alternative, we build the utility function from bottom-up. Let the random utility of each lower level discrete alternative in Figure 1 be:

$$W_{l4} = \beta' x_4 + \gamma' z_{l4} + \eta_{l4}, \ l = 1, 2 \ . \tag{3}$$

In the above expression, $\beta' x_4$ is the overall observed utility component of active recreation (see Figure 1), z_{l4} is an exogenous variable vector influencing the utility of discrete alternative l within active recreation, γ is a corresponding coefficient vector to be estimated, and η_{l4} is an unobserved standard Gumbel error component specific to subpurpose l. We further write η_{l4} as $\eta_{l4} = \lambda_4 + \lambda_{l4}$, where λ_4 is a common unobserved utility component shared by the two discrete alternatives in the lower level, and λ_{l4} is an extreme value term distributed identically with scale parameter θ_4 ($0 < \theta_4 \leq 1$). Let the λ_{l4} (l = 1, 2) terms be independent of one another and the λ_4 term. Also, assume that η_{l4} is independent of ε_j for j = 1, 2, 3. The baseline utility for the 4th upper level alternative is then written as:

$$\psi(x_4, \varepsilon_4) = \exp\left[\underset{l \in (1,2)}{Max} \{W_{l4}\} \right]$$

$$= \exp\left[\beta' x_4 + \theta_4 \ln \sum_{l \in (1,2)} \exp\left(\frac{\gamma' z_{l4}}{\theta_4} \right) + \varepsilon_4 \right], \tag{4}$$

where ε_4 is also now standard extreme value distributed (the last expression in Equation (4) may be derived based on the properties of the Gumbel distribution and the assumptions made; see Bhat, 2005).

The overall random utility function then takes the following form:

$$\tilde{U} = \sum_{j=1}^{3} \left[\exp(\beta' x_j + \varepsilon_j) \right] (t_j + 1)^{\alpha_j} + \left[\exp\left(\beta' x_4 + \theta_4 \ln \sum_{l \in (1,2)} \exp\left(\frac{\gamma' z_{l4}}{\theta_4} \right) + \varepsilon_4 \right) \right] (t_4 + 1)^{\alpha_4} \tag{5}$$

From the analyst's perspective, the individual is maximizing random utility ($\tilde{U}$) subject to the time budget constraint that $\sum_{j=1}^{4} t_j = T$, where T is the time available for allocation among the four upper level activity-travel categories.

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

$$L = \tilde{U} - \lambda \left[\sum_{j=1}^{4} t_j - T \right] \tag{6}$$

where λ is the Lagrangian multiplier associated with the time constraint. Then, following the derivation of the MDCEV model in Bhat (2005), the marginal probability that the individual participates in the first M of the J activity purposes ($M \geq 1$ and $M \leq 4$) for durations t_1^*, t_2^*, ..., t_M^* may be written as:

$$p(t_1^*,...t_M^*,0,...0) = \left[\prod_{j=1}^{M} r_j \right] \left[\sum_{j=1}^{M} \frac{1}{r_j} \right] \left[\frac{\prod_{j=1}^{M} e^{V_j}}{\left(\sum_{j=1}^{4} e^{V_j} \right)^M} \right] (M-1)!, \tag{7}$$

where

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

$$V_j = \beta' x_j + \ln \alpha_j + (\alpha_j - 1)\ln(t_j^* + 1), \quad j = 1, 2, 3$$

$$= \beta' x_4 + \theta_4 \ln \sum_{l \in N_j} \exp\left(\frac{\gamma' z_{l4}}{\theta_4} \right) + \ln \alpha_4 + (\alpha_4 - 1)\ln(t_4^* + 1), \quad j = 4 \tag{8}$$

The conditional probability that subpurpose l will be participated in for an amount of time t_4^*, given that $t_4^* > 0$, may be obtained from Equation (3) as:

$$P(l \mid t_4^* > 0; \; l = 1, 2) = \frac{\exp\left(\dfrac{\gamma' z_{l4}}{\theta_4} \right)}{\sum_{g=1}^{2} \exp\left(\dfrac{\gamma' z_{g4}}{\theta_4} \right)} \tag{9}$$

Finally, one can then write the unconditional probability that an individual chooses to participate in discrete alternative 1 ($l = 1$) or discrete alternative 2 ($l = 2$) for a certain duration by taking the product of Equation (7) and (9). For example, the probability that an individual participates for a duration t_1^* in purpose 1 and t_{41}^* in discrete alternative 1 of purpose 4 is:

$$P(t_1^*,0,0,t_{41}^*) = (r_1 r_4)\left[\frac{1}{r_1} + \frac{1}{r_4}\right]\left[\frac{e^{V_1} \cdot e^{V_4}}{\left(\sum_{j=1}^{4} e^{V_j}\right)^2}\right] \cdot \left[\frac{e^{\left(\frac{\gamma' z_{14}}{\theta_4}\right)}}{e^{\left(\frac{\gamma' z_{14}}{\theta_4}\right)} + e^{\left(\frac{\gamma' z_{24}}{\theta_4}\right)}}\right] \tag{10}$$

The reader will note that the γ and θ_4 parameters appear in both the MDCEV probability expression (through the V_4 term) as well as the single discrete choice probability expression (the last term in parenthesis in the expression above). This creates the jointness model in the multiple discrete and single discrete choices. If $\theta_4 = 1$, the nested model in Figure 1 collapses to the simple MDCEV model with 5 alternatives, with the satiation parameter being the same for the recreational active activity and recreational active travel categories.

3.3   Mixed Joint Model and Model Estimation

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

The joint model can be estimated in a straightforward manner using the maximum likelihood inference approach. The parameters to be estimated in the basic model structure include the β vector, the α_j scalars for each alternative j, the θ_4 scalar, and the γ vector. The parameters to be estimated in the mixed joint structure include additional parameters from the mixing distribution. The integrals in the likelihood function of the mixed joint structure are estimated using simulation techniques (see Bhat, 2005; Sivakumar *et al.*, 2005).

4.   EMPIRICAL ANALYSIS

4.1   Variables Specification

Several types of variables were considered in the model.   These included individual demographics and employment characteristics (age and teenage status, gender, license holding to drive, employment status, and ethnicity), household socio-demographics (household size, number of children, number of household vehicles, number of bicycles in the household, household income, and family structure), and the neighborhood demographic variables, land-use variables, transportation network variables, and characteristics of the weekend day (day of week, season of the year, and presence and amount of precipitation) discussed in Section 2[5].

4.2   Empirical Results

4.2.1 Error-Component Specification and Logsum Parameter

In our analysis, we considered many error component specifications in the MDCEV part of the joint model to introduce heteroscedasticity and correlation in the utilities of the four activity-travel categories. The best statistical result included the following two error components: (1) an error component to accommodate correlation between the two purposes of passive activity and passive travel, and (2) an error component to accommodate correlation between the two purposes of utilitarian active travel and active recreation.

The logsum parameter, θ_4, was not significantly different from 1 in our empirical estimation, indicating the absence of common unobserved factors specific to the two active recreation purposes. Thus, the logsum parameter is constrained to 1 in the empirical analysis.

4.2.2. Variable Effects

In this section, we discuss the exogenous variable effects separately at the multiple discrete-continuous level and 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 active recreation alternative in the MDCEV model through the logsum variable, $\ln \sum_{g=1}^{2} \exp\left(\dfrac{\gamma' z_{g4}}{\theta_4} \right)$.

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[5] In a previous binary choice analysis of participation in physical activity, young children (less than 13 years) and teenagers were split into separate groups. However, the analysis results were not statistically different in the effects of almost all variables.   Therefore, we decided to include young children and teenagers in the same model, while controlling for age, teenage status, and employment through the inclusion of relevant variables.

4.2.2.1 MDCEV Model   The final specification results of the MDCEV model are presented in Table 2. Passive activity is the base category in the MDCEV model for all variables. In addition, a '−' for a variable for an alternative indicates that the alternative also represents the base category along with passive activity.

Individual Demographics and Employment Characteristics

Among the individual demographics, the effects of the age-related variables indicate that older children are more likely to undertake utilitarian active travel than younger children. Further, teenagers have a lower preference for both passive travel and active recreation.

The effect of the "male" variable indicates that males participate in both utilitarian active travel and active recreation more than females. Also, and not surprisingly, children who have a driver's license are less likely to use walking and biking as a means of transportation to an activity. A final observation concerning individual demographics is that Caucasians and Asians have a high baseline preference for passive travel. Asians also have a low preference for utilitarian active travel. Overall, the results suggest that if Asians need to get to an activity, they will not usually do so by walking or biking. We did not find any statistically significant differences based on employment status.

Household Demographics

The effect of household demographics indicates that households who own several motorized vehicles have a high likelihood of participating in passive travel and are averse to utilitarian travel, relative to households who own fewer motorized vehicles.   On the other hand, households who own bicycles are associated with high participation levels in utilitarian active travel and active recreation.

The effects of the household structure variables suggest that children living in nuclear and single parent families are more likely to participate in utilitarian active travel than those living in other family arrangements (such as joint families with several adults), a finding that needs more exploration in future studies. The "number of children" variable suggests an overall higher likelihood of participation in utilitarian active travel among households with many children relative to households with few children.

Neighborhood Demographics

Among the neighborhood demographics variables, the larger the population within one mile of an individual's residence, the higher is the individual's preference for passive travel, a result that

does not have any obvious intuitive explanation. The other interesting result concerning neighborhood demographics is that individuals living in an area with a high percentage of non-Hispanic blacks have a low preference for both utilitarian active travel and active recreation. This may reflect a still prevailing inequality in the quality of streets and businesses, as well as a lack of good recreational facilities and a good quality of life, in predominantly black areas. Additional research needs to be conducted to understand the underlying reasons for this result.

Land-Use Variables

Individuals who live within one mile of an urban area have a high preference for utilitarian active travel, while individuals who live within one mile of a rural area have a low preference for utilitarian travel. It is also found that the more restaurants and food stores within one mile of an individual's residence, the more likely the individual is to participate in utilitarian active travel.

The other land-use variables indicate a lower baseline preference for passive travel among individuals residing in an area with a high share of residential acreage, and a high baseline preference for active recreation among individuals residing in an area with a high share of commercial/industrial acreage and multi-family units. None of the many other land-use variables we considered turned out to be even marginally statistically significant.

Transportation Network Attributes

Only one transportation network attribute directly impacts the MDCEV component of the joint model. Specifically, the larger the average block size area within one mile of an individual's residence, the greater is the individual's preference for active recreation. This is in contrast to Ewing *et al.*'s (2003) finding that a lower degree of sprawl leads to more minutes walked among adults. However, it can be argued that larger block size areas create fewer conflicts between motorists and children walking/bicycling around the block, making areas with large block sizes conducive for active recreation. Interestingly, we did not find any impact of block size area on utilitarian active travel.

Characteristics of the Weekend Day

The presence of rain is associated with a higher preference for passive travel, suggesting that, if people do travel or attend activities on a rainy day, they will spend more time in a motorized mode then they would on a clear day. Summer is also associated with a higher preference for passive travel. This may indicate a change in weekend scheduling for summer compared to the rest of the year, leading to more time spent in the car to reach farther away destinations such as

amusement parks or the beach. Finally, among the weekend day variables, the results suggest that individuals are more likely to participate in passive travel and active recreation on Saturdays compared to Sundays.

Baseline Preference Constants

We are able to empirically estimate only two baseline preference constants in the MDCEV model, one for the utilitarian active travel category and the other for the active recreation category. Theoretically, it should be possible to estimate a constant for the passive travel category. However, the participation rates in passive activity and passive travel are very high and about the same (95%), making it impossible to empirically distinguish between the two constants. Thus, the baseline preference constant for the passive travel category is constrained to zero.

The baseline preferences for utilitarian travel and active recreation are highly negative, consistent with the very low participation rates in these activity categories compared to the passive activity and passive travel categories (see discussion in Section 2.2).

4.2.2.2 Binary Choice Model for Active Recreation   Table 3 provides the results for the binary logit model of the choice of participation between recreational active recreation and recreational active travel, conditional on participation in active recreation. The base category is "recreational active activity", and the parameters are specific to the "recreational active travel" category.

Older children, and individuals residing in areas with high bikeway density, are more likely to participate in recreational active travel than recreational active activity. On the other hand, individuals who own a driver's license are unlikely to participate in recreational active travel. The results also indicate the low prevalence of participation in recreational active travel on Saturdays compared to Sundays.

The negative sign on the constant is an indicator of the much lower overall participation in recreational active travel compared to recreational active activity (see Table 1).

4.2.3 Satiation Parameters

The following are the estimated values of the satiation parameters, α_j, and the t-statistics (in parentheses) with respect to the null hypothesis of α_j = 1 (note that standard discrete choice models assume α_j = 1) for passive activity, passive travel, utilitarian active travel, and active recreation, respectively: 0.4028 (22.03), 0.0291 (54.97), 0.5776 (7.13), and 0.9305 (2.52).

Several important observations may be made from these values. <u>First</u>, all the satiation parameters are significantly different from 1, thereby rejecting the linear utility structure employed in standard discrete choice models. That is, there are clear satiation effects in the time-use decisions of individuals. <u>Second</u>, the satiation effect is very high for passive travel compared to passive activity (note that the smaller the satiation parameter, the higher is the satiation level). The much higher satiation associated with passive travel is because the percentage of individuals participating in passive travel and passive activities is about equal (95%), but individuals participate in passive travel for a much shorter duration compared to passive activities. For the same reason, the satiation effect is higher for utilitarian active travel compared to active recreation. It should be noted that shorter or longer utilitarian travel time does not reflect mechanisms of satiation directly, but rather measures, to some degree, the willingness to travel long distances to access activity locations. <u>Third</u>, there is low satiation for active recreation. This is because of the relatively high durations of participation in the active recreation categories of recreational active activity and recreational active travel among those who participated in these active recreation categories.

4.2.4 Random Error Components

The error components introduced in the baseline preference function generate covariance in unobserved factors across activity/travel. The results are as follows: (1) the standard deviation of the passive activity/travel error component is 1.6451 (t-statistic of 2.251), suggesting the presence of unobserved inertial tendencies to participate in physically active pursuits, and (2) the standard deviation of the error component between the utilitarian active travel and active recreation purposes is 2.0154 (t-statistic of 3.346), indicating individual-specific unobserved components related to a general affinity for physically active pursuits

4.2.5 Overall Likelihood-Based Measures of Fit

The log-likelihood value at convergence of the final joint model is -9357.4. The corresponding value for the model with only the constants in the MDCEV and single discrete choice components, the satiation parameters, and a unit logsum parameter for θ_4, is -9679.6. The likelihood ratio test for testing the presence of exogenous variable effects and the error components is 644, which is substantially larger than the critical chi-square value with 36 degrees of freedom at any reasonable level of significance.

5.   IMPACT OF BUILT ENVIRONMENT ATTRIBUTES ON PHYSICAL ACTIVITY

The model estimated in this paper can be used to determine the change in children's time use patterns due to changes in any independent variables over time, including the land-use and transportation network-related variables (see Copperman and Bhat, 2005 for details of the prediction mechanism).

In this paper, we demonstrate the application of the model by studying the effect of the following built environment changes within a one mile radius of each household: (1) Increasing the number of restaurants and food stores by 25%, (2) Increasing the share of multi-family housing units by 25%, except that the resulting variable is capped at 1.00, and (3) Increasing the miles of bikeways by 25%. The predicted aggregate time use patterns before and after these changes are estimated, and percentage changes from the baseline estimates are obtained.

Table 4 presents the results. The table does not show the effect of the change in the built environment variables on the passive activity and passive travel categories because these changes are less than 0.5%. The results indicate that an increase in the number of restaurants and food stores around households' neighborhoods by 25% leads to about a 9% increase in time spent on utilitarian active travel. However, the overall time budget constraint as well as the higher sensitivity across the utilitarian active travel and active recreation categories due to unobserved factors (see Section 4.2.1) combine to draw away time from the recreational active activity and recreational active travel categories. The net overall effect is a modest 2.26% increase in total physical activity time[6].

Similar results as above are also found for the changes in the share of multi-family units and miles of bike lanes. A change in the share of multi-family units increases the time spent on both recreational active activity and recreational active travel because the variable appears in the MDCEV component of the model (and affects the active recreation baseline preference; see Table 2). However, for the "miles of bike lanes" variable, the dominant effect is on recreational active travel because this variable affects the utility of recreational active travel in the binary choice model and does not appear directly in the MDCEV component. However, there is a small increase in recreational active activity too because of the overall increase in the active recreation baseline preference through the logsum term.

Overall, the results indicate that increases in one type of physical activity can lead to decreases in other types of physical activity. Thus, from the standpoint of evaluating the effectiveness of design policies in promoting active lifestyles, it is important to focus on all types

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[6] The specified forecasts should be verified empirically in intervention studies.

of physical activity jointly, rather than focusing only on utilitarian travel or recreation. The results also provide some support for the view that the urban environment can be engineered to influence physical activity. However, the inelastic nature of the response also points to the rather limited design-driven influence that can be exercised on children's physical activity patterns. Of course, the results above should be viewed with caution, since our analysis does not consider potential direct or indirect self-selection effects in residential choice based on desired activity time-use patterns.

6.   CONCLUSION

Epidemiological studies have clearly established the benefits of regular physical activity, and the negative consequences of a physically inactive lifestyle, on health. On the other hand, a majority of the American population is not participating in adequate amounts of physical activity to accrue health benefits. This has led to a concerted effort to examine the determinants of physical activity, recreational physical activity and non-motorized transportation for utilitarian trips.

In this research, we have focused on the out-of-home, weekend, physical activity participation of children (aged 5 through 17 years) as a function of individual and household demographics, neighborhood demographics, built environment variables (land-use variables and transportation network attributes), and variables characterizing the weekend day. All of the three major kinds of physical activity – utilitarian active travel, recreational active activity, and recreational active travel – are considered. The trade-offs and potential substitution/complementary effects among these three physically active activity-travel categories, and passive activity and passive travel, are examined using a joint nested multiple discrete-continuous extreme value-binary choice model. The sample used in the empirical analysis is drawn from the 2000 San Francisco Bay Area Travel Survey (BATS) and from several other secondary data sources. A large number of land-use and transportation network measures characterizing the built environment around each household's residence were compiled and included in the empirical analysis.

There are several important findings from the study. First, individuals, as represented by this study, participate in either recreational active activity or recreational active travel, but not in both of these active recreation categories on a given weekend day. This result suggests that there is a high degree of substitution between these two active recreation categories in general. Second, both utilitarian active travel and active recreation (recreational active activity and recreational active travel) are important components of total physical activity, and need to be

considered in efforts to promote physical activity. <u>Third</u>, there are variations in the participation (and level of participation) in the components of total physical activity based on individual demographics (age, gender, driver's license holding, and ethnicity), household demographics (number of motorized vehicles and bicycles owned by the household, and household structure), neighborhood demographics (population and percentage of non-Hispanic blacks), land-use variables (residence in an urban/rural area, number of restaurants and food stores around the household's residence, share of multi-family housing units around the household's residence, and share of commercial/industrial acreage around the household's residence), transportation network attributes (average block size area and miles of bike lanes around the household's residence), and characteristics of the weekend day (presence of precipitation, season of year, and day of the weekend). <u>Fourth</u>, unobserved person factors make individuals predisposed to a passive lifestyle or an active lifestyle. <u>Fifth</u>, the results provide support for the view that the built environment can be designed to promote overall physical activity levels, though the results also emphasize the rather limited ability to do so. <u>Sixth</u>, changes in the built environment can affect the different kinds of physical activity in different ways, further reinforcing the need to examine utilitarian active travel, recreational active activity, and recreational active travel distinctly and jointly.

To summarize, the model developed in the paper can be used to assess the impacts of changing demographics and built environment characteristics on children's physical activity levels and its many components. The study represents the first formulation and application of a comprehensive econometric framework to consider participation, and levels of participation, in physically passive and physically active episodes among children on weekend days. Future research needs to focus on accommodating potential residential sorting.

ACKNOWLEDGEMENTS

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Abbreviations:
>   CDC   Center for Disease Control and Prevention
>   EPA   Environmental Protection Agency
>   USDHHS   U.S. Department of Health and Human Services

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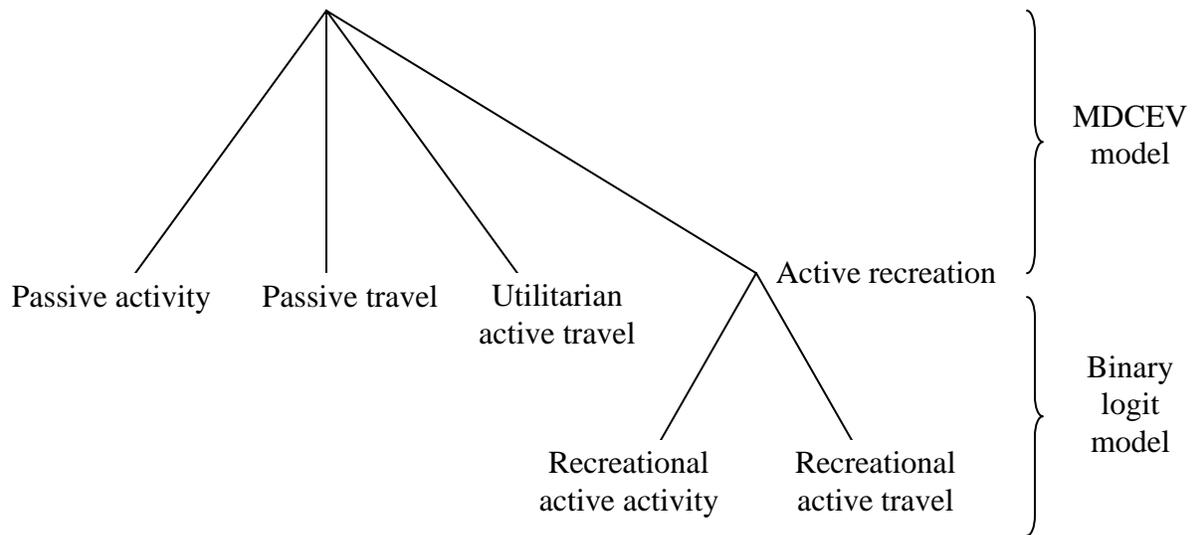
FIGURE 1 Model Structure

TABLE 1 Descriptive Statistics of Activity Type Participation

Activity-Travel Type	Total number (%) of individuals participating	Mean duration of participation among those participating (min.)	Number of individuals (% of total number participating) who participate….	
			Only in activity-travel category	In the activity-travel category and other activity types
Passive Activity	1051 (95%)	297.13	10 (1%)	1041 (99%)
Passive Travel	1048 (95%)	85.07	0 (0%)	1048 (100%)
Utilitarian Active Travel	210 (19%)	41.72	0 (0%)	210 (100%)
Recreational Active Activity	177 (16%)	170.86	1 (0.6%)	176 (99.4%)
Recreational Active Travel	35 (3%)	89.31	0 (0%)	35 (100%)
Total (one or more discretionary activity types)	1104 (100%)			

TABLE 2 MDCEV Model Results*

	Passive Travel	Utilitarian Active Travel	Active Recreation
Individual Demographics and Employment Characteristics			
Age-related variables			
Age (x10^{-1})	--	0.7215 (2.039)	--
Teenager	-0.2057 (-1.499)	--	-0.6409 (-2.485)
Male	--	0.5547 (2.249)	0.5990 (2.224)
Driver's license	--	-1.0781 (-2.067)	--
Ethnicity			
Asian	0.4903 (1.776)	-1.0571 (-2.439)	--
Non-Hispanic white	0.4160 (2.995)	--	--
Household Demographics			
Number of Vehicles			
Number of motorized vehicles	2.1548 (2.184)	-3.3055 (-1.877)	--
Number of bicycles	--	1.9320 (2.441)	2.5788 (2.935)
Household Structure			
Nuclear family	--	0.4389 (1.522)	--
Single parent family	--	0.5945 (1.428)	--
Number of children	--	3.8028 (3.259)	--
Neighborhood Demographics (within one-mile of residence)			
Log of the total population (x10^{-1})	3.3565 (4.469)	--	--
Percentage of Non-Hispanic blacks	--	-5.061 (-2.621)	-6.2525 (-2.105)
Land-Use Variables (within one-mile of residence)			
Zonal Characteristics			
Urban	--	0.3457 (1.423)	--
Rural	--	-0.7400 (-3.009)	--
Log of the number of restaurants and food stores (x10^{-1})		3.2390 (4.043)	--
Share of Acreage in…			
Residential land-use	-1.3414 (-2.921)	--	--
Commercial and Industrial land-use	--	--	4.2139 (4.258)
Share of multi-family units	--	--	0.8124 (1.032)
Transportation Network Attributes (within one-mile of residence)			
Average block area (in square miles)	--	--	0.3112 (1.245)
Characteristics of the Weekend Day			
Presence of rain (dummy variable)	0.3206 (1.259)	--	--
Summer	0.2338 (1.702)	--	--
Saturday	0.2691 (2.071)	--	1.1052 (4.939)
Baseline preference constants	--	-8.5506 (-10.198)	-9.0558 (-15.863)

* The base category is passive activities

TABLE 3 Binary Logit Model Results for Physically Active Recreation**

Variable	Parameter	t-statistic
Individual Demographics and Employment Characteristics		
Age $(x10^{-1})$	1.6097	1.96
Driver's license	-2.0957	1.71
Transportation Network Attributes (within one mile of residence)		
Miles of bike lanes$(x10^{-2})$	4.1953	1.78
Characteristics of the Weekend Day		
Saturday	-1.6440	-3.32
Constant	-2.7996	-2.79

** The base category is recreational active activity

TABLE 4 Impact of Changes in Built Environment Variables

25% increase in	Net % change in mean duration of participation in…			Overall % change in mean duration of physical activity
	Utilitarian active travel	Recreational active activity	Recreational active travel	
Number of restaurants and food stores within 1 mile of residence	9.28	-0.54	-1.09	2.26
Share of multi-family units within 1 mile of residence	-1.89	10.27	11.99	6.91
Miles of bike lanes within 1 mile of residence	-1.02	0.40	15.21	1.59