A MULTIPLE DISCRETE-CONTINUOUS NESTED EXTREME VALUE (MDCNEV) MODEL: FORMULATION AND APPLICATION TO NON-WORKER ACTIVITY TIME-USE AND TIMING BEHAVIOR ON WEEKDAYS

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ABSTRACT

This paper develops a multiple discrete-continuous nested extreme value (MDCNEV) model that relaxes the independently distributed (or uncorrelated) error terms assumption of the multiple discrete-continuous extreme value (MDCEV) model proposed by Bhat (Bhat, 2005 and Bhat, 2008). The MDCNEV model captures inter-alternative correlations among alternatives in mutually exclusive subsets (or nests) of the choice set, while maintaining the closed-form of probability expressions for any (and all) consumption pattern(s).

The MDCNEV model is applied to analyze non-worker out of home discretionary activity time-use and activity timing decisions on weekdays using data from the 2000 San Francisco Bay Area data. This empirical application contributes to the literature on activity time-use and activity timing analysis by considering daily activity time-use behavior and activity timing preferences in a unified utility maximization-based framework. The model estimation results provide several insights into the determinants of non-workers' activity time-use and timing decisions, and highlight the importance of the nested model.

INTRODUCTION

A variety of consumer demand choice situations are characterized by multiple discreteness (*i.e.,* the simultaneous choice of one or more alternatives from a set of alternatives that are not mutually exclusive) as opposed to single discreteness (*i.e.,* the choice of a single alternative from a set of mutually exclusive alternatives). In addition, there can be a continuous choice corresponding to the amount of consumption of each chosen discrete alternative, which leads to a multiple discrete-continuous choice situation. In the recent econometric literature, several important choice situations, including grocery purchases (Kim *et al.,* 2002), individual activity participation and time-use (Bhat, 2005; Srinivasan and Bhat, 2006; and Pinjari *et al.,* 2008), household expenditure allocation patterns (Ferdous *et al.,* 2008), household travel expenditures (Rajagopalan and Srinivasan, 2008), and household vehicle ownership and usage (Fang, 2008; and Bhat *et al.,* 2008) have been analyzed as multiple discrete-continuous choice situations.

A variety of modeling frameworks have been used to analyze multiple discrete/discrete-continuous choices, and these can be broadly classified into: (a) multivariate single discrete-continuous modeling frameworks (see for example, Srinivasan and Bhat, 2006 and Fang, 2008), and (b) utility maximization-based Kuhn-Tucker (KT) demand systems (Hanemann, 1978, Wales and Woodland, 1983, Kim *et al.,* 2002, von Haefen and Phaneuf, 2005, Bhat, 2005, and Bhat, 2008). Among the available modeling frameworks, the recently proposed multiple discrete-continuous extreme value (MDCEV) model structure (see Bhat, 2005, 2008) is particularly attractive because of at least two important features. First, the model is based on utility maximization theory and captures important features of consumer choice making, including the diminishing nature of marginal utility with increasing consumption. Second, the model offers closed-form consumption probability expressions and, thus, obviates the need for numerical/simulation-based methods of estimation. These probability expressions simplify to the well-known multinomial logit (MNL) probabilities when all decision makers choose a single alternative out of all available alternatives in the choice set.

An important limitation of the MDCEV model formulation, however, is the neglect of potential interdependence (or similarity) among alternatives. This is due to the assumption that the stochastic components (or the error terms) associated with the utility expressions of the alternatives are independent (or uncorrelated) and identically distributed (IID). This assumption is analogous to the IID error term assumption in the multinomial logit (MNL) model. The simplifying IID assumption can potentially result in a misrepresentation of the substitution patterns among the choice alternatives, statistically inferior model fit, biased estimation of model parameters, and distorted policy implications. To relax the IID assumption, the empirical applications in the literature have used a mixed MDCEV (MMDCEV) model formulation. A problem with this approach, however, is that the consumption probabilities resulting from the mixed MDCEV model formulation do not have closed-form expressions. This necessitates a simulation-based estimation that can be computationally expensive, and saddled with technical problems associated with the accuracy of simulation and the identification of parameters.

In view of the issues discussed above, in this paper, we propose a multiple discrete-continuous nested extreme value (MDCNEV) model that captures interdependence among alternatives in mutually exclusive subsets (or nests) of the choice set, while maintaining the closed-form of probability expressions for any (and all) consumption pattern(s). Specifically, we prove the existence of closed-form probability expressions in the MDCNEV model, and derive a general and compact form for the expressions for any (and all) consumption pattern(s) in the case of a general two-level nested extreme value error structure.[1,2] The MDCNEV model accommodates correlations among the stochastic utilities, and allows flexible substitution patterns across the discrete-continuous choices, of the alternatives within a nest. In the current paper, we provide an empirical application of the MDCNEV framework to jointly model and analyze non-workers' out-of-home discretionary activity time-use patterns and activity timing decisions on weekdays using data from the 2000 San Francisco Bay Area Travel Survey.

The remainder of this paper is organized as follows. Section 2 presents the structure of the MDCNEV model, along with the proof of the existence of, and the derivation of, the closed-form expressions for the consumption probabilities. Section 3 presents a simulation analysis to assess the importance of capturing inter-alternative correlations and to understand the properties

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[1] To be sure, Bhat (2008) has indicated that an extension of the MDCEV model to a multiple discrete-continuous generalized extreme value (MDCGEV) model can accommodate general patterns of correlations and at the same time yield closed-form expressions for consumption probabilities. However, in his paper, Bhat mentions that "*the derivation [of the consumption probability expressions] is tedious and the expressions get unwieldy*". Further, Bhat provides no formal proof of the existence of closed-form probability expressions for the MDCGEV model. His paper provided expressions for only a specific and simple nested logit error structure with 4 alternatives.

[2] It would be desirable to extend the MDCNEV model to incorporate more general Generalized Extreme Value (GEV) error structures such as cross-nested structures (see Small, 1987, Vovsha, 1997, Bhat, 1998, Ben-Akiva and Bierlaire, 1999, and Wen and Koppelman, 2001 for single discrete choice models with cross-nested error structures). Such an extension is anything but straightforward in the multiple discrete-continuous case (see footnote 6). We leave such an extension for future research.

of the MDCNEV model. Section 4 provides a brief discussion of the empirical context to which the MDCNEV model is applied. Section 5 discusses the data sources and the data sample used in the analysis. Section 6 presents and discusses the empirical results. Section 7 concludes the paper with a summary of the contributions and identifies avenues for future research.

2 THE MDCNEV MODEL: A TWO LEVEL NESTED CASE

Consider the following functional form for utility proposed by Bhat (2008):[3]

$$U(\boldsymbol{t}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}; \psi_k > 0, \alpha_k \leq 1, \gamma_k > 0 \tag{1}$$

In the above expression, $U(\boldsymbol{t})$ is the total utility accrued from consuming non-negative amounts of each of the K alternatives (or goods) available to the decision maker, and $\boldsymbol{t}$ is the corresponding consumption quantity (Kx1)-vector with elements t_k ($t_k \geq 0$ for all k). The term ψ_k (k = 1, 2, 3, …, K) represents the random marginal utility of one unit of consumption of alternative k at the point of zero consumption for the alternative. Thus, ψ_k controls the discrete consumption decision for alternative k. We will refer to this term as the baseline preference for alternative k (see Bhat, 2008). The γ_k terms (for k = 1, 2, 3, …, K) are translational parameters that allow corner solutions for the consumer demand problem. That is, these terms allow for the possibility that a decision-maker may not consume certain alternatives. The γ_k terms, in addition to serving as translation parameters, also serve the role of satiation parameters that reduce the marginal utility accrued from consuming increasing amounts of any alternative. Specifically, values of γ_k closer to zero imply higher satiation effects (*i.e.*, lower consumptions) in activity k (see Bhat, 2008). The α_k terms (for k = 1, 2, 3, …, K) also serve to capture satiation effects. Specifically, values of α_k farther away from 1 imply higher satiation effects (see Bhat, 2008).

In the above utility function, the impact of observed and unobserved alternative attributes, decision-maker characteristics, and the choice environment factors may be conveniently introduced through the ψ_k parameters:

$$\psi_k = \exp(\beta' z_k + \varepsilon_k) \tag{2}$$

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[3] The index for the decision-maker is suppressed in this discussion.

where, z_k is a set of attributes characterizing alternative *k*, the decision-maker and the choice environment, and ε_k captures unobserved factors that impact the baseline utility for good *k*.[4]

From the analyst's perspective, the decision-makers maximize the random utility given by Equation (1) subject to a linear budget constraint and non-negativity constraints on t_k:

$$\sum_{k=1}^{K} t_k = T \text{ (where } T \text{ is the total budget) and } t_k \geq 0 \;\forall\; k \;(k = 1,2,...,K) \tag{3}$$

The optimal consumptions can be found by forming the Lagrangian and applying the Kuhn-Tucker (KT) conditions. The Lagrangian function for the problem is (Bhat, 2008):

$$\mathscr{L} = \sum_k \frac{\gamma_k}{\alpha_k}\left[\exp(\beta' z_k + \varepsilon_k)\right] \left\{\left(\frac{t_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right\} - \lambda\left[\sum_{k=1}^{K} t_k - T\right], \tag{4}$$

where λ is the Lagrangian multiplier associated with the budget constraint. The KT first-order conditions for the optimal consumptions $(t_k^*; k = 1,2,...,K)$ are given by:

$$\exp(\beta' z_k + \varepsilon_k) \left(\frac{t_k^*}{\gamma_k}+1\right)^{\alpha_k - 1} - \lambda = 0 \text{, if } t_k^* > 0, \;(k = 1, 2,\ldots, K) \tag{5}$$

$$\exp(\beta' z_k + \varepsilon_k) \left(\frac{t_k^*}{\gamma_k}+1\right)^{\alpha_k - 1} - \lambda < 0 \text{, if } t_k^* = 0, \;(k = 1, 2,\ldots, K)$$

Next, without any loss of generality, designate alternative 1 as an alternative to which the individual allocates some non-zero amount of consumption. For this alternative, the KT condition may be written as:

$$\lambda = \exp(\beta' z_k + \varepsilon_k)\left(\frac{t_1^*}{\gamma_1}+1\right)^{\alpha_1 - 1} \tag{6}$$

Substituting for λ from above into Equation (5) for the other alternatives (*k* = 2,…, *K*), and taking logarithms, we can rewrite the KT conditions as (see Bhat, 2008):

$$V_k + \varepsilon_k = V_1 + \varepsilon_1 \text{ if } t_k^* > 0, \;(k = 2, 3,\ldots, K)$$

$$V_k + \varepsilon_k < V_1 + \varepsilon_1 \text{ if } t_k^* = 0, \;(k = 2, 3,\ldots, K) \tag{7}$$

[4] The γ_k and α_k terms may also be parameterized as functions of observed and unobserved alternative attributes, decision-maker characteristics, and the choice environment factors (see Bhat, 2008).

where, $V_k = \beta' z_k + (\alpha_k - 1)\ln\left(\frac{t_k^*}{\gamma_k} + 1\right)$, ($k$ = 1, 2, 3,…, K).

The stochastic KT conditions of Equation (7) can be used to write the joint probability expression of consumption patterns if the density function of the stochastic terms (*i.e.,* the ε_k terms) is known. In the general case, let the joint probability density function of the ε_k terms be $g(\varepsilon_1,\ \varepsilon_2,\ \ldots,\ \varepsilon_K)$, let M alternatives be chosen out of the available K alternatives, and let the consumptions of these M alternatives be $(t_1^*,\ t_2^*,\ t_3^*,\ \ldots,\ t_M^*)$. As given in Bhat (2008), the joint probability expression for this consumption pattern is as follows:

$$P(t_1^*,\ t_2^*,\ t_3^*,\ \ldots,\ t_M^*,\ 0,\ 0,\ \ldots,\ 0) = \ |J| \int_{\varepsilon_1=-\infty}^{+\infty} \int_{\varepsilon_{M+1}=-\infty}^{V_1-V_{M+1}+\varepsilon_1} \int_{\varepsilon_{M+2}=-\infty}^{V_1-V_{M+2}+\varepsilon_1} \cdots \int_{\varepsilon_{K-1}=-\infty}^{V_1-V_{K-1}+\varepsilon_1} \int_{\varepsilon_K=-\infty}^{V_1-V_K+\varepsilon_1}$$
$$g(\varepsilon_1,\ V_1 - V_2 + \varepsilon_1,\ V_1 - V_3 + \varepsilon_1,\ \ldots,\ V_1 - V_M + \varepsilon_1,\ \varepsilon_{M+1},\ \varepsilon_{M+2},\ \ldots,\ \varepsilon_{K-1},\ \varepsilon_K) \qquad (8)$$
$$d\varepsilon_K d\varepsilon_{K-1} \ldots d\varepsilon_{M+2} d\varepsilon_{M+1} d\varepsilon_1\ ,$$

where J is the Jacobian whose elements are given by (see Bhat, 2005) $J_{ih} = \frac{\partial[V_1 - V_{i+1} + \varepsilon_1]}{\partial t_{h+1}^*} = \frac{\partial[V_1 - V_{i+1}]}{\partial t_{h+1}^*}$; i, h = 1, 2, …, M – 1.

In this paper, we rewrite the above probability expression as an integral of the Mth order partial derivative of a K-dimensional joint cumulative distribution of the error terms $(\varepsilon_1, \varepsilon_2, .., \varepsilon_K)$:

$$P(t_1^*,\ldots,t_M^*,0,\ldots,0) = |J| \int_{\varepsilon_1=-\infty}^{+\infty} \left[\left\{ \frac{\partial^M}{\partial\varepsilon_1 \ldots \partial\varepsilon_M} F(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K) \right\} \Bigg|_{\varepsilon_2 = V_1 - V_2 + \varepsilon_1, \varepsilon_3 = V_1 - V_3 + \varepsilon_1, \ldots, \varepsilon_K = V_1 - V_k + \varepsilon_1} \right] d\varepsilon_1 \qquad (9)$$

where $F(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$ is the joint cumulative distribution of the error terms $(\varepsilon_1, \varepsilon_2, .., \varepsilon_K)$. The reader will note here that the order of the partial derivative in the above expression is equal to the number of chosen alternatives (M), and that the differentials in the partial derivative are with respect to the stochastic utility components of the chosen alternatives.

The specification of the joint cumulative distribution $F(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$ of the error terms $(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_K)$ determines the form of the consumption probability expressions. In this paper, we assume a nested extreme value distributed error term structure that has the following joint cumulative distribution:

$$F(\varepsilon_1,\varepsilon_2,..,\varepsilon_K)=\exp\left[-\sum_{s=1}^{S_K}\left\{\sum_{i\in s^{\text{th}}\text{nest}}\exp\left(-\frac{\varepsilon_i}{\theta_s}\right)\right\}^{\theta_s}\right] \quad (10)$$

In the above cumulative distribution function, $s(=1,2,...,S_K)$ is the index to represent a nest of alternatives and S_K is the total number of nests the K alternatives belong to. $\theta_s(0<\theta_s\le 1; s=1,2,...,S_K)$ is the (dis)similarity parameter introduced to capture correlations among the stochastic components of the utilities of alternatives belonging to the s^{th} nest.[5]

Next, without loss of generality, let $1,2,...,S_M$ be the nests the M chosen alternatives belong to, let q_s be the number of chosen alternatives in the s^{th} nest (hence $q_1+q_2+...+q_{S_M}=M$), and let $\varepsilon_{1s},\varepsilon_{2s},...,\varepsilon_{qs}$ be the stochastic terms associated with each of the chosen alternatives in the s^{th} nest. Also, for simplicity in notation, let $F(\varepsilon_1,\varepsilon_2,..,\varepsilon_K)$ be represented as F. Using this notation and based on the functional form of F from equation (10), the M^{th} order partial derivative of the joint cumulative distribution in Equation (9) can be simplified into a product of S_M number of smaller partial derivatives, one for each nest. That is:

$$\frac{\partial^M F}{\partial\varepsilon_1\partial\varepsilon_2...\partial\varepsilon_M}=F\prod_{s=1}^{S_M}\left(\frac{1}{F}\frac{\partial^{q_s}F}{\partial\varepsilon_{1s}\partial\varepsilon_{2s}...\partial\varepsilon_{q_s}}\right) \quad (11)$$

The order of each smaller partial derivative in the right side of the above equation is equal to the number of chosen alternatives in the s^{th} nest.[6] Using the above expression, Equation (9) may now be rewritten as:

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[5] This error structure assumes that the nests are mutually exclusive and exhaustive (*i.e.,* each alternative can belong to only one nest and all alternatives are allocated to one of the S_K nests).

[6] The independence of the stochastic terms across different nests allows the M^{th} order partial derivative of F to be simplified into a product of smaller partial derivatives. This simplification forms the basis for the subsequent derivation of the MDCNEV choice probability expressions. However, if the error structure is relaxed to allow cross-nested structures, the M^{th} partial derivative cannot be reduced into a simple product of smaller partial derivates. This makes it difficult and cumbersome to derive the consumption probability expressions for a cross-nested case. Different and more general approaches, such as the use of recursive functional forms in the derivation, would be needed for the cross-nested case.

$$P(t_1^*,...,t_M^*,0,...,0)=|\,J\,|\int_{\varepsilon_1=-\infty}^{+\infty}\left\{F\Big|_{\varepsilon_i=V_1-V_i+\varepsilon_1;i=1,2,...K}\times\prod_{\eth=1}^{S_M}\left(\frac{1}{F}\frac{\partial^{q_\eth}F}{\partial\varepsilon_{1\eth}\partial\varepsilon_{2\eth}...\partial\varepsilon_{q_\eth}}\Bigg|_{\varepsilon_{i\eth}=V_1-V_{i\eth}+\varepsilon_1;\,i=1,2,...,q}\right)\right\}\mathrm{d}\varepsilon_1$$

(12)

Next, in the above equation, consider the $q_\eth{}^{th}$ order partial derivative for the $\eth^{th}$ nest, which, after several algebraic manipulations (details are available with the authors), can be expanded as follows:

$$\frac{\partial^{q_\eth}F}{\partial\varepsilon_{1\eth}...\partial\varepsilon_{q_\eth}}=F\left(\prod_{\substack{i\in\eth^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}}e^{-\frac{\varepsilon_i}{\theta_\eth}}\right)\sum_{r_\eth=1}^{q_\eth}\left\{\left(\sum_{i\in\eth^{\text{th}}\text{nest}}e^{-\frac{\varepsilon_i}{\theta_\eth}}\right)^{(q_\eth-r_\eth+1)\theta-q_\eth}sum(X_{r_\eth})\right\}, \text{ and}$$

$$\frac{1}{F}\frac{\partial^{q_\eth}F}{\partial\varepsilon_{1\eth}...\partial\varepsilon_{q_\eth}}\Bigg|_{\varepsilon_{i\eth}=V_1-V_{i\eth}+\varepsilon_1;\,i=1,2,...,q}=\left(\prod_{\substack{i\in\eth^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}}e^{-\frac{V_1-V_i}{\theta_\eth}}\right)\sum_{r_\eth=1}^{q_\eth}\left\{e^{-\varepsilon_1(q_\eth-r_\eth+1)}\left(\sum_{i\in\eth^{\text{th}}\text{nest}}e^{-\frac{(V_1-V_i)}{\theta_\eth}}\right)^{(q_\eth-r_\eth+1)\theta-q_\eth}sum(X_{r\eth})\right\}$$

(13)[7]

In the above two expressions, $sum(X_{r\eth})$ is a sum of the elements of a row matrix $X_{r\eth}$. This matrix takes a form described in Appendix A.

Substitution of the second expression of Equation (13) into Equation (12), followed by further expansion and algebraic rearrangements (shown in Appendix B), leads to the following expression for the consumption probability[8]:

$$P(t_1^*,t_2^*,...t_M^*,\ 0,...,0)=|\,J\,|\left(\prod_{i\in\{\text{chosen alts}\}}e^{-\frac{V_1-V_i}{\theta_i}}\right)\times$$
$$\times\sum_{r_1=1}^{q_1}...\sum_{r_\eth=1}^{q_\eth}...\sum_{r_{S_M}=1}^{q_{S_M}}\left\{\prod_{\eth=1}^{S_M}\left(\sum_{i\in\eth^{\text{th}}\text{nest}}e^{-\frac{(V_1-V_i)}{\theta_\eth}}\right)^{(q_\eth-r_\eth+1)\theta_\eth-q_\eth}\prod_{\eth=1}^{S_M}sum(X_{r\eth})\int_{\varepsilon_1=-\infty}^{+\infty}e^{-\varepsilon_1\sum_{\eth=1}^{S_M}(q_\eth-r_\eth+1)}\exp\left(-e^{-\varepsilon_1}f\right)d\varepsilon_1\right\} \quad (14)$$

[7]For presentation ease, in this equation (and from this point onward), we use the notation '$r\eth$' for '$r_\eth$' as the subscript of X in $sum(X_{r\eth})$.

[8] In the Equation below, θ_i is the dis(similarity) parameter associated with the nest to which alternative 'i' belongs to. Both θ_i and $\theta_\eth$ are used (at different places) in the expression to represent the same parameters (dissimilarity parameters) for the sake of notational and representational clarity.

where $f = \sum_{\varsigma=1}^{S_K} \left\{ \left(\sum_{i \in \varsigma^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\varsigma}} \right)^{\theta_\varsigma} \right\}$

The integral in the above Equation has the following closed-form expression (proved/derived in Appendix C):

$$I = \int_{\varepsilon_1=-\infty}^{+\infty} e^{-\varepsilon_1 \sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1)} \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1 = \frac{\left(\sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1) - 1 \right)!}{f^{\sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1)}}$$

that proves and gives rise to the following closed-form consumption probability expression for the MDCNEV model:

$$P(t_1^*, t_2^*, \ldots t_M^*,\ 0, \ldots, 0) =$$

$$|J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \sum_{r_1=1}^{q_1} \ldots \sum_{r_\varsigma=1}^{q_\varsigma} \ldots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\varsigma=1}^{S_M} \left(\sum_{i \in \varsigma^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\varsigma}} \right)^{(q_\varsigma - r_\varsigma + 1)\theta_\varsigma - q_\varsigma} \left(\prod_{\varsigma=1}^{S_M} sum(X_{r\varsigma}) \right) \frac{\left(\sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1) - 1 \right)!}{f^{\sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1)}} \right\} \tag{15}$$

After further algebraic rearrangements (details are available with the authors), the above expression simplifies to:

$$P(t_1^*, t_2^*, \ldots t_M^*,\ 0, \ldots, 0) =$$

$$|J| \frac{\prod_{i \in \{\text{chosen alternatives}\}} e^{\frac{V_i}{\theta_i}}}{\prod_{\varsigma=1}^{S_M} \left(\sum_{i \in \varsigma^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\varsigma}} \right)^{q_\varsigma}} \sum_{r_1=1}^{q_1} \ldots \sum_{r_\varsigma=1}^{q_\varsigma} \ldots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\varsigma=1}^{S_M} \left[\frac{\left(\sum_{i \in \varsigma^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\varsigma}} \right)^{\theta_\varsigma}}{\sum_{\varsigma=1}^{S_k} \left\{ \left(\sum_{i \in \varsigma^{\text{th}}\text{nest}} e^{\frac{V_i}{\theta_\varsigma}} \right)^{\theta_\varsigma} \right\}} \right]^{q_\varsigma - r_\varsigma + 1} \left(\prod_{\varsigma=1}^{S_M} sum(X_{r\varsigma}) \right) \left(\sum_{\varsigma=1}^{S_M}(q_\varsigma - r_\varsigma + 1) - 1 \right)! \right\} \tag{16}$$

The general expression above represents the MDCNEV consumption probability for any consumption pattern with a two-level nested extreme value error structure. This expression can be used in the log-likelihood formation and subsequent maximum likelihood estimation of the parameters for any dataset with mutually exclusive groups (or nests) of interdependent multiple discrete-continuous choice alternatives (*i.e.,* mutually exclusive groups of alternatives with correlated utilities).[9] It may be verified that the MDCNEV probability expression in Equation (16) simplifies to Bhat's (2008) MDCEV probability expression when each of the utility functions are independent of one another (*i.e.,* $\theta_{\mathscr{s}} = 1$ and $q_{\mathscr{s}} = 1 \, \forall \mathscr{s}$, and $S_M = M$). Also, one may verify that the above expression simplifies to the probability expressions derived by Bhat (2008) for a simple nested error structure with four alternatives. Finally, and importantly, it should be noted here that the nested extreme value extension developed in this paper is applicable not only for Bhat's MDCEV model, but also for all Kuhn-Tucker (KT)-based consumer demand model systems involving multiple continuous choices or multiple discrete-continuous choices (see von Haefen and Phaneuf, 2005 for a review of KT-demand model systems).

3 PROPERTIES OF THE MDCNEV MODEL

In this section, we present a simulation experiment and analysis to examine the importance and the properties of the MDCNEV model. Section 3.1 describes the simulation experiment, and Section 3.2 presents and discusses the results of the experiment.

3.1 Simulation Experiment

We consider the following utility structure with three choice alternatives (this is a simplistic special case of the general utility function proposed by Bhat, 2008):

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\begin{aligned}
u_1 &= \exp(\beta_1 + \xi_1)\ln(t_1) \\
u_2 &= \exp(\beta_2 x_2 + \xi_2)\ln(t_2) \\
u_3 &= \exp(\beta_3 x_3 + \xi_3)\ln(t_3)
\end{aligned}
\tag{17}
$$

In the above equation, the terms u_1, u_2, and u_3 represent the utility accrued from consuming t_1, t_2, and t_3 amounts of alternatives 1, 2, and 3, respectively. x_2 and x_3 are explanatory variables affecting the baseline utility of alternatives 2 and 3 (The data corresponding to these explanatory variables was generated assuming that x_2 and x_3 were uniformly distributed in the

[9] The analytic gradients of the MDCNEV model are rather tedious, and have not been coded at this point. Thus, the MDCNEV model takes about 10 hours to estimate relative to the MDCEV model that takes about 20 minutes. But this is not a fair comparison since we have written the gradients down for the MDCEV model. If we run the MDCEV model without the analytic gradients, it takes about 8 hours to estimate. Thus, the MDCNEV model takes about 25% longer to estimate than the MDCEV. The authors are currently coding the gradients, though this is proving to be difficult for a general nested logit case. In any event, it is important to note that the MDCNEV model without analytic gradients is still faster than a mixed MDCEV model with gradients. This latter model takes about 12 hours to run for the analogous "nested" specification of the final MDCNEV model of this paper.

interval [0, 2]). β_1, β_2, and β_3 are the parameters affecting the deterministic part of the baseline utilities ($\beta_1 = 1.5, \beta_2 = 1.2$, and $\beta_3 = 2.5$). ξ_1, ξ_2, and ξ_3 are the stochastic utility terms (or error terms) assumed to be nested extreme value distributed as below:

$$F(\xi_1, \xi_2, \xi_3) = \exp\left[-\left\{ \exp\left(-\frac{\xi_1}{\theta} \right) + \exp\left(-\frac{\xi_2}{\theta} \right) \right\}^{\theta} - \exp\left(-\xi_3 \right) \right] \tag{18}$$

The reader will note from the above distribution function that the alternatives 1 and 2 are assumed to be in a nest with a nesting parameter that is equal to θ.

Using the above utility structure and a consumption budget T = 100, we generated the consumption data (t_1^*, t_2^*, and t_3^*) for 2500 hypothetical individuals, assuming that each individual chooses the consumption amounts t_1^*, t_2^*, and t_3^* to maximize the total random utility of consumption ($U_R = u_1 + u_2 + u_3$) subject to a budget constraint $T = t_1^* + t_2^* + t_3^*$. Five sets of consumption data were generated, each with a specific value of θ (θ=0.1, 0.3, 0.5, 0.7, and 0.9).

Subsequently, for each of the above identified values of θ, using the corresponding consumption data and the explanatory variable data, we estimated both MDCEV and MDCNEV models to retrieve the model parameters β_1, β_2, and β_3 (the nesting parameter θ associated with the nest with alternatives 1 and 2 was also estimated with the MDCNEV model). Further, we used the parameter estimates (of both the models) to predict the consumption patterns of all the 2500 hypothetical individuals. These predictions were compared with the simulated "true" consumptions used to estimate the parameters. Finally, we employed the parameter estimates to analyze the impact of a policy in which the explanatory variable x_2 was increased by 30%. These exercises were carried out for each of the above-identified values of θ.[10] The results are discussed in the following section.

3.2 Experiment Results and Discussion

Table 1 presents the results of the simulation experiments and analysis conducted for all the five datasets. As indicated in the second row of the table, each dataset corresponds to a specific value of θ (0.1, 0.3, 0.5, 0.7, and 0.9). The subsequent four blocks of rows present the following

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[10]We conducted the same experiments with datasets simulated using additional values of θ, including 0.2, 0.4, 0.6, and 0.8. The corresponding results are not reported in the paper to conserve on space.

results for both MDCEV and MDCNEV models: (1) The model estimation results (in the row block labeled "Parameter Estimates" with the standard errors in parenthesis), (2) The goodness of fit measures, (3) The model prediction performance results, and (4) The policy analysis results.

3.2.1 Parameter Estimates and Goodness of Fit Measures

The block of rows labeled "Parameter Estimates" shows the parameter estimates $\hat{\theta}$, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ (with corresponding standard errors in parentheses) estimated from each of the five simulated datasets using both MDCEV and MDCNEV models. As can be observed from the row labeled "$\hat{\theta}$", the MDCNEV model estimation was able to recover the θ parameters to the second decimal place. However, for values of θ that are closer to 1, the standard errors of $\hat{\theta}$ are higher. This may be because of larger sample size requirements to efficiently estimate values of θ that are closer to 1.

A comparison of the MDCEV and MDCNEV model estimates of other parameters (i.e., the beta parameter estimates: $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$) indicates that for datasets simulated using smaller values of θ (i.e., for values of θ less than 0.7), the MDCNEV model parameter estimates are much closer (than the MDCEV model parameter estimates) to the "true" model parameters. It can also be observed that the standard errors of the MDCNEV model parameter estimates are substantially smaller than those corresponding to the MDCEV model. As the value of θ becomes closer to 1, the MDCNEV model estimates for β_3 are the only ones closer to the corresponding true value than that of the MDCEV model. It is interesting to note that, for β_1 and β_2, the MDCEV model estimates appear to be slightly closer to the true values than that of the MDCNEV model estimates. However, the standard errors of the MDCNEV model parameter estimates are consistently smaller than (or equal to) those of the MDCEV model parameter estimates. Overall, with larger correlations in the data (i.e., for smaller values of θ) the simpler MDCEV model is not able to recover the parameters well. On the other hand, for values of θ that are closer to 1, there appears to be no substantial difference between the two models in terms of the ability to recover model parameters.

The next block of rows corresponds to goodness of fit measures. Both the $\bar{\rho}^2$ (adjusted rho-bar squared) and the log-likelihood ratio test values (for the comparison of the MDCNEV model with the MDCEV model) indicate that the MDCNEV model clearly outperforms the MDCEV model when the true values of θ are small. As the true values of θ become closer to 1, although the MDCEV model can be rejected on the basis of the log-likelihood ratio test between the MDCEV and the MDCNEV models, there is no substantial difference in the $\bar{\rho}^2$ values.

In summary, these results indicate that ignoring the dependency between alternatives due to common unobserved factors, especially when highly significant (i.e., for values of θ that are smaller than 0.7), can lead to biased model estimates and inferior model fit.

3.2.2 Prediction Performance

The block labeled "Model Prediction Performance Results" shows the differences between the predicted average percentage consumptions (obtained using the parameter estimates of both the models) and the simulated average percentage consumptions for the three alternatives. It is clear from these results that the MDCEV model substantially underperforms in predicting the consumption in datasets generated using values of θ that are less than 0.7. Even for datasets generated using values of θ that are closer to 1 (i.e., for θ = 0.7 or 0.9), the differences between the predicted consumptions and the simulated consumptions are not negligible for the MDCEV model. On the other hand, the MDCNEV model predictions match closely with the simulated consumptions. This underscores the importance of accommodating inter-alternative correlations, from a prediction point of view, even when modest to low levels of correlations exist in the data (i.e., for values of θ that are close to 1).

3.2.3 Policy Analysis

For policy analysis, the attribute corresponding to the second alternative was improved by 30% (*i.e.,* x_2 was increased by 30%). The analysis results are reported in the last block of rows of Table 1 in terms of the percentage change in average consumption from before policy to after policy.

As expected, for all datasets, both the models showed an increase in the consumption of the second alterative and a decrease in the consumption of the other alternatives. However, again for all datasets, between the MDCNEV and the MDCEV models, the proportional consumption drawn from the first alternative (that belongs to the nest to which the second alternative belongs) is higher in the case of the MDCNEV model. This highlights the higher rate of substitution between the first and the second alternatives when they are in a nest (than the rate of substitution when they are not in a nest). Ignoring these differential substitution patterns between pairs of alternatives, when present, can potentially result in distorted policy implications. When the substitution effects are compared across the different datasets (simulated using different values of θ), stronger substitution effects (between the first and second alternatives) can be observed for the MDCNEV model results for smaller values of θ, as expected. For values of θ that are closer to 1, the differences in the substitution effects and in the policy implications between the MDCEV and the MDCNEV models are not negligible, if not substantial.

In summary, the simulation experiment results presented in this section demonstrates the need to account for the presence of inter-alternative error term correlations from model fit, forecasting, and policy analysis standpoints. As expected, the repercussions of ignoring the error term correlations are severe in the presence of stronger correlations. In the presence of modest to low levels of error term correlations (i.e., when the values of θ are closer to 1), it appears that using a simpler MDCEV model (rather than the MDCNEV model) may not severely affect the model parameter estimates. However, the impact on model predictions and elasticity effects (or policy impacts) is not negligible. Given that the end-objective of a model is for use in prediction and policy analysis (and not parameter estimation per se), the simulation results clearly illustrate the need to consider error correlation among utilities when present.

In the subsequent sections, we present an empirical application of the MDCNEV model to further explore the presence of, and the impact of ignoring, error correlation among utilities in real empirical contexts.

4 EMPIRICAL CONTEXT

The appropriate treatment of the time dimension of activity-travel behavior is one of the most important prerequisites to accurately forecasting travel demand. Hence, in the activity-based approach to travel demand analysis, "time" is viewed as the main backdrop/setting against which the entire activity-travel decision making process is assumed to unfold (see Kurani and Lee-Gosselin, 1996). Specifically, in the travel demand literature, a significant amount of research has been devoted to two specific aspects of the time-dimension of activity participation behavior:

(1) Activity time-use, and (2) Activity timing. In this section we briefly discuss these two topics, and then position the empirical context of the current study.

4.1 Activity Time-use and Activity Timing Analysis

Activity time-use analysis is concerned with understanding how individuals use (or allocate) the time available to them among various activities and travel. Such an analysis is central to the activity-based approach to travel modeling, because, in this approach, individuals' activity-travel patterns are viewed as a result of their activity time-use decisions (see Bhat and Koppelman, 1999; Pendyala and Goulias, 2002; and Arentze and Timmermans, 2004). On the other hand, activity timing analysis pertains to understanding the *timing* decisions (*i.e.,* the *when*-dimension) of individual activity participation. Such an analysis is essential to understanding individual responses to travel demand management policies.

As indicated earlier, both of the above-identified topics have received considerable research attention over the past decade. A notable gap in the literature, however, is that the research efforts in the two directions have largely been independent of each other (see Pinjari and Bhat, 2008 and Rajagopalan *et al*., 2008). That is, while most activity time-use studies have ignored the timing dimension of activity participation by limiting their focus to only activity participation and time-use behavior, most activity timing studies have neglected the broader time-use context within which activity-travel timing decisions take place. It has only recently been explicitly recognized that individual preferences regarding activity time-use and activity timing jointly (rather than independently) shape activity-travel patterns, (see Ettema *et al.,* 2007). Thus, only a handful of recent studies have considered activity time-use behavior and activity timing behavior in a joint framework (see Bhat, 1998, Yamamoto, *et al.,* 2000, Chu, 2005, Joh *et al.,* 2002, Ashiru *et al.,* 2004, and Ettema *et al.,* 2007). Most of these studies, however, consider activity participation during only certain specific portions of the day (Bhat, 1998; and Yamamoto *et al.,* 2000), or consider only a single activity purpose or a very restricted set of activity purposes (Ettema et al., 2007, Ashiru et al., 2004 and Chu, 2005). Further, almost all of these studies are focused around a typical workday of commuters (see, Rajagopalan *et al.,* 2008 for a discussion on these studies).

4.2 Current Empirical Research

The empirical research in this paper contributes to the literature on activity time-use and activity timing analysis by developing a random utility maximization-based weekday activity generation model for non-workers that considers daily activity time-use behavior and activity timing preferences in a unified framework. More specifically, the MDCNEV model proposed in Section 2 is employed to analyze non-workers' activity participation and time allocation patterns in several activity purposes at different time periods of a weekday. The activity purposes considered in this study include: (1) In-home (IH) and out-of home (OH) maintenance, (2) IH discretionary/leisure, (3) OH volunteering, (4) OH socializing, (5) OH recreation, (6) OH meals, and (7) OH non-maintenance shopping.[11] The activity timing intervals are defined by partitioning the day into six time periods: (1) Early morning (3am-7am), (2) Morning (7am-9am), (3) Late morning (9am-12 noon), (4) Afternoon (12 noon-4pm), (5) Evening (4pm-7pm), and (6) Night (7pm-3am). In this first joint study of non-worker activity time-use and timing behavior, we limited the activity timing analysis to out-of-home (OH) discretionary activities. Thus, the model developed in the paper predicts the discrete choice of participation in, and the continuous choice of time allocated to: (1) maintenance activities, (2) IH discretionary activities, and (3) each of the five OH discretionary activity purposes at each of six time periods (for a total of 30 OH discretionary activity purpose-time period combination alternatives).

5 DATA AND DESCRIPTIVE ANALYSIS

5.1 Data Sources

The primary source of the data used for this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS), designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission (MTC). The data contains information on: (1) Individual and household socio-demographics from over 15,000 households in the Bay Area, and (2) All activity episodes (including activity type, start and end times of the activity, geo-referenced location of activity participation, and mode of travel to the activity) undertaken by the individuals from all the surveyed households for a two-day period.

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[11]We use the terms, "IH and OH maintenance" and "maintenance" interchangeably and the terms "non-maintenance shopping" and "shopping" interchangeably.

In addition to the 2000 BATS data, several other sources of secondary data, including the land-use data, travel level-of-service data, Census population and housing data, and geo-referenced data on businesses, bicycling facilities, highways and local roads were used to derive spatial variables characterizing the activity-travel environment (ATE) in and around the household locations of the individuals in the BATS data.[12]

5.2 Descriptive Analysis of Activity Time-use and Timing Behavior in the Sample

The final estimation sample consists of 6167 non-working adults (*i.e.,* individuals of age>16 years who are either unemployed, or employed but did not go to work on the survey day) from the San Francisco Bay area. Table 2 presents the descriptive statistics of these non-workers' activity participation and time-use by activity type and activity timing.

The grey-shaded column in the table presents the total number and percentage of non-workers participating, and the average amount of time invested (for those who participated in the activity) in each activity purpose. As is evident from the first numbered row of this column, all non-workers in the sample participated in maintenance activities. Also the mean duration of time investment in maintenance activities is rather high, at about $10\frac{1}{2}$ hours. The mean durations of time investments in in-home (IH) discretionary activities and in out-of-home (OH) discretionary activities are about $5\frac{1}{2}$ hours and 3 hours, respectively (see second and third numbered-rows in the same column). The rows within the OH discretionary activity category provide the activity participation rates (*i.e.,* the number of non-workers and the percentage out of the 3383 non-workers who participated in at least one OH discretionary activity purpose) and average amounts of time investment (for those who participated in that activity purpose) in different OH discretionary activity purposes. These descriptive statistics indicate a low participation rate and a high amount of time investment in OH volunteering activities, and the reverse for OH non-maintenance shopping activities.

Within the OH discretionary activity category, the grey-shaded row of the table provides the activity participation rates and the average amounts of time investment (for those who participated) in OH discretionary activities that start during different time periods of the day. The

[12]The details of these secondary data sources, spatial variable computation, and the sample formation process are being suppressed here due to space considerations. The reader is referred to Guo and Bhat (2004) and Pinjari *et al.* (2008) for additional information on the secondary data sources and the procedures used to derive spatial variables. Details of the sample formation process are available from the authors.

activity participation rates indicate that, in general, non-workers' OH discretionary activity participation is more likely to start in the late morning to evening periods (*i.e.,* between 9am to 7pm) rather than during the early morning, morning, and night periods. However, from the average time investment values, it appears that the OH discretionary activities that start in the early morning (3am-7am) and morning periods (7am- 9am) are undertaken for longer durations than those that start later in the day.

Next, between the second to the last numbered columns, in the OH discretionary activity rows, the activity participation rates are provided for different time periods for each OH discretionary activity purpose. These activity participation rates indicate that most OH discretionary activity pursuits (irrespective of the activity purpose) are likely to start in the late morning to evening periods (*i.e.,* between 9am to 7pm). Further, non-maintenance shopping is most likely to be undertaken during the afternoon period (12 noon-4pm) and least likely to be undertaken during the early morning, morning, and night periods. This is reasonable, given the nature of shopping activity and the temporal constraints due to shopping store opening and closing hours. Also, socializing activities are least likely to start before 9am.

An important point from the descriptive statistics of Table 2 is that the non-worker, weekday, OH discretionary activity time-use and timing patterns are considerably different from those of workers reported elsewhere in the literature. For example, based on the comparison of the non-worker descriptives in Table 2 with similar descriptives on workers' activity time-use and timing patterns by Rajagopalan *et al.* (2008), the non-worker OH discretionary activity participation rates as well as average time investments appear to be significantly higher than those for workers. Further, while non-workers' activity time allocations are longer during the morning periods (*i.e.,* before 9am) compared to the later parts of the day, workers' activity time allocations reported by Rajagopalan *et al.* (2008) are longer during the evening period (*i.e.,* after they return home from work). Such differences between non-workers and workers warrant the development of separate models for these two population groups.

The non-worker MDCNEV model estimation results are presented and discussed in the following section.

6 MODEL ESTIMATION RESULTS

6.1 Utility Function

For the empirical model estimation, we considered various estimable forms of the general utility function in Equation (1) proposed by Bhat (2008). The following form of the utility function provided the best fit to the current empirical data:

$$U(\boldsymbol{t}) = \psi_1 \ln t_1 + \gamma_2 \psi_2 \ln\left(\frac{t_2}{\gamma_2} + 1\right) + \sum_{k=3}^{32} \gamma_k \psi_k \ln\left(\frac{t_k}{\gamma_k} + 1\right) \tag{19}$$

In the above utility equation, on the right hand side, the first term ($\psi_1 \ln t_1$) corresponds to the utility contribution of the time invested in maintenance activities, the second term corresponds to the utility contribution due to participation in, and the time investment in, the IH discretionary activities, and the next 30 terms (for $k = 3, 4, ..., 32$) correspond to the utility contribution due to participation in, and the time investment in, each of the 30 OH discretionary activity purpose-time period combination alternatives.

The reader will note here that the above equation can be obtained by constraining all the α_k terms (for $k = 1, 2, 3..., 32$) in Equation (1) to be equal to zero (see Bhat, 2008). Further, there is no γ_k term for the maintenance activity category, because all individuals in the estimation sample participated in that activity (see Bhat, 2008). Note that, to distinguish the activity purpose-specific satiation and activity timing-specific satiation, we reparameterized γ_k (for k = 3,4,…,32) as $\gamma_k = \gamma_{l_k} \times \gamma_{h_k}$, where γ_{l_k} and γ_{h_k} are the activity purpose-specific and activity timing-specific satiation parameters, respectively, corresponding to the activity purpose–activity timing combination alternative *k*.

6.2 Variables Considered

Several types of variables were considered in the MDCNEV model of non-worker activity time-use and activity timing behavior. These included: (1) household socio-demographics (household size, family structure and household composition, income, race/ethnicity, and vehicle and bicycle ownership, *etc.*), (2) individual socio-demographics (gender, age, license holding to drive, physical ability/disability status, and employment status), (3) contextual variables such as day of the week and season of the year, and (4) a host of spatial variables characterizing the activity-travel environment (ATE) around the household locations. The ATE variables included: (a) household, population, and employment density measures, (b) land-use composition measures, (c) demographic composition variables, (d) activity opportunity variables, for various discretionary activities, including recreation, shopping, and eating out (or meals), and (e) transportation network measures (see Pinjari *et al.,* 2008 for details on these variables). These ATE measures were considered at the residential TAZ (traffic analysis zone) level of spatial resolution, as well as at finer levels of spatial resolution. Specifically, to assess the impact of the ATE characteristics around a household's immediate neighborhood, the above-mentioned variables were considered for 0.25 mile, 1 mile, and 5 mile radii around the residential coordinates of each individual in the sample (see Guo and Bhat, 2004).

In the next section (Section 6.3), we discuss the estimation results of the MDCNEV model. Section 6.4 focuses on likelihood-based measures of data fit.

6.3 Estimation Results

The final specification results of the MDCNEV model are presented in Tables 3 and 4. Table 3 presents the parameter estimates corresponding to household and individual socio-demographics, day of the week and seasonal effects, and activity-travel environment (ATE) attributes on the baseline utility specification. Table 4 presents the baseline preference constants and satiation parameter estimates. The maintenance activity purpose serves as the base activity purpose category and the night time period serves as the base activity timing category for most (but not all) variables. Further, the model is specified (and the results are presented) in such a way that the effect of each variable is first identified separately along the activity purpose and activity timing dimensions. Subsequently, any interaction effects of the variable over and beyond the unidimensional effects are identified. A '-' entry corresponding to the effect of a variable for a particular activity purpose in the top "activity purpose dimension" panel of Table 3 indicates no significant effect of the variable on the corresponding activity purpose utility. The same holds for the "activity timing dimension" panel and the "activity purpose-activity timing" panel. Further, the effects of variables on the baseline utilities have been constrained to be equal in Table 3 if coefficient equality could not be rejected based on statistical tests. Finally, the t-statistic of each estimated parameter is presented in parenthesis beneath the parameter.

6.3.1 Effects of Household Socio-Demographics on Baseline Utility

Among the household socio-demographic variables, the lone coefficient of the household size variable indicates that, with increasing household size, non-workers tend to spend more time on maintenance activities as opposed to IH leisure and OH discretionary activities. This is perhaps due to an increase in household maintenance needs as the number of household members rises. The reader will note here that this coefficient, although marginally significant with a t-statistic of 1.62, was retained in the model specification due to intuitive considerations (see Kitamura *et al.,* 1996 for a similar result). With respect to the timing decisions of non-workers' OH discretionary activities, household size did not show any significant impacts.

The next household socio-demographic attribute is a dummy variable indicating if a household comprises of a single adult. The coefficients on this variable indicate that non-workers who live alone are more likely to participate in out-of-home (OH) socializing and OH meal activities compared to non-workers not living alone. Single individuals are also more likely to participate in OH discretionary activity during the evening time period. These effects reflect the need for human interactions when living alone. The preference for the evening period may be simply because this period offers better opportunities to coordinate discretionary activities jointly with other individuals. Further, non-workers who live alone are more likely (than those who do not live alone) to undertake OH recreation activities during the night time period. This inclination toward recreation activities during the night time may again be because of the potential opportunities for social contact, the nature of the activity purpose under consideration (such as movies, theatre shows, *etc.*), and the lesser extent of household responsibilities and greater available free time during night time (relative to non-workers who do not live alone).

The impact of the presence of children was explored using several explanatory variables, including continuous variables for the number of children, and dummy variables for the presence of children, of different age groups. The final model specification has two dummy variables: (1) Presence of children of age less than 5 years, and (2) Presence of children of age between 5 and 15 years. Interestingly, none of the children-related variables showed any direct impact on the activity purpose preferences of non-workers. However, presence of children, when interacted with the female dummy variable, had a significant impact on maintenance activity pursuits. With respect to activity timing, non-workers with children of age below 5 years are less likely to time their OH discretionary activities during the morning, late morning, evening, afternoon, and evening periods (*i.e.,* between 9 am and 7pm). A likely explanation is that, on weekdays, other adults of the household (for example, working adults) may not be available during these time periods. This may necessitate non-workers to take care of the children, and prevent them from pursuing OH discretionary activities. In contrast to these impacts of the presence of young children, the presence of older children (of age between 5 and 15 years) increases the propensity of non-workers to participate in OH discretionary activity pursuits during the morning and evening periods. A plausible explanation is that non-workers may combine OH discretionary activities within the pick-up/drop-off tours associated with assisting older children with their travel needs (such as travel to/from school) during (and around) the morning and evening time periods.

The next household socio-demographic variable is the number of adults in the household who worked on the survey day. As the number of working adults in the household increases, non-workers avoid OH discretionary activity pursuits during the late morning and afternoon periods. This may be because non-workers jointly undertake OH discretionary activities with working individuals in the household, and the late morning and afternoon periods are less likely to offer a common time window for such joint activity pursuits.

The effect of household income is introduced in the form of dummy variables, with the "medium income" category (annual income between 45K and 100K) being the base. The corresponding coefficients reveal that non-workers from low income (annual income <45K) households are more likely to spend their time on maintenance and IH discretionary activities (as opposed to OH discretionary activities), while those from high income (annual income >100K) households are more likely to spend their time on OH discretionary activities such as socializing, recreation, meals, and shopping. These effects reflect the high "*consumption potential"* associated with high income levels (see Chu, 2005). In contrast to such significant activity purpose-specific impacts, household income does not influence activity timing decisions.

The coefficient on the vehicle ownership variable suggests a lower propensity to participate in IH discretionary activities as vehicle ownership levels rise, perhaps due to the flexibility and improved mobility to pursue OH discretionary activities. Finally, within the category of household demographics, the coefficient corresponding to the number of bicycles shows a positive association between bicycle ownership and OH recreational activity pursuits.

This may be because bicycle owners are outdoor-oriented and physical fitness conscious (see Pinjari *et al.,* 2008).

6.3.2 Effects of Individual Socio-Demographics on Baseline Utility

Among the individual socio-demographic variables, the coefficients on the female gender dummy variable indicate that female non-workers are more likely (than males) to spend their time in maintenance and OH volunteering activities. Further, non-working women with children in the household are even more likely to invest time in maintenance activities (see the coefficient on the variable “female with kids”). This association of women with maintenance activity responsibilities reiterates the traditional gender role that has been documented in a number of studies (see, for example, Bhat and Misra, 1999; Yamamoto and Kitamura, 1999; Srinivasan and Bhat, 2006; Gossen and Purvis, 2005; Chen and Mokhtarian, 2006; and Goulias and Henson, 2006). In the context of OH discretionary activity pursuits, the activity timing-related results suggest that non-working women are least (most) likely to time their OH discretionary activities during the early morning and morning (late afternoon and evening) periods. These timing preferences may again be traced to the maintenance activity responsibilities of non-working women during the early morning, morning and night periods (see Bradley and Vovsha, 2005).

The coefficients on the age-related variables (introduced as dummy variables – age<30years and age>65years, with age between 30-65years as the base) point to the higher tendency of the younger (age<30years) non-workers toward OH socializing activities, and the older (age>65years) non-workers toward OH volunteering activities With respect to activity timing decisions, younger non-workers are more likely to time their OH discretionary activity pursuits during the evening and night time periods, while the older non-workers are less likely to do so during the night time period. The evening and night time preferences of the younger demographic segment may be because of the nature of the social activities they are most likely to undertake. That is, as discussed earlier (in Section 6.3.1), on weekdays, evening and night time periods may be more conducive for joint activities such as socialization that usually involve multiple individuals. On the other hand, older people may refrain from OH discretionary activity pursuits during the night time to avoid late night driving.

The impacts of the next two variables - holding of a license to drive and being physically disabled - reflect the expected association between how mobile a person is and the level of OH discretionary activity participation.

Finally, among the individual socio-demographic attributes, the coefficients on the employed dummy variable indicate that employed adults who did not go to work on the survey day are less likely to undertake maintenance and IH discretionary activities. Specifically, they are least likely to undertake maintenance activities. This may be because employed individuals are more likely to undertake maintenance activities during their work-days and, consequently, avoid maintenance activities during non-work days. Further, they might have chosen not to go to work specifically to carry out OH discretionary activities.

6.3.3 Day of the Week and Seasonal Effects

Non-workers are more likely to participate in OH discretionary activities such as socialization, recreation, meals, and shopping on Fridays than on other weekdays. On Fridays, the OH discretionary activities are more likely to be undertaken during the night time period. Further, there is a lower propensity for IH discretionary and OH recreation activities during the Fall season, and a higher propensity for OH recreation activity during the Summer season.

6.3.4 Effects of Activity-Travel Environment (ATE) Attributes on Baseline Utility

A variety of ATE effects were explored in the model specification. However, and interestingly, most of the ATE effects did not turn out to be statistically significant in the empirical specification. The only statistically significant ATE effect in the final model specification corresponds to retail employment (*i.e.,* the number of jobs in the retail sector) within 0.25 mile radius of the household location. The corresponding parameter estimates indicate that, with higher retail employment density around the household, non-workers are more likely to undertake OH meals during the afternoon period. This activity purpose preference may be a reflection of the availability of OH meal activity opportunities (such as restaurants and eat-out centers) around the household. The afternoon time period preference may be due to the nature of the activity purpose (*i.e.,* meals) under consideration.

6.3.5 Baseline Preference Constants

The estimated baseline preference constants and the corresponding t-statistics are presented in the first half of Table 4. Maintenance activity is treated as the base alternative. Note also that, in the column labeled "In-home Discretionary", the rows corresponding to different time periods have no entries because we did not model the timing of in-home discretionary activities.

The baseline preference constants do not have any substantive interpretations. They capture generic tendencies to participate in each activity purpose-time period category as well as accommodate the range of the continuous independent variables in the model. However, all the baseline preference constants are negative, indicating the high participation level of non-workers in maintenance activities relative to IH discretionary and OH discretionary activities. Also, the baseline preference constant for the IH discretionary activity is higher than those for all the OH discretionary activity purpose-time period combinations, indicating the higher participation level of non-workers in IH discretionary activities relative to OH discretionary activities.

6.3.6 Satiation (γ_k) Parameters

The satiation parameter estimates and the corresponding t-statistics are provided in the second half of Table 4. These satiation parameters were introduced dimension-wise in the model specification. That is, instead of estimating 31 satiation parameters (*i.e.,* one parameter for in-home discretionary activity, and one parameter each for the 30 OH discretionary activity purpose-timing combination alternatives), 11 satiation parameters were estimated. Among these 11 estimated satiation parameters, 6 were estimated to distinguish the satiation effects for each of the 6 activity purposes and an additional 5 satiation parameters were estimated to distinguish satiation effects for five time periods (the night time period satiation parameter was fixed at 1.00 due to estimability considerations). The dimension-wise estimates are presented in grey-shaded cells in Table 4. Further, as explained in Section 6.1, the satiation parameters for each of the 30 activity purpose-activity timing combination alternatives have been obtained through appropriate combination of the dimension-wise estimates. [13]

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[13] Hence, from Table 3, the γ_k estimate for OH meals activity during afternoon time period is (0.92)×(66.05) = 60.50. The appropriate t-statistics (against zero) are also shown in the table.

From the satiation parameter estimates and the corresponding t-statistics provided in Table 4, it can be observed that significant satiation effects exist in the time investment patterns for each activity purpose-timing combination. Further, it can be observed that the satiation levels show larger variation across different activity purposes than across different time periods. Among different activity purposes, IH discretionary activities are associated with low satiation (hence high durations) when compared with those of OH discretionary activities. Within OH discretionary activities, the shopping category is associated with the highest level of satiation (hence low durations). With regard to the activity timing categories, consistent with the descriptive results in Section 5.2, the early morning and morning periods are associated with low satiation levels (hence high durations of OH discretionary activity participation). Overall, these satiation trends are in agreement with the average amounts of time investment reported in Table 2.

6.3.7 Nesting (θ) Parameters

Several nesting structures were considered and later refined based on intuitive and statistical considerations. The final specification included two nests – (1) Nest 1 that includes OH meal activities during evening and night time periods and OH socializing and OH recreation activities during the night time period (*i.e.,* a total of 4 activity purpose-timing alternatives), and (2) Nest 2 that includes OH meals and OH shopping activities during both late morning and afternoon periods (*i.e.,* a total of 4 activity purpose-timing alternatives). The nesting parameter for Nest 1 is 0.94 (with a t-statistic of 2.74), and that of Nest 2 is 0.98 (with a t-statistic of 1.56), respectively.[14]

6.3.8 Comparison with MDCEV Model Parameters

The preceding discussions in this Section have focused on the MDCNEV model parameter estimates. The estimation results of the simpler MDCEV model are neither presented nor discussed. This is because the parameter estimates are not substantially different (between the MDCNEV and MDCEV models) to affect variable effect interpretations. This is due to the modest levels of inter-alternative error term correlations (i.e., the nesting parameters are closer to 1). Nonetheless, as in the simulation experiments, it is possible that ignoring even modest levels

[14] These statistics are computed for the null hypothesis that the nesting parameters are equal to 1.

of error term correlations may result in tangible differences in goodness of fit and policy predictions between the two models, as we demonstrated in the simulation experiments earlier. Hence, the subsequent sections focus on model fit and policy simulations.

6.3.9 Goodness of Fit Measures

The log-likelihood value for the MDCEV model with only the constants in the baseline preference (and with the satiation/translation parameters) is -74,012.6. The log-likelihood value at convergence of the MDCEV model with the explanatory variables is -73,690.1. For the MDCNEV model with the explanatory variables and with two additional parameters for the two nests, the log-likelihood at convergence is -73,603.1. The likelihood ratio between the final MDCNEV and the MDCEV models is 173.91, which is substantially larger than the critical chi-square value with 2 restrictions (one for each nest) at any reasonable level of significance. This highlights the importance of the nested model from a goodness-of-fit standpoint.

Another approach to compare the model fit is the Bayesian Information Criterion (BIC), which incorporates a penalization to an apparent improvement in model fit due to larger sample sizes. The BIC for a model is equal to $-2\times\ln(L)+\textit{number of parameters}\times\ln(Q)$, where $\ln(L)$ is the log-likelihood value at convergence and Q is the number of observations. The model that results in the lowest BIC value is the preferred model. The BIC value for the MDCNEV model (with 79 model parameters) is 147895.6, which is lower than that for the simpler MDCEV model (148052.2 with 77 model parameters). Thus, the BIC favors the MDCNEV model.

A third measure of model fit is the adjusted rho-bar square ($\bar{\rho}^2$), which is equal to 0.0038 for the MDCEV model and 0.0050 for the MDCNEV model. Given the complexity of the models with 36 alternatives, it is not surprising to obtain such low values of $\bar{\rho}^2$.

7 POLICY SIMULATIONS WITH EMPIRICAL DATA

Goodness of fit measures, as discussed above, favor the MDCNEV model over the MDCEV model. However, it is worth noting here that both of the nesting parameter estimates are close to 1 (and one of the nesting parameters is in fact only marginally significant), indicating low levels of correlations. Besides, the model coefficients were not substantially different between the two models. This leaves a possibility that the MDCNEV model may not be necessary (over the simpler MDCEV model) to model activity time-use and timing choices in the current empirical context. To explore this further, we conducted policy simulations using the estimates obtained from both the MDCEV and MDCNEV models.

The policy simulation was conducted in the context of a five-fold across-the-board increase in the "Retail employment within 0.25 miles of household" variable for 20 individuals in the sample. This variable positively affects the time individuals expend in OH meals during the afternoon period. The OH meals-afternoon alternative is in Nest 2, which includes the four alternatives of OH meals-late morning, OH meals-afternoon, OH shopping-late morning, and OH shopping-afternoon. Thus, to keep the presentation focused, we examine the impact of a change in the retail employment variable on time use in only these four OH alternatives and two other alternatives – maintenance activity and IH discretionary activity (for all other alternatives, the policy impact was negligible enough to be ignored) . For each individual, we used 250 sets of error term draws to determine the time use before and after the change in retail employment. The results are reported in Table 5, which provide, for each of the six alternatives identified-above, the percentage change in time-use due to the increase in retail employment as averaged across the 20 individuals used in the simulation. These results clearly show the higher draw from the OH meals-late morning, OH shopping-late morning, and OH shopping-afternoon alternatives. This is as expected given that these alternatives are in the same nest as the OH meals-afternoon alternative. Further, the MDCEV model overpredicts the increase in time-use for OH meals in the afternoon by about 25%, and also overpredicts the draw from the maintenance and IH discretionary activities.

In summary, although the nesting parameters indicate low levels of correlations in the current empirical context, there are differences in the policy results as predicted by the MDCEV and MDCNEV models. These results are in line with the results of the simulation experiment, and reinforce the notion that model predictions and policy results can be quite different between the MDCEV and MDCNEV models even at low levels of correlation implied by the MDCNEV model.

8 SUMMARY AND CONCLUSIONS

This paper develops a multiple discrete-continuous nested extreme value (MDCNEV) model that relaxes the independently distributed (or uncorrelated) error terms assumption of the MDCEV model proposed by Bhat (Bhat, 2005 and Bhat, 2008). Specifically, the MDCNEV model proposed in this paper captures inter-alternative correlations among alternatives in mutually exclusive subsets (or nests) of the choice set, while maintaining the closed-form of probability expressions for any (and all) consumption pattern(s).

The MDCNEV model is applied to analyze non-worker out of home discretionary activity time-use and activity timing decisions on weekdays using data from the 2000 San Francisco Bay Area data. This empirical application contributes to the literature on activity time-use and activity timing analysis by considering daily activity time-use behavior and activity timing preferences in a unified utility maximization-based framework. The model estimation results provide several insights into the determinants of non-workers' activity time-use and timing decisions and highlight the importance of the nested model. Also, the knowledge of the activities (and the corresponding time allocations and timing decisions) predicted by this model can potentially be used for the subsequent scheduling and sequencing of activities and related travel in regional activity-based travel demand microsimulation models.

In the current empirical context, the MDCNEV model performs better than the MDCEV model in terms of goodness of fit. The nesting parameters are, however, very close to 1 (even though one of them is statistically different from one), indicating low levels of correlation. Nonetheless, even with such low correlation levels, empirical policy simulations with the Bay area data indicate that it is possible that there are non-negligible differences in policy predictions and substitution patterns exhibited by the two models. These findings are in line with the results of the experiments conducted with simulated data. Of course, when the levels of inter-alterative error correlations are higher, the MDCNEV model clearly outperforms the MDCEV model in our simulations. In any event, it behooves the analyst to, at the least, estimate the MDCNEV model to test for the presence of inter-alternative correlations in the data before employing the simpler MDCEV model.

The research in this paper may be extended in several ways, including: (1) The consideration of more general nesting structures (such as cross nesting) and GEV-based error term specifications, and (2) The development of an integrated model of activity time-use, activity timing, activity sequencing and scheduling decisions, and travel-related decisions. These are important areas for future research that the authors are currently pursuing.

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APPENDIX A

For $r_{\delta}=1$, $X_{r\delta}=\{1\}$.

For $r_{\delta}=2$, $X_{r\delta}=\left\{\frac{(q_{\delta}-1)(1-\theta_{\delta})}{\theta_{\delta}}+\frac{(q_{\delta}-2)(1-\theta_{\delta})}{\theta_{\delta}}+\ldots+\frac{2(1-\theta_{\delta})}{\theta_{\delta}}+\frac{1(1-\theta_{\delta})}{\theta_{\delta}}\right\}$.

For $r_{\delta}=3,4,\ldots,q_{\delta}$, $X_{r\delta}$ is a matrix of size $\begin{bmatrix} q_{\delta}-2 \\ r-2 \end{bmatrix}$ which is formed as described below:

Consider the following row matrices $A_{q_{\delta}}$ and $A_{r\delta}$ (with the elements arranged in the descending order, and of size $q_{\delta}-1$ and $r_{\delta}-2$, respectively):

$$A_{q_{\delta}}=\left\{\frac{(q_{\delta}-1)(1-\theta_{\delta})}{\theta_{\delta}},\frac{(q_{\delta}-2)(1-\theta_{\delta})}{\theta_{\delta}},\frac{(q_{\delta}-3)(1-\theta_{\delta})}{\theta_{\delta}},\ldots,\frac{3(1-\theta_{\delta})}{\theta_{\delta}},\frac{2(1-\theta_{\delta})}{\theta_{\delta}},\frac{1(1-\theta_{\delta})}{\theta_{\delta}}\right\}$$

$$A_{r\delta}=\left\{r_{\delta}-2,r_{\delta}-3,r_{\delta}-4,\ldots,3,2,1\right\}.$$

Choose any $r_{\delta}-2$ elements (other than the last element, $\frac{1-\theta_{\delta}}{\theta_{\delta}}$) of the matrix $A_{q_{\delta}}$ and arrange them in the descending order into another matrix $A_{iq_{\delta}}$. Note that we can form $\begin{bmatrix} q_{\delta}-2 \\ r_{\delta}-2 \end{bmatrix}$ number of such matrices. Subsequently, form another matrix $A_{irq_{\delta}}=A_{iq_{\delta}}+A_{r\delta}$. Of the remaining elements in the $A_{q_{\delta}}$ matrix, discard the elements that are larger than or equal to the smallest element of the $A_{iq_{\delta}}$ matrix, and store the remaining elements into another matrix labeled $B_{irq_{\delta}}$. Now, an element of $X_{r\delta}$ (*i.e.,* $x_{irq_{\delta}}$) is formed by performing the following operation:

$x_{irq_{\delta}}=\text{Product}(A_{irq_{\delta}})\times\text{Sum}(B_{irq_{\delta}})$; that is, by multiplying the product of all elements of the matrix $A_{irq_{\delta}}$ with the sum of all elements of the matrix $B_{irq_{\delta}}$. Note that the number of such elements of the matrix $X_{r\delta}$ is equal to $\begin{bmatrix} q_{\delta}-2 \\ r_{\delta}-2 \end{bmatrix}$.

APPENDIX B

From Equation (13),

$$\frac{1}{F}\frac{\partial^{q_s} F}{\partial\varepsilon_{1s}\ldots\partial\varepsilon_{q_s}}\Bigg|_{\varepsilon_{is}=V_1-V_{is}+\varepsilon_1;\; i=1,2,\ldots,q} = \left(\prod_{\substack{i\in s^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}} e^{-\frac{V_1-V_i}{\theta_s}}\right)\sum_{r_s=1}^{q_s}\left\{e^{-\varepsilon_1(q_s-r_s+1)}\left(\sum_{i\in s^{\text{th}}\text{nest}} e^{-\frac{(V_1-V_i)}{\theta_s}}\right)^{(q_s-r_s+1)\theta-q_s} sum(X_{r_s})\right\} \tag{B1}$$

Equation (B1) can be used to expand the M^{th} order partial derivative of Equation (9) as follows:

$$\left\{\frac{\partial^M}{\partial\varepsilon_1\ldots\partial\varepsilon_M}F(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_K)\right\}\Bigg|_{\varepsilon_2=V_1-V_2+\varepsilon_1,\varepsilon_3=V_1-V_3+\varepsilon_1,\ldots,\varepsilon_K=V_1-V_k+\varepsilon_1} =$$

$$=F\Big|_{\varepsilon_2=V_1-V_2+\varepsilon_1,\ldots,\varepsilon_K=V_1-V_k+\varepsilon_1}\prod_{s=1}^{S_M}\left[\left(\prod_{\substack{i\in s^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}} e^{-\frac{V_1-V_i}{\theta_s}}\right)\sum_{r_s=1}^{q_s}\left\{e^{-\varepsilon_1(q_s-r_s+1)}\left(\sum_{i\in s^{\text{th}}\text{nest}} e^{-\frac{(V_1-V_i)}{\theta_s}}\right)^{(q_s-r_s+1)\theta-q_s} sum(X_{r_s})\right\}\right]$$

$$=\exp\left(-e^{-\varepsilon_1}f\right)\prod_{s=1}^{S_M}\left[\left(\prod_{\substack{i\in s^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}} e^{-\frac{V_1-V_i}{\theta_s}}\right)\sum_{r_s=1}^{q_s}\left\{e^{-\varepsilon_1(q_s-r_s+1)}\left(\sum_{i\in s^{\text{th}}\text{nest}} e^{-\frac{(V_1-V_i)}{\theta_s}}\right)^{(q_s-r_s+1)\theta-q_s} sum(X_{r_s})\right\}\right] \tag{B2}$$

where $f=\sum_{s=1}^{S_K}\left\{\left(\sum_{i\in s^{\text{th}}\text{nest}} e^{-\frac{(V_1-V_i)}{\theta_s}}\right)^{\theta_s}\right\}$

The above expression for the M^{th} order partial derivative can be substituted into the probability expression of Equation (9) as follows:

$$P(t_1^*,t_2^*,\ldots,\ t_M^*,0,\ldots,0)=$$

$$|J|\int_{\varepsilon_1=-\infty}^{+\infty}\exp\left(-e^{-\varepsilon_1}f\right)\prod_{s=1}^{S_M}\left[\left(\prod_{\substack{i\in s^{\text{th}}\text{nest, and}\\ i\in\{\text{chosen alts}\}}} e^{-\frac{V_1-V_i}{\theta_s}}\right)\sum_{r_s=1}^{q_s}\left\{e^{-\varepsilon_1(q_s-r_s+1)}\left(\sum_{i\in s^{\text{th}}\text{nest}} e^{-\frac{(V_1-V_i)}{\theta_s}}\right)^{(q_s-r_s+1)\theta-q_s} sum(X_{r_s})\right\}\right]d\varepsilon_1 \tag{B3}$$

The probability expression in Equation (B3) can be rewritten as follows:

$$P(t_1^*, t_2^*, \ldots,\ t_M^*, 0, \ldots, 0)$$

$$= |J| \int\limits_{\varepsilon_1=-\infty}^{+\infty} \exp\left(-e^{-\varepsilon_1} f\right) \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \prod_{\delta=1}^{S_M} \left[\sum_{r_\delta=1}^{q_\delta} \left\{ e^{-\varepsilon_1 (q_\delta - r_\delta + 1)} \left(\sum_{i \in \delta^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} sum(X_{r_\delta}) \right\} \right] d\varepsilon_1$$

$$= |J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \int\limits_{\varepsilon_1=-\infty}^{+\infty} \exp\left(-e^{-\varepsilon_1} f\right) \prod_{\delta=1}^{S_M} \left[\sum_{r_\delta=1}^{q_\delta} \left\{ e^{-\varepsilon_1 (q_\delta - r_\delta + 1)} \left(\sum_{i \in \delta^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} sum(X_{r_\delta}) \right\} \right] d\varepsilon_1,$$

(B4)

The reader will observe that the expression in Equation (B4) involves a product over all nests (*i.e.,* over $\delta = 1,2,\ldots,S_M$) of summations over all alternatives in a nest (*i.e.,* over $r_\delta = 1,2,\ldots,q_\delta$). This product of summations can be expressed as a summation of products and the Equation (B4) can be rewritten as follows:

$$P(t_1^*, t_2^*, \ldots,\ t_M^*, 0, \ldots, 0)$$

$$= |J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \int\limits_{\varepsilon_1=-\infty}^{+\infty} \exp\left(-e^{-\varepsilon_1} f\right) \left[\sum_{r_1=1}^{q_1} \sum_{r_2=1}^{q_2} \ldots \sum_{r_\delta=1}^{q_\delta} \ldots \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \left(\prod_{\delta=1}^{S_M} e^{-\varepsilon_1 (q_\delta - r_\delta + 1)} \right) \prod_{\delta=1}^{S_M} \left(\sum_{i=1}^{q_\delta} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} \prod_{\delta=1}^{S_M} sum(X_{r\delta}) \right\} \right] d\varepsilon_1$$

(B5)

In the above expression, all the terms containing ε_1 are moved to the right corner and the other terms are moved out of the integral as follows:

$$P(t_1^*, t_2^*, \ldots,\ t_M^*, 0, \ldots, 0)$$

$$= |J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \int\limits_{\varepsilon_1=-\infty}^{+\infty} \sum_{r_1=1}^{q_1} .. \sum_{r_\delta=1}^{q_\delta} .. \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\delta=1}^{S_M} \left(\sum_{i \in \delta^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} \prod_{\delta=1}^{S_M} sum(X_{r\delta}) \left(\prod_{\delta=1}^{S_M} e^{-\varepsilon_1 (q_\delta - r_\delta + 1)} \right) \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1 \right\}$$

$$= |J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \sum_{r_1=1}^{q_1} .. \sum_{r_\delta=1}^{q_\delta} .. \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\delta=1}^{S_M} \left(\sum_{i \in \delta^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} \prod_{\delta=1}^{S_M} sum(X_{r\delta}) \int\limits_{\varepsilon_1=-\infty}^{+\infty} \left(\prod_{\delta=1}^{S_M} e^{-\varepsilon_1 (q_\delta - r_\delta + 1)} \right) \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1 \right\}$$

(B6)

Finally, the product of exponentials in the integral above is expressed as a single exponential, and the probability expression is as below:

$$P(t_1^*, t_2^*, \ldots,\ t_M^*, 0, \ldots, 0)$$

$$= |J| \left(\prod_{i \in \{\text{chosen alts}\}} e^{-\frac{V_1 - V_i}{\theta_i}} \right) \sum_{r_1=1}^{q_1} .. \sum_{r_\delta=1}^{q_\delta} .. \sum_{r_{S_M}=1}^{q_{S_M}} \left\{ \prod_{\delta=1}^{S_M} \left(\sum_{i \in \delta^{\text{th}}\text{nest}} e^{-\frac{(V_1 - V_i)}{\theta_\delta}} \right)^{(q_\delta - r_\delta + 1)\theta_\delta - q_\delta} \prod_{\delta=1}^{S_M} sum(X_{r\delta}) \int\limits_{\varepsilon_1=-\infty}^{+\infty} e^{-\varepsilon_1 \sum_{\delta=1}^{S_M} (q_\delta - r_\delta + 1)} \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1 \right\}$$

(B7)

This expression is the same as the consumption probability expression given in Equation (14). The expression includes an integral that has a closed-from expression (proved in Appendix C).

APPENDIX C

Consider the integral $I = \int\limits_{\varepsilon_1=-\infty}^{+\infty} e^{-\varepsilon_1 \sum_{\mathscr{s}=1}^{S_M} (q_{\mathscr{s}} - r_{\mathscr{s}} + 1)} \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1$ from Equation (14).

The above integral is in the following form:

$$I = \int\limits_{\varepsilon_1=-\infty}^{+\infty} \left(e^{-\varepsilon_1}\right)^n \exp\left(-e^{-\varepsilon_1} f\right) d\varepsilon_1, \quad \text{where}\, n = \sum_{\mathscr{s}=1}^{S_M} (q_{\mathscr{s}} - r_{\mathscr{s}} + 1) \tag{C1}$$

Now, let $e^{-\varepsilon_1} = x$, then $d\varepsilon_1 = {-dx}/{e^{-\varepsilon_1}}$.

Using the above substitution, the integral can be expressed as:

$$\begin{aligned}
I &= \int\limits_{x=+\infty}^{0} x^n \exp\left(-xf\right)\left(\frac{-dx}{x}\right) \\
&= -\int\limits_{x=+\infty}^{0} x^{n-1} \exp\left(-xf\right) dx \\
&= \int\limits_{x=+\infty}^{0} \frac{x^{n-1}}{f} d\left(e^{-xf}\right)
\end{aligned} \tag{C2}$$

Applying integration by parts, the above integral can be simplified as follows:

$$\begin{aligned}
I &= \left| \frac{x^{n-1}}{f} e^{-xf} - \int \frac{(n-1)x^{n-2}}{f} e^{-xf} dx \right|_{x=+\infty}^{0} \\
&= \left| \frac{x^{n-1}}{f} e^{-xf} + \left(\frac{(n-1)x^{n-2}}{f^2} e^{-xf} - \int \frac{(n-1)(n-2)x^{n-3}}{f^2} e^{-xf} dx \right) \right|_{x=+\infty}^{0} \\
&= \left| \frac{x^{n-1}}{f} e^{-xf} + \frac{(n-1)x^{n-2}}{f^2} e^{-xf} + \left(\frac{(n-1)(n-2)x^{n-3}}{f^3} e^{-xf} - \int \frac{(n-1)(n-2)(n-3)x^{n-4}}{f^3} e^{-xf} dx \right) \right|_{x=+\infty}^{0} \\
&\vdots \\
&= \left| e^{-xf} \left(\frac{x^{n-1}}{f} + \frac{(n-1)x^{n-2}}{f^2} + \frac{(n-1)(n-2)x^{n-3}}{f^3} + \ldots + \frac{(n-1)(n-2)\ldots 2\, x^1}{f^{n-1}} + \frac{(n-1)!\; x^0}{f^n} \right) \right|_{x=+\infty}^{0} \\
&= \frac{(n-1)!}{f^n}
\end{aligned}$$

$$or, \;\; I = \frac{\left(\sum_{\mathscr{s}=1}^{S_M} (q_{\mathscr{s}} - r_{\mathscr{s}} + 1) - 1 \right)!}{f^{\sum_{\mathscr{s}=1}^{S_M} (q_{\mathscr{s}} - r_{\mathscr{s}} + 1)}} \tag{C3}$$

LIST OF TABLES

Table 1. Simulation Experiment Results

	Dataset 1		Dataset 2		Dataset 3		Dataset 4		Dataset 5	
True Model Parameters	$\theta = 0.1$, $\beta_1 = 1.50$, $\beta_2 = 1.20$, $\beta_3 = 2.50$		$\theta = 0.3$, $\beta_1 = 1.50$, $\beta_2 = 1.20$, $\beta_3 = 2.50$		$\theta = 0.5$, $\beta_1 = 1.50$, $\beta_2 = 1.20$, $\beta_3 = 2.50$		$\theta = 0.7$, $\beta_1 = 1.50$, $\beta_2 = 1.20$, $\beta_3 = 2.50$		$\theta = 0.9$, $\beta_1 = 1.50$, $\beta_2 = 1.20$, $\beta_3 = 2.50$	
Parameter Estimates	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV
$\hat{\theta}$	1.00 (fixed)	0.10 (0.00)	1.00 (fixed)	0.30 (0.00)	1.00 (fixed)	0.50 (0.01)	1.00 (fixed)	0.70 (0.03)	1.00 (fixed)	0.90 (0.13)
$\hat{\beta}_1$	1.61 (0.09)	1.50 (0.01)	1.58 (0.06)	1.48 (0.02)	1.55 (0.05)	1.47 (0.03)	1.52 (0.05)	1.46 (0.04)	1.47 (0.05)	1.44 (0.04)
$\hat{\beta}_2$	1.28 (0.06)	1.20 (0.01)	1.26 (0.05)	1.19 (0.02)	1.24 (0.04)	1.17 (0.03)	1.20 (0.04)	1.16 (0.03)	1.16 (0.04)	1.14 (0.04)
$\hat{\beta}_3$	2.30 (0.04)	2.48 (0.03)	2.32 (0.04)	2.47 (0.03)	2.34 (0.04)	2.46 (0.04)	2.38 (0.04)	2.45 (0.04)	2.42 (0.04)	2.44 (0.04)
Goodness of Fit Measures	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV
$\bar{\rho}^2$	0.071	0.290	0.070	0.159	0.070	0.107	0.070	0.082	0.071	0.073
Log-likelihood ratio	8737.00		3540.15		1498.25		492.85		53.20	
Model Prediction Performance Results	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV
Alternative 1	4.02	0.17	3.62	0.16	2.89	0.14	1.91	0.13	0.72	0.11
Alternative 2	4.09	0.17	3.62	0.11	2.81	0.05	1.76	0.00	0.53	-0.06
Alternative 3	-8.11	-0.35	-7.24	-0.27	-5.71	-0.19	-3.67	-0.13	-1.25	-0.05
Policy Analysis Results	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV	MDCEV	MDCNEV
Alternative 1	-2.29 (-8.00)	-2.76 (-11.15)	-2.22 (-7.85)	-2.63 (-10.55)	-2.13 (-7.65)	-2.41 (-9.58)	-2.02 (-7.39)	-2.16 (-8.48)	-1.88 (-7.08)	-1.92 (-7.39)
Alternative 2	5.21 (21.77)	5.57 (27.80)	5.10 (21.50)	5.38 (26.65)	4.94 (21.16)	5.11 (24.82)	4.74 (20.72)	4.81 (22.75)	4.50 (20.14)	4.51 (20.70)
Alternative 3	-2.92 (-6.16)	-2.80 (-5.08)	-2.88 (-6.00)	-2.76 (-5.02)	-2.81 (-5.76)	-2.70 (-4.98)	-2.73 (-5.47)	-2.64 (-4.95)	-2.62 (-5.13)	-2.58 (-4.95)

Table 2. Descriptive Statistics of Activity participation and Time-Use by Activity Purpose and Activity Timing[15]

		ACTIVITY TIMING					
		Early Morning (3am-7am)	Morning (7am-9am)	Late Morning (9am-12pm)	Afternoon (12pm-4pm)	Evening (4pm-7pm)	Night (7pm-3am)
ACTIVITY PURPOSE	Number (%) of non-workers participating, and mean duration of participation among those participating	88 (1.8%)[16] 193 min	469 (9.6%) 172 min	1416 (28.9%) 123 min	1556 (31.7%) 101 min	894 (18.2%) 102 min	485 (9.9%) 111 min
Maintenance	6167 (100%) 630 min	--	--	--	--	--	--
IH Discretionary	2427 (40.4%) 333 min	--	--	--	--	--	--
OH Discretionary	3383 (54.9%) 170 min	--	--	--	--	--	--
Volunteering	494 (14.6%)[17] 151 min	10 (2.0%)[18]	97 (19.6%)	171 (34.6%)	113 (22.9%)	85 (17.2%)	87 (17.6%)
Socializing	667 (19.7%) 149 min	7 (1.0%)	30 (4.5%)	187 (28.0%)	239 (35.8%)	149 (22.3%)	115 (17.2%)
Recreation	1099 (32.5%) 154 min	47 (4.3%)	165 (15.0%)	386 (35.1%)	310 (28.2%)	182 (16.6%)	126 (11.5%)
Meals	1183 (35.0%) 115 min	19 (1.6%)	127 (10.7%)	318 (26.9%)	403 (34.1%)	317 (26.8%)	139 (11.7%)
Non-Maintenance Shopping	1485 (43.9%) 64 min	7 (0.5 %)	60 (4.0%)	519 (34.9%)	764 (51.4%)	233 (15.7%)	77 (5.2%)

[15] The reader will note here that the average time investments reported in this table are for only those who participated in the corresponding activity purpose or for those who participated in OH discretionary activities during the corresponding time period. Also, the activity participation percentages across all activity purposes (and across all time periods) may sum to more than 100% because of multiple discreteness (*i.e.,* participation in multiple activity purposes and/or during multiple time periods). For example, a non-worker can undertake both OH recreation and OH meal activities on a day. Similarly, a non-worker can undertake OH meal activity during both afternoon and night periods.

[16] Percentages in this row are out of the 3383 non-workers who participated in at least one OH discretionary activity during the day.

[17] Percentages in this column, from this row onward, are out of the 3383 non-workers who participated in at least one OH discretionary activity during the day.

[18] Percentages from this row and column onward are based on total number of non-workers participating in row activity purpose [(10/494)×100=2.0%].

Table 3. The MDCNEV Model Results: Baseline Parameter Estimates

	Household (HH) Socio-demographics								
	HH size	Single member HH	Kids of age <5 yrs present	Kids of age 5-15 yrs present	# of adults in HH who worked on the day	HH annual income < 45k	HH annual income >100k	# of vehicles in HH	# of bicycles in HH
'Activity Purpose' Dimension									
IH and OH Maintenance	0.031 (1.62)	-	-	-	-	0.117 (2.45)	-	-	-
IH Discretionary	-	-	-	-	-	0.247 (3.98)	-	-0.092 (-3.31)	-
OH Volunteering	-	-	-	-	-	-	-	-	-
OH Socializing	-	0.384 (3.99)	-	-	-	-	0.169 (3.61)	-	-
OH Recreation	-	-	-	-	-	-	0.169 (3.61)	-	0.076 (4.11)
OH Meals	-	0.274 (3.55)	-	-	-	-	0.169 (3.61)	-	-
OH Non-Maintenance Shopping	-	-	-	-	-	-	0.169 (3.61)	-	-
'Activity Timing' Dimension									
Early Morning	-	-	-	-	-	-	-	-	-
Morning	-	-	-0.079 (-1.22)	0.232 (1.85)	-	-	-	-	-
Late Morning	-	-	-0.079 (-1.22)	-	-0.125 (-3.72)	-	-	-	-
Afternoon	-	-	-0.079 (-1.22)	-	-0.125 (-3.72)	-	-	-	-
Evening	-	0.266 (2.94)	-0.079 (-1.22)	0.294 (3.19)	-	-	-	-	-
Night	-	-	-	-	-	-	-	-	-
Activity Purpose-Activity Timing									
OH Recreation – Night	-	0.528 (2.34)	-	-	-	-	-	-	-

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

	Individual Socio-demographics							Day of week and seasons			ATE attributes
	Female	**Female with kids**	**Age < 30 yrs**	**Age > 65 yrs**	**Licensed to drive**	**Physically disabled**	**Employed**	**Friday**	**Fall**	**Summer**	**Retail employment within 0.25 miles of HH (in 1000s of jobs)**
'Activity Purpose' Dimension											
IH and OH Maintenance	0.325 (7.56)	0.138 (2.13)	-	-	-	-	-0.208 (-4.72)	-	-	-	-
IH Discretionary	-	-	-	-	-	-	-0.152 (-2.46)	-	-0.117 (-2.29)	-	-
OH Volunteering	0.420 (4.65)	-	-	0.625 (7.45)	0.531 (6.72)	-0.292 (-3.49)	-	-	-	-	-
OH Socializing	-	-	0.381 (2.81)	-	0.531 (6.72)	-0.292 (-3.49)	-	0.290 (5.34)	-	-	-
OH Recreation	-	-	-	-	0.531 (6.72)	-0.292 (-3.49)	-	0.290 (5.34)	-0.178 (-2.19)	0.213 (3.05)	-
OH Meals	-	-	-	-	0.531 (6.72)	-0.292 (-3.49)	-	0.290 (5.34)	-	-	-
OH Non-Maintenance Shopping	-	-	-	-	0.531 (6.72)	-0.292 (-3.49)	-	0.260 (3.77)	-	-	-
'Activity Timing' Dimension											
Early Morning	-0.267 (-2.76)	-	-	-	-	-	-	-	-	-	-
Morning	-0.267 (-2.76)	-	-	-	-	-	-	-	-	-	-
Late Morning	0.237 (4.77)	-	-	-	-	-	-	-	-	-	-
Afternoon	0.237 (4.77)	-	-	-	-	-	-	-	-	-	-
Evening	-	-	0.315 (2.44)	-	-	-	-	-	-	-	-
Night	-	-	0.775 (5.99)	-0.551 (-4.92)	-	-	-	0.342 (3.27)	-	-	-
'Activity Purpose-Activity Timing'											
OH Meals – Afternoon	-	-	-	-	-	-	-	-	-	-	0.554 (2.18)

Table 4. The MDCNEV Model Results: Baseline Preference Constants and Satiation Parameters

Baseline Preference Constants

Activity Timing	Activity Purpose					
	In-home Discretionary	Out-of-home Discretionary				
		Volunteering	Socializing	Recreation	Meals	Shopping
	-6.40 (-80.61)	-	-	-	-	-
Early Morning	-	-13.09 (-38.01)	-13.13 (-32.80)	-11.27 (-60.13)	-12.08 (-47.31)	-13.03 (-31.68)
Morning	-	-10.84 (-62.19)	-11.70 (-53.55)	-10.04 (-69.80)	-10.20 (-73.44)	-10.91 (-62.29)
Late Morning	-	-10.49 (-68.61)	-10.04 (-80.16)	-9.33 (-76.93)	-9.45 (-81.60)	-8.87 (-80.47)
Afternoon	-	-10.91 (-69.20)	-9.78 (-79.11)	-9.56 (-76.95)	-9.26 (-79.03)	-8.45 (-78.96)
Evening	-	-11.22 (-68.47)	-10.33 (-77.36)	-10.16 (-73.48)	-9.48 (-81.06)	-9.75 (-78.93)
Night	-	-10.98 (-63.23)	-10.46 (-68.67)	-10.48 (-67.21)	-10.19 (-72.20)	-10.77 (-68.06)

Satiation Parameters

Activity Timing	Gamma (γ_k) estimates for activity timing (t-statistics)	Activity Purpose					
		In-home Discretionary	Out-of-home Discretionary				
			Volunteering	Socializing	Recreation	Meals	Shopping
		395.80 (16.86)	115.73 (6.01)	111.11 (7.16)	127.75 (6.95)	66.05 (7.46)	36.38 (7.27)
Early Morning	1.19 (3.87)	-	138.02 (3.26)	132.50 (3.41)	152.35 (3.38)	78.77 (3.44)	43.38 (3.42)
Morning	1.25 (6.31)	-	144.43 (4.35)	138.66 (4.74)	159.43 (4.67)	82.43 (4.82)	45.39 (4.77)
Late Morning	1.10 (7.19)	-	127.01 (4.61)	121.94 (5.07)	140.20 (5.00)	72.49 (5.18)	39.92 (5.11)
Afternoon	0.92 (7.19)	-	106.02 (4.61)	101.78 (5.08)	117.03 (5.00)	60.50 (5.18)	33.32 (5.11)
Evening	0.99 (6.75)	-	114.64 (4.49)	110.06 (4.91)	126.55 (4.84)	65.42 (5.01)	36.03 (4.95)
Night	1.00 (Fixed)	-	115.73 (6.01)	111.11 (7.16)	127.75 (6.95)	66.05 (7.46)	36.38 (7.27)

Table 5. Elasticity Effects of a Five-fold Increase in "Retail Employment within 0.25 Miles of the Household"

Activity Purpose	Time period	% Change in time use	
		MDCEV	MDCNEV
OH Meals	Late morning	-0.232	-0.584
OH Meals	Afternoon	27.743	21.873
OH Shopping	Late morning	-0.321	-0.387
OH Shopping	Afternoon	-0.213	-0.378
Maintenance	All day	-0.189	-0.170
IH Leisure	All day	-0.244	-0.229