Modeling the Connection between Activity-Travel Patterns and Subjective Well-Being

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ABSTRACT
Transportation models are currently unable to adequately reflect the impacts of policy and investment decisions on people's well-being and overall quality of life. This paper presents a multivariate ordered response probit model that is able to capture the influence of activity-travel characteristics on subjective well-being, while accounting for unobserved individual traits and attitudes that predispose people when it comes to their emotional feelings.

INTRODUCTION

The recognition that transportation infrastructure investments and service changes have direct impacts on people's activity and travel patterns – and therefore, quality of life – has led to a stream of research at the nexus of traveler attitudes and perceptions, activity-travel behavior, and "subjective well-being" (*1-5*). In this context, subjective well-being (or simply, well-being) refers to the level of satisfaction that people associate with their daily activity-travel patterns.

Developing models capable of relating activity-travel behavior with measures of well-being is important from a policy analysis perspective (*6,7*). Concerns about energy and environmental sustainability, air quality, and global climate change have many metropolitan areas around the world contemplating a variety of travel demand management strategies to stem the use of fossil-fuel burning vehicles (*8*). Such strategies may take the form of pricing policies, car ownership and usage restrictions, or limits on highway capacity expansion – all with a view to curtail private vehicle use. Traditional travel demand models – whether four-step models or newer activity-based models – would forecast the impacts of these strategies on vehicular miles of travel and potentially lead to the inevitable conclusion that they are "beneficial" because energy consumption and harmful vehicular emissions would be curtailed. However, if the policies resulted in changes in activity-travel patterns that offered lower levels of satisfaction/happiness or "well-being" to people, then it may be important to reconsider the deployment of such policies as societal quality of life is adversely affected. Analysis of the transportation–well-being connection has taken added importance in light of recent evidence that the time spent on more enjoyable activities (such as recreation) has decreased since the 1960s (*9*).

The advent of activity-based modeling approach to travel behavior analysis and forecasting has further contributed to an interest in studying the connections among activity engagement, time use, travel patterns, and well-being. Activity-based travel microsimulation models allow the evaluation of policy impacts at a very disaggregate level and provide a framework to conduct rigorous social equity and environmental justice studies. With such models, it is possible to identify winners and losers (those whose well-being increases or decreases due to a policy action) and make informed decisions regarding the trade-offs involved in implementing alternative policies.

The recognition that subjective well-being and happiness are inextricably linked to how people engage in activities, travel, and spend time motivated the Bureau of Labor Statistics (BLS) in the United States to add a well-being module to the 2010 American Time Use Survey (ATUS). In this study, the ATUS survey data set with the well-being module is used to develop a comprehensive model of people's feelings of well-being as a function of activity-travel and time use patterns, besides the usual person and household socio-demographics. In the survey, respondents are asked to provide ratings representative of the level of emotion associated with various measures of well-being, including happiness, stress, meaningfulness, pain, tiredness, and sadness. The study explicitly distinguishes between in-home and out-of-home activity engagement to recognize differences in well-being that may arise from the location of the activity.

The remainder of this paper is organized as follows. The next section provides examples of studies that have examined the connection between well-being and travel behavior. The third section presents a description of the data set used in the study. The fourth section presents the modeling methodology while the fifth section offers detailed model estimation results. Concluding thoughts are offered in the sixth and final section.

WELL-BEING AND TRAVEL BEHAVIOR

Recent work in the travel behavior-well-being domain illustrates the connections between activity-travel and time use patterns on the one hand and measures of subjective well-being on the other. Duarte *et al.* (*10*) focus on the importance of including measures of well-being within behavioral choice models. They estimated four different models to examine the impact of happiness on mode choice behavior. They found that subjective well-being is a significant determinant of mode choice with generally happier people more prone to using public transportation. However, the model specifications that included happiness variables were found to offer poorer fit than specifications that did not include such explanatory variables. The results of this study, although informative, do not provide clear insights into the relationships between travel choices and happiness suggesting that the nexus is a complex one. In a study of the elderly in Finland, Siren and Hakamies-Blomqvist (*11*) studied mobility patterns and their relation to happiness and well-being with a view to identifying potential social exclusion implications of transportation services. Elderly with a car (and the ability to drive it) were generally more mobile, participated in greater levels of activity outside the home, and reported higher levels of well-being. A key point brought out in this study is the need to also study negative emotions (such as sadness, pain, and stress) when attempting to evaluate well-being. Stanely *et al.* (*12*) also examined social exclusion aspects of mobility and the implications for well-being. They find that people who are more engaged in community activities report a greater level of subjective well-being. Although trip making did not directly impact subjective well-being, they note that lower levels of trip making are associated with social exclusion, and hence lower levels of well-being.

Several studies have examined the relationship between well-being and activity-travel behavior directly. Ettema *et al.* (*2*) found strong connections between the two entities noting that people feel a greater sense of well-being when they engage in activities that are enjoyable or make progress towards achieving goals. Bergstad *et al.* (*13*) found significant relationships among cognitive subjective well-being (CSWB), mood of the individual, and out-of-home activity participation in a study of Swedish residents. More recently, Abou-Zeid and Ben-Akiva (*14*) presented a detailed analysis of the relationships between well-being and activity-travel engagement using a structural equations model system. They postulated that people's activity-travel patterns are a manifestation of their desire to enhance well-being and satisfy needs – and noted that the incorporation of concepts of well-being in activity-travel models can enhance the behavioral realism and forecasting accuracy of such models. In another paper, Abou-Zeid *et al.* (*15*) analyzed the impacts of a mode change on happiness and found that satisfaction ratings (with choice of mode) are influenced by reference points and by cognitive awareness (where a change in travel mode makes people think more deeply about the happiness they derive from the use of different modes of transportation).

Even the brief review of recent literature presented here suggests that there is much interest in connecting measures of well-being with activity-travel and time use patterns. This paper aims to contribute in this domain by using a recent large sample data set to estimate a multivariate ordered response model capable of accounting for correlations across alternatives in the measurement of subjective well-being.

DATA

The data used in this study is derived from the 2010 American Time Use Survey (ATUS) that is administered by the United States Bureau of Labor Statistics (BLS) to a sample of households that completed the Current Population Survey (CPS) of the US Census Bureau. The ATUS is administered to one adult in each selected household and collects detailed information about all activities and travel undertaken by the person over a 24 hour period. The data provides a complete 24 hour time use profile for each respondent together with their socio-economic and demographic characteristics.

The well-being module was administered immediately after the completion of the ATUS. This survey module asked respondents to rate their emotions on a number of well-being measures for three randomly selected activity episodes. The well-being measures included in the survey were happiness, meaningfulness, pain, sadness, stress, and tiredness. For each of these six measures of well-being, respondents were asked to rate the degree of emotion on a scale of 0 to 6 where 0 corresponded to the person not experiencing the feeling at all and 6 corresponded to the person identifying with the feeling in a very strong way. Thus a rating of 6 on the happiness scale meant that the person experienced great joy while pursuing the activity episode; conversely, a rating of 0 means the person experienced no happiness at all while pursuing the activity episode.

For purposes of analysis in this paper, the scale was collapsed into fewer categories. Original responses of 0 or 1 were recoded to 0, signifying a low emotion; original responses of 2, 3, or 4 were recoded to 1 to signify medium level of emotion; and original responses of 5 or 6 were coded to 2 to signify a high level of emotion. This was done because the variation in the original 0-to-6 scale was found to have too much noise to draw any meaningful inferences about the effects of various explanatory variables in the modeling exercise.

About 13,200 individuals from the 2010 ATUS survey were chosen to participate in the well-being module. After extensive data cleaning, a data set with 11,607 cases with complete data was obtained. As the sample is drawn from a nationwide census, it is quite representative of the general population and does not exhibit any significant biases in demographic or socio-economic characteristics. For some of the individuals, it was found that the same activity type repeated itself (among the three episodes chosen for well-being assessment). As it is not possible to distinguish between episodes of the same activity type, duplicates had to be removed. Through a random elimination of duplicates, the final data set of activity episodes was constructed for the analysis effort of this paper. The final data set included 28,177 activity episodes for 11,607 individuals.

The ATUS collects information at a fine activity purpose categorization scheme. These activity types are classified by BLS into 17 major categories (see http://www.bls.gov/tus/lexicons.htm for a description of the categories). In order to further simplify the representation of activity purposes in this study, the 17-category scheme was collapsed into a 9-category scheme for the analysis in this paper. Two possible locations were considered for each of the nine activity purposes, namely, in-home and out-of-home. This was done to capture any differences in strengths of feelings that might result from pursuing the same activity inside the home versus outside the home.

The average duration of activity episodes in the final data set is 67 minutes with the minimum at five minutes and the maximum at 1419 minutes. Specifically, work (in-home: 127; out-of-home: 228 minutes), social (in-home: 115; out-of-home: 102 minutes), out-of-home religious (114 minutes), in-home personal care (106 minutes), and volunteer activities (in-home: 91; out-of-home: 84 minutes) are among the activities with higher average duration of participation. Maintenance (in-home: 53; out-of-home: 42 minutes), out-of-home personal care (67 minutes), in-home active recreation (56 minutes), in-home religious (53 minutes), and eat and drink (in-home: 32; out-of-home: 49 minutes) activity episodes have lower average durations. The average start time of the activity episodes is 817 minutes past midnight (about 1:30 PM); the earliest start time is right at the beginning of the day at midnight and the latest start time of an activity episode was just five minutes before the end of the day (at 1435 minutes). About 23 percent of activity episodes involved child-accompaniment.

Table 1 presents the distribution of responses on the emotion scale for various feelings of well-being across activity purposes when undertaken outside the home. As expected, lower percentages of respondents indicate a high level of happiness when undertaking work or personal care (just over 40 percent indicate a high level of happiness), followed by maintenance activities and travel (just over 50 percent). On other activities, it is found that well over 65 percent experience high level of happiness, with 77 percent indicating a high level of happiness when pursuing religious activities. What is interesting to note is that 54 percent of respondents reported a high level of happiness when "traveling", contrary to the traditional notion that travel is a cost that people attempt to minimize. This finding may be consistent with some evidence on the positive utility of travel (*16*), although it also calls for the need for more research into isolating the strength of emotions derived from the activity at the destination from those derived purely from the travel episode. These results are consistent with the strength of emotions on other feelings of well-being; a larger percent of respondents are stressed when undertaking work, personal care, and maintenance and a very small percent are stressed when pursuing recreation, social, and religious activities.

A large proportion of religious activity episodes are considered highly meaningful (more than 90 percent), which is consistent with expectations. In terms of pain, over 13 percent of personal care episodes are associated with the highest pain level, at least in part due to health related self-care which constitutes an important component of personal care activities. For all other activity purposes, including work, only about 5 percent or less of the episodes are considered highly painful. A high degree of tiredness is reported for 16 percent of work episodes and nearly 20 percent of personal care, both of which are higher than the 13.6 percent of travel episodes that are reported as being highly tiring. With respect to sadness, it is noteworthy that 6.5 percent of religious episodes are associated with high levels of sadness (just second to personal care). It is possible that people turn to religion in times of sadness or some of the religious activity episodes may be pursued at a time of sadness.

Table 2 presents the same data, but for in-home activity episodes. It is seen, virtually across all activity purposes, that greater percentages of episodes are associated with highest levels of happiness when they are pursued *outside the home* as opposed to *inside the home*. In general, across all measures of well-being, it appears that people experience greater stress, pain, and sadness when pursuing activities in-home than out-of-home. The differences are not necessarily very substantial, except for the case of personal care where much higher percentages of personal care episodes are reported as being highly stressful and painful when pursued inside the home. For other activity categories, the percentages are more similar, but (barring a few exceptions) the trend clearly suggests that there is a greater level of well-being when activities are undertaken outside the home rather than inside the home. This finding supports the separate treatment of in-home and out-of-home activity episodes in the model estimation part of this study.

MODELING METHODOLOGY

As mentioned earlier, survey respondents in the ATUS well-being module are asked to rate levels of emotion (on a number of measures of well-being) on an ordinal scale. Therefore, an ordered response based model is used in this study. Furthermore, given that for any well being measure (say, happiness), the emotion levels that an individual experiences can be correlated across different activity purpose-location (APL) combinations, this study employs a cross-sectional multivariate ordered probit (CMOP) model system which assumes an underlying set of multivariate continuous latent variables that are mapped into the observed emotion levels by threshold parameters. The resulting multivariate model system allows for a generic covariance matrix for the underlying latent propensity variables. In this discussion, the index for the well being measure (*e.g.*, happiness, stress, and meaningfulness) is suppressed because the same methodology applies to all indices or measures considered.

Let q (q = 1, 2,…, Q) be the index for individuals where Q denotes the total number of individuals in the dataset and let i (i = 1, 2,…., I) be the index for the APL types where I denotes the total number of APL types for each individual.[1] In the current empirical context, I = 17 = [8 activity purposes] × 2 + 1 [travel activity purpose]. Let m_{qi} be the observed level of the emotion by the q^{th} individual in the i^{th} APL type where m_{qi} may take one of K values, *i.e.*, $m_{qi} \in \{1,2,.....K\}$ for APL type i.[2] Then, in the usual ordered response framework notation, the latent demand intensity y_{qi}^* is written as a function of a $(L \times 1)$-vector of observed covariates $\boldsymbol{x}_{qi}$ (excluding the constant) as:

$$y_{qi}^* = \boldsymbol{b}_i' \, \boldsymbol{x}_{qi} + \varepsilon_{qi} \qquad y_{qi} = m_{qi} \text{ if } \psi_{i,m_{qi}-1} < y_{qi}^* < \psi_{i,m_{qi}} \tag{1}$$

In the above specification, $\boldsymbol{b}_i$ is a $(L \times 1)$-vector whose elements capture the effects of the elements in the $\boldsymbol{x}_{qi}$ variable vector on latent propensity y_{qi}^*.[3] Finally, ε_{qi} captures individual specific unobserved factors that increase or decrease the latent propensity underlying the emotion for APL type i. These error terms are assumed to be independent and identical realizations of a standard normal error term uncorrelated across individuals q. For identification purposes, the variance of each ε_{qi} term is set to 1. However, the ε_{qi} terms may be correlated across different APL types for the same individual because of individual-level unobserved factors that influence the underlying propensity of the emotion across different APL types. Specifically, define $\boldsymbol{\varepsilon}_q = (\varepsilon_{q1}, \varepsilon_{q2}, \varepsilon_{q3}, \ldots, \varepsilon_{qI})'$. Then, $\boldsymbol{\varepsilon}_q$ is multivariate normally distributed with a mean vector of zeros and a correlation matrix as follows:

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[1] For any given individual, a maximum of only three of the I APL types are observed since the survey asks well-being questions only for three randomly chosen activity episodes for each individual. Furthermore, given that duplicate records where an individual participated in the same activity purpose at the same location during multiple episodes have been removed, the number of observed alternatives can vary across individuals. This varying number of observed outcomes per individual can be easily accommodated within the estimation method used in the paper.

[2] In the current empirical context, K = 3 for all I APL types. So, the subscript i for K is suppressed in the model formulation.

[3] The number of exogenous variables *i.e.*, the size of the $\boldsymbol{x}_{qi}$ vector can vary across the APL types. However, it is assumed that the same variables are used in all I APL types for notational simplicity. The values of these variables (such as activity duration or activity start time) may differ across APL types.

$$\boldsymbol{\varepsilon}_q = N\left[\begin{pmatrix}0\\0\\.\\.\\.\\0\end{pmatrix}, \begin{pmatrix}1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I}\\ \rho_{21} & 1 & \rho_{23} & . & .\\ \rho_{31} & \rho_{32} & 1 & . & .\\ . & . & . & . & .\\ \rho_{I1} & \rho_{I2} & . & . & 1\end{pmatrix}\right] \tag{2}$$

or $\boldsymbol{\varepsilon}_q \sim N[\mathbf{0}, \boldsymbol{\Sigma}]$. If all off-diagonal elements in $\boldsymbol{\Sigma}$ are zero, the model system reduces to an independent ordered probit model for each APL type.

The parameter vector to be estimated in the CMOP model is $\boldsymbol{\theta} = (\boldsymbol{b}', \boldsymbol{\psi}'_1, \boldsymbol{\psi}'_2, ...\boldsymbol{\psi}'_I, \boldsymbol{\Omega}')'$, where $\boldsymbol{b} = (\boldsymbol{b}'_1, \boldsymbol{b}'_2, \boldsymbol{b}'_3, ..., \boldsymbol{b}'_I)'$ ($IL \times 1$ vector), $\boldsymbol{\psi}_i = (\psi_{i,1}, \psi_{i,2}, ...\psi_{i,K-1})'$ for i=1, 2, …, I, and $\boldsymbol{\Omega}$ is a column vector obtained by vertically stacking all the correlation parameters (*i.e.*, off-diagonal elements of $\boldsymbol{\Sigma}$). Also, let $\boldsymbol{R}_q$ be a vector containing the indices of the observed outcomes for individual q and $\boldsymbol{R}_q(g)$ refer to the g^{th} element of the $\boldsymbol{R}_q$ vector. For instance, if the three activity episodes of an individual correspond to APL types 2, 4, and 6 respectively, then $\boldsymbol{R}_q = (2,4,6)'$. The likelihood function for individual q may then be written as:

$$L_q(\boldsymbol{\theta}) = P(y_{q,\boldsymbol{R}_q(1)} = m_{q,\boldsymbol{R}_q(1)}, y_{q\boldsymbol{R}_q(2)} = m_{q\boldsymbol{R}_q(2)}, y_{q,\boldsymbol{R}_q(3)} = m_{q,\boldsymbol{R}_q(3)}) \tag{3}$$

$$L_q(\boldsymbol{\theta}) = \int_{v_1=\tilde{\vartheta}_1}^{\tilde{\varphi}_1} \int_{v_2=\tilde{\vartheta}_2}^{\tilde{\varphi}_2} \int_{v_3=\tilde{\vartheta}_3}^{\tilde{\varphi}_3} \phi_3(v_1, v_2, v_3 \,|\, \boldsymbol{\Delta}_q)\, dv_1 dv_2 dv_3, \tag{4}$$

where $\tilde{\varphi}_g = \psi_{\boldsymbol{R}_q(g), m_{q,\boldsymbol{R}_q(g)}} - \boldsymbol{b}'_{\boldsymbol{R}_q(g)} \boldsymbol{x}_{q,\boldsymbol{R}_q(g)}$ and $\tilde{\vartheta}_g = \psi_{\boldsymbol{R}_q(g), m_{q,\boldsymbol{R}_q(g)-1}} - \boldsymbol{b}'_{\boldsymbol{R}_q(g)} \boldsymbol{x}_{q,\boldsymbol{R}_q(g)}$ for $g = 1, 2, 3$, $\boldsymbol{\Delta}_q$ is the correlation matrix of the latent variables $y_{q,\boldsymbol{R}_q(1)}, y_{q,\boldsymbol{R}_q(2)}$, and $y_{q,\boldsymbol{R}_q(3)}$ which can be obtained from the overall correlation matrix $\boldsymbol{\Sigma}$, and $\phi_3(.)$ is a trivariate normal density function.[4] The likelihood function in Equation (4) above is evaluated using the pairwise composite marginal likelihood (CML) method. Specifically, the pairwise marginal likelihood function for individual q may be written for the CMOP model as follows:

$$\begin{aligned} L_{CML,q}^{CMOP}(\boldsymbol{\theta}) &= \prod_{g=1}^{2} \prod_{g'=g+1}^{3} \Pr(y_{q,\boldsymbol{R}_q(g)} = m_{q,\boldsymbol{R}_q(g)}, y_{q,\boldsymbol{R}_q(g')} = m_{q,\boldsymbol{R}_q(g')}) \\ &= \prod_{i=1}^{I-1} \prod_{g=i+1}^{I} \left[\begin{matrix} \Phi_2(\tilde{\varphi}_g, \tilde{\varphi}_{g'}, \rho_{gg'}) - \Phi_2(\tilde{\varphi}_g, \tilde{\vartheta}_{g'}, \rho_{gg'}) \\ -\Phi_2(\tilde{\vartheta}_g, \tilde{\varphi}_{g'}, \rho_{gg'}) + \Phi_2(\tilde{\vartheta}_g, \tilde{\vartheta}_{g'}, \rho_{gg'}) \end{matrix}\right], \end{aligned} \tag{5}$$

where $\Phi_2(.,.,\rho_{gg'})$ is the standard bivariate normal cumulative distribution function with correlation $\rho_{gg'}$.

Under usual regularity assumptions, the CML estimator of $\boldsymbol{\theta}$ is consistent and asymptotically normally distributed with asymptotic mean $\boldsymbol{\theta}$ and covariance matrix given by the inverse of Godambe's sandwich information matrix (*17,18*):

$$\mathbf{V}_{CML}(\hat{\boldsymbol{\theta}}) = [\mathbf{G}(\boldsymbol{\theta})]^{-1} = [\mathbf{H}(\boldsymbol{\theta})]^{-1} \mathbf{J}(\boldsymbol{\theta}) [\mathbf{H}(\boldsymbol{\theta})]^{-1}, \tag{6}$$

[4] The likelihood function for individuals who have two or one activity episodes involves evaluating only bivariate and univariate normal integrals, respectively.

where $\mathbf{H}(\boldsymbol{\theta}) = E\left[-\dfrac{\partial^2 \log L_{CML}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}'}\right]$ and $\mathbf{J}(\boldsymbol{\theta}) = E\left[\left(\dfrac{\partial log L_{CML}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}}\right)\left(\dfrac{\partial log L_{CML}(\boldsymbol{\theta})}{\partial\boldsymbol{\theta}'}\right)\right]$.

The reader is referred to Bhat *et al.* (*19*) and Bhat (*20*) for complete details regarding the estimation of the matrices $\mathbf{H}(\boldsymbol{\theta})$ and $\mathbf{J}(\boldsymbol{\theta})$ in Equation (6) above as well as the techniques for ensuring the positive definiteness of the correlation matrix $\boldsymbol{\Sigma}$ during model estimation. For comparing two nested models estimated using the CML approach, the adjusted composite likelihood ratio test (*ADCLRT*) statistic may be used; this statistic is asymptotically chi-squared distributed similar to the likelihood ratio test statistic for the maximum likelihood approach.

ESTIMATION RESULTS

In this study, three separate multivariate ordered probit model systems were estimated.[5] The three separate model systems corresponded to the three different measures of well-being-happiness, stress, and meaningfulness. For purposes of brevity, results are presented and detailed discussions are provided in this paper for only one model system – namely, the model system for "happiness".[6] The discussion in this section will include some comments on results obtained from models estimated on "stress" and "meaningfulness" with a view to provide some comparative perspective across dimensions of well-being.

Table 3 presents estimation results for the multivariate ordered probit model of happiness across 17 different APL types. A systematic process of variable selection, addition, transformation, and elimination was followed to arrive at the final model specification. Several variables were retained in the final model specification due to their intuitive coefficient estimates even if they were not statistically significant at the usual levels of confidence. The results are summarized according to the types of explanatory variables considered.

Individual Demographics

Relative to females, males appear to have a lower propensity for happiness in maintenance, eat/drink, volunteer, and social activities. In particular, the highly negative coefficient on social activities suggests that males enjoy social events significantly less than females. However, as Tesch-Römer *et al.* (*21*) noted, gender effects on well-being can vary significantly depending on the societal conditions and the life course of an individual. Future research should examine such time-varying effects using longitudinal data on well-being and time use. Age has a positive impact on happiness propensity with older individuals being more likely to express happiness for out-of-home work, and in-home maintenance, social, and eat/drink activities. This result is different from the U-shaped effect of age reported by Bergstad *et al.* (*13*). Race is significantly associated with happiness; Asians are less prone to enjoy maintenance activities, Caucasians are less prone to enjoy personal, social, and religious activities in-home (as well as work out of home), and African Americans are more prone to enjoying eat/drink in-home in comparison to other groups. Foreign-born individuals appear to have a higher happiness propensity for maintenance activities. These findings suggest that culture plays an important role in determining

[5] It is possible that the level of emotion experienced by an individual in an APL type is correlated across different emotions (*i.e.*, happiness, meaningfulness, pain, sadness, stress, and tiredness). Exploring these correlations is an avenue for future research. It should be noted that the methodology used in this paper can be easily extended to explore cross-emotion correlations.

[6] The estimation results for the other two emotions' model systems are available at: http://www.ce.utexas.edu/prof/bhat/ABSTRACTS/WellBeing/SuppNote.pdf.

subjective well-being (*22*). Individuals at all levels of education (relative to the base alternative of "did not complete high school") report lower levels of happiness with social activities – whether in-home or out-of-home, suggesting that people with higher levels of education may have time constraints and other stressors that make social visits less pleasurable. Those with a post-graduate degree report a lower propensity towards happiness for out-of-home work, suggesting that these individuals may be in higher-stress jobs (*23*, *24*). The same constraint-based effect on happiness associated with social activities is observed for those with multiple jobs, presumably a subpopulation that also has time constraints or is very wedded to work.

An examination of the last column of the table shows the association between individual-level demographics and level of happiness associated with travel. There are gender differences with males deriving less happiness from travel episodes. Ory and Mokhtarian (*5*) did not find significant gender differences for overall travel liking, but did find that women have a higher liking for travel in personal vehicles - a finding similar to that obtained in this study. Older individuals are found to have greater happiness propensity for travel episodes, possibly because they pursue a range of discretionary activities (that involve the presence of children – which, as described later, contributes positively to happiness). Minority groups have a higher happiness propensity for travel episodes (relative to other groups); the underlying cultural aspects that contribute to this finding are worthy of further exploration. As expected, time-pressured individuals holding multiple jobs derive lower happiness from travel episodes. Individuals employed in specific industrial sectors are found to have a lower happiness propensity. Construction and manufacturing sector employees have lower happiness propensity for out-of-home social activities; trade and transportation sector employees have lower happiness propensity for out-of-home work activities; and professional business employees have lower happiness propensity for in-home volunteer activities. These results might be indicative of the nature of the jobs and the constraints and stresses they place on the individuals. For example, it has been reported that construction and manufacturing sector employees are less likely to have a telecommuting option, and thus mostly work on site which is why they prefer to stay at home during non-work time (*25*).

Household Characteristics

A couple household is more likely to have greater happiness propensity for in-home activities, including work, maintenance, social, and eat/drink. It is likely that the individuals enjoy participating in activities in-home due to the ability to engage in joint activities (*26*). This finding extends to travel episodes as well. When children are present, however, social activities in the home become less enjoyable and so do maintenance activities outside the home. It is likely that children contribute to greater levels of constraints and stress in the context of these specific activities. The presence of children also contributes to lower happiness propensity for in-home maintenance activities, but slightly greater happiness propensity for in-home eat/drink when there is a very young child 0-5 years old in the household. Lower happiness propensity is derived from travel episodes when children are present in the household; this is possibly because individuals in households with children are more time-constrained and find travel burdensome (see Craig and Bittman (*27*) for a discussion on the impact of children on the time use of adults in a household).

Persons in households with a greater number of workers are prone to have a higher happiness propensity for in-home social and eat/drink activities. It is possible that persons in these households are quite constrained due to the work obligations of multiple workers in the household, and hence derive happiness from participating in leisure type activities within the home. However, as the number of adults in the household increases, then there is a lower happiness propensity associated with in-home social activities, presumably because they would rather socialize with others outside the home. On the other hand, number of adults has a negative impact on happiness propensity associated with recreational activities outside the home, suggesting that the logistics associated with identifying and engaging in recreational activities outside the home that *all* adults in the home would enjoy is challenging. Housing tenure is found to have a significant influence only on the happiness propensity of out-of-home religious activities with home owners having lower happiness propensity compared to renters. Individuals in households with better education attainment tend to enjoy out-of-home social activities more than households with lower education attainment. This result is in agreement with earlier literature on well-being (*28*).

Some geographical differences are observed in the results. Persons in households in the Midwest appear to be more out-of-home oriented with negative coefficients on in-home social, recreation, and personal care activities. Those in the West and South have a higher happiness propensity for work and maintenance activities; the exact reasons underlying such findings merit further investigation. Those residing in a metropolitan area have lower happiness propensity for in-home work and maintenance activities, as well as out-of-home recreation and volunteer activities. It appears that households in metropolitan areas experience greater time constraints and possibly higher levels of traffic congestion that contribute to these findings. If people are time constrained and have to deal with high levels of traffic congestion, then the happiness propensity derived from discretionary activities (such as recreation and volunteering) is likely to be diminished. Similarly, the stress associated with residing in a metropolitan area may be contributing to diminished happiness propensity in the context of obligatory work and maintenance activities inside the home; clearly, people would rather relax in-home. This explanation extends to the negative coefficient associated with travel episodes for individuals residing in metropolitan areas. On the other hand, individuals residing in the South (where levels of traffic congestion may be less, weather is nicer and there is no driving in the snow) derive higher happiness propensity from travel episodes. It appears that, while policies promoting denser mixed land use neighborhoods might be effective in reducing greenhouse gas (GHG) emissions associated with travel, they may also negatively impact the well-being of residents in that neighborhood by reducing happiness associated with activity engagement.

Activity Characteristics

Three activity characteristics appear in the final model specification. Activity duration has a positive impact on happiness propensity for maintenance and social activities. While it is clear why activity duration would positively impact happiness propensity for social activities, it is less clear why there is a positive impact on maintenance. It is possible that some maintenance activities are pleasurable in nature (*e.g.*, shopping may not always be viewed as a chore), thus contributing to the positive coefficient. Activity start time (measured in minutes past midnight) affects happiness propensity for various activities with a positive impact on social activities outside home and eat/drink inside home. As people are likely to participate in and enjoy these activities towards the end of the day, the positive coefficients are intuitive and reasonable. Otherwise, it is found that a later start to the activity generally contributes to lower happiness propensity, possibly because a later start time contributes to time pressure and people would rather participate in social type activities. It is found that activity start time has a negative impact on the happiness propensity derived from work (out of home), religious (in and out of home), and volunteering activities (out of home). Interestingly, it is found that a later start time is associated with higher happiness propensity for travel – suggesting that travel undertaken towards the latter part of the day is for enjoyable and desirable activities (as opposed to the less desirable mandatory work and obligatory maintenance activities). Also, it is possible that travel in the later part of the day is intrinsically more enjoyable due to lower congestion levels. Finally it is found that child accompaniment generally contributes to higher happiness propensity for a range of activities both in-home and out-of-home, suggesting that spending time with children is regarded enjoyable and contributing to happiness. The only exception appears to be religious activities inside the home, where it is possible that the presence of a child is distracting and not conducive to pursuing a quiet or focused religious activity. The accompaniment of a child also contributes to positive feelings of happiness for travel.

Model Fit and Assessment

Overall, it can be seen that the model coefficients are quite intuitive and reasonable and offer indications of how various individual, household, and activity characteristics contribute to happiness propensity for various activity and travel episodes. An examination of the error correlation matrix (across 17 APL types) for the model of happiness showed that 75 off-diagonal elements of $\mathbf{\Sigma}$ are statistically significant in the final model specification. This finding indicates that the happiness levels experienced and reported by individuals are strongly correlated across activities and locations. It is found that *all* correlation parameters are positive suggesting that unobserved factors which increase the happiness propensity for one activity/location combination also contribute positively to the happiness propensity of other activity/location combinations. It is likely that these unobserved factors are individual-specific personality and attitudinal traits that are not typically measured or observed in surveys, but are key explanatory factors of happiness, liking, and other emotional feelings (*5*). For example, unobserved personality traits such as being fun-loving and an extrovert may contribute positively to happiness levels across the full range of activities and travel episodes. Such individuals are likely to be the happy- and positive-type, regardless of the activity or travel episode and location; resulting error correlations capturing the influence of such traits would be significant and positive.

Although the statistically significant correlation parameters underscore the importance of adopting a multivariate modeling system to analyze well-being of individuals across a range of activities and locations, the *ADCLRT* test statistics which are asymptotically chi-squared distributed are computed to compare the final CMOP model against an independent ordered response (IOP) model which ignores all cross-APL type correlation effects. The composite marginal log-likelihood value of the CMOP model is -36399.3, while that for the IOP model is -38492.1. The *ADCLRT* test statistic value is 2102.4, which is greater than the critical chi squared value corresponding to 75 degrees of freedom at any reasonable level of significance. This finding is not necessarily limited to the happiness emotion. Similar *ADCLRT* test statistics of comparison between CMOP and IOP models for “Stress” and “Meaningful” emotions came out to be 2571.4 and 1652.1, respectively. The number of correlation parameters that are significantly different from zero in the CMOP models for “Stress” and “Meaningfulness” are 68 and 84, respectively. The *ADCLRT* test values computed above are greater than the critical chi squared values at any reasonable level of significance, clearly establishing the superior data fit obtained in the CMOP models.

A restricted market share model (MS) for "happiness" emotion which assigns market share probabilities (*i.e.*, only thresholds) to all the APL alternatives was also estimated. In comparing the CMOP model with the MS model, the *ADCLRT* test statistic of comparison was found to be 2879.9, which is greater than the critical chi-squared value corresponding to 206 degrees of freedom at any reasonable significance level, once again establishing the superior data fit of the CMOP model. To further explore the fit of the CMOP model, the average probability of correct prediction of observed happiness levels in different APL alternatives in the data was computed for the CMOP, IOP, and MS models. This disaggregate level data fit measure indicates an average probability of correct prediction of 0.2246 for the CMOP model. The corresponding values for the IOP and MS models are considerably lower at 0.1876 and 0.1756, respectively. This clearly shows that the CMOP model outperforms the other two restrictive models.

CONCLUSIONS

This paper offers a detailed examination of the determinants of subjective well-being with a view to shedding light on the connections between activity-travel characteristics and the well-being of people. The well-being of individuals is an important ingredient of the quality of life that people experience as they go about their daily lives. If transportation and land use policies are formulated and implemented in such a way that people's daily lives (activity-travel patterns and time use) are adversely affected, then well-being (and hence, quality of life) diminishes – calling into question the wisdom of implementing of such policies. Policies that appear beneficial from traditional cost-benefit analysis perspectives may not necessarily appear beneficial when the impacts on activity-travel patterns are closely tied to the well-being of people.

The analysis in this paper is done using the well-being module of the 2010 American Time Use Survey data set, which includes self-reported ratings on a range of well-being measures including happiness, meaningfulness, stress, tiredness, pain, and sadness. A multivariate ordered response model is estimated on this data set for each well-being measure while explicitly accounting for error correlations across different activity purpose-location (APL) combinations. This model can be integrated in an activity-based microsimulation model system that simulates activity-travel patterns at the level of the individual traveler. Characteristics of activity-travel patterns that are simulated, together with individual and household demographics, can be input to models of emotion (*e.g.*, happiness) to obtain measures of well-being that can be used to assess the impacts of alternative policies or transport investments on quality of life. In the particular model presented in this paper, for example, it is found that social activity duration contributes positively to happiness. If a policy measure (such as a pricing policy, parking capacity reduction, or modal disinvestment) results in greater generalized travel costs that reduce the amount of social activity participation, then the happiness that people derive from their activity-travel pattern will decrease. Although the policy may be considered positive from a traditional transport planning perspective (*e.g.*, lower vehicle miles of travel, lower congestion levels), it may not be truly beneficial if it results in diminished happiness and quality of life for people. The integration of models of well-being, such as that presented in this paper, in activity-based microsimulation models of travel demand would allow the computation of additional measures of performance or effectiveness (or cost-benefit measures) that have hitherto been ignored. Armed with such measures, planners and policy makers would be able to make more informed decisions that truly reflect impacts on people's well-being.

REFERENCES

1. Steg, L., and R. Gifford. Sustainable transportation and quality of life. *Journal of Transport Geography*, Vol. 13, No. 1, 2005, pp. 59-69.
2. Ettema, D., T. Gärling, L.E. Olsson, and M. Friman. Out-of-home activities, daily travel, and subjective well-being. *Transportation Research Part A*, Vol. 44, No. 9, 2010, pp. 723-732.
3. Abou-Zeid, M. (2009). *Measuring and Modeling Activity and Travel Well-Being*. PhD Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA, 2009.
4. Ye, X., K. Konduri, R.M. Pendyala, and B. Sana. Formulation of an activity-based utility measure of time use: an application to understanding the influence of constraints. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2135, 2009, pp. 60-68.
5. Ory, D., and P.L. Mokhtarian. When is getting there half the fun? Modeling the liking for travel. *Transportation Research Part A*, Vol. 39, No. 2-3, 2005, pp. 97-123.
6. O'Brien, C. Planning for sustainable happiness- harmonizing our internal and external landscapes. Paper prepared for the *Second International Conference on Gross National Happiness, Rethinking Development: Local Pathways to Global Wellbeing*, Nova Scotia, Canada, June 20-24, 2005.
7. Diener, E. Guidelines for national indicators of subjective well-being and ill-being. *Applied Research in Quality of Life*, Vol. 1, No. 2, 2006, pp. 151–157.
8. Gärling, T., and G. Schuitema. Travel demand management targeting reduced private car use: effectiveness, public acceptability and political feasibility. *Journal of Social Issues*, Vol. 63, No. 1, 2007, pp. 139-153.
9. Krueger, A.B. Are we having more fun yet? Categorizing and evaluating changes in time allocation. *Brookings Papers on Economic Activity*, Vol. 2, 2007, pp. 193-215.
10. Duarte, A., C. Garcia, C, G. Giannarakis, S. Limão, A. Polydoropoulou, and N. Litinas. New approaches in transportation planning: happiness and transport economics. *NETNOMICS: Economic Research and Electronic Networking*, Vol. 11, No. 1, 2009, pp. 5-32.
11. Siren, A., and L Hakamies-Blomqvist. Private car as the grand equaliser? Demographic factors and mobility in Finnish men and women aged 65+. *Transportation Research Part F*, Vol. 7, No. 2, 2004, pp. 107-118.
12. Stanley, J. K., D.A. Hensher, J.R. Stanle J. R., and D. Vella-Brodrick. Mobility, social exclusion and well-being: exploring the links. *Transportation Research Part A*, Vol. 45, No. 8, 2011, pp. 789-801.
13. Bergstad, C.J., A. Gamble, O. Hagman, M. Polk, T. Gärling, D. Ettema, M. Friman, and L.E. Olsson. Influences of affect associated with routine out-of-home activities on subjective well-being. *Applied Research in Quality of Life*, Vol. 7, No. 1, 2012, pp. 49-62.
14. Abou-Zeid, M., and M. Ben-Akiva. Well-being and activity-based models. *Transportation* (in press), 2012.
15. Abou-Zeid, M., R. Witter, M. Bierlaire, V. Kaufman, and M. Ben-Akiva. Happiness and travel mode switching: findings from a Swiss public transportation experiment. *Transport Policy*, Vol. 19, No. 1, 2012, pp. 93-104.
16. Mokhtarian, P.L., and I. Salomon. How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation Research Part A*, Vol. 35, No. 8, 2001, pp. 695-719.
17. Godambe, V.P. An optimum property of regular maximum likelihood estimation. *The Annals of Mathematical Statistics*, Vol. 31, No. 4, 1960, pp. 1208-1211.

18. Zhao, Y., and H. Joe. Composite likelihood estimation in multivariate data analysis. *Canadian Journal of Statistics*, Vol. 33, No. 3, 2005, pp. 335-356.
19. Bhat, C. R., C. Varin, N. Ferdous. A comparison of the maximum simulated likelihood and composite marginal likelihood estimation approaches in the context of the multivariate ordered response model. In Greene, W., Hill, R.C. (Eds.), *Advances in Econometrics: Maximum Simulated Likelihood Methods and Applications*, 65-106, Emerald Group Publishing Limited, Bingley, UK, 2010.
20. Bhat, C.R. The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models, *Transportation Research Part B*, Vol. 45, No. 7, 2011, pp.923-939
21. Tesch-Römer, C., A. Motel-Klingebiel, M.J. Tomasik. Gender differences in subjective well-being: Comparing societies with respect to gender equality. *Social Indicators Research*, Vol. 85, No. 2, 2008, pp.329–349.
22. Diener, E., S. Oishi, and R.E. Lucas. Personality, culture, and subjective well–being. *Annual Review of Psychology,* Vol. 54, 2003, pp. 403–425.
23. Clark, A.E. A note on unhappiness and unemployment duration. *Applied Economics Quarterly,* Vol. 52, No. 4, pp. 291-308.
24. Clark, A. E., and A.J. Oswald. Unhappiness and unemployment. *The Economic Journal,* Vol. 104, No. 424, 1994, pp. 648–659.
25. Singh, P., R. Paleti, S. Jenkins, and C.R. Bhat. On modeling telecommuting behavior: Option, choice, and frequency. *Transportation* (in press), 2012.
26. Sullivan, O. (1996). Time co-ordination, the domestic division of labour and affective relations: Time use and Enjoyment of Activities within couples. *Sociology*, Vol. 30, 1996, pp. 79-100.
27. Craig, L., and M. Bittman. The incremental time costs of children: an analysis of children’s impact on adult time use in Australia. *Feminist Economics*, Vol. 14, No. 2, 2008, pp. 57–85.
28. Argyle, M. Causes and correlates in happiness. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), Well-being: The foundations of hedonic psychology (pp. 353–373). New York: Russell Sage, 1999.

TABLE 1 Frequency Distribution of Dependent Variables: Out-of-Home Activity Pursuits

Group	Level	Activity Purpose (Out-of-home)								
		Work	*Maint*	*Personal*	*Social*	*Recreatn*	*Eat/Drink*	*Religious*	*Volunteer*	*Travel*
Sample Size		1800	1958	190	1372	452	1396	293	427	6282
Happiness										
All	*Low*	8.3	8.1	19.5	4.7	2.2	4.3	5.8	2.8	6.4
	Med	50.6	40.0	38.4	29.4	31.6	31.7	17.4	29.3	39.9
	High	41.1	51.9	42.1	65.9	66.2	64.0	76.8	67.9	53.7
Stress										
All	*Low*	37.0	62.6	55.8	72.0	74.3	69.2	82.3	64.6	62.8
	Med	47.9	29.9	31.6	22.7	22.2	25.4	11.6	28.1	29.9
	High	15.1	7.5	12.6	5.3	3.5	5.4	6.1	7.3	7.3
Meaningfulness										
All	*Low*	8.0	11.4	15.2	7.8	4.6	8.6	2.7	4.9	16.0
	Med	32.8	35.3	23.2	28.6	26.3	31.4	6.2	19.2	32.1
	High	59.2	53.3	61.6	63.6	69.1	60.0	91.1	75.9	51.9
Pain										
All	*Low*	76.9	79.7	64.7	80.0	68.4	81.4	79.5	75.4	79.8
	Med	18.7	15.4	22.1	15.7	27.0	15.3	15.7	19.4	15.5
	High	4.4	4.9	13.2	4.3	4.6	3.3	4.8	5.2	4.7
Tiredness										
All	*Low*	35.1	45.3	44.2	46.4	44.9	46.5	63.1	46.2	44.8
	Med	48.6	42.0	36.3	42.2	42.9	43.4	26.3	39.6	41.6
	High	16.3	12.7	19.5	11.4	12.1	10.1	10.6	14.2	13.6
Sadness										
All	*Low*	79.8	85.2	73.2	84.7	88.5	88.7	85.3	88.8	84.1
	Med	16.4	11.8	19.4	11.3	9.5	8.9	8.2	7.0	12.4
	High	3.8	3.0	7.4	4.0	2.0	2.4	6.5	4.2	3.5

TABLE 2 Frequency Distribution of Dependent Variables: In-Home Activity Pursuits

Group	Level	Activity Purpose (In-home)								
		Work	*Maint*	*Personal*	*Social*	*Recreatn*	*Eat/Drink*	*Religious*	*Volunteer*	*Travel*
Sample Size:		549	5356	173	3999	125	3557	93	155	--
Happiness										
All	*Low*	11.7	7.7	23.7	7.3	3.2	6.21	5.4	6.5	--
	Med	56.3	41.2	45.7	39.8	41.6	35.3	21.5	21.3	
	High	32.0	51.1	30.6	52.9	55.2	58.6	73.1	72.2	
Stress										
All	*Low*	36.1	64.2	38.7	70.2	69.6	70.3	74.2	61.3	--
	Med	47.7	28.7	34.1	23.4	24.0	23.5	19.4	33.5	
	High	16.2	7.1	27.2	6.4	6.4	6.2	6.4	5.2	
Meaningfulness										
All	*Low*	7.5	10.9	20.2	16.1	5.6	10.7	1.1	7.1	--
	Med	36.0	30.6	25.4	39.2	28.0	31.4	4.3	14.2	
	High	56.5	58.5	54.4	44.7	66.4	57.9	94.6	78.7	
Pain										
All	*Low*	76.1	73.4	25.4	73.3	57.6	75.0	75.2	73.5	--
	Med	19.0	19.9	32.9	19.1	32.8	17.9	14.0	20.0	
	High	4.9	6.7	41.7	7.6	9.6	7.1	10.8	6.5	
Tiredness										
All	*Low*	35.9	39.2	19.7	40.3	40.0	43.2	50.5	40.0	--
	Med	47.3	44.1	35.3	43.4	45.6	42.3	38.7	42.6	
	High	16.8	16.7	45.1	16.3	14.4	14.5	10.8	17.4	
Sadness										
All	*Low*	79.2	83.5	55.8	80.9	91.2	83.5	77.4	87.1	--
	Med	17.5	12.9	26.2	14.4	5.6	12.7	17.2	9.0	
	High	3.3	3.6	18.0	4.7	3.2	3.8	5.4	3.9	

TABLE 3 CMOP Model Estimation Results for Happiness

Variable	Location	Work	Maint	Personal	Social	Recreation	Eat/Drink	Religious	Volunteer	Travel
Threshold 1	In-home	-1.206	-1.267	-1.859	-1.567	-2.737	-1.013	-2.584	-2.094	N/A
	Out-Home	-1.629	-1.215	-1.186	-1.858	-2.278	-1.668	-2.216	-2.261	-1.134
Threshold 2	In-home	0.476	0.135	-0.608[a]	-0.178	-0.765	0.347	-1.246	-1.029	N/A
	Out-Home	0.166[a]	0.149	0.008[a]	-0.568	-0.720	-0.291	-1.358	-0.826	0.287
Male	In-home	--	--	--	-0.040[a]	--	--	--	--	N/A
	Out-Home	--	-0.085[a]	--	-0.197	--	-0.108[b]	--	-0.216[b]	-0.084
Age 30 to 45 years	In-home	--	--	--	--	--	0.098	--	--	--
	Out-Home	--	--	--	--	--	--	--	--	--
Age 46 to 65 years	In-home	--	--	--	--	--	0.118	--	--	N/A
	Out-Home	0.174	--	--	--	--	--	--	--	0.139
Age >65 years	In-home	--	0.283	--	0.184	--	0.301	--	--	N/A
	Out-Home	0.560	--	--	--	--	--	--	--	0.401
Caucasian	In-home	--	--	-0.557[a]	-0.203	--	--	-0.659	--	N/A
	Out-Home	-0.227	--	--	--	--	--	--	--	--
African American	In-home	--	--	-0.596[a]	--	--	0.256	--	--	N/A
	Out-Home	--	--	--	--	--	--	-0.206[a]	--	0.134
Asian	In-home	--	-0.195	--	-0.179[a]	--	--	--	--	N/A
	Out-Home	-0.251[b]	-0.265[b]	--	--	--	--	--	--	--
Hispanic	In-home	--	--	--	0.115[b]	--	--	--	--	N/A
	Out-Home	--	--	--	--	0.573	0.228	--	--	0.128
Foreign-born Citizen	In-home	--	0.228	--	--	--	--	--	--	N/A
	Out-Home	--	--	-0.612	--	--	--	--	--	0.093[a]
Foreign-born Non-Citizen	In-home	--	0.245	--	--	--	0.185	--	--	N/A
	Out-Home	--	0.278	--	--	--	--	--	--	0.146
Student	In-home	-0.240[b]	--	--	--	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	--
High School	In-home	--	--	-0.300[a]	-0.059[a]	-0.490[b]	--	--	--	N/A
	Out-Home	--	--	--	-0.482	--	--	--	--	--
College Degree	In-home	--	--	-0.386	-0.163	-0.491[b]	--	--	--	N/A
	Out-Home	--	--	--	-0.491	--	--	--	--	--
Postgrad Degree	In-home	--	--	--	-0.226	--	--	--	--	N/A
	Out-Home	-0.056[a]	--	--	-0.454	--	--	--	--	--
Full-time Employed	In-home	--	--	--	--	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	-0.225[b]	--
Multiple Jobs	In-home	0.313[b]	--	--	-0.188[b]	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	-0.123
Construction/Manufact	In-home	--	--	--	--	--	--	--	--	N/A
	Out-Home	--	--	--	-0.191	--	--	--	--	--
Trade/Transportation	In-home	--	--	--	--	--	--	--	--	N/A
	Out-Home	-0.149[a]	--	--	--	--	--	--	--	--
Professional/Business	In-home	--	--	--	--	--	--	--	-0.495	N/A
	Out-Home	--	--	--	--	--	--	--	--	--

Note: [a] Not significant at 90% level; [b] Significant at 90% level; All other coefficients significant at 95% level; N/A: Not Applicable

TABLE 3 (Continued) CMOP Model Estimation Results for Happiness

Variable	Location	Work	Maint	Personal	Social	Recreation	Eat/Drink	Religious	Volunteer	Travel
Government	In-home	--	--	--	-0.135[b]	--	--	--	--	N/A
	Out-Home	--	--	--	-0.154[a]	--	--	--	--	--
Couple Household	In-home	0.201	0.114	--	0.188	--	0.212	--	--	N/A
	Out-Home	--	0.210	--	--	--	--	--	--	0.130
Couple with Children	In-home	--	--	--	-0.085[a]	--	--	--	--	N/A
	Out-Home	--	-0.234	--	--	--	--	--	--	-0.089
Child 0-5 years in HH	In-home	--	0.049[a]	--	--	0.323[a]	0.130	--	--	N/A
	Out-Home	0.085[a]	--	-0.451	0.135	--	--	--	--	--
Child 6-10 years in HH	In-home	--	-0.072[b]	--	--	0.323[a]	--	--	--	N/A
	Out-Home	0.085[a]	--	--	--	--	--	--	--	--
Child 11-15 years in HH	In-home	--	-0.072[b]	--	--	0.323[a]	--	--	--	N/A
	Out-Home	0.085[a]	0.127	--	--	--	--	--	--	--
No. of Workers	In-home	--	--	--	0.088	--	0.066	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	0.072
No. of Adults	In-home	--	--	--	-0.048[b]	--	0.035[a]	0.388	0.200[a]	N/A
	Out-Home	--	--	--	--	-0.175	--	--	-0.056[a]	--
Own Household	In-home	--	--	--	--	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	-0.276[a]	--	--
HH Max Edu: High School	In-home	--	--	--	--	--	--	-0.658	--	N/A
	Out-Home	--	--	--	--	--	--		--	--
HH Max Edu: College Deg	In-home	--	--	--	0.078[a]	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	--
HH Max Edu: Postgrad	In-home	--	--	--	0.142[a]	--	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	--
Location: Mid-West	In-home	--	--	-0.460	-0.073[b]	-0.396[b]	--	--	--	N/A
	Out-Home	--	--	--	--	--	--	--	--	--
Location: West	In-home	0.189[a]	--	--	--	--	--	--	--	N/A
	Out-Home	0.106[b]	0.082[a]	--	--	--	--	--	--	--
Location: South	In-home	0.259	--	--	--	--	--	--	--	N/A
	Out-Home	0.175	0.052[a]	--	--	--	--	--	0.311	0.090
Location: Metropolitan Area	In-home	-0.204[b]	-0.096	--	--	--	--	--	--	N/A
	Out-Home	--	--	--	--	-0.207[a]	--	--	-0.240[b]	-0.067[b]
Activity Duration (min)/100	In-home	--	--	--	--	--	--	--	--	N/A
	Out-Home	--	1.631	--	0.947	--	--	--	--	--
Act Start Time (min)/1000	In-home	--	--	--	--	-0.564[b]	0.128	-0.813[b]	--	N/A
	Out-Home	-0.236	--	--	0.320	--	--	-0.601	-0.818	0.167
Child Accompaniment	In-home		0.251	--	0.140	0.754	0.188	-0.933	0.384	N/A
	Out-Home	0.631	0.291	--	0.259	0.470	0.394	--	--	0.256

Note: [a] Not significant at 90% level; [b] Significant at 90% level; All other coefficients significant at 95% level; Worst p-value: 0.47; N/A: Not Applicable