Extended Abstract

Paper #: 18-06590

A MULTIVARIATE EXPLORATION OF EMOTIONAL FEELINGS OF SUBJECTIVE WELL-BEING DURING TRAVEL EPISODES

Felipe F. Dias
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712
Tel: 512-471-4535; Email: fdias@utexas.edu

Sebastian Astroza
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712
Tel: 512-471-4535; Email: sastroza@utexas.edu

Venu M. Garikapati
National Renewable Energy Laboratory, Systems Analysis & Integration Section
15013 Denver West Parkway, Golden, CO 80401
Tel: 303-275-4784; Email: venu.garikapati@nrel.gov

Ram M. Pendyala
Arizona State University, School of Sustainable Engineering and the Built Environment
660 S. College Avenue, Tempe, AZ 85287-3005
Tel: 480-727-4587; Email: ram.pendyala@asu.edu

Chandra R. Bhat (corresponding author)
The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712
Tel: 512-471-4535; Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Patricia L. Mokhtarian
Georgia Institute of Technology, School of Civil and Environmental Engineering
Mason Building, 790 Atlantic Drive, Atlanta, GA 30332-0355
Tel: 404-385-1443; Email: patmokh@gatech.edu

ACKNOWLEDGEMENTS

This research was partially supported by the Center for Teaching Old Models New Tricks (TOMNET) as well as the Data-Supported Transportation Operations and Planning (D-STOP) Center, both of which are Tier 1 University Transportation Centers sponsored by the US Department of Transportation.

1 INTRODUCTION

How much do people enjoy traveling? This is the central question that motivates the data analysis and exploration presented in this paper. Addressing this question is important from a number of perspectives.

First, the amount of travel that people undertake is likely to be strongly related to the extent to which they enjoy (or not) the travel experience or episode. If travel to activity destinations is perceived to be enjoyable and produces positive emotional feelings, then it is likely that the amount of travel that people undertake will increase as various types of constraints are relaxed. Therefore, an understanding of the 'joy of the journey' is fundamental to forecasting future travel demand in the wake of emerging mobility innovations.

Second, transportation is an important determinant of quality of life (Frank, 2000). As planners and decision-makers around the world strive to improve the quality of life in their communities, they invest scarce resources in the transportation infrastructure with a view to enhance mobility and accessibility for all segments of the population. An enhanced understanding of the effects of various attributes on feelings of well-being perceived by individuals during travel would help planning professionals target investments in transportation such that the user experience is benefited as much as possible.

Third, there is excitement surrounding the potential advent of autonomous transportation technologies and increasing use of transportation network companies or mobility-on-demand services (Dias et al., 2017). Future research studies attempting to quantify the impacts of new transportation technologies on travel demand would benefit from an understanding of how travelers perceive (and enjoy) traveling by various modes of transportation under different system conditions.

The inability to fully assess and understand well-being associated with travel episodes may be largely attributed to a lack of rich well-being data on activity-travel episodes. In this study, a special travel episode well-being data set has been assembled using multiple years of the well-being module of the American Time Use Survey (ATUS), which includes information about the travel episode itself, as well as the preceding and subsequent activity episodes. Travelers' socio-economic and demographic attributes are also available. Six emotions are measured and reported in the data on an ordered scale – happiness, meaningfulness, sadness, stressfulness, tiredness, and painfulness. A multivariate ordered response model system that accounts for the presence of correlated unobserved attributes that affect multiple measures of emotion is estimated and presented in this paper to quantify the true effects of various attributes on travel episode well-being.

Results suggest that mode of transportation, travel duration, the nature and location of the preceding and subsequent activities, and socio-economic and demographic variables are important determinants of travel episode related social well-being (SWB). Travel in public transport vehicles is viewed more negatively than in private vehicles, even after controlling for all other variables. This suggests that shared (autonomous) mobility services of the future need to offer benefits and a level of service that significantly outweigh the discomfort associated with riding in non-personal (public transit) vehicles of today. Furthermore, the statistical significance of the correlation terms for the unobserved attributes serve as evidence that the multivariate approach was, indeed, justified.

2 METHODOLOGY

2.1 Data

The data for this study is derived from the American Time Use Survey, a repeated cross-sectional survey conducted each year for the past decade by the Bureau of Labor Statistics in the United States on a nationally representative sample. In 2010, 2012, and 2013, the ATUS included a well-being module, in which respondents rated their feelings of well-being on six different emotional scales for three randomly selected activities (from those appearing in their activity-time use record). The six emotions considered were happiness, meaningfulness, sadness, stressfulness, tiredness, and painfulness, measured on a scale of zero to six, with higher scores indicating a greater intensity of emotional feeling.

All records from 2010, 2012, and 2013 were first pooled together to create a single large data set. Next, the travel episodes for which individuals reported emotional ratings were isolated from the data set. Then, information about the activities that were undertaken just prior to and just after the travel activity episode (for which emotional ratings are available) was extracted from the ATUS records and appended to the travel activity episode records. We also included the nature and attributes of preceding and subsequent activities. The final data set assembled through this process included well-being information for 15,000+ travel episodes. For purposes of computational tractability, a random sample of 10,000 travel episodes was extracted and used in this study. In some cases, individuals reported well-being information for multiple travel episodes; therefore, the 10,000 travel episodes in the data set correspond to 8,800 unique individuals.

2.2 Model framework

Let q be an index for individuals (q = 1, 2, …, Q), and let i be the index for episode category (i = 1, 2, …, I, where I denotes the total number of well-being variables for each individual; in the current study, I = 6). Let the number of categories for well-being variable i be K_i + 1 (*i.e.*, the response of well-being variable i is indexed by k and belongs in {0, 1, 2, …, K_i}). Following the usual ordered response framework notation, we write the latent propensity (y_{qi}^*) for each well-being variable as a function of relevant covariates and relate this latent propensity to the observed ordered outcome (y_{qi}) through threshold bounds (see McKelvey and Zavoina, 1975):

$$y_{qi}^* = \beta_i' x_{qi} + \varepsilon_{qi}, y_{qi} = k \text{ if } \theta_i^k < y_{qi}^* < \theta_i^{k+1}, \tag{1}$$

where x_{qi} is a $(L\times 1)$ vector of exogenous variables (not including a constant), β_i is a corresponding $(L\times 1)$ vector of coefficients to be estimated, ε_{qi} is a standard normal error term, and θ_i^k is the lower bound threshold for count level k of well-being variable i ($\theta_i^0 < \theta_i^1 < \theta_i^2 ... < \theta_i^{K_i+1}$; $\theta_i^0 = -\infty$, $\theta_i^{K_i+1} = +\infty$ for each well-being variable i). The ε_{qi} terms are assumed independent and identical across individuals (for each and all i). Due to identification restrictions, the variance of each ε_{qi} term is normalized to 1. However, correlations are allowed in the ε_{qi} terms across well-being variables i for each individual q. Specifically, define $\varepsilon_q = (\varepsilon_{q1}, \varepsilon_{q2}, \varepsilon_{q3}, \dots, \varepsilon_{qI})'$. Then, ε_q is multivariate normal distributed with a mean vector of zeros and a correlation matrix as follows:

$$\varepsilon_q \sim N\left[\begin{pmatrix}0\\0\\\vdots\\0\end{pmatrix}, \begin{pmatrix}1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1I}\\ \rho_{21} & 1 & \rho_{23} & \cdots & \rho_{2I}\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ \rho_{I1} & \rho_{I2} & \rho_{I3} & \cdots & 1\end{pmatrix}\right], \text{ or} \tag{2}$$

$$\varepsilon_q \sim N\left[\mathbf{0}, \mathbf{\Sigma}\right]$$

The off-diagonal terms of Σ capture the error correlations across the underlying latent continuous variables of the different well-being variables; that is, they capture the effect of common unobserved factors influencing the choice of intensity for each well-being variable. Thus, if ρ_{12} is positive, it implies that individuals with a higher than average propensity to report high levels for the first well-being variable are also likely to have a higher than average propensity to report high levels for the second well-being variable. If all correlation parameters (*i.e.*, off-diagonal elements of Σ) stacked into a vertical vector, Ω, are identically zero, the model system in Equation (1) collapses to independent ordered response probit models for each well-being variable.

The parameter vector of the multivariate probit model is $\delta = (\beta_1', \beta_2', ..., \beta_I';\ \theta_1', \theta_2', ..., \theta_I';\ \Omega')'$, where $\theta_i = (\theta_i^1, \theta_i^2, ..., \theta_i^{K_i})'$ for $i = 1, 2, ..., I$. Let the actual observed well-being level for individual q and well-being variable i be m_{qi}. In that case, the likelihood function for individual q may be written as follows:

$$L_q(\delta) = \Pr(y_{q1} = m_{q1}, y_{q2} = m_{q2}, ..., y_{qI} = m_{qI})$$

$$L_q(\delta) = \int_{v_1=\theta_1^{m_{q1}} - \beta_1' x_{q1}}^{\theta_1^{m_{q1}+1} - \beta_1' x_{q1}} \int_{v_2=\theta_2^{m_{q2}} - \beta_2' x_{q2}}^{\theta_2^{m_{q2}+1} - \beta_2' x_{q2}} \cdots \int_{v_I=\theta_I^{m_{qI}} - \beta_I' x_{qI}}^{\theta_I^{m_{qI}+1} - \beta_I' x_{qI}} \phi_I(v_1, v_2, ..., v_I \mid \Omega) dv_1 dv_2 ... dv_I \tag{3}$$

Calculating the I-dimensional rectangular integral above can be computationally challenging. In order to sidestep these problems, we use a composite marginal likelihood (CML) approach based on bivariate margins (see Apanasovich et al., 2008, Varin and Vidoni, 2008, Bhat et al., 2010, and Ferdous et al., 2010).

3 FINDINGS

The results from the estimation process show that travelers, in general, rate traveling by non-personal vehicles (i.e., public transit and taxi) more negatively across a broad range of measures in comparison to travel by personal vehicles. Travel by non-motorized modes is viewed positively, except for the feelings of tiredness and/or painfulness, presumably due to the physical exertion involved. However, the effects of riding in a public vehicle on feelings of happiness and meaningfulness largely disappear after controlling for myriad explanatory variables in the joint model system, placing public transport on par with driving a personal vehicle with respect to these two positive emotions. Conversely, public transport is associated with greater levels of sadness and tiredness even after controlling for myriad variables. This suggests that level of service, comfort, privacy, and vehicle (ride) quality are likely important determinants of travel episode well-being; current public transit modes generally fare more poorly than private vehicles in these aspects and hence struggle to gain substantial ridership in most US markets. Future shared mobility systems should be designed to compete with personal vehicles in these attributes if they are to see widespread usage.

The results also show that the nature of the activities before and after the travel episode are important determinants of well-being during the travel episode. As expected, travel to or from more desirable activities is viewed more positively than travel to or from less desirable activities such as work and maintenance.

The error correlations are statistically significant for a broad array of emotional feeling pairs. In a symmetric correlation matrix involving six emotions, there are 15 possible unique error correlation values. Except for one error correlation value that is statistically significant at the 0.1 level, all other error correlations are significant at the 0.05 level. This signifies that there are common unobserved attributes that simultaneously affect multiple emotional measures of SWB, thus justifying the adoption of a multivariate ordered response modeling approach in this study.

4 CONCLUSION

This study offers a few useful insights from a policy and practice perspective. For example, estimation results show that a travel episode is viewed more negatively when the preceding and/or subsequent activity is also a travel episode, suggesting that mid-journey transfers are considered undesirable. Planners should therefore strive to design (public) transportation systems that are flexible and offer direct origin-destination connectivity. Also, the model system developed in this study can be used in conjunction with activity-travel forecasting models to derive measures of travel well-being associated with predicted activity-travel patterns. Through the application of this model, planners and policy-makers can assess the increase or decrease in travel well-being that different policy scenarios and investments may produce. Future research efforts should aim to examine additional interaction effects among different variables, perform equity analyses to determine whether some groups systematically experience lower travel-related well-being, and integrate models of well-being in activity-based travel demand model systems.

REFERENCES

Apanasovich, T.V., D. Ruppert, J.R. Lupton, N. Popovic, N.D. Turner, R.S. Chapkin, and R.J. Carroll. Aberrant Crypt Foci and Semiparametric Modelling of Correlated Binary Data. *Biometrics*, 64(2), 2008, 490-500.

Bhat, C.R., C. Varin, and 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 *Advances in Econometrics: Maximum Simulated Likelihood Methods and Applications* (W. Greene and R.C. Hill, eds.), Emerald Group Publishing Limited, Bingley, United Kingdom, 26, 2010, 65-106.

Dias, F.F., P. Lavieri, V.M. Garikapati, S. Astroza, R.M. Pendyala, and C.R. Bhat. A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services. *Transportation* (*Forthcoming*), 2017.

Ferdous, N., N. Eluru, C.R. Bhat, and I. Meloni. A Multivariate Ordered Response Model System for Adults' Weekday Activity Episode Generation by Activity Purpose and Social Context. *Transportation Research Part B*, 44(8-9), 2010, 922-943.

Frank, L.D. Land Use and Transportation Interaction: Implications on Public Health and Quality of Life. *Journal of Planning Education and Research*, 20(1), 2000, 6-22.

McKelvey, R. D., and W. Zavoina. A Statistical Model for the Analysis of Ordinal Level Dependent Variables. *Journal of Mathematical Sociology*, 4(1), 1975, 103-120.

Varin, C., and P. Vidoni. Pairwise Likelihood Inference for General State Space Models. *Econometric Reviews*, 28(1-3), 2008, 170-185.