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

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ABSTRACT

This paper is concerned with understanding the determinants of subjective well-being (SWB) in the context of travel episodes. The amount of travel that people undertake, both in terms of frequency and distance or duration, is likely influenced by the emotional feelings that are engendered by the travel experience. Not only is very little known about how people feel during travel episodes, but even less is known about the determinants of those feelings. This paper offers a comprehensive analysis of the emotional feelings associated with travel episodes using a rich data set extracted from the well-being module of the American Time Use Survey (ATUS), in which respondents rated their SWB for travel episodes on six different emotional scales. A multivariate ordered probit model system that accounts for error correlation structures is estimated and presented in this paper. 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 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.

Keywords: well-being, travel episodes, multivariate analysis, ordered response models, time use

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. As has been well-documented (Hägerstraand, 1970; Pendyala et al., 2002), there are a number of forces that constrain human activity-travel schedules and behaviors. These include time-space prism constraints, coupling constraints, household constraints, institutional constraints, monetary constraints, and physiological constraints. If technological innovations, rising incomes, flexible work schedules, and autonomous vehicles loosen constraints in the future, then it is likely that the extent to which travel demand increases is inextricably tied to the degree to which individuals actually enjoy traveling. 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. Unfortunately, there is very limited knowledge of the influence of various factors on travel episode well-being, thus rendering it difficult for decision-makers to effectively deploy transportation policies and investments. It is likely that there are many different factors that affect how people feel during a travel episode, including characteristics of the journey itself, characteristics of the preceding and subsequent activities, and other built environment and socio-economic/demographic attributes. 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 considerable excitement surrounding the potential advent of autonomous transportation technologies and increasing use of transportation network companies (TNCs) or mobility-on-demand (MOD) services (Dias et al., 2017). While there have been some attempts to model the potential effects of transformative technologies on future travel demand, these studies are largely speculative and rely on a number of unverified assumptions about traveler behavior and values (Kornhauser, 2013; Fagnant and Kockelman, 2014). 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. For example, it has been hypothesized that the ability to multitask in an autonomous vehicle may contribute to an increase in travel (Malokin et al., 2015). By examining how people perceive and value traveling in modes of transportation that currently allow multitasking, it may be possible to draw insights on the extent to which such a hypothesis is likely to hold true in an autonomous vehicle future. Similarly, on-demand mobility services are often touted as a means to realize dramatic gains in transit ridership by providing "first-mile last-mile" transit access and connectivity (Shaheen and Chan, 2016). It would be helpful to examine traveler perceptions of well-being in the context of journeys that involve multimodal connections to better understand whether such visions can truly be realized.

The inability to fully assess and understand well-being associated with travel episodes (in isolation of the well-being derived from preceding or subsequent activity 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). Not only does the data set include information about the travel episode itself, but it also includes information about the preceding and subsequent activity episodes together with the usual socio-economic and demographic attributes of the traveler. 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.

The remainder of this paper is organized as follows. The next section presents a brief discussion on measuring and modeling activity-travel well-being. The third section offers a description of the data, the fourth section presents the methodology, and the fifth section documents model estimation results. A discussion and concluding thoughts comprise the sixth and final section.

2. ACTIVITY-TRAVEL CHOICES AND WELL-BEING

Subjective well-being (SWB) may be defined as an individual's subjective assessment of quality of life, and has been used by psychologists to study how people feel about their lives. For example, Marks and Fleming (1999) investigated the causes and consequences of SWB using the 1980-1995 Australian Youth in Transition panel dataset. They find that women and married individuals show higher levels of well-being, while unemployed individuals show substantially lower levels of well-being. Van Praag et al. (2003) used the German Socio-Economic Panel dataset to estimate a simultaneous equations model of SWB that considers different aspects of life including health, financial situation, job status, leisure, housing, and the environment. They conclude that SWB can be viewed as an aggregate mix of the individual domain satisfactions. Using data from the United States and Canada, as well as the World Values Survey, Helliwell and Putnam (2004) find that social capital (marriage and family, ties to friends and neighbors, and workplace ties) is a strong determinant of SWB.

In travel behavior research, models based on utility maximization theory are often used to assess people's satisfaction with their travel choices. Such models are based on random utility theory and inferences about level of satisfaction are drawn based on observed choices (e.g., mode choice). More recently, there has been a growing interest in the notion of SWB in transportation, largely because SWB may be more stable over time and better represent experienced utility (Kahneman et al., 1997) and general satisfaction in life. Ettema et al. (2011) developed a Satisfaction with Travel Scale (STS) to measure travel related SWB, and demonstrated its efficacy using data from a survey in which participants evaluated three hypothetical weekdays with varying activity-travel patterns. Abou-Zeid and Ben-Akiva (2011) developed a framework to capture the indirect effect of social comparisons on comparative happiness. They find that individuals derive greater comparative happiness when their commute compares favorably to that of others at the workplace. Bergstad et al. (2011) found that car use plays only a minor role in determining an individual's satisfaction with daily travel and overall SWB.

De Vos et al. (2016) explore the relationship between mode choice (observed utility) and travel satisfaction (experienced utility), and conclude that mode choice, in conjunction with residential location and travel-related attitudes, affects travel satisfaction. Their results show that active travel (especially walking) is associated with the highest levels of travel satisfaction, while public transit usage is associated with the lowest. Ravulaparthy et al. (2013) find that older individuals 50-95 years of age who are socially active and enjoy better mobility options report higher levels of SWB. Lee et al. (2015) conducted a survey of university students and find a positive and significant correlation between sense of place and SWB. They also find that moderate long distance travel (1-4 times per month) is associated with a higher level of SWB.

The analysis in this paper aims to offer rich insights on the extent to which individuals enjoy the travel episode itself, a notion that Mokhtarian and Salomon (2001) posited as the positive utility of travel. In a survey of 1,900 residents in the San Francisco Bay Area, they find evidence of a positive utility for travel and a desired travel time budget that varies across individuals. In another study, Ory et al. (2004) developed empirical models for Objective Mobility, Subjective Mobility, Travel Liking, and Relative Desired Mobility for commute travel. Not only did they find that one-half of the sample was generally satisfied with their commute distance/time, but they also found a small segment that actually desired a longer commute. A number of more recent studies (Mokhtarian et al., 2015; Morris and Guerra, 2015; Archer et al, 2013) have explored the factors contributing to satisfaction and well-being associated with travel and other activities. This study aims to build substantially on these and other research efforts by examining multiple emotional feelings simultaneously with a view to more comprehensively assess well-being. The study is unique in that it focuses exclusively on well-being during travel episodes and explicitly controls for attributes of preceding and subsequent activities.

3. DATA AND SAMPLE DESCRIPTION

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. Respondents rated their well-being on a scale of zero to six, with higher scores indicating a greater intensity of emotional feeling.

For this paper, all well-being 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. It was felt that the nature and attributes of preceding and subsequent activities may influence feelings of emotional well-being associated with the travel episode itself. The final data set assembled through this process included well-being information for 20,000+ 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.

Table 1 offers a descriptive summary of the sample.

TABLE 1 Descriptive Statistics for Sample (N=10,000 Travel Episodes)

Age		**Family income**	
18-34	26.3%	Less than $25,000	21.7%
35-54	22.4%	$25,000 to $49,999	25.6%
55-64	36.1%	$50,000 to $99,999	32.1%
65 and older	15.3%	$100,000 and over	20.6%
Race		**Education**	
White	80.5%	High school graduate or lower education level	33.4%
Black	13.9%	Some college or college graduate	52.3%
Other	5.7%	Master's degree or higher	14.3%
Day of the week		**Metropolitan Status**	
Weekday	50.7%	Metropolitan	84.2%
Weekend	49.3%	Non-metropolitan	15.8%
Employment		**Mode**	
Unemployed	31.9%	Driver (Car, truck or motorcycle)	76.2%
Employed - Part time	12.3%	Passenger (Car, truck or motorcycle)	15.4%
Employed - Full time	55.8%	Walk	5.2%
Sex		Passenger in public transit (non-personal) vehicle	2.6%
Male	47.7%	Bicycle	0.4%
Female	52.3%	Other	0.1%
Household Structure			
Multiple adults no kids	30.0%	Single person	25.0%
Multiple adults with kids	38.7%	Single parent (one adult with one or more kids)	6.4%

Activity	**Before Travel Episode**	**After Travel Episode**
Personal Maintenance	2.2%	1.8%
Household Maintenance	18.6%	25.3%
Meal	12.9%	13.8%
Passive Social Activities	17.8%	20.3%
Active Recreation Activities	2.6%	2.8%
Shopping	18.7%	16.1%
Work and School	15.1%	10.2%
Travel	3.5%	3.1%
Other	8.7%	6.8%

Accompaniment	**Before Travel Ep**	**During Travel Ep**	**After Travel Ep**
Alone	34.3%	51.3%	35.6%
Accompanied by household/family members only	38.8%	38.7%	42.5%
Accompanied by non-household/family members only	21.8%	8.2%	17.2%
Accompanied by both household/family and non-household/family members	5.1%	1.8%	4.8%

Location of Activity	**Before Travel Ep**	**During Travel Ep**	**After Travel Ep**
At home	26.5%	0%	37.8%
Out of home	73.5%	100%	62.2%

It can be seen that a little over one-quarter of all travel episodes are undertaken by those 18-34 years of age (largely millennials) while 36.1 percent are undertaken by those 55-64 years of age (largely baby boomers). The sample is predominantly white, with just under 20 percent of the episodes reported by non-white individuals. There is an even split of episodes between weekdays and weekend days. More than one-half of the episodes are undertaken by those employed full-time; also more than one-half of the episodes are reported by females. More than three-quarters of all episodes are undertaken by driving a personal vehicle (car, truck, or motorcycle). The sample includes multimodal trips (involving multimodal connections) as evidenced by the small percent of travel episodes that precede and succeed the travel episode in question. Just over one-half of the travel episodes are pursued alone; however, the preceding and succeeding activities show a greater level of accompaniment – especially by non-household members or a combination of household and non-household members. Thus, it appears that some amount of travel is undertaken from and/or to social or other activities that involve joint engagement.

Table 2 presents a detailed overview of the distribution of emotional ratings by mode of transportation. The table shows distributions across the six emotions for all modes. For ease of presentation and subsequent analysis and model estimation, the seven point scale of emotional well-being is collapsed into a three-point scale. The first two levels constitute a low level of emotion, the next three levels represent a medium level of emotion, and the highest two levels indicate a high level of emotion.

From Table 2, it can be observed that a majority of travel episodes are rated as providing a medium or high level of meaningfulness, albeit with 24 percent of public transit and taxi trips (both of these are together considered as 'passenger in public vehicle' mode) rated low on the meaningfulness scale. It is found that a very small percent of travel episodes rate low on the happiness scale. Being a passenger in a personal vehicle, traveling by bicycle, and traveling by other modes (airplane, for instance) seem to be associated with the most positive feelings of happiness. A larger percent of trips are rated in the medium sadness category for public transit and bicycle, suggesting that the use of these modes is not as pleasant. Public transit also shows a higher percent of trips in the higher intensity categories for stressfulness and tiredness. It is rather surprising to note that only two percent of bicycle trips are categorized as highly tiring in nature; however, it should be noted that 58 percent are categorized in the medium tiredness category. Despite public transit trips being rated less positively on other emotions, they actually fare best in the pain emotion.

An examination of the correlation matrix of emotional ratings (table omitted for brevity) shows that all emotions are significantly correlated with one another and show expected signs. The only correlation coefficient that offers a seemingly counter-intuitive sign is that between ratings of meaningfulness and painfulness. The coefficient is positive, suggesting that episodes that are rated more meaningful are also rated more painful. A deeper exploration of the reasons for this reveals that these trips are largely those in which an individual, who is presumably in pain, is traveling to obtain help (medical or religious/spiritual). It is reasonable for such trips to be rated as painful, and yet meaningful. The presence of significant correlations among measures of well-being calls for the joint modeling of emotions using a multivariate simultaneous equations modeling framework capable of capturing error covariances that reflect the presence of correlated unobserved attributes simultaneously affecting multiple emotions. The model system in this paper takes the form of a multivariate ordered probit model system that recognizes the ordered nature of emotional scales and the inter-dependencies across emotional measures.

TABLE 2 Distribution of Emotional Levels by Travel Mode (N=10,000 Travel Episodes)

Emotion	Level	Mode						
		Personal Vehicle Driver	Personal Vehicle Passenger	Walk	Public Vehicle Passenger	Bicycle	Other	Total
Meaningful	Low	16	10	14	24	14	8	15
	Medium	33	32	32	32	35	33	33
	High	51	58	54	45	51	58	52
Happy	Low	6	4	8	8	2	0	6
	Medium	40	31	36	45	37	25	38
	High	55	65	57	47	61	75	56
Sad	Low	86	85	84	78	74	92	85
	Medium	12	11	12	18	19	8	12
	High	3	4	4	4	7	0	3
Stressed	Low	64	70	65	58	63	58	65
	Medium	30	23	28	34	33	42	29
	High	7	7	7	8	5	0	7
Tired	Low	45	42	43	35	40	42	44
	Medium	43	43	43	43	58	50	43
	High	13	15	14	22	2	8	13
Pain	Low	80	76	77	82	72	67	79
	Medium	16	18	18	13	19	25	16
	High	4	6	5	5	9	8	5
Note: All values are in percent. Columns add up to 100 percent within each mode-emotion pair.								

4. MODELING METHODOLOGY

The mathematical formulation used in this paper very closely follows that in Ferdous et al. (2010). 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 count 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

$\varepsilon_q = (\varepsilon_{q1}, \varepsilon_{q2}, \varepsilon_{q3}, \ldots, \varepsilon_{qI})'$. Then, ε_q is multivariate normal distributed with a mean vector of zeros and a correlation matrix as follows:

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

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

The off-diagonal terms of Σ capture the error covariance 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 $\delta = (\beta_1', \beta_2', \ldots, \beta_I';\ \theta_1', \theta_2', \ldots, \theta_I';\ \Omega')'$, where $\theta_i = (\theta_i^1, \theta_i^2, \ldots, \theta_i^{K_i})'$ for $i = 1, 2, \ldots, I$. 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:

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

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

Calculating the high-order *I*-dimensional rectangular integral above can prove to be computationally challenging. In order to sidestep these problems, a pairwise marginal likelihood estimation approach is employed. This involves using a composite marginal approach based on bivariate margins (see Apanasovich et al., 2008; Varin and Vidoni, 2008; and Bhat et al., 2010 for the use of the pairwise likelihood approach in the past). The pairwise marginal likelihood function for individual *q* may be written as:

$$L_{CML,q}(\delta) = \prod_{i=1}^{I-1} \prod_{g=i+1}^{I} \Pr(y_{qi} = m_{qi}, y_{qg} = m_{qg})$$

$$= \prod_{i=1}^{I-1} \prod_{g=i+1}^{I} \left[\begin{array}{l} \Phi_2\left(\theta_i^{m_{qi}+1} - \beta_i' x_{qi}, \theta_g^{m_{qg}+1} - \beta_g' x_{qg}, \rho_{ig}\right) - \Phi_2\left(\theta_i^{m_{qi}+1} - \beta_i' x_{qi}, \theta_g^{m_{qg}} - \beta_g' x_{qg}, \rho_{ig}\right) \\ - \Phi_2\left(\theta_i^{m_{qi}} - \beta_i' x_{qi}, \theta_g^{m_{qg}+1} - \beta_g' x_{qg}, \rho_{ig}\right) + \Phi_2\left(\theta_i^{m_{qi}} - \beta_i' x_{qi}, \theta_g^{m_{qg}} - \beta_g' x_{qg}, \rho_{ig}\right) \end{array}\right], \quad (4)$$

and $L_{CML}(\delta) = \prod_q L_{CML,q}(\delta)$

The approach above requires much less computational resources and involves just as much effort in estimation as a simple bivariate ordered probit due to its ease of maximization. Some advantages of using the pairwise approach include it being more robust against misspecifications (see Varin and Vidoni, 2008; Varin, 2008) and absolutely no convergence-related issues, which cannot be said about the full likelihood function.

The pairwise estimator $\hat{\delta}_{CML}$ obtained by maximizing the logarithm of the function in Equation (4) with respect to the vector δ is consistent and asymptotically normally distributed with asymptotic mean δ and covariance matrix given by Godambe's (1960) sandwich information matrix (see Zhao and Joe, 2005):

$$G(\delta) = [H(\delta)]^{-1} J(\delta)\, [H(\delta)]^{-1}, \text{ where}$$

$$H(\delta) = E\left[-\frac{\partial^2 \log L_{CML}(\delta)}{\partial\delta\partial\delta'} \right] \text{ and} \tag{5}$$

$$J(\delta) = E\left[\left(\frac{\partial \log L_{CML}(\delta)}{\partial\delta} \right)\left(\frac{\partial \log L_{CML}(\delta)}{\partial\delta'} \right) \right]$$

$H(\delta)$ and $J(\delta)$ can be estimated in a straightforward manner at the CML estimate ($\hat{\delta}_{CML}$):

$$\hat{H}(\hat{\delta}) = -\left[\sum_{q=1}^{Q} \frac{\partial^2 \log L_{CML,q}(\delta)}{\partial\delta\partial\delta'} \right]$$

$$= -\left[\sum_{q=1}^{Q} \sum_{i=1}^{I-1} \sum_{g=i+1}^{I} \frac{\partial \log \Pr(y_{qi} = m_{qi}, y_{qg} = m_{qg})}{\partial\delta} \frac{\partial \log \Pr(y_{qi} = m_{qi}, y_{qg} = m_{qg})}{\partial\delta'} \right]_{\hat{\delta}}, \text{ and} \tag{6}$$

$$\hat{J}(\hat{\delta}) = \sum_{q=1}^{Q} \left[\left(\frac{\partial \log L_{CML,q}(\delta)}{\partial\delta} \right)\left(\frac{\partial \log L_{CML,q}(\delta)}{\partial\delta'} \right) \right]_{\hat{\delta}}$$

Additional details regarding the evaluation of the performance of the pairwise CML approach using simulations may be found in Ferdous et al. (2010).

5. MODEL ESTIMATION RESULTS

Model estimation results are shown in Tables 3 and 4. The results have been split into two components for ease of explanation. Because of the richness of the data set, the number of possible model specifications is extremely large. In addition to including the entire range of main effects, it is possible to include many combinations of interaction effects in the model specification. It is virtually impossible to test every possible combination. In this study, main effects were tested first and then a series of interaction effects that may be of interest were introduced. The final model specification is presented here, but it should be recognized that there are additional specifications incorporating myriad interaction effects that remain to be explored.

Table 3 presents the effects of socio-economic variables as well as attributes of the travel episode itself on emotions. Individuals living in households with no children find travel episodes less meaningful, but also less stressful and less tiring. On the other hand, single parents report travel episodes as being less happy, sadder, more stressful, and more painful than other groups. Single parents are likely juggling many activities with little support, thus inducing these feelings.

TABLE 3 Effects of Socio-Economic/Trip Characteristics on Underlying Emotion Intensities

Variable	Meaningful	Happy	Sad	Stressed	Tired	Painful
Threshold 1	-0.873	-1.383	1.038	0.314	-0.406	0.929
Threshold 2	0.153	0.081	1.904	1.493	0.925	1.856
Single Person	-0.073	-0.048	0.046	-0.081	-0.083	-0.074
Single Parent	0.000	-0.165	0.209	0.206	0.000	0.120
Multiple Adults, No Children	-0.039	0.000	0.000	-0.067	-0.084	0.000
Multiple Adults, With Child(ren) (*base*)	---	---	---	---	---	---
Income <$25K (*base*)	---	---	---	---	---	---
Income 25K to <$50K	-0.086	0.048	-0.140	-0.140	-0.104	-0.192
Income $50K to <$100K	-0.135	0.048	-0.140	-0.140	-0.059	-0.292
Income $100K or more	-0.249	-0.047	-0.140	-0.140	-0.178	-0.483
Age 18-34 years (*base*) – Millennials	---	---	---	---	---	---
Age 35-44 years: Generation X	0.181	0.065	0.118	0.000	-0.098	0.271
Age 45-64 years: Baby Boomers	0.317	0.085	0.239	0.000	-0.159	0.441
Age 65 years+: Silent Generation	0.536	0.361	0.000	-0.392	-0.450	0.208
High School Graduate or Less (*base*)	---	---	---	---	---	---
Some College or College Graduate	-0.151	-0.105	-0.046	0.056	0.054	-0.079
Master's Degree or Higher	-0.272	-0.105	-0.148	0.110	0.054	-0.079
Unemployed	-0.078	-0.093	0.174	0.150	-0.051	0.285
Employed Part-time	-0.112	-0.093	0.070	0.000	-0.116	0.000
Employed Full-time (*base*)	---	---	---	---	---	---
White x Female	0.110	0.163	0.000	0.092	0.202	0.000
Black x Female	0.462	0.335	0.000	-0.057	0.129	0.000
Other x Female	0.300	0.206	0.100	0.000	0.129	0.260
White x Male (*base*)	---	---	---	---	---	---
Black x Male	0.264	0.163	0.000	-0.185	-0.066	0.000
Other x Male	0.264	0.163	0.000	-0.185	0.000	-0.177
Residing in Metropolitan Area (*base*)	---	---	---	---	---	---
Residing in Non-Metropolitan Area	0.038	0.036	-0.071	-0.126	0.000	-0.036
Weekday (*base*)	---	---	---	---	---	---
Weekend Day	0.000	0.073	-0.030	-0.179	-0.148	-0.084
Mode – Personal Vehicle (Driver) *(base)*	---	---	---	---	---	---
Mode – Personal Vehicle (Passenger)	0.000	0.049	0.134	-0.065	0.126	0.122
Mode – Walk	0.181	0.049	0.097	0.000	0.058	0.112
Mode – Public Transit/Taxi Vehicle (Passenger)	0.000	0.000	0.169	0.000	0.209	-0.090
Mode – Bicycle	0.291	0.341	0.463	0.000	0.000	0.407
Mode – Other	0.374	0.677	0.000	0.000	0.000	0.581
Accompaniment: Alone (*base*)	---	---	---	---	---	---
Accompaniment: Household Members Only	0.256	0.152	-0.257	0.000	-0.035	-0.045
Accompaniment: Non-household Members Only	0.256	0.152	-0.140	0.000	0.000	0.000
Accompaniment: Both Hhld & Non-hhld Members	0.000	0.000	0.000	0.147	0.000	0.000
Trip Duration (minutes)	0.000	-0.395	0.748	0.750	0.814	0.000

Note: All parameters are statistically significant at the 0.05 level; a 0.000 indicates no statistically significant effect of the corresponding row variable, while a "---" indicates a base category for the exogenous variable.

Higher levels of income are associated with reduced levels of sadness, stress, tiredness, and painfulness, suggesting that higher income individuals are likely enjoying superior levels of service in their travel. On the happiness emotion, however, middle income groups report higher levels than the lowest and highest income groups. Advancing age is associated with reporting higher levels of meaningfulness and happiness. An in-depth exploration of the data shows that individuals 65 years and over are engaging to a lesser degree in work, school, and household maintenance activities, and more so in social, shopping, religious, and volunteer activities. Compared to 18-34 year-olds (millennials), it is found that older age groups experience lower levels of tiredness – which appears counter-intuitive on the surface. However, millennials use alternative modes of transportation such as walk, bicycle, and public transit to a greater degree than other age groups; as noted earlier, use of these modes is associated with higher levels of tiredness. Unemployed and part-time employed individuals are likely to derive lower meaningfulness and happiness from their travel episodes when compared with full-time employed individuals, who presumably enjoy a sense of purpose and satisfaction through their work.

The gender-race interaction effects show that all subgroups enjoy greater meaningfulness and happiness during travel than white-males (the reference group), a finding that merits further investigation. A finding that is consistent with expectations is that all female groups report greater levels of tiredness, presumably because females handle a greater share of household errands and child transportation. Residing in a non-metropolitan area is associated with higher levels of meaningfulness and happiness, and lower levels of negative emotions. This finding reflects the more relaxed and less stressful lifestyle enjoyed outside the city. As expected, travel episodes on weekend days engender greater levels of happiness and lower levels of all negative emotions, consistent with the more discretionary nature of weekend travel.

Emotional outcomes vary by mode of transportation. Walk and bicycle modes are associated with higher levels of meaningfulness and happiness, but the physical exertion leads to greater levels of sadness, tiredness, and painfulness. Riding in a public transport vehicle – which is not generally viewed as a pleasant experience – is associated with a greater level of sadness and tiredness, but a lower level of painfulness (as the rider can relax). Although the univariate descriptive statistics suggested that public transport trips are more stressful, this indicator did not reveal a significant coefficient in the multivariate model after controlling for all other variables. Moreover, riding in a public transport vehicle fared just as well as driving a personal vehicle on the meaningfulness and happiness scales, suggesting that the public vehicle ride experience is not all that inferior to personal vehicle driving trips after controlling for all other variables.

Having household members present during the travel episode contributes positively to meaningfulness and happiness, suggesting that people enjoy traveling with family. However, when combined with non-household members, the travel episode is viewed as more stressful, presumably due to more complex inter-personal dynamics in the presence of non-household members. Travel duration is found to contribute to increased sadness, stress, and tiredness, and lower levels of happiness. In other words, after controlling for all other attributes, travel duration is viewed as a burden. The largely positive ratings for travel episodes (reported in Table 2) likely stem from the benefits derived from the travel episode *experience* and the activities before and after the travel episode; and these benefits are large enough to more than offset the burden of travel time.

Table 4 shows the effects of preceding and succeeding activity attributes on feelings engendered during the travel episode. The incorporation of a detailed set of activity attributes in the multivariate modeling framework provides a robust basis to isolate the effects of activity engagement from the effects of the travel episode itself on a person's mood. It is found that travel episodes following activities involving non-household members are viewed with increased happiness, reduced stress, and greater exhaustion – suggesting that people do not necessarily perceive joint activities involving non-household members as all that relaxing. Travel episodes that involve joining household members for a subsequent activity are viewed positively with higher levels of meaningfulness and happiness, and yet they also engender greater sadness, tiredness, and pain. It is not immediately clear as to why this is the case. It is also found that individuals rate travel episodes to activities involving both household and non-household members higher on the happiness scale and lower on the sadness scale, suggesting that travel which facilitates social interactions is generally viewed positively.

The next two sets of variables represent interaction effects of the prior or subsequent activity purpose and location (at or out-of-home). The idea is that the nature of these activities may affect the mood of the individual during the intervening travel episode. In general, it is found that many a prior activity contribute significantly to positive feelings on the subsequent travel episode. Exceptions include household maintenance at home and personal maintenance outside home; as these activities are largely chores and errands, it is not surprising that they have a deleterious effect on the subsequent mood of an individual during travel. After engaging in pleasant activities at home (meal, social, and recreational activities), people report lower levels of stress on the subsequent travel episode.

Trips undertaken to reach a variety of activity type-location combinations are viewed as providing less meaningfulness and happiness in comparison to the base category of passive social activities outside home, which is presumably a very pleasant and desirable activity purpose. Exceptions include recreational activities at home or out-of-home, and meal out-of-home. Trips to such activities are understandably viewed with higher levels of happiness. In a similar vein, trips destined to various activities are viewed with greater levels of sadness, stressfulness, tiredness, or painfulness when compared with the base category (social activities out-of-home). Exceptions, once again, include active recreational activities and eat-meal activities out-of-home.

A key finding is that, when travel is the preceding or succeeding activity, more negative emotional feelings are reported by respondents. This effect is particularly apparent in the case where the subsequent activity is to travel out-of-home. This is likely a situation where the trips in question constitute segments of a multimodal journey that involves transfers across or within modes of transportation. The negative emotional feelings and greater levels of stress reported by respondents confirm that transfers are viewed as undesirable, at least in the current travel context. For this reason, travel behavior models have viewed transfers and transfer time as more burdensome than in-vehicle travel time in mode choice (Iseki and Taylor, 2009). Findings in this paper confirm the existence of a transfer penalty. Recently, there has been considerable excitement at the prospect of shared (and autonomous) on-demand mobility services providing first-mile last-mile connectivity for transit systems (Shaheen and Chan, 2016), thereby potentially contributing to a dramatic increase in transit ridership and usage. Even though on-demand mobility services could provide a very high quality of service in furnishing transit connectivity, their use would still involve transfers; and this study shows that transfers are viewed as undesirable by travelers. It is therefore questionable as to whether first-mile last-mile connectivity facilitated by shared on-demand mobility services will truly lead to dramatic increases in transit ridership (Polzin, 2017).

TABLE 4 Effects of Preceding and Succeeding Activity Attributes on Underlying Emotion Int.

Variable	Meaningful	Happy	Sad	Stressed	Tired	Painful
Prior Activity Accompaniment						
Alone (*base*)	---	---	---	---	---	---
Household Members Only	0.000	0.000	0.090	0.000	0.000	0.000
Non-household Members Only	0.000	0.047	0.000	-0.040	0.054	0.000
Both Hhld and Non-hhld Members	0.000	0.142	-0.085	-0.135	0.127	-0.086
Subsequent Activity Accompaniment						
Alone (*base*)	---	---	---	---	---	---
Household Members Only	0.169	0.099	0.079	0.000	0.035	0.037
Non-household Members Only	-0.065	0.046	0.000	0.000	0.000	0.000
Both Hhld and Non-hhld Members	0.109	0.125	-0.181	0.000	0.000	0.000
Prior Activity x Location						
Personal Maintenance x At Home	0.000	0.000	0.287	0.000	0.000	0.709
Household Maintenance x At Home	0.114	-0.055	0.000	0.077	-0.261	0.000
Meal x At Home	0.207	0.091	-0.159	-0.102	-0.253	-0.167
Passive Social Activity x At Home	0.000	0.000	0.000	-0.052	-0.327	-0.085
Active Recreational Activity x At Home	0.283	0.430	0.000	-0.471	0.000	0.000
Shopping x At Home	0.000	0.412	0.000	0.000	0.000	0.000
Work/School x At Home	0.201	0.000	0.000	0.194	-0.191	0.000
Other x At Home	0.000	0.000	0.175	0.269	0.000	-0.238
Personal Maintenance x Out-of-Home	0.120	-0.203	0.217	0.237	-0.213	0.281
Household Maintenance x Out-of-Home	0.163	0.000	-0.125	0.074	-0.119	0.000
Meal x Out-of-Home	0.000	0.085	0.000	-0.085	-0.110	-0.068
Passive Social Activity x Out-of-Home (*base*)	---	---	---	---	---	---
Active Recreational Activity x Out-of-Home	0.090	0.127	0.000	-0.183	0.000	0.242
Shopping x Out-of-Home	0.038	0.000	0.000	0.059	-0.151	0.089
Work/School x Out-of-Home	0.204	0.093	0.000	0.299	0.152	0.129
Travel x Out-of-Home	-0.088	0.000	0.000	0.000	0.000	0.000
Other x Out-of-Home	0.247	0.121	0.000	0.000	-0.089	0.000
Subsequent Activity x Location						
Personal Maintenance x At Home	0.000	0.000	-0.596	0.417	1.140	1.173
Household Maintenance x At Home	-0.207	-0.056	0.000	0.067	0.119	0.062
Meal x At Home	-0.213	-0.060	0.000	0.087	0.172	0.088
Passive Social Activity x At Home	-0.238	-0.058	-0.079	-0.099	0.152	0.000
Active Recreational Activity x At Home	0.000	0.336	0.000	0.000	0.277	0.000
Shopping x At Home	0.000	-0.250	0.000	0.000	-0.242	0.000
Work/School x At Home	-0.196	-0.178	0.146	0.000	0.000	0.000
Other x At Home	0.000	0.000	0.385	0.237	0.193	0.318
Personal Maintenance x Out-of-Home	-0.163	-0.258	0.000	0.120	-0.082	0.207
Household Maintenance x Out-of-Home	0.000	0.000	0.000	0.000	0.056	-0.118
Meal x Out-of-Home	0.000	0.107	-0.250	-0.126	-0.148	0.000
Passive Social Activity x Out-of-Home (*base*)	---	---	---	---	---	---
Active Recreational Activity x Out-of-Home	0.000	0.129	-0.438	-0.269	-0.303	-0.122
Shopping x Out-of-Home	-0.227	-0.140	0.000	0.130	0.000	0.078
Work/School x Out-of-Home	-0.147	-0.249	0.181	0.289	-0.162	0.083
Travel x Out-of-Home	-0.301	-0.267	0.000	0.130	0.000	0.082
Other x Out-of-Home	0.140	0.000	0.000	0.070	0.000	0.000

Goodness-of-Fit Statistics: Predicted Log-Likelihood of Full Model: -42644.532
Predicted Log-Likelihood of Null Model (only thresholds and no correlation terms): -47623.622
LRT = 9958.180; p-value = 0.000

Note: All parameters are statistically significant at the 0.05 level; other notes are as in Table 3.

6. DISCUSSION AND CONCLUSIONS

This study is motivated by the desire to better understand how people feel during travel and identify the determinants of those feelings. Insights on people's feelings of well-being during travel can help inform predictions of how travel demand may change in a future that will see the increasing emergence of shared mobility services, autonomous vehicle technologies, and ubiquitous connectivity. In addition, such insights would help planners and policy-makers identify strategies and investments that may enhance feelings of well-being during travel, thus improving quality of life in communities (as transportation is often a key ingredient of quality of life indicators).

The study involved an examination of emotional feelings of subjective well-being (SWB) that individuals attribute to travel episodes. Three years of data corresponding to the well-being module of the American Time Use Survey data set is used to conduct the analysis and modeling effort. Travel episodes are extracted from the pooled three-year data set and information about the individual as well as attributes of activities preceding and succeeding each travel episode are appended to the travel records to construct a comprehensive data set. The data set includes ratings on a seven-point scale for six different emotions – happiness, meaningfulness, sadness, stressfulness, tiredness, and painfulness. A multivariate ordered probit model system, capable of jointly modeling all emotional measures while incorporating the presence of correlated unobserved attributes that affect multiple measures, is estimated on a data set of 10,000 observations to understand the influence of various attributes on feelings of well-being during travel episodes.

It is found 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. However, 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.

Model estimation results 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. Another important finding is that trip duration has a negative impact on travel well-being across a range of emotional measures. Thus, it appears that travel time, by itself, is generally considered a burden or cost that reduces the state of well-being (after controlling for all other variables). Travel is likely viewed positively for the experience it offers and the activities that it enables, and any disutility due to time spent traveling is more than overcome by the utility of the experience and enabled activity opportunities (if that were not the case, then the travel episode would not have occurred in the first place). This suggests that, unless autonomous vehicles greatly enhance the travel experience and the ability to access desirable activities and destinations, it is unlikely that individuals will dramatically increase travel time expenditures in an autonomous vehicle future as some fear (Wadud et al., 2016).

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.

From a policy and practice perspective, this study offers a few useful insights. 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.

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