Project Report

An Integrated Model of Activity-Travel Behavior and Subjective Well-being

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract The notion that people's activity-travel patterns influence well-being and overall quality of life is well recognized. Nonetheless, activity-travel demand model outputs do not provide explicit measures of well-being that can be used to assess the impacts of alternative policies, investments, and technologies. Since activity-travel demand models lack information about in-home activity time allocation, it is virtually impossible to derive measures of well-being that account for in-home activity engagement. This study presents a model of well-being that overcomes this challenge. The model serves as a tool to assess the quality of life implications of activity-travel patterns for diverse groups of the population. Given the critical role that transportation plays in shaping wellbeing of communities, this tool will prove valuable in assessing and comparing the potential impacts of alternative transportation investments, policies, and mobility options on societal wellbeing.		
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EXECUTIVE SUMMARY

The notion that people's activity-travel patterns influence well-being and overall quality of life is well recognized. Nonetheless, activity-travel demand model outputs do not provide explicit measures of well-being that can be used to assess the impacts of alternative policies, investments, and technologies. Since activity-travel demand models lack information about in-home activity time allocation, it is virtually impossible to derive measures of well-being that account for in-home activity engagement. This study presents a model of well-being that overcomes this challenge. The model is developed using the 2010, 2012, and 2013 well-being modules of the American Time Use Survey (ATUS) and includes two major components. First, a multiple discrete-continuous extreme value (MDCEV) model of in-home activity time allocation is estimated using the ATUS data. Second, regression models of well-being scores are estimated using data available in the ATUS, yielding a set of equations that compute well-being scores as a function of socio-economic characteristics and attributes of the activities or travel episodes. This well-being model system is then applied to a small sample of records from the National Household Travel Survey (NHTS) to demonstrate the efficacy of the model. The MDCEV component predicts in-home time allocation for various activities, and the regression equations provide episode-level well-being measures (for all in-home/out-of-home activities and travel episodes) that can be aggregated to derive a daily activity-travel well-being metric for each individual. The model serves as a tool to assess the quality of life implications of activity-travel patterns for diverse groups of the population.

INTRODUCTION

Transportation plays a critical role in shaping the quality of life in communities around the world by making it possible for people to engage in activities, participate in societal functions, and interact with various agents and entities that make up a region's ecosystem. Additionally, transportation enables mobility, thus providing people and businesses access to goods, services and opportunities. By enabling these functions, transportation and logistics systems directly impact the economic vitality of a region, along with the state of the environment, energy consumption, public health, and safety and security.

Because of the tight connection between transportation and quality of life, considerable attention has been paid to understanding the linkage between mobility and subjective well-being (Ziems et al., 2010; Bergstad et al., 2011; Lee and Sener, 2016; Friman et al., 2017). Measures of subjective well-being capture the emotions that people feel as they go about their daily lives, undertake activities, and travel. While quality of life may be viewed as a notion that captures the broader and longer-term outlook that people have on their lives, the notion of subjective well-being may be viewed as capturing the emotions experienced in a specific context or situation (National Research Council, 2013). Although important distinctions can and should be drawn between broader quality of life measures and measures of subjective well-being, it can be said that a healthy accumulation of positive feelings of well-being will contribute (over time) to a higher quality of life. To the extent that transportation can engender such positive feelings of well-being (through access to opportunities and destinations, enabling participation in activities and society at large, and provision of pleasant mobility experiences and options), it would be of value to be able to measure and quantify well-being that people derive from their daily activity-travel and time use patterns. Armed with knowledge about the well-being implications of the activity-travel ecosystem, transportation professionals will be able to plan built environments, design mobility systems, and implement policies that enhance well-being – and consequently, quality of life.

However, transportation demand forecasting models do not output measures of well-being, and household travel surveys never collect information about feelings of well-being associated with various activity-travel episodes reported in a travel diary. In the absence of any knowledge or data about actual subjective feelings of well-being that are derived from activities and trips, inferences about well-being are often drawn based on the time use pattern. There is a rich body of literature that is devoted to the notions of time poverty (Williams et al., 2016) and social exclusion (Lucas, 2012; Schwanen et al., 2015). This body of literature has generally posited that individuals who do not travel (report zero trips) may be experiencing social exclusion (Lucas, 2012), i.e., they are not participating in society and engaging in activities outside the home. In the absence of interactions with the outside world, they may suffer from loneliness, depression, and other mental health issues. In the time poverty literature, individuals who do not engage in leisure time activities for a duration that exceeds a certain threshold are considered to be "time poor" (Williams et al., 2016). The time poverty criterion is often pegged to the median (or some fraction of the median) leisure activity time depicted by the population under consideration. Those who experience time poverty are assumed to have a lower well-being and overall quality of life.

While a time-based definition of well-being (and quality of life) certainly has merit, there remains some uncertainty as to the extent to which time use based measures truly represent the feelings of well-being experienced by individuals. Some may find staying at home to be pleasurable (especially if the in-home activities are of a discretionary and social nature), while others may find work very rewarding and satisfying (even though they spend little to no time on discretionary leisure activities). In other words, there is a need to develop a measure of well-being that can be computed based on standard outputs of an activity-based transportation demand forecasting model. Activity-based travel models, which simulate activity-travel patterns at the level of the individual agent, are increasingly being adopted in metropolitan areas for transportation planning and forecasting purposes. These models are able to provide rich information about individual activity-travel patterns under a wide range of conditions, essentially providing an output that mimics data collected in a travel diary survey. For each and every individual in a representative synthetic population of agents, the activity-based model furnishes activity-travel records at fine-grained spatial and temporal resolution. It would be of considerable value if the activity-travel and time use measures implied by an individual's pattern can be translated into a measure of well-being, thus enabling planners to assess the well-being implications of the transportation system and alternative actions.

This paper presents an integrated model of activity-travel behavior and subjective well-being that can essentially serve as a well-being scoring tool for activity-travel patterns. The model, when interfaced with an activity-based travel demand model that outputs activity-travel records at the level of the individual agent, can be used to compute well-being scores that are based on the predicted activity-travel and time use patterns. A couple of challenges need to be addressed, however, in the development of such a model, and this paper presents a data fusion approach to help overcome the challenges. The first challenge is that travel surveys do not contain any information about subjective well-being, and hence the calibration of a model of well-being is difficult in the absence of data. To overcome this issue, well-being data from the 2010, 2012, and 2013 editions of the American Time Use Survey (ATUS) data collected in the United States is used to estimate well-being scores as a function of activity engagement and time use allocation patterns. The second challenge is that activity-based travel models (and the surveys upon which they are estimated and calibrated) provide no information about in-home activity engagement patterns. However, activity engagement inside the home is likely to contribute substantially to feelings of well-being (or lack thereof). Hence, in-home time use allocation patterns need to be estimated so that appropriate well-being measures (that account for both in-home and out-of-home activity engagement and time use) can be developed and computed. To overcome this challenge, a multiple discrete-continuous extreme value (MDCEV) model of in-home activity participation and time use allocation is estimated on the American Time Use Survey (ATUS) data. This model can be applied to the activity-travel records output by any activity-based travel model to infer in-home activity engagement and time use patterns for each agent in the synthetic population. This information can, in turn, be used to compute a holistic well-being score that accounts for the entire slate of activities pursued by an individual inside and outside home. The paper describes the model development and data fusion process, and demonstrates the efficacy of the model by presentation an application of the model to a small sample of 2017 National Household Travel Survey (NHTS) records (which represent the output of an activity-based travel model for purposes of the demonstration in this paper).

The remainder of this paper is organized as follows. A brief literature review is presented in the next section. The third section presents the modeling methodology and conceptual framework. The fourth section offers a description of the data. The fifth section presents the model estimation results, while the sixth section presents illustrative model application results. Concluding thoughts are offered in the seventh and final section.

LITERATURE REVIEW

Subjective well-being (SWB) has been a topic of much interest in many different domains including the field of transportation. According to the National Research Council (2013), SWB may be viewed as a self-assessment of one's life in the context of specific domains and activities. SWB may be measured as a series of momentary states through time. The notion is characterized by multiple dimensions and emotions, and it is important to acknowledge the role of different emotions in shaping SWB. Negative emotions are more complex to unravel than positive emotions, and hence more measures are needed to decipher the underlying forces contributing to negative emotions. Negative emotions and positive emotions are not necessarily polar opposites of one another and hence they need to be considered together when evaluating SWB (National Research Council, 2013).

A number of researchers have explored the connection specifically between travel and SWB. Travel can influence SWB through a variety of mechanisms. Mokhtarian and Pendyala (2018) identify five sources of influence that impact travel satisfaction: experiences during destination-oriented travel, activities during destination-oriented travel, trips where travel is the activity, travel-facilitated activity, and utility. Gärling (2019) posited that positive and negative emotional responses are evoked by transient critical incidents (such as disruptions) and non-transient factors (such as noise) during travel. Ettema et al. (2010) identified three sources of the impacts of travel on SWB: positive and negative effects during travel, accessibility to activities through travel, and impacts of travel on the amount of stress associated with the activities that are performed over the course of a day. Lee and Sener (2016) conceptualize four transportation-related quality of life dimensions – physical, mental, social, and economic. They identify three components of the transportation system as affecting these four dimensions: mobility/accessibility, built environment attributes, and vehicular traffic volumes. Waygood et al. (2017) evaluated child well-being and found that transport influences well-being in three ways: as an access (destination-based) mechanism, through its intrinsic features (the travel experience itself), and by external connections (e.g., transporting or being transported by others). Interestingly, Gao et al. (2017) found that satisfaction with travel had a relatively small effect on overall well-being after controlling for socio-economic and demographic characteristics and personality traits (self-discipline, impatience, easy-going, reserved, and calm).

There are a number of studies that have documented the SWB associated with different modes of transport. Delbosc (2012) noted that transit can enhance life satisfaction in two ways, directly through physical mobility and indirectly through accessibility to important activities. Friman et al. (2017) and Mokhtarian and Pendyala (2018) both report that public transit is associated with a lower SWB, while active modes are associated with a higher level of SWB. The most positive emotions were reported by car passengers (Mokhtarian and Pendyala, 2018). On the other hand, Ferenchak and Katirai (2015) found a negative association between use of carpooling and public transportation modes and mental state, while driving alone to work was found to have a significant positive association. Greater use of active commuting modes is associated with higher levels of physical well-being, regardless of time spent in other domains of physical activity (Humphreys et al., 2013). Reduced car use has been found to contribute to reduced SWB (Bergstad et al., 2011). All of these studies have clearly identified a linkage between travel and SWB.

In addition to travel, household and person socio-economic and demographic attributes are found to influence SWB. Males are found to report lower SWB for travel episodes than females (Archer et al., 2013). Low income individuals report a wider range of emotions than high income individuals, presumably because they have a number of other factors (related to monetary constraints) that affect their life (Mokhtarian and Pendyala, 2018). Contrary to studies that suggest older people are at risk of social exclusion and depression (Glass et al., 2006; Liu et al., 2014), Archer et al. (2013) found that older people report higher levels of happiness for all types of activities including out-of-home activities, in-home activities, and travel episodes. Bergstad et al. (2011) also report that older people are more satisfied with their daily travel patterns, presumably because they do not have the same constraints and busy schedules as their younger counterparts. Ziems et al. (2010) found that older people derived higher values of utility from their time use patterns in comparison to other age groups. Although older people spent less time outside home, losses in utility due to fewer out-of-home activities seemed to be compensated by utility derived from discretionary in-home activities. Abou-Zeid and Ben-Akiva (2012) found that frequent activity engagement is associated with higher levels of happiness and greater satisfaction with life; similarly, Mokhtarian and Pendyala (2018) found that emotions are more positive for out-of-home activities than similar in-home activities. Geographic context is also an important determinant of well-being. Archer et al. (2013) found that individuals in the sunbelt of the United States reported higher levels of happiness for household maintenance and work activities compared to other regions of the country. Delbosc and Currie (2011) found that the correlation between transportation disadvantage and well-being was consistently higher for rural residents outside the boundaries of major metropolitan areas. Ye and Titheridge (2017) note that the built environment plays a significant role in shaping satisfaction through its influence on commute characteristics.

Given the linkage between activity-travel patterns/choices and SWB, an integrated model system that connects these dimensions directly would be of value so that policy makers can determine the SWB implications of their investments and actions. Many integrated model systems have been developed and documented in the literature (e.g., Eluru et al., 2010; Sener et al., 2011; De Abreu e Silva et al., 2012); however, while these studies account for multiple travel behavior dimensions (e.g., residential location, car ownership, amount of travel by mode, destination choice), they do not link activity-time use patterns and subjective well-being. Understanding this linkage is critically important as communities seek to improve quality of life for residents.

Undoubtedly, there are few studies that have attempted to connect SWB with daily activity-travel and time use patterns. Archer et al. (2013) found that activity start time, activity duration, child accompaniment, and activity location influenced SWB. Ye et al. (2009) developed a time use utility measure based on activity engagement patterns, but did not explicitly consider measures of well-being (emotions) in defining the time use utility measure. Their effort was, however, aimed at developing a time use utility measurement tool that could be applied as a post-processor for activity-based travel demand models so that the utility that people derive from their activity-travel and time use patterns could be evaluated. Their tool, however, did not sufficiently account for the array of in-home activities that people pursue each day. Therefore, an integrated model system that tightly connects the daily activity-time use patterns and well-being, while explicitly accounting for in-home time use and activity engagement is needed.

Defining well-being based on activity engagement, travel, and time use has its merits, but may not capture the true emotions that people associate with their daily lives. Krueger et al. (2009) notes that interpreting SWB based on activity engagement has limitations, particularly because people are very heterogeneous. Workaholics may derive great satisfaction from work; shopaholics may derive great happiness from shopping. On the other hand, there are those who dislike work and/or dislike shopping. Some enjoy traveling and experiencing destinations; others like to stay at home. In other words, it is important to directly model and assess measures of well-being that are reported by individuals. Such data can be used to develop models of subjective well-being that tie emotions to activity-travel and time use patterns, thus providing a basis to more accurately assess SWB that people derive from their daily lives. This paper aims to develop such an integrated model system so that SWB measures can be computed for agents in an activity-based travel demand model. Not only should the model account for well-being derived from out-of-home activities and travel, but it should also account for well-being derived from in-home activities. The integrated model system presented in this paper is able to do so through the use of data contained in the American Time Use Survey (ATUS) data set.

CONCEPTUAL FRAMEWORK AND MODEL STRUCTURE

This section presents the conceptual framework for the well-being estimation and analysis tool developed in this paper. Figure 1 presents the framework with a view to identifying the components and steps that are involved in developing a well-being score for each individual in a synthetic population of agents. The fundamental premise underlying the conceptual framework is that well-being is determined by how people feel spending time traveling and engaging in different types of activities inside and outside the home.

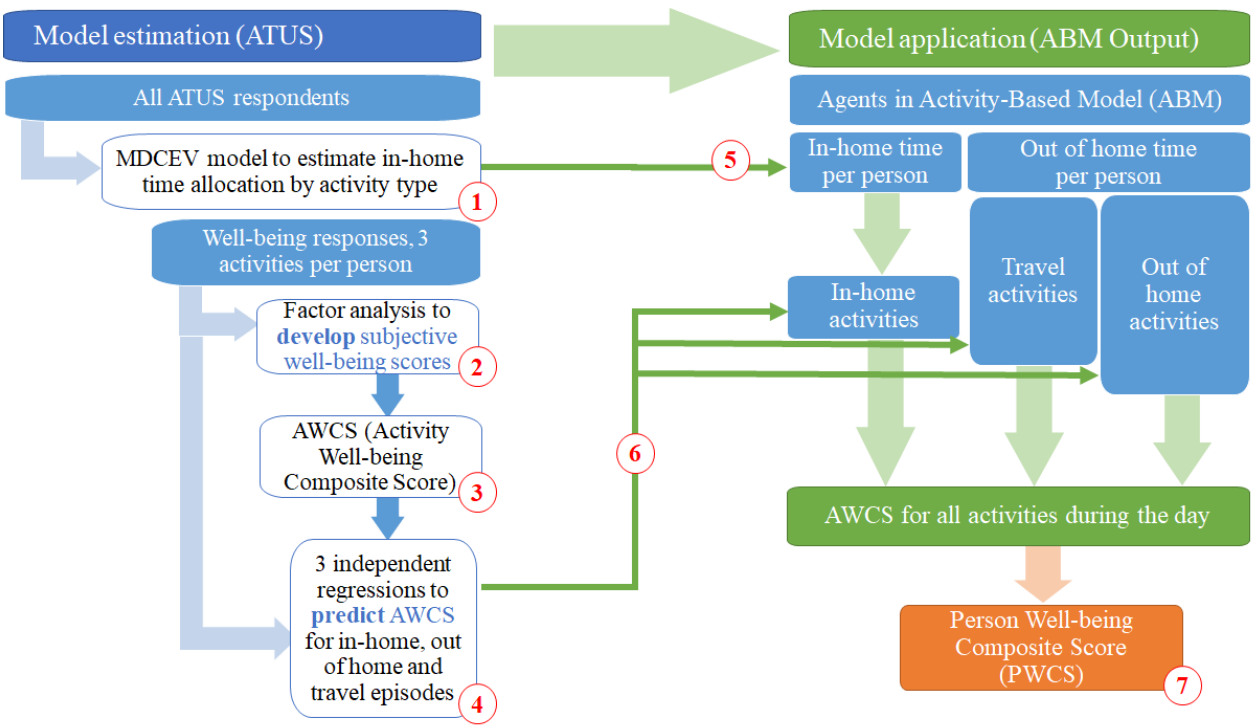

FIGURE 1 Summary of the Study Approach to Compute Daily Well-being Composite Score

Any output of an activity-based model includes information about out-of-home activities and travel episodes but includes no information about specific activities pursued inside the home. These activities do, however, contribute to well-being of an individual. Therefore, to compute a person well-being score, it is necessary to post-process the output of an activity-based model so that the time allocated to various activities inside the home can be determined. Once a full-fledged daily activity profile (in-home and out-of-home) is constructed for an individual, then a person-day level well-being score can be computed.

The process starts with the estimation of a multiple discrete continuous extreme value

(MDCEV) model of in-home time allocation to various activity purposes. The MDCEV model (Bhat, 2008) essentially allocates a budget of resources (in this case, time at home) to various goods that are consumed (in this case, activities inside the home). The budget of resources is the total time spent at home. This can be easily computed from the output of an activity-based model for each synthetic agent by simply subtracting total out-of-home activity time and travel time from 1440 minutes. The MDCEV model of in-home activity participation and time allocation can be applied to the output of an activity-based travel model to construct the full daily activity and time use profile for each individual in the synthetic population. The MDCEV model of in-home time use allocation is estimated using the American Time Use Survey (ATUS) data set that provides detailed information about in-home and out-of-home activity engagement and time use.

The data used in this study is presented in greater detail in the next section. In short, the 2010, 2012, and 2013 editions of the American Time Use Survey (ATUS) data included a well-being module. All survey respondents were asked to rate three randomly identified activities that they reported in their time use diary on six emotional measures – happiness, meaningfulness, sadness, painfulness, stress, and tiredness. The respondents rated each emotion on a scale of 0 through 6, with higher scores indicating a greater intensity of the emotion. While happiness and meaningfulness can be characterized as positive emotions, the other four constitute negative emotions. In order to consolidate these emotions into positive and negative scores, a factor analysis is conducted to identify two subjective well-being scores for each activity episode. The two positive emotions are combined into a positive well-being score while the four negative emotions are combined into a negative well-being score. The factor analysis essentially yields latent constructs that serve as indicators of positive and negative emotions; the factor scores (positive and negative) constitute linear combinations of the numeric ratings assigned by individuals to the various individual emotions.

It should be recognized that the positive factor score is computed based on two emotions and the negative factor score is computed based on four emotions. Hence the positive and negative factor scores are not directly comparable. Nevertheless, because they are both based on emotions that were rated on a scale of 0 through 6, they provide continuous scores reflective of the degree to which an individual felt positively or negatively towards an activity. In order to obtain a "net" emotional score for each activity episode, the difference between the two scores (positive score – negative score) may be computed. This difference is termed the Activity Well-being Composite Score (AWCS). Due to the lack of symmetry in emotional measurements and the different numbers of positive and negative emotions, a zero AWCS does not necessarily imply a neutral emotion or indifference. At the end of this step, every record in the ATUS (for which emotions data was collected) had an AWCS appended to it.

Next, a set of linear regression equations of AWCS was estimated for three activity episode types, namely, out-of-home activities, in-home activities, and travel. The regression equations included a number of socio-economic and demographic variables as well as activity episode attributes as explanatory variables. The AWCS served as the dependent variable in each regression equation. Ideally, a more intricately connected simultaneous equations modeling approach would be appropriate to account for possible correlations in error terms that may signify the presence of unobserved variables that simultaneously impact the AWCS of different activity types. For example, if a person is inherently an outdoor-oriented adventurous individual, then the AWCS scores for out-of-home activities and travel are likely to be high while the AWCS score for in-home activities is likely to be low for this individual. For simplicity, independent regression equations were estimated and implemented in the initial version of the model system, with plans to transition to a simultaneous equations model system in future versions. The regression equations can be applied to all of the activities and travel episodes that constitute an individual's daily activity engagement profile. In this way, an AWCS can be computed and attached to every activity undertaken by an individual in a synthetic population.

In the end, the model system is intended to provide a single day-level Person Well-being Composite Score (PWCS) for each individual agent in the synthetic population of an activity-based travel demand model. The PWCS is computed as a simple summation of all AWCS scores associated with various activities in the day. The summation operation implies that the scores associated with various activities are additive and that well-being is derived from an accumulation of emotions experienced over the course of pursuing various activities and travel episodes in a day. While a summation may not necessarily represent the exact way in which people aggregate their emotional experiences and feelings over the course of a day, this approach was adopted for simplicity. Moreover, in the absence of any data about how people aggregate their emotional feelings associated with various activities over the course of a day, the summation approach seemed as reasonable as any other. The right-hand side of Figure 1 depicts how the model system may be applied to activity-travel records (such as those obtained as output from an activity-based travel demand model) to compute PWCS for synthetic agents. Because an activity-travel model output was not specifically available, the efficacy of the model is demonstrated in this paper by applying it to a small random sample of records from the 2017 National Household Travel Survey (NHTS) data set (the activity-travel records in the NHTS data set are very similar to a typical activity-travel model output).

DATA

This section presents an overview of the data used in this model development effort. As noted previously, the primary source of data is the American Time Use Survey (ATUS), which is administered on an annual basis by the Bureau of Labor Statistics (BLS) in the United States to a representative sample of individuals aged 15 years or over. The survey involves collecting detailed activity engagement and time use information with a very detailed activity purpose classification scheme, thus providing a high degree of fidelity in terms of activity attributes. In addition to all of the attributes of the activity episodes, the data set includes information about travel episodes as well as socio-economic and demographic characteristics of the individual and the household to which the individual belongs. In 2010, 2012, and 2013, the ATUS included a well-being module in which individuals were asked to rate their feelings on a scale of 0 through 6 for six different emotions – happiness, meaningfulness, sadness, tiredness, painfulness, and stress. A higher score implied a higher intensity or degree of a particular emotion. Respondents were asked to do this for three randomly identified activity or travel episodes in their time use pattern. A total of 31,103 respondents were selected to provide this information for a total of 92,417 activity and travel episodes.

Table 1 shows the distribution of ratings for all six emotions considering three broad activity types – namely, in-home activities, out-of-home activities, and travel episodes. A higher rating on the positive (negative) emotions implies that the individual derived more positive (negative) feelings from the activity episodes. In general, it can be seen that people rate their activity episodes positively and derive positive feelings of emotion. This is quite consistent with expectations as people are likely to shun activities that they do not enjoy or find undesirable if they can help it. In the table, each row adds up to 100 percent, thus enabling the identification of the fraction of episodes of any given type rated at each level of an emotional measure.

An examination of the positive emotions shows that nearly one-third of activities are rated at the highest level of happiness and nearly 40 percent are rated at the highest level of meaningfulness. Only small fractions of activities of any type fall into the lowest ratings of happiness and meaningfulness; the percentages at either end of the spectrum are higher for meaningfulness than happiness. It appears that individuals are able to draw a more clear distinction in meaningfulness than in happiness. About 10 percent of episodes are characterized as not being meaningful. It is interesting to note that travel depicts a higher percent of episodes that are deemed not meaningful, relative to in-home and out-of-home activities. This is reasonable in that travel is a means to access and pursue an activity; the activity at the destination is what provides value and meaningfulness, with the travel episode merely serving as the conduit to access the activity. In both happiness and meaningfulness, it is found that in-home activities are consistently viewed a little less positively than out-of-home activities.

TABLE 1 Distribution of Emotion Ratings by Activity Type (N=92,417 activities)

Wellbeing Emotional Score		0 (weak)	1	2	3	4	5	6* (strong)
Happiness	In-home activity	5.7%	2.1%	5.5%	15.4%	17.5%	22.1%	31.7%
	Out of home activity	4.1%	1.9%	4.8%	13.9%	18.1%	23.9%	33.2%
	Travel activity	4.4%	1.9%	5.1%	14.9%	18.4%	23.6%	31.7%
	All activities	5.0%	2.0%	5.2%	14.9%	17.9%	22.9%	32.1%
Meaning-fullness	In-home activity	9.6%	3.5%	6.5%	13.0%	12.4%	15.7%	39.4%
	Out of home activity	6.2%	2.5%	4.9%	11.9%	13.4%	17.9%	43.2%
	Travel activity	12.2%	4.3%	6.9%	13.3%	12.2%	14.2%	37.0%
	All activities	9.3%	3.4%	6.2%	12.8%	12.6%	15.9%	39.8%
Pain	In-home activity	66.1%	6.3%	6.9%	7.2%	6.1%	3.9%	3.5%
	Out of home activity	71.3%	6.6%	7.0%	6.1%	4.5%	2.6%	2.0%
	Travel activity	73.0%	6.5%	6.2%	5.7%	4.1%	2.6%	2.0%
	All activities	69.0%	6.4%	6.7%	6.6%	5.2%	3.3%	2.8%
Sadness	In-home activity	77.1%	6.0%	5.3%	4.9%	2.9%	2.0%	1.9%
	Out of home activity	78.9%	6.5%	5.2%	4.1%	2.3%	1.4%	1.6%
	Travel activity	78.8%	6.4%	5.0%	4.3%	2.4%	1.6%	1.5%
	All activities	77.9%	6.2%	5.2%	4.6%	2.6%	1.8%	1.7%
Stressed	In-home activity	57.3%	10.1%	10.7%	8.8%	5.9%	3.7%	3.3%
	Out of home activity	52.0%	10.9%	11.7%	10.3%	7.2%	4.4%	3.4%
	Travel activity	53.6%	11.3%	12.1%	9.5%	6.6%	3.9%	3.1%
	All activities	55.2%	10.6%	11.3%	9.4%	6.4%	3.9%	3.3%
Tired	In-home activity	32.2%	8.5%	13.0%	16.0%	13.9%	9.4%	7.0%
	Out of home activity	34.2%	10.2%	14.3%	16.2%	12.1%	7.8%	5.2%
	Travel activity	34.2%	10.1%	13.4%	15.6%	12.5%	8.2%	5.9%
	All activities	33.2%	9.2%	13.4%	16.0%	13.2%	8.7%	6.3%

* Each row adds up to 100%.

An examination of the distribution of ratings on negative emotions reveals a somewhat similar pattern. Higher ratings imply greater displeasure with the activities in question. Less than two percent of all activities are rated in the highest level of sadness, and less than three percent are rated in the highest level of painfulness. In general, it appears that individuals do not feel that their activities engender sadness or create pain. Large percentages of activities are rated with a zero on the painfulness and sadness scales. The sentiment shifts a little bit for the stressfulness and tiredness emotions. Just over three percent of activities are viewed as engendering the highest level of stress. When it comes to tiredness, over six percent of activities are rated at the highest level. Only one-third of activities are rated zero on the tiredness scale, suggesting that people do experience tiredness more so than other negative emotions. In general, out-of-home activities are rated lower on the sadness, painfulness, and tiredness scales than in-home activities. This implies that people generally enjoy out-of-home activities more than in-home activities, supporting the notion that engaging in travel and out-of-home activities has a positive impact on well-being (and consequently quality of life). In the case of stress, however, it is found that out-of-home activities are viewed as being more stressful than in-home activities. This is largely due to the high prevalence of work episodes among out-of-home activities and the very low prevalence of work episodes among in-home activities. Travel activities depict a slightly lower level of painfulness when compared with in-home and out-of-home activities, presumably because there is nothing painful about travel episodes (for the most part). The travel episodes are associated with a slightly higher level of tiredness than out-of-home activities. As travel may involve physical and mental exertion (walking, bicycling, waiting for transit, driving), it is not surprising that people rate travel episodes more negatively on this emotion.

To develop the integrated activity-travel well-being model system, a MDCEV model of activity time allocation (for in-home time) had to be specified and estimated. As a sample size of 31,000+ is somewhat large and unwieldy, a two percent random sample of individuals is extracted from the ATUS data base. The two percent random sample was further filtered to include only those that had complete socio-economic and demographic data (no missing data) and reported time use for weekdays. This yielded an estimation sample of 5,069 individuals. Table 2 shows the socio-economic profile of the ATUS person sample. It can be seen that the sample has a slightly higher proportion of females than males. The sample shows an age distribution that is consistent with expectations for a nationally representative sample. The largest percentage of individuals falls within the 31-49 year age bracket. About 19 percent of the sample is 65 years or age and over. Smaller percentages of individuals fall within the extreme education categories; about 27.7 percent of the sample has some college or an associates degree. About one-in-five individuals is a college graduate. The household income distribution shows a healthy spread across the various income categories with 8.4 percent reporting incomes greater than or equal to $150,000 per year. Finally, the household size distribution shows that about 26 percent of individuals are in single-person households, and another 26.6 percent are in two-person households. Overall, the distributions are consistent with expectations.

To demonstrate the efficacy of the well-being model system presented in this paper, the model system needs to be applied to the output of an activity-based travel demand model that includes activity-travel records for an entire synthetic population of agents. As a full-fledged activity-based model output was not readily available, the model system is illustrated in this paper through an application to a small sample of records drawn from the National Household Travel Survey (NHTS) sample. Once again, a random two percent sample of driving age individuals was drawn from the NHTS and then extensively cleaned and filtered to eliminate records with missing data on key socio-demographic variables of interest.

TABLE 2 Socio-demographic Characteristics of ATUS and NHTS Samples

Variable	ATUS		NHTS	
	N (5,069)	%	N (6,810)	%
Gender				
Female	2836	55.9	3609	53.0
Male	2233	44.1	3201	47.0
Age				
15-20 years	312	6.1	370	5.4
21-30 years	687	13.6	694	10.2
31-49 years	1826	36.1	1651	24.2
50-64 years	1283	25.3	2062	30.3
65+ years	961	18.9	2033	29.9
Educational Attainment				
Less than a high school diploma	714	14.1	489	7.2
High school graduate or GED	1312	25.9	1349	19.8
Some college or associates degree	1404	27.7	2012	29.5
Bachelor's degree	1022	20.1	1564	23.0
Graduate degree or professional degree	617	12.2	1396	20.5
Household income				
Less than $10,000	379	7.5	259	3.8
$10,000 to $14,999	375	7.4	269	4.0
$15,000 to $24,999	586	11.6	535	7.9
$25,000 to $34,999	594	11.7	597	8.8
$35,000 to $49,999	673	13.3	808	11.9
$50,000 to $74,999	971	19.1	1217	17.9
$75,000 to $99,999	544	10.7	994	14.6
$100,000 to $149,999	526	10.3	1225	18.0
$150,000 and over	421	8.4	906	13.3
Household size				
1	1319	26.0	1169	17.2
2	1348	26.6	3096	45.5
3	856	16.9	1103	16.2
4	903	17.8	889	13.1
5+	643	12.7	553	8.1

The resulting sample includes 6,810 records. Because this is an unweighted sample, the distributions are unlikely to be representative of the general population and likely to diverge from those depicted by the ATUS subsample (because the ATUS sample is representative of the general population). Indeed, it can be seen that some of the distributions in the NHTS sample exhibit a skew. For example, the NHTS sample has a higher percent of older people (than ATUS) and a higher percent of individuals with graduate and professional degrees (highly educated). One-in-five individuals in the NHTS sample has an advanced college degree. The NHTS sample is also skewed in favor of individuals in high-income households. While 18.7 percent of ATUS individuals reside in households that make $100,000 or more, 31.3 percent of NHTS individuals do so. Finally, the household size distribution shows that the NHTS sample has an over-representation of two-person households, subsequently contributing to an under-representation on the other household size categories.

However, for purposes of illustrating the application of the model, none of these skews are of any concern. The model system can be applied to any market segment and hence representativeness of the NHTS sample is not of much consequence in this paper. Also, there is no specific reason for drawing a two percent random sample. A random sample of any size could have been drawn to demonstrate the efficacy of the model. The two percent sample yielded usable estimation and application data sets of at least 5,000 individuals, which was considered an appropriate number to facilitate model estimation and application (i.e., sufficient sample sizes to perform analysis of well-being for various market segments).

MODEL ESTIMATION RESULTS

This section presents a brief overview of model estimation results for the various components of the integrated model system. In the interest of brevity, detailed model estimation results tables are not furnished here, but available from the authors by request. The first major model component is the MDCEV model of in-home activity engagement and time allocation that is estimated on the subsample of ATUS records extracted from the data set. The MDCEV model is a discrete-continuous extreme value model that is capable of allocating a budget among multiple discrete alternatives. As a result, not only is it possible to identify the discrete alternatives that are consumed, but it is also possible to determine the amount of budget (time) allocated to each consumed alternative. The budget is determined by subtracting out-of-home time and travel time from the daily available time of 1440 minutes (24 hours). The MDCEV model accounts for satiation effects through the estimation of corresponding satiation parameters which can also account for the existence of corner solutions (i.e., some alternatives are not consumed at all). Further details about the MDCEV model used for this effort can be found in Bhat (2008).

The estimated MDCEV model was applied to the estimation sample (not a holdout sample) to ensure that the model is able to adequately replicate the observed patterns in the data set. This effort did not serve as a validation per se, but serves as a basic indicator of the ability of the model to replicate observed patterns in the estimation data set. All goodness-of-fit measures of the MDCEV model were in line with expectations and were similar to those that have been reported in the literature in the time use context (Astroza et al., 2017). The model specification was refined until the replication exercise showed that the model reproduces time allocation patterns in the estimation sample quite well (based on a qualitative and quantitative assessment).

The MDCEV model was then applied to the small sample of NHTS records extracted for purposes of demonstrating the efficacy of the model. A total of 6,810 NHTS records were extracted (a two percent sample, further filtered and cleaned to remove missing data and retain only weekday records) for use in the illustrative application. The results of the model application are discussed later in Section 6, but the patterns predicted by the MDCEV model on this NHTS sample were assessed to ensure that predictions are reasonable and consistent with expectations. The summary results of the replication (on ATUS estimation sample) and prediction (on NHTS sample) exercise are displayed in Table 3. It should be noted that many comparisons were performed before determining that the model was appropriate and providing satisfactory results; in particular, distributions of time allocation to various activities were assessed for several market segments to ensure that the model is replicating time use patterns for various subgroups in the sample appropriately. In the interest of brevity, only the summary table is furnished here.

In general, the patterns are as expected. Work, education, shopping, and religious activities are not pursued to a great degree inside the home. These are activities that are typically undertaken outside the home and hence the time allocation to these activities within the home is small. Sleep accounts for more than eight hours, on average; it should be noted that this average is computed over all records that includes non-workers, retirees, and teenagers. In that context, this average duration for sleep and nap is quite reasonable. Within the home, waking hours are generally spent taking care of household obligations (maintenance activities, including cooking, cleaning, and taking care of children) and engaging in social/recreational activities (which includes watching TV or other screen-based devices). The predictions are in good agreement with observed values, although minor deviations are seen. Given the predictor variables available in the ATUS, these deviations are not unexpected. An examination of the time allocation distributions for various subgroups naturally showed higher levels of deviation, but the predictions were generally consistent with patterns observed in the data set.

TABLE 3 Average Time Spent at Home by Activity Category: MDCEV Model Results

Activity Category	Observed Time Allocation (ATUS)	MDCEV Model Replication (ATUS)	MDCEV Model Application (NHTS)
	N= 5,069		N= 6,810
	Average (min)	Average (min)	Average (min)
In-home - Sleep	531.8	527.6	508.5
In-home - Maintenance	185.3	188.6	177.6
In-home - Work	18.8	13.0	14.0
In-home - Education	6.5	5.8	5.4
In-home - Eating and drinking	42.7	65.5	66.4
In-home - Recreation/Social	248.5	233.0	233.0
In-home - Shopping	0.7	0.7	0.7
In-home - Religious	2.5	3.0	2.9
In-home - Other	15.6	15.8	16.2

Next, the model development process involved performing a factor analysis and constructing latent factors using the latent variable structural equations modeling approach. Two latent variables or factors were estimated – one for positive emotions and one for negative emotions. The two positive emotions loaded onto the positive factor and the four negative emotions loaded onto the negative factor. The factor analysis results were consistent with expectations and the structural equations model provided goodness-of-fit measures which indicated that the latent factors significantly captured the variance in the different emotions depicted by the sample of ATUS records. The happiness variable depicted a higher loading onto the positive emotion factor (than the meaningfulness emotion). For the negative emotion factor, all of the negative emotions loaded about equally on the factor, although stress was found to have a slightly higher factor loading. By adopting a structural equations modeling approach, the factors were estimated jointly, while accommodating covariance between them. The covariance is found to be negative and significant, which implies that unobserved attributes that contribute to positive emotions are negatively correlated with unobserved attributes that contribute to negative emotions.

This is also consistent with expectations. It should be noted that this particular model was estimated on the full sample of 92,417 activities for which six emotional ratings were available in the data set. It was considered prudent to use full information available in the data set to estimate factor loadings, given that the well-being score computation lies at the core of the model system developed in this effort.

The results of the factor analysis were used to estimate a positive factor score and a negative factor score for each activity episode in the ATUS data set. The difference between the two scores was computed (positive score – negative score) and designated as a single activity well-being composite score (AWCS) for each episode. The negative factor score varied from -1.00 to 3.65 with a mean of 0 and standard deviation of 0.86. The positive factor score varied from -5.51 to 4.16 with a mean of 0 and a standard deviation of 1.56. The factor score values do not have a ready interpretation, other than the fact that a larger numerical value indicates a stronger intensity of emotion for that factor. Thus, a higher positive factor implies a stronger positive emotion, and a higher negative factor implies a stronger negative emotion. As expected, the positive emotion shows greater variance, presumably because people try to shun performing activities that are unpleasant or undesirable. Consistent with statistics presented in Table 1, it is likely that people generally consider their activities positively, thus yielding a narrow range for the negative factor. It should be noted that this is seen despite the fact that only two emotions load onto the positive factor and four emotions load onto the negative factor. The AWCS varies from -7.35 to 3.30 with a mean of 0 and standard deviation of 1.99. A higher AWCS is indicative of a positive emotion associated with an activity and vice versa.

The next step involved estimating linear regression models of the AWCS for out-of-home, in-home, and travel episodes separately. To estimate the linear regression models, samples of 5000 activities were extracted for each of in-home activities, out-of-home activities, and travel episodes (total of 15,000 episodes). There is no special reason for choosing 5000 activities for performing the linear regression estimations. Rather than estimate regression models on the full data set of ATUS episodes, models were estimated on random sets of 5,000 activities so that the sizes of data sets used for model estimation in this effort are generally consistent with sample sizes typically encountered in the travel demand modeling domain. Each set of 5000 records was used to estimate the linear regression of AWCS as a function of socio-economic/demographic attributes and activity/travel episode attributes.

Regression model estimation results are presented in Table 4 and found to provide behaviorally intuitive interpretations. A delicate balance had to be struck between inclusion of socio-economic and demographic attributes, and activity episode attributes. Because activity episode attributes are strongly correlated with and themselves dependent upon socio-economic and demographic characteristics, they often turned out to be insignificant when extensive sets of socio-economic and demographic variables were included in the models. However, the primary goal of the integrated model system is to capture the well-being that people experience from their activity engagement and time use patterns. Hence, it was considered critical to retain as many attributes of the activity and travel episodes as possible, even if that meant compromises had to be made with respect to the inclusion of socio-economic and demographic attributes. Therefore, the model specifications include only a modest set of socio-economic variables. There is endogeneity that is undoubtedly impacting the model estimation results. Strictly speaking, a simultaneous equations model system should have been estimated, where activity-travel episode attributes are modeled as a function of truly exogenous variables, and then the AWCS is modeled as a function of activity-travel episode attributes and exogenous variables. The estimation of a more advanced simultaneous equations model system is left for a future phase of the model development effort; for simplicity, this first version of the model adopts a single regression equation approach for the three activity categories.

TABLE 4 Linear Regression Results for Activity Well-being Composite Score Estimation

		Variable	In-home (N=5000)	Out-of-home (N=5000)	Travel (N=5000)
		Constant	-0.736 (0.001)	-0.283 (0.045)	-0.064 (0.652)
Socioeconomic Attributes	Gender	Female		0.176 (0.001)	0.105 (0.114)
	Age (Base: 75+ years)	15-20 years old		-0.580 (0.000)	-0.407 (0.007)
		21-30 years old		-0.598 (0.000)	-0.402 (0.001)
		31-49 years old		-0.699 (0.000)	-0.654 (0.000)
		50-64 years old	-0.247 (0.000)	-0.556 (0.000)	-0.530 (0.000)
		65-74 years old		-0.297 (0.048)	
	Income	Less than $25,000		-0.185 (0.005)	-0.141 (0.090)
Activity/Travel Attributes	Activity Type / Trip Purpose (Base: Work)	Home (travel only)			0.286 (0.004)
		Maintenance	0.754 (0.000)	0.608 (0.000)	0.203 (0.073)
		Education	-0.462 (0.181)	0.057 (0.784)	-0.449 (0.203)
		Eating/Drinking	1.0924 (0.000)	1.062 (0.000)	0.767 (0.000)
		Recreation/Social	0.885 (0.000)	1.151 (0.000)	0.583 (0.000)
		Shopping	0.207 (0.761)	0.679 (0.000)	0.282 (0.016)
		Religious	1.789 (0.000)	0.920 (0.000)	0.559 (0.009)
		Other	0.824 (0.000)	1.007 (0.000)	
	Accompaniment			0.176 (0.000)	0.079 (0.087)
	Time	Night (12-4 AM)		-0.587 (0.050)	
	Episode Duration (min)	Up to 10 min			0.168 (0.098)
		11 to 20 min			0.210 (0.046)
		21 to 30 min			0.310 (0.010)
		Up to 60 min		-0.153 (0.021)	
		Up to 4 hours	0.163 (0.224)		
	Travel Mode	HOV Driver			0.196 (0.050)
		HOV Passenger			0.218 (0.062)
R^2			0.028	0.076	0.044

Note: The empty cells are either not significant or not applicable. No sleep episodes were rated.

The estimation results show that, relative to the oldest age group, all age groups experience a greater degree of negative emotions from out-of-home and travel episodes. In the case of out-of-home activities, this appears to be occurring because of the high prevalence of work episodes. Indeed, an examination of the coefficients associated with activity purpose show that all purposes exhibit a positive coefficient relative to work. Even after controlling for the work activity purpose, the age variables return negative coefficients, suggesting that younger groups may be experiencing time constraints and stresses more so than those 75+ years old. These time pressures manifest themselves in the form of lower well-being scores. The negative coefficients for age groups in the travel episode regression equation suggest that travel is largely viewed as a cost, particularly for those in age groups less than 65 years of age (for whom time constraints and pressures may be higher). Low income individuals have lower well-being scores for out-of-home activities and travel episodes; monetary constraints likely impact the type of activities and travel episodes they can pursue and experience (Cheng et al., 2019).

An examination of the activity and travel episode attribute effects shows that all activities are viewed more positively than work – in-home, out-of-home, and travel. Although insignificant, the education category was retained in the model for its behavioral interpretation. In general, one would expect studying at home or traveling to study (education) to be viewed negatively relative to other activities; however, the small (but insignificant) positive coefficient for education in the out-of-home regression equation suggests that people may not view the out-of-home (education) activity experience itself as negatively. Having accompaniments (companions) elevates the well-being score, particularly for out-of-home and travel episodes. Activities in the middle of the night are viewed more negatively. Travel time is an important predictor of well-being for travel episodes. As expected, travel episodes of shorter duration (categories under 30 minutes) exhibit positive coefficients, suggesting that these are the durations in which people find travel palatable. Interestingly enough, the coefficient values increase steadily from the lowest category of 0-10 minutes to the category of 21-30 minutes, suggesting that people may be rating medium length trips as more pleasant than very short trips. It is possible that the longer trips are being made to more desirable destinations or that such travel episodes serve as a useful transition between activities (Mokhtarian and Salomon, 2001). Short activity durations outside home are viewed more negatively (up to 60 minutes), presumably because these are more maintenance type activities. In-home activities up to four hours are viewed more positively than those longer than four hours, presumably due to diminishing returns setting in with prolonged duration of participation in an activity. The R^2 values are low, suggesting that there is much to be learned about the factors that affect and explain activity well-being scores. However, given that these regression equations were estimated on large sample disaggregate person-level data sets, the R^2 values are not all that inconsistent with those typically encountered in person-level regression models of activity-travel demand. Nevertheless, future research efforts should aim to enrich the specification of the models with attributes that enhance the degree to which activity well-being composite scores (AWCS) are explained and predicted accurately.

ILLUSTRATIVE APPLICATION OF THE MODEL

The integrated well-being analysis and estimation model system was applied to a small sample of NHTS records (6,810 records) to demonstrate the efficacy of the model system. The model system could be applied to a full-fledged output of an activity-based travel demand model that may include millions of agents and their corresponding activity and travel episodes. As an activity-based model output was not readily available for use in this study, and since the objective of this exercise is to merely demonstrate the applicability of the model system, it was considered sufficient to use a small NHTS subsample for illustrative purposes. However, it should be noted that the model system can be applied to large activity-based model outputs to compute person well-being composite scores (PWCS) at the level of the individual agent without any problem. The model system is computationally simple, and the only potentially time-consuming step is the application of the MDCEV model to predict in-home time allocation for agents in an activity-based travel model output. However, forecasting applications using the MDCEV model are now commonplace and quite efficient and can be easily executed without any difficulty.

The illustrative application of the model system proceeds as follows. For the 6,810 individuals in the demonstration data set, the in-home time budget is computed by subtracting total out-of-home time and travel time from 1,440 minutes. This budget is then used to apply the

MDCEV model of in-home activity participation and time allocation to the sample of 6,810 individuals. This step will yield a detailed in-home activity profile for each individual. In the next step of the application, the linear regression equations are applied to each of the activity episodes undertaken by an individual. In the NHTS data set, out-of-home activity episodes and travel episodes are given, but they should be viewed (for purposes of an application context) as the outputs of an activity-based travel demand model that furnishes complete information about all out-of-home activity and travel episodes for each agent in a synthetic population. The in-home activity episodes and time use patterns are those predicted by the MDCEV model when applied in forecasting mode to the NHTS data set (which is being treated as equivalent to an activity-based travel model output). The application of the linear regression models will return AWCS (activity well-being composite scores) for each and every activity and travel episode pursued by an individual. Finally, all AWCS values for each person are added up to create a daily person well-being composite score (PWCS). This PWCS is considered a measure of daily subjective well-being that considers the entire activity-travel pattern undertaken by an individual over the course of a day. Table 5 furnishes the average PWCS for various demographic groups in the data set.

TABLE 5 Average PWCS by Socio-economic and Demographic Attributes (N=6,810)

Attributes	Categories	Average PWCS	Attributes	Categories	Average PWCS
Gender	Male	-0.48	Age	15 to 20 years	-1.70
	Female	0.33		21 to 30 years	-2.05
Tenure	Not own	-2.30		31 to 49 years	-3.22
	Own	0.54		50 to 64 years	-2.65
Student	Not student	0.05		65 to 74 years	6.28
	Student	-2.40		75 to 84 years	6.45
Place of Birth	Not US born	-0.51		85+ years	4.16
	US born	0.00	Work Status	Worker	-3.06
Disability	Not disabled	0.68		Retired	7.39
	Disabled	-6.50		Unemployed	-3.56
Driver Status	Driver	0.06	Vehicle Ownership	0	-1.96
	Not Driver	-1.16		1	0.31
Household Structure	1 adult, no children	-4.90		2	0.34
	2+ adults, no children	-3.05		3+ cars	-0.61
	1 adult, youngest child 0-5	-2.63	Income	Less than $10,000	-2.60
	2+ adults, youngest child 0-5	-2.40		$10,000 to $14,999	-1.27
	1 adult, youngest child 6-15	-3.22		$15,000 to $24,999	0.15
	2+ adults, youngest child 6-15	-2.24		$25,000 to $34,999	0.62
	1 adult, youngest child 16-21	-3.65		$35,000 to $49,999	0.69
	2+ adults, youngest child 16-21	-2.82		$50,000 to $74,999	0.69
	1 adult, retired, no children	6.12		$75,000 to $99,999	0.40
	2+ adults, retired, no children	5.15		$100,000 to $149,999	-0.61
Mode Use	No walk trip	-0.54		$150,000 or more	-0.92
	At least one walk trip	0.14	Health	Excellent	-0.33
	No bike trip	0.00		Very good	0.44
	At least one bike trip	-0.61		Good	0.44
	No transit use	0.12		Fair	-1.61
	At least one transit trip	-1.50		Poor	-4.24
	No ridehailing trip	0.09	Location	Urban	-0.30
	At least one ridehailing trip	-1.90		Rural	0.77

The results are quite intuitive, suggesting that the model system developed in this study could serve as a useful tool in assessing the feelings of well-being that people derive from their activity-travel patterns and in identifying subgroups of the population that are experiencing lower levels of daily well-being (although further investigations would need to be made to determine *why* these subgroups are experiencing lower well-being). The trends in the table suggest that females experience a higher degree of well-being as do individuals in households who own their home. Females may be spending more time inside the home taking care of household obligations, but also spending more time with other household members (e.g., children) and engaging in flexible and discretionary activities that add value (Cheng et al., 2019; Meloni et al., 2007). Homeowners are likely to experience a higher degree of ownership in the community, may live in nicer residences, and have amenities in the neighborhood that facilitate pursuit of desirable leisure activities (McCabe, 2013). Students presumably experience a lower level of well-being because of participation in the education activity – a mandatory activity that is unlikely to be pleasant. Those not born in the USA (immigrants) experience lower levels of well-being, possibly due to their greater use of transit (Blumenberg 2009; Farber et al., 2018) and inability to afford participating in discretionary activities that require monetary resources (Farber et al., 2018). As expected, those who are disabled experience a lower level of well-being, presumably due to mobility and activity engagement limitations. Drivers experience a higher level of well-being, largely due to their ability to drive and engage in activities. The auto mode has been found to engender more positive emotions for travel episodes (Mokhtarian and Pendyala, 2018), and the results in Table 4 illustrate this as well – particularly for high-occupant auto trips that involve accompaniment.

Household structure categories show that individuals in retired households experience a higher level of well-being than other household categories, a finding reported in prior studies (Ziems et al., 2010; Frijters and Beatton, 2012; Jensen et al., 2019). For all other (non-retired) categories, it is found that the single-adult groups consistently experience less well-being than the equivalent multi-adult group. This pattern suggests that the presence of multiple adults engenders a higher quality of life, presumably because of the companionship and ability to split household obligations and responsibilities (Stutzer and Frey, 2006). The results with respect to age confirm that those who are in the retired age groups experience higher sense of well-being. Although there is literature that speaks to the mobility limitations, social exclusion, and lower quality of life that the elderly experience (Glass et al., 2006; Liu et al., 2014), the results in this study and others (Archer et al., 2013; Ziems et al., 2010) show that the elderly are experiencing (on average) a high sense of well-being and quality of life relative to younger age groups. The breakpoint in the pattern is clearly seen at the 65-74 years of age, suggesting that the transition from a life of work to a life of leisure and play and fewer household obligations is met with a significant leap in well-being. Indeed, workers are found to experience a lower well-being than retired individuals; but unemployed individuals of working age have an average well-being score similar to that of workers – suggesting that the well-being in retirement is not necessarily due solely to transition away from a work-oriented life. Non-workers of non-retirement age are taking care of household obligations and maintenance activities, may be seeking work, and may not have the income and time needed to engage in discretionary activities that offer positive emotions (Katz, 2015; Gaddis and Wadhwa, 2018).

Vehicle ownership and mode use affect the well-being score. Vehicle ownership is associated with higher levels of well-being, but there is a drop in well-being at 3+ car ownership level. This is likely reflecting larger household sizes, more household obligations, and more time spent participating in work activities to afford the 3+ car lifestyle. However, individuals in zero-car households experience the lowest level of well-being (consistent with Bergstad, 2011), presumably due to lack of access to opportunities that comes with zero-car ownership. Those who walk report a higher level of well-being, suggesting that walking (which might be undertaken for leisure purposes as well) is associated with a more positive lifestyle. On the other hand, use of all other alternative modes (which may be indicative of lower access to personal vehicles) is associated with lower degrees of well-being – suggesting that policies and investments are needed to improve the travel experience and destination accessibility for alternative modes.

The final set of variables in the table pertain to household income, health condition, and location. The findings related to income are consistent with the notion that "money can't buy happiness" (Kahneman and Deaton, 2010). While well-being increases with income up to a certain level, well-being decreases after the $75,000 income level, suggesting that those in the high income brackets have stresses and work-activity durations that decrease well-being (Gardner and Oswald, 2001; Kahneman and Deaton, 2010). As expected, those in poor health report lower well-being; these individuals are likely to be in pain, tire easily, and not able to engage in activities and travel as much as their healthier counterparts (Fox, 1999). Finally, urban residents experience lower well-being than rural residents, presumably due to higher congestion, pollution, and stresses in the urban ecosystem (Amato and Zuo, 1992).

To further illustrate the well-being scores output by the model system, the distributions of well-being scores are shown in Figure 2. The entire sample of 6,810 respondents was divided into quintiles based on a sorting of well-being scores. The top quintile has the highest well-being scores while the bottom quintile has the lowest. These five quintiles are labeled as having very positive to very negative well-being. The figure show how each demographic group is distributed across the five bands of well-being quintiles. For example, consider work status; 27 percent of workers and 26 percent of unemployed fall into the very negative category, but only four percent of retirees do so. While 65 percent of retirees fall into the highest very positive category, only one percent of workers and unemployed individuals do so. In the interest of brevity, detailed explanations for all demographic groups are not provided in text form; however, the patterns can be easily discerned from the figure, and the patterns in the figure provide an underlying basis for the comparisons seen in Table 5. The pattern across age groups shows that the percent of individuals in the very negative category increases with age (as household obligations and other stresses of life take hold), but a dramatic shift in the distribution occurs as soon as the retirement age of 65+ years is reached. However, a drop in the percentage of individuals in the very positive category is seen at 85+ years old, presumably due to mobility and health limitations setting in at that age. The income relationship shows a pattern consistent with the notion that well-being increases with income up to a certain point, but drops at the highest income levels. Those with poor health fall disproportionately into the lowest negative category, suggesting that this group is experiencing a low quality of life and needs assistance.

One of the major reasons why these patterns of well-being may be seen in Figure 2 is that time use patterns differ across groups. These distributions are shown in Figure 3. For each group, the distribution of time allocation to various types of activities is shown; the activities have been aggregated into mandatory activities (e.g., work and school), travel, flexible activities (e.g., shopping and personal errands), and discretionary activities (e.g., social and recreational). Travel can only be undertaken outside home and sleep can only be undertaken inside home. These distributions should be viewed in the context of the well-being distributions shown in Figure 2.

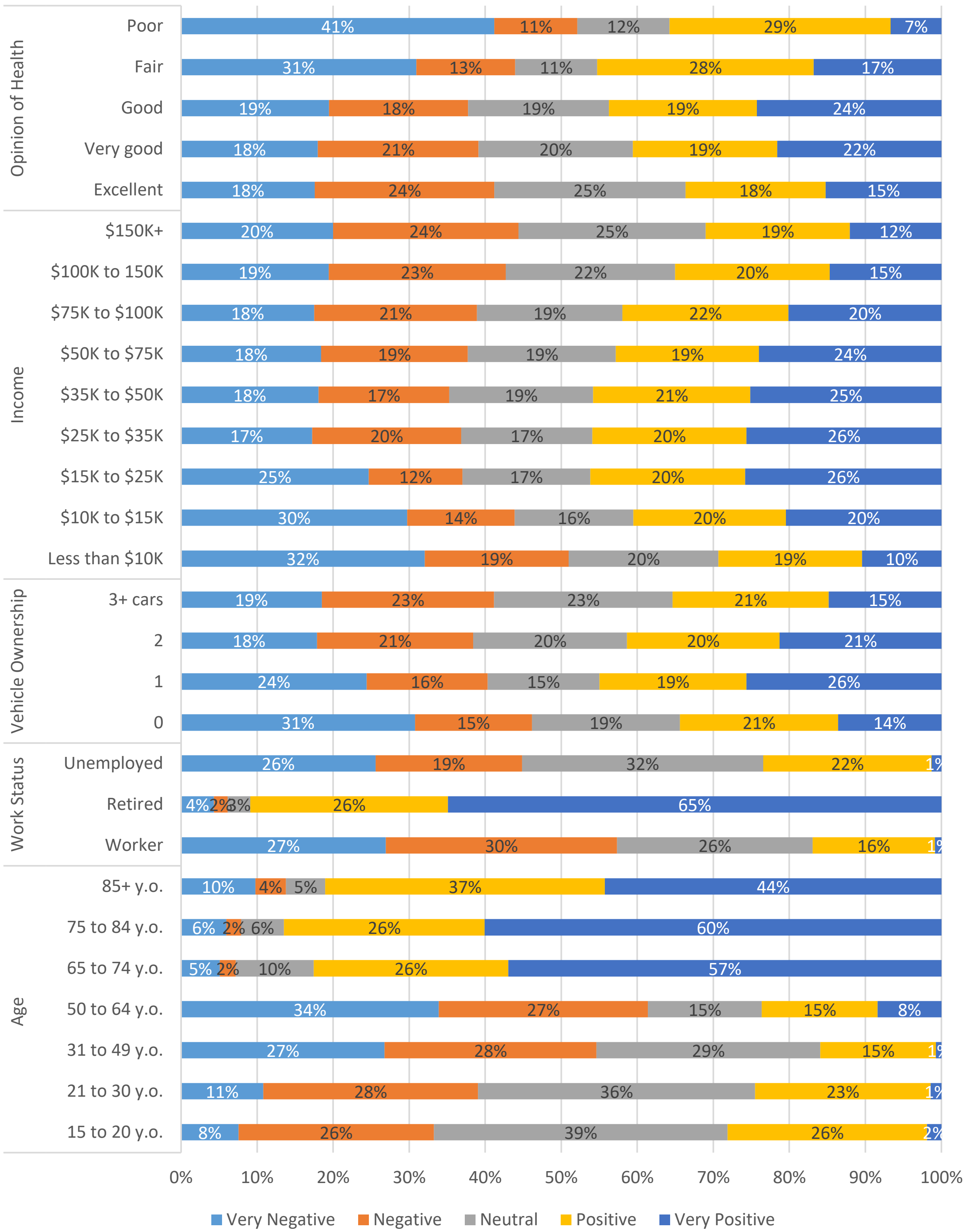

FIGURE 2 Distribution of Demographic Groups by PWCS Segment (N=6,810)

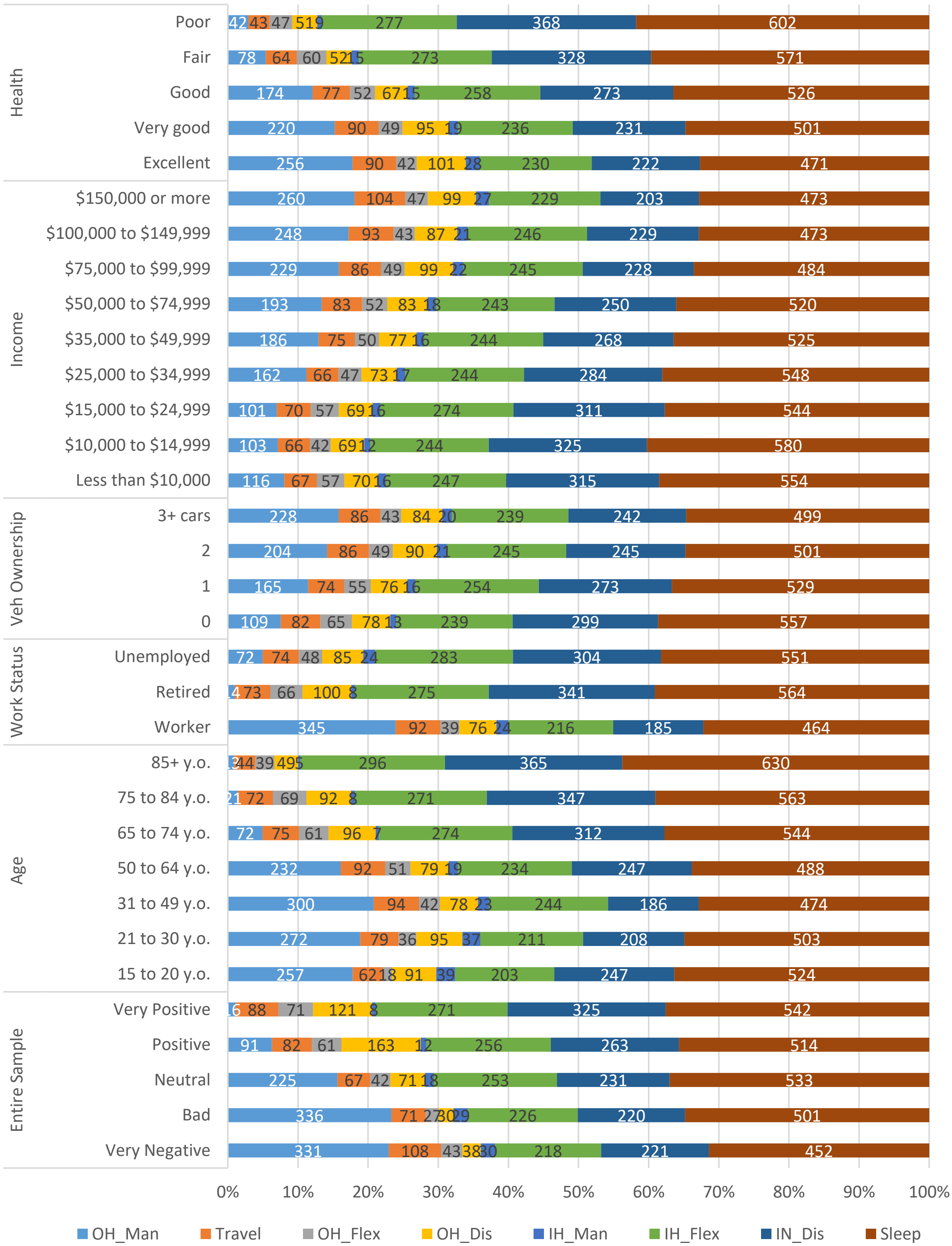

FIGURE 3 Distribution of Groups by Time Allocation to Activities (N=6,810)

Patterns of association between time use and well-being can be seen across the figures. For the sample as a whole, it can be seen that those in the very negative groups (bottom of Figure 3) spend a lot more time on mandatory activities and travel, and a lot less time on in-home or out-of-home discretionary activities (and less time on sleep). Those in the highest well-being quintile spend much less time on mandatory activities and a lot more time on in-home and out-of-home discretionary activities. For the elderly above 65 years, the dramatic drop in work duration is accompanied by longer sleep duration, and significant increases in in-home and out-of-home discretionary activity durations. These patterns of time use engender a higher level of well-being, thus suggesting that a mere reduction in travel is not necessarily an indicator of a lower quality of life. Older individuals do spend a lot more time in-home, but that is not necessarily leading to a lower well-being because they are presumably relaxed, not saddled with household and child-rearing obligations, and able to engage in activities that they enjoy. The highest income individuals spend more time working and more time traveling, both of which contribute to a decrease in well-being. They do spend more time in out-of-home discretionary activities, but the dramatically lower time spent in in-home discretionary activities lowers well-being overall.

However, well-being is obviously not tied solely to activity and time use patterns. The different health subgroups illustrate the more complex relationships at play. While those with poor health spend less time on out-of-home and in-home mandatory activities and less time traveling, they do not enjoy a higher well-being score. They do spend more time at in-home discretionary activities, but they also spend less time on out-of-home discretionary activities. They also spend more time sleeping (which has considerable diminishing marginal returns at high values) and more time fulfilling household obligations (in-home flexible activities). Their mobility limitations and other health related factors contribute to a lower well-being score, even though the time use patterns show that their mandatory activity time allocation is the lowest.

CONCLUSIONS

Transportation and well-being are inextricably connected with one another due to the activities and experiences that mobility enables. Transportation planners and policy makers strive to implement policies and direct investments in ways that would enable mobility for all, enhance access to destinations and opportunities for all, and increase quality of life. Despite the widespread recognition of the connection between well-being and activity-travel patterns, little progress has been made in translating measures of activity-travel behavior into measures of well-being. As a result, the time use patterns themselves are often viewed as indicators of well-being and quality of life. Those who do not travel are viewed as experiencing isolation and social exclusion; those who do not engage in discretionary activities are viewed as experiencing time poverty. While these notions are useful, the lack of a model that explicitly delivers measures of well-being as a function of socio-economic attributes, built environment attributes, and activity-travel pattern attributes renders it challenging to truly assess the quality of life (well-being) impacts of alternative investments, technologies, and policies.

To fill this void, this paper presents a comprehensive model system of well-being and activity-travel behavior that can be used in conjunction with any standard activity-based travel model system as a post-processor. The model development process involved using the well-being module of the American Time Use Survey (ATUS) to develop models of well-being scores as a function of socio-economic and activity-travel variables. One of the challenges associated with developing a comprehensive well-being model system (that can be used in conjunction with travel models) is that travel models do not output any information about activity engagement and time use patterns inside the home. However, feelings of well-being are undoubtedly experienced by virtue of in-home activity engagement. To overcome this challenge, a multiple discrete-continuous extreme value (MDCEV) model of in-home activity engagement and time allocation is estimated on the ATUS data set. This MDCEV model can be applied to any activity-based travel model output to predict in-home time use patterns for each individual in a synthetic population. With the benefit of full information about the in-home and out-of-home activities and travel undertaken by an individual, well-being scores can be computed for each individual using the model system developed in this study. The paper summarizes model estimation results and illustrates the efficacy of the model through an application to a small sample of records drawn from the National Household Travel Survey (NHTS), which are meant to be representative of a typical activity-based model output. The results are intuitive and consistent with the notion that out-of-home discretionary activity engagement contributes positively to well-being.

A key finding that was derived from the analysis of the well-being module of the time use data set and the application of the well-being score models (to the random sample of NHTS records) is that well-being is not necessarily dependent on out-of-home activity engagement and travel. Discretionary activity engagement inside the home is found to contribute positively to well-being, while high amounts of travel are found to be associated with lower levels of well-being. Older individuals do not appear to be experiencing lower quality of life; in fact, they appear to be experiencing the highest well-being, presumably because of their discretionary activity engagement (inside the home) and relief from work obligations and stresses of life. In other words, the connection between well-being and time poverty (i.e., time devoted to discretionary activities) appears to be a stronger one, rather than the connection between well-being and traveling outside the home (to participate in societal activities). The findings suggest that it is important to take a holistic accounting of all activity engagement, both inside and outside the home, to assess well-being, degree of social exclusion, and quality of life. What is found is that those with poor health experience the lowest degrees of well-being, calling for greater interventions, investments, and policies that enable their participation in society and discretionary activities. While workers score low on the well-being metric presumably due to long durations at work, unemployed individuals also score low on the well-being metric despite much less mandatory activity time allocation. These individuals spend lot more time sleeping (which yields diminishing returns rapidly above a certain threshold) and more time fulfilling in-home obligations and maintenance activities. These chores are unlikely to yield much in the way of well-being. For this group (unlike the elderly groups), the substantial time spent in-home may indeed be leading to a lower quality of life; thus the connection between well-being and out-of-home activity engagement (and travel) is much more nuanced and varies across demographic segments.

Overall, the model system developed in this study may be used in conjunction with activity-based travel models to assess well-being implications of transportation investments and actions for different subgroups of the population. This is useful in the context of environmental justice and equity analyses. Future developments could focus on enriching the models of well-being scores with additional attributes (such as built environment variables), estimating simultaneous equations models of well-being scores to recognize endogeneity of activity-travel attributes, and applying the model system to a full-fledged activity-based travel model output of millions of agents to test the model in a real-world setting.

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