Understanding and Modeling the Nexus of

Mobility, Time Poverty, and Wellbeing

by

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ABSTRACT

The primary objective of this dissertation is to advance the existing empirical literature on the relationship between transportation and quality of life, with a specific focus on wellbeing indicators and their applicability in the transportation sector. To achieve this, the dissertation is structured around four primary areas of inquiry. Firstly, it introduces a subjective wellbeing scoring method that generates episode-level wellbeing scores, which can be aggregated to produce daily person-level wellbeing scores. This method can be utilized as a post-processor of activity-based travel demand model outputs to assess equity implications in various planning scenarios. Secondly, the dissertation examines the intricate relationships between mobility poverty, time poverty, and subjective wellbeing. It compares the rates of time poverty and zero-trip making among different socio-demographic groups and evaluates their alignment with subjective wellbeing. Thirdly, this research investigates the association between automobile use and satisfaction with daily travel routines (thus, wellbeing). This analysis aims to provide an understanding of why automobile use remains the primary mode of transportation, despite attempts to shift towards alternative modes of transportation. The fourth area of investigation focuses on the wellbeing impacts of the COVID-19 pandemic. Specifically, the chapter examines the resurgence in travel and discretionary out-of-home activities, as well as the slow return of workers to workplaces by using the subjective wellbeing indicator and time poverty. Additionally, the chapter identifies groups that were disproportionately impacted and provides strategies to mitigate adverse consequences for vulnerable socio-economic and demographic groups in future disruptions.

Overall, this dissertation contributes to the literature on transportation and quality of life by introducing a reliable subjective wellbeing scoring method that can be used to evaluate the quality of life implications of transportation systems. It also offers practical applications of wellbeing indicators in identifying differences in wellbeing across the population and provides opportunities for targeted interventions and the development of transportation policies to address equity and sustainability issues. Furthermore, to demonstrate the practicality of the generated knowledge in this dissertation, a web-based wellbeing platform is developed to track changes in the wellbeing of individuals that arise from their daily activity and travel patterns.

DEDICATION

This dissertation is dedicated to the countless victims of human rights violations around the world, including those in my home country, Turkey. The unimaginable tragedies and injustices they endure have been an unceasing source of motivation throughout my academic journey.

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INTRODUCTION

1. Background

Transportation systems are an integral part of the fabric of our cities. They act as the veins that keep society's lifeblood flowing, connecting neighborhoods and geographically distant communities, and enabling social interactions. By providing workers with access to their daily jobs and facilitating the delivery of goods from one location to another, transportation systems play a vital role in stimulating economic growth. They also provide citizens with access to essential services such as education and healthcare, contributing significantly to societal wellbeing. Moreover, transportation systems contribute to the vibrancy and dynamism of cities, creating hubs of creativity and innovation. These various functions of transportation illustrate its crucial role in facilitating everyday life and driving economic growth while improving the overall quality of life for people.

The critical connection between (passenger) transportation and societal wellbeing makes it imperative that transportation systems are designed to be equitable, just, and sustainable. Failing to provide such systems leads to significant inequalities, with some members of society experiencing a lower sense of wellbeing. Some people's access to jobs and essential services (education, healthcare, and other necessities) is restricted due to a lack of or inability to operate a personal vehicle, poor public transportation, or unequally distributed job opportunities and services that lead to travel times being excessively long. Many individuals in these circumstances are faced with a difficult choice: they must either accept the additional costs associated with driving or paying for expensive public transportation in order to secure the job they desire; or be unemployed or work for jobs that are nearby but not necessarily desired. Those who choose to travel to destinations with excessively long travel times (due to traffic or distance) often experience stress and time poverty, as they have less time available for other enjoyable activities. These are some of the issues that arise due to inadequate transportation systems that fail to meet the transportation needs of all members of society, underscoring the importance of ensuring that transportation systems are just, equitable, and sustainable.

The negative impacts of inadequate transportation systems are not experienced evenly across all members of society. Certain subgroups, such as women (especially single mothers), older individuals, people of color, those with disabilities, and employees in specific occupations are more vulnerable to these inequalities than others (Motte-Baumvol et al., 2012; Adeel et al., 2018; Corran et al., 2018). To ensure that everyone has a certain level of wellbeing, it is critical to identify and understand who is experiencing transportation-related inequalities and to what extent, as well as the underlying reasons. Only in this way can transportation investments, programs, and policies be tailored to meet the diverse needs of all individuals in society, improving equity and ensuring a higher quality of life for everyone.

2. Defining the Concept of Wellbeing

Wellbeing is regarded as an important indicator of social progress and a major facilitator of desirable policy outcomes (even economic ones) (Diener and Seligman, 2004). Hence, developing appropriate tools and measures to assess wellbeing in society is an active research area that extends far beyond the transportation domain. In addition, not only what to measure but how to measure it has also received considerable scholarly attention in academic discussions of societal wellbeing. Researchers from diverse fields, such as public policy, economics, psychology, and sociology, have proposed two distinct approaches for defining and measuring overall wellbeing as a metric of societal progress: objective wellbeing and subjective wellbeing (Voukelatou et al., 2021).

Objective wellbeing is thought to be reflected in people's material living conditions and the quality of their lives (Alkire, 2002; Voukelatou et al., 2021) and is identified in six dimensions: health, job opportunities, socio-economic development, environment, safety, and politics (OECD, 2011). The assessment of objective wellbeing is thus materialized through measuring the extent to which peoples' needs in these six dimensions are satisfied. Observable data, such as average life expectancy, graduation rates, and income levels, are commonly used for this purpose (IEEE, 2022). The Human Development Index (HDI) is a well-known example of a summary measure of objective wellbeing, which takes into account life expectancy, mean years of schooling, and standard of living (UNDP, 2022).

Subjective wellbeing is characterized by individuals' own evaluations of their lives, in contrast to objective wellbeing – note here that despite minor differences, the terms, *life satisfaction*, *happiness*, and *domain satisfaction* are all used interchangeably to describe subjective wellbeing (Gärling and Gamble, 2017). The concept of subjective wellbeing has a long history in (Western) philosophy, with notions developed by philosophers such as Epicurus and Aristotle still influencing contemporary thinking (McMahan and Estes, 2011). In this context, two main philosophical approaches to define subjective wellbeing have emerged: hedonic and eudaimonic (McMahan and Estes, 2011). According to the hedonic approach, wellbeing is subjectively shaped by life satisfaction, positive affect, and the absence of negative affect, with these three components combined to form an individual's overall happiness in life. Conversely, the eudaimonic approach suggests that people should find meaning and purpose in life by identifying and developing their best qualities and using them to serve the greater good. This way, individuals can realize and fulfill their potential and live purposeful lives – resulting in experiencing higher levels of wellbeing. As implied by the definitions of both approaches, there is a blurry line between hedonic and eudaimonic wellbeing, especially regarding the life satisfaction component.

In a more formal way, subjective wellbeing is defined by Veenhoven (2013) as *"the degree to which an individual judges the overall quality of (their) life favorably"*. Whether the judgment on the overall quality of life is made following the hedonic or eudaimonic conceptions, it is clear that objective wellbeing measures (such as the Human Development Index or Gross Domestic Product) cannot truly reflect subjective wellbeing as it requires self-reported data from individuals. To address this, various methods have been developed to measure affect, eudaimonia, and satisfaction with life and conditions of life (McMahan and Estes, 2011) – reflecting the hedonic and eudaimonic aspects of people's lives. Examples of well-known subjective wellbeing measuring methods include the Positive and Negative Affect Schedule (PANAS) (Watso et al., 1988), the Swedish Core Affect Scale (SCAS) (Västfjäll et al., 2002), and the Scale of Positive and Negative Experience (SPANE) (Diener et al., 2010). It is worth noting that these methods were developed for a myriad of purposes, and each has shortcomings and is debatable in different ways (Mokhtarian, 2019); as a result, no single method outperforms others across all circumstances.

3. The Connection Between Wellbeing and Travel Behavior

Over 20 years ago Kitamura et al. (1997) asserted that the ultimate goal of transportation planning and policies should be to enhance the wellbeing of people. As a result, they emphasized the need for planning tools (and new methodologies) to evaluate the impact of transportation planning options on the quality of life, which led to the incorporation of various wellbeing measures in transportation planning. For example, Lee and Sener (2016) recently conducted a study of 148 long-term transportation plans in the United States and found that the majority of them include wellbeing as a performance metric (with physical wellbeing being prioritized over mental and social wellbeing). Meanwhile, the research community has shown increasing interest in exploring the relationship between travel and wellbeing in the transportation domain (Delbosch et al., 2020). These efforts have been extensively examined and documented in the literature (Delbosc, 2012; DeVos et al., 2013; Reardon and Abdallah, 2013; Nordbakke and Schwanen, 2014), where subjective wellbeing is particularly focused.

Studies examining the impact of travel behavior on subjective wellbeing have identified at least five ways in which travel behavior affects one's wellbeing (Mokhtarian, 2019; DeVos et al., 2013).

I. **Experiences occurring during travel:** One way in which travel behavior can affect subjective wellbeing is through experiences that occur during travel. This refers to the emotions people experience while enroute to their destination, such as feeling stressed during traffic or feeling happy while driving through scenic mountainous terrain. People's subjective wellbeing is influenced by how they feel while traveling as well as how they feel while participating in activities at their destination, with the former having a significant impact on the latter (Bergstad et al., 2011; Ettema et al., 2010). A poor-quality trip to a destination can have negative effects on the activity carried out, which can diminish the activity's potential to enhance wellbeing.

II. **Activities conducted while traveling:** Another way in which travel behavior can impact subjective wellbeing is through the activities conducted during travel. Many people view travel time as an inconvenience, particularly those with limited time for non-mandatory activities. To mitigate this, some engage in travel-related activities or travel-based multitasking, such as reading a book, listening to a podcast, or even working or studying. These activities can alter one's perception of travel time, as they provide a sense of utility or positive experience during an otherwise unfavorable time spending. As a result, engagement in travel-related activities can influence overall satisfaction with travel and contribute to one's overall wellbeing.

III. **Engagement in out-of-home activities:** The third way in which travel behavior can affect subjective wellbeing is through engagement in out-of-home activities. As people's daily activities are spread out across different locations and fulfill their personal and social needs, travel can facilitate participation in these activities, thereby enhancing wellbeing. On the other hand, individuals who are unable to engage in activities due to travel limitations may experience lower levels of wellbeing, as they may feel socially excluded.

IV. **Travel as the activity:** The fourth way in which travel behavior can impact subjective wellbeing is through the activity of travel itself. Unlike the concept of derived demand, which views travel as a means to reach a specific destination and engage in activities that enhance wellbeing, some trips are solely undertaken for the purpose of traveling (Mokhtarian et al., 2015a; Russell and Mokhtarian, 2015). This type of travel, also known as "undirected travel," is typically discretionary and pursued for the purpose of experiencing satisfaction, joy, or contentment through movement, thereby directly contributing to one's subjective wellbeing.

V. **Motility, the potential to travel:** The fifth and last way in which travel behavior can impact subjective wellbeing is through the concept of motility, which refers to the potential for travel rather than the act of traveling itself. Economists refer to this concept as "option value," which is the price someone is willing to pay for a good or service simply to have it available for use, rather than the benefit gained from actually using it. In this context, Kaufman et al. (2004) introduced the term motility to describe the option of mobility, which relates to individuals' capacity to become mobile. Motility is connected to wellbeing because it provides individuals with a sense of freedom to act, even if individuals choose not to exercise that option. Having the option to travel (thus, having choices) and the ability to act if desired can foster a sense of wellbeing.

The foundation for the effects of travel behavior on subjective wellbeing underscores the need to incorporate subjective wellbeing as a key criterion in assessing the efficacy of transportation policies, programs, and systems, in addition to other objective measures of quality of life. Ettema et al. (2010) emphasized the importance of accounting for subjective wellbeing in transportation policies, stating that *"Transportation policies should aim to contribute to the subjective wellbeing, even if there also are other, more concrete objectives such as increasing accessibility, avoiding negative externalities or increasing economic productivity."* Despite this, the transportation field has traditionally relied on monetary and objective measures, such as travel times and cost-benefit ratios, to assess the performance of transportation systems and policies, which are inadequate indicators of wellbeing and fail to address the aforementioned issues arising from current transportation systems. This highlights the imperative of developing innovative planning tools and methods to evaluate the impact of transportation planning options on the quality of life of individuals.

Developing such tools and methods that are capable of relating activity-travel behavior with measures of wellbeing is intrinsically useful from a policy analysis perspective. With concerns about environmental sustainability issues associated with widespread personal car use, including climate change, air pollution, and energy consumption, governments and metropolitan areas worldwide are implementing various strategies to reduce personal vehicle travel demand. These strategies could involve pricing policies, car ownership and usage restrictions, highway expansion limits, and street and public space reconfiguration to accommodate the needs of other road users. When the impacts of these strategies are forecasted using travel demand models, it is expected that they will lead to reduced vehicle mileage of travel, yielding significant environmental sustainability gains. However, some segments of society may be adversely affected by the implementation of these policies, as they will impose changes in activity-travel behaviors that may not be desirable, leading to diminished wellbeing for some. To address the unintended equity and wellbeing consequences that may arise from implementing such strategies, there is a clear need for new models that can evaluate policy impacts at a very disaggregate level and provide a framework for conducting rigorous social equity and environmental justice analyses. This approach can identify the *winners* and *losers* in response to a policy action and enable informed decisions about the trade-offs involved in implementing alternative policies.

4. Integrating Wellbeing Measures in Analyzing Travel Behavior

Over the last decades, three concepts have emerged in the field of transportation and sociological domains that attempt to capture different aspects of wellbeing: accessibility, zero-trip making (mobility poverty), and time poverty. First, *accessibility* is characterized by proximity to jobs, healthcare facilities, and other life amenities, which reflects the extent to which transportation systems enable people to reach activities or destinations using one or more modes of transportation (Welch and Mishra, 2013). This definition implies that accessibility is inextricably linked to motility, or the ability to travel, and thus has a close relationship with individual wellbeing. Accessibility, like motility, may or may not manifest in action, but it measures the extent to which individuals have access to critical elements of psychological wellbeing, such as employment, social relationships, and health. Individuals with limited accessibility face barriers to out-of-home activity participation, potentially leading to decreased wellbeing resulting from an inability to meet their daily needs, which is critically important to improving their wellbeing. Second, *zero-trip making* characterizes a situation in which people make no trips at all throughout the day. As a result of being unable to interact in person with others outside the home, people may experience feelings of social exclusion, depression, and other mental health issues. Zero-trip making is thus widely regarded as a negative wellbeing indicator, implying that those who do not undertake any trips for a full day may be experiencing a lower quality of life. Lastly, the concept of *time poverty* has emerged as a means of understanding wellbeing and quality of life beyond the conventional notion of income poverty. Although various researchers have proposed different definitions and measurement criteria for time poverty (Vickery, 1977; Williams et al., 2016), the concept generally refers to spending limited time on leisure activities. Individuals who spend less time on leisure activities than a certain threshold are deemed to be experiencing time poverty and, as a result, may have a diminished sense of wellbeing.

While these measures have some utility in reflecting the state of wellbeing, they also have inherent limitations that must be addressed to provide a more accurate and nuanced picture of individual and societal wellbeing. Specifically, the concept of accessibility, which is based on motility or the capacity to travel, fails to account for whether an individual has the time and resources to put this ability into action. For example, it assumes that two people who live near each other and have similar transportation access have the same level of accessibility (and therefore wellbeing). However, this fails to consider that someone who suffers from time poverty (i.e., lacks available time to engage in discretionary activities that can enhance wellbeing) will have a lower level of wellbeing despite having the same level of accessibility as someone else. Therefore, a person's time allocation patterns across various activities play a crucial role in determining the time, modalities, and means they require to actuate their potential to travel. Consequently, the concept of accessibility falls short in addressing individual-level heterogeneity when assessing whether someone can actuate their potential to travel.

Likewise, the limitation of using zero-trip making as a wellbeing indicator stems from the heterogeneity of the population and their varied needs, lifestyles, and mobility patterns. It is plausible that zero-trip makers consist of at least two distinct segments: those who are mobility disadvantaged and thus unable to participate in activities they desire, and those who choose not to travel because they can comfortably fulfill their activity needs at home. While the former group is more likely to experience lower levels of wellbeing due to their inability to participate in desired activities, the latter group may not necessarily have a lower sense of wellbeing. In fact, the latter group may experience higher levels of wellbeing due to the convenience of being able to do activities from home without having to navigate traffic, find parking, wait for public transportation, or face other negative aspects of traveling.

Furthermore, time poverty, by definition, only reflects the situation where individuals lack available time to engage in non-mandatory activities (those that people enjoy and benefit from to enhance their wellbeing), but it makes no distinction as to how transportation systems can assist time poor individuals. For example, two individuals who are both considered time poor under this definition may have different reasons for their time poverty. One may spend an excessive amount of time traveling due to traffic or slow transit, while the other may work from home but allocate significant time to household chores and caregiving responsibilities. Although both are time poor, their circumstances differ significantly, and improvements in the transportation system can only mitigate the time poverty challenges of the former individual. Therefore, while time poverty is a useful measure of wellbeing to identify those who lack time to engage in discretionary activities, it does not offer detailed insights into how transportation systems can help alleviate time poverty for individuals with varying circumstances.

Although these measures have sound theoretical foundations and can be used as wellbeing indicators, their empirical validity remains largely unproven. Specifically, there is limited empirical research demonstrating that individuals with limited accessibility, zero-trip makers, and those who are time poor consistently and continuously experience lower levels of wellbeing than their counterparts. Therefore, these measures require further empirical validation, in addition to their inherent limitations, to confirm their reliability and validity. Establishing their empirical validity would shed light on the extent to which these measures can serve as wellbeing indicators and aid policymakers in making informed decisions.

The above implies that more sound and detailed wellbeing methods are required to overcome the shortcomings of these wellbeing measures as well as to establish their empirical validity. These new methods need to be capable of translating the outputs of activity-based models into measures of wellbeing by considering wellbeing as a function of activity engagement, mobility choices, transit usage, and time use while controlling for socio-economic and demographic factors. By using methods developed with this approach, it then becomes possible to identify disparities at the individual level that arise from activity-time use patterns and inform the development of potential solutions to mitigate them, particularly in the realm of transportation systems.

5. Contemporary Wellbeing Issues in Transportation

Among various wellbeing issues arising from the current practices in the transportation sector, two have risen to the forefront as major concerns. The first is car dependence, which continues to be associated with a multitude of negative impacts, the most pressing of which is climate change. Other impacts include, but are not limited to, congestion, air pollution, road safety, health problems, and land degradation. Furthermore, since alternative transportation modes are typically less available and viable in car-dominated contexts, access to a car becomes the most valuable resource for transportation. Consequently, individuals who lack access to a car experience reduced access to services and opportunities, as well as restrictions on their participation in out-of-home activities. This is especially problematic for disadvantaged communities, which are disproportionately affected by these limitations.

In an attempt to address the externalities arising from car-dominant transportation systems, alternative modes of transportation are largely promoted, especially in the Global North. Voluntary behavior change programs have been established to encourage the use of alternative modes, with the aim of creating a more sustainable and livable transportation ecosystem (Stopher, 2005; Batur, 2015). The expectation was that, in conjunction with sufficient transit systems and infrastructure for biking and walking, many individuals would transition from automobiles to alternative modes of transportation. Despite these efforts to stem the tide of automobile use, automobiles remain the primary mode of transportation in many jurisdictions across the United States and other areas (International Transport Forum, 2021; U.S. Department of Transportation Federal Highway Administration, 2021).

It is possible to argue that many citizens may find the automobile to be so satisfying and critical to their overall sense of wellbeing that the transition from automobiles to alternative modes is extremely difficult in the current context. Prior research has found a link between the mode of transportation and the level of satisfaction derived from daily travel. According to the literature, this relationship is somewhat context-specific and sensitive to how satisfaction with travel is measured (Ettema et al., 2011; De Vos et al., 2016; Molin et al., 2016; Singleton, 2019). Despite the evidence in the literature to date, the extent to which automobile use affects the level of satisfaction with daily travel routine remains a question worth investigating, especially because the relationship between these dimensions – after controlling for a variety of socio-economic and demographic variables, as well as attitudinal and lifestyle preference variables – is not fully understood.

The second issue is concerned with the COVID-19 pandemic's impacts on activity time use patterns, which in turn affects societal wellbeing. The pandemic has brought about significant changes in human activity, including changes in travel patterns, time use, and activity modalities (virtual, physical, or hybrid). Due to the prolonged nature of the pandemic, people and organizations have developed new routines and habits, and organizations have changed their operations and interactions with employees and customers. The implementation of lockdowns and movement restrictions in various countries has led to a substantial decrease in traffic on roads, highways, and public transportation. Consequently, rush hour traffic in many cities virtually disappeared, and the roads remained relatively empty throughout the day. Such changes can be attributed to various factors such as the closure of schools and universities, a decrease in tourism and leisure activities, and an increase in the number of people working from home.

Two noteworthy phenomena emerged during the COVID-19 pandemic due to changes in activity-travel patterns. The first is characterized by a rapid resurgence in travel and non-essential activities outside the home. Following the development of vaccines and the slowdown of virus spread, lockdowns and movement restrictions were lifted, and individuals promptly resumed non-essential travel and activities outside the home. In contrast, while pandemic restrictions have been lifted, many workers exhibited a tepid return to the workplace, and opted to continue working remotely from home. Both phenomena are likely a consequence of changes in activity and time use patterns during the pandemic, which can have implications for individual wellbeing. It is plausible that the first phenomenon occurred because people experienced a lower sense of wellbeing during the peak of the pandemic when non-essential out-of-home activity participation was limited. Given that these activities are likely to have had the largest contribution to individual wellbeing, it is possible that this is why people resumed non-essential travel so quickly after the lifting of restrictions. As for the second phenomenon, working from home may have allowed many employees to have greater control and flexibility over their work schedules, and the elimination of the daily commute allowed for more discretionary time that could be used for non-essential activities, thereby reducing time poverty and improving wellbeing. Nonetheless, to truly understand the underlying reasons for these two phenomena, it is necessary to examine how and why they occurred in the context of changes in individual activity time use patterns induced by the pandemic.

In addition to the pandemic-induced changes in lifestyle, activity engagement, and time use that are likely to have impacted quality of life and wellbeing, there have been reports in both mainstream media and scientific literature that suggest the pandemic has had a disproportionate impact on different segments of the population (Bu et al., 2020; Cohen, 2020; Pabilonia and Vernon, 2022; Shen et al., 2022; Leonhardt, 2022). Certain groups may have experienced a reduced sense of wellbeing due to a lack of available time for discretionary activities, a disparity that existed prior to the pandemic. While changes in daily activity-travel routines during the pandemic may have mitigated the problem of time poverty for some, it may have worsened it for others, making them more susceptible to time poverty than ever before. Despite this, there is limited research examining the impact of pandemic-induced changes in daily activity time use patterns on individual wellbeing.

A thorough investigation of the two issues, namely satisfaction with automobile use and wellbeing implications of the pandemic-induced changes (both desirable and undesirable) in activity time use patterns, is imperative. This will provide a broader perspective on how to design future transportation systems that are free of externalities associated with excessive car use while improving societal wellbeing. Moreover, it will help us identify population groups that may experience the burdens of disruptions disproportionately and determine strategies to mitigate these negative impacts. Exploring how individuals adapt their activity, travel, and time use patterns to cope with disruptions can lead to uncovering new insights that can be instrumental in promoting individual wellbeing during future disruptions.

6. Research Questions, Aims, and Contributions

Despite the growing body of research on how transportation systems contribute to societal wellbeing, there is still a need for further research. Firstly, there is a lack of practical use of current subjective wellbeing measures due to the unavailability of wellbeing data in traditional household travel surveys; whereas the empirical validity of commonly used measures such as accessibility, time poverty, and zero-trip making as proxies of wellbeing is still questionable as they may not capture all factors influencing wellbeing. Meanwhile, car dependence and resulting transportation disparities continue to pose challenges to building equitable and sustainable transportation systems. The level of satisfaction derived from daily travel routines and how it relates to the extent of automobile use need to be better understood. Uncovering the magnitude and significance of mode choice in travel satisfaction (and thus its contribution to individual wellbeing) can help allocate resources and efforts more effectively. Additionally, the COVID-19 pandemic has underscored the importance of daily activity-travel patterns in individual wellbeing. As the pandemic's impacts were unevenly distributed, some segments of the population experienced a greater loss of wellbeing than others. Therefore, identifying these vulnerable groups is critical to planning for future disruptions and mitigating negative impacts. Given this context, this dissertation aims to contribute to the empirical literature on the relationship between travel and subjective wellbeing by exploring the following lines of inquiry.

The first set of questions:

- Considering the well-established notion that activity-travel patterns influence wellbeing and overall quality of life, how can a daily individual wellbeing scoring method be developed based on the outputs of activity-travel demand models?
- Is it feasible to use such a wellbeing scoring method in situations where in-home activity time allocation information is not available, as is the case in traditional household travel surveys? If so, how?

Research contribution: The main objective of this research is to develop and apply a wellbeing scoring method that can capture the quality of life implications of activity-travel patterns. The method is based on the estimation of a latent joint model of activity wellbeing scores for each set of in-home, travel, and out-of-home activities, using the 2010, 2012, and 2013 wellbeing modules of the American Time Use Survey (ATUS). The model system generates episode-level wellbeing scores that can be added up to produce daily person-level wellbeing scores when applied to activity/travel time use data. These scores can be used to compare the wellbeing of different population segments and to assess the wellbeing impacts of various transportation planning scenarios. The second part of this research illustrates how this wellbeing scoring method can be used in situations where in-home time allocation data is missing, such as in household travel surveys. This part involves the estimation of a multiple discrete-continuous extreme value (MDCEV) model of in-home activity time allocation based on the ATUS data, which can be used to impute in-home activity data for surveys lacking such information. The effectiveness of this approach is demonstrated using a random sample of the National

Household Travel Survey (NHTS). Therefore, this research not only provides a reliable subjective wellbeing scoring method for evaluating the quality of life implications of transportation systems but also demonstrates its use in the absence of in-home activity time allocation data.

<u>The second set of questions:</u>

- To what extent do ATUS and NHTS, two major data sets used in the transportation field, report similar zero-trip making patterns?
- What is the relationship between mobility poverty (zero-trip making), time poverty, and subjective wellbeing?
- Are time poverty and zero-trip making reliable wellbeing indicators that can be used when detailed wellbeing data is unavailable?

Research contribution: This chapter investigates the connection between zero-trip making, time poverty, and subjective wellbeing. Firstly, it compares the zero-trip making rates from ATUS and NHTS in 2017. The increase in zero-trip making rates in recent years has led to concerns about the negative impact on wellbeing for those with limited mobility. By comparing the two datasets, this research aims to determine whether this trend is consistent across both datasets and whether conclusions drawn from one dataset can be applied to the other. Secondly, the chapter examines the ATUS dataset to identify the rates of time poverty experienced by different socio-demographic groups and assess whether mobility-disadvantaged groups are particularly vulnerable to time poverty. Finally, using a subjective wellbeing scoring method, the chapter compares zero-trip makers to trip makers and time poor individuals to non-time poor individuals. This comparison aims to determine the extent to which zero-trip making and time poverty align with subjective wellbeing and assess whether there are differences among specific demographic groups. The results of this chapter provide valuable insights into the relationship between mobility poverty, time poverty, and subjective wellbeing. Additionally, the chapter sheds light on the practical application of wellbeing measures in identifying differences in wellbeing across the population. By identifying the groups that are most vulnerable to diminished wellbeing resulting from mobility poverty and time poverty, the chapter offers opportunities for targeted interventions and the development of transportation policies to address these challenges.

<u>The third set of questions:</u>

- Despite all the efforts to stem the tide of automobile use, why does it continue to grow and be the dominant mode of transportation?
- To what extent does automobile mode use impact the level of satisfaction that people derive from their daily travel routine?

Research contribution: This research aims to understand why automobile use continues to grow and remains unabated, specifically focusing on its impact on people's wellbeing. It is possible that people use automobiles excessively because there are no viable, sustainable transportation options, leaving them with no other choice but to use automobiles. This may result in automobile use contributing little to, or even diminishing, their satisfaction and overall wellbeing in terms of their daily travel routine.

Alternatively, the excessive use of automobiles could be associated with higher satisfaction with their travel routines, leading to an overall increase in their wellbeing. Data collected from four automobile-dominated metropolitan areas in the United States (Phoenix, Austin, Atlanta, and Tampa) are used to assess the impact of individuals' driving routines on the level of satisfaction they derive from their daily travel routines. The chapter acknowledges the presence of endogeneity when modeling multiple behavioral phenomena of interest, as well as the role that latent attitudinal constructs reflecting lifestyle preferences play in shaping the relationship between behavioral mobility choices and level of satisfaction. The Generalized Heterogeneous Data Model (GHDM) methodology is used to estimate the model. It is intended in this research effort to unravel whether the amount of driving influences satisfaction with daily travel routines, which could have important implications for promoting mode shifts toward more sustainable alternatives, which remains a formidable challenge – particularly in automobile-centric contexts.

<u>The fourth set of questions:</u>

- How has individual wellbeing been impacted by changes in daily activity time use patterns during the COVID-19 pandemic?
- Who are the winners and losers – the groups that disproportionately suffered degradation of the quality of life as a consequence of the pandemic?
- What insights can be offered to devise strategies that can help mitigate the adverse consequences of future disruptions for vulnerable socio-economic and demographic groups?

Research contribution: The COVID-19 pandemic caused changes in daily activity patterns, but little research has been done to understand their impact on individual wellbeing. This chapter aims to fill this research gap by leveraging two key wellbeing indicators (subjective wellbeing score and time poverty), which can translate an individual's time use patterns into measures of wellbeing. Using data from the 2019 and 2020 ATUS, the chapter analyzes and compares the two data sets to identify groups that fared better or worse during the pandemic. By doing so, it seeks to answer two noteworthy phenomena that emerged during the pandemic. After the development of vaccines and the slowdown of virus spread, lockdowns and movement restrictions were lifted; why did we see a rapid resurgence in travel and non-essential activities outside the home, and why did many workers exhibit a tepid return to the workplace, opting to continue working remotely from home? The chapter explains the underlying reasons for these phenomena from the perspectives of subjective wellbeing and time poverty. It also provides significant insights into the equity implications of the pandemic, identifying groups that were disproportionately impacted and offering strategies to mitigate adverse consequences for vulnerable socio-economic and demographic groups in future disruptions.

7. Organization of the Dissertation

The remainder of the dissertation is organized as follows. Chapter 2 focuses on the first set of research questions and introduces the development of a wellbeing scoring method and its application in the context of national household travel surveys. Chapter 3 examines the relationship between mobility poverty, time poverty, and subjective wellbeing, addressing the second set of research questions. The third set of research questions is addressed in Chapter 4, which explores the underlying reasons why the use of automobiles continues to be unabated in the transportation landscape from the perspective of satisfaction with daily travel routines. Chapter 5 investigates the impact of COVID-19 pandemic-induced changes in activity, travel, and time use patterns on individual wellbeing. In Chapter 6, a real-world application of the three wellbeing indicators developed and/or used in this dissertation is demonstrated on a web-based wellbeing platform. Finally, Chapter 7 presents conclusions and suggestions for future research. Chapters 2-5 have been published or are in the process of being published in international peer-reviewed scientific journals. Chapter 6 has been made available as an open-source interactive wellbeing platform, allowing for rapid analysis and graphical representation of changes in wellbeing across time and place for different population groups. It is also worth noting that each chapter is designed to be read independently, so there may be some inevitable repetition of literature reviews, methodologies, and data descriptions throughout the dissertation.

8. References

Adeel, M., & Yeh, A. G. (2018). Gendered immobility: influence of social roles and local context on mobility decisions in Pakistan. *Transportation Planning and Technology*, *41*(6), 660-678.

Alkire, S. (2002). Dimensions of human development. *World Development*, *30*(2), 181-205.

Batur, I. (2015). *Social behavioral change for sustainable urban transportation under TDM concept: A case study of Istanbul* (Master's thesis, Istanbul Sehir University).

Bergstad, C. J., Gamble, A., Gärling, T., Hagman, O., Polk, M., Ettema, D., ... & Olsson, L. E. (2011). Subjective well-being related to satisfaction with daily travel. *Transportation*, *38*, 1-15.

Cohen, P. (2020). Recession With a Difference: Women Face Special Burden. Retrieved from https://www.nytimes.com/2020/11/17/business/economy/women-jobs-economy-recession.html

Corran, P., Steinbach, R., Saunders, L., & Green, J. (2018). Age, disability and everyday mobility in London: An analysis of the correlates of 'non-travel' in travel diary data. *Journal of transport & health*, *8*, 129-136.

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V., & Witlox, F. (2016). Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. *Transportation*, *43*, 771-796.

De Vos, J., Schwanen, T., Van Acker, V., & Witlox, F. (2013). Travel and subjective well-being: A focus on findings, methods and future research needs. *Transport Reviews*, *33*(4), 421-442.

Delbosc, A. (2012). The role of well-being in transport policy. *Transport Policy*, *23*, 25-33.

Delbosc, A., Kroesen, M., Van Wee, B., & de Haas, M. (2020). Linear, non-linear, bi-directional? Testing the nature of the relationship between mobility and satisfaction with life. *Transportation*, *47*(4), 2049-2066.

Diener, E., & Seligman, M. E. (2004). Beyond money: Toward an economy of well-being. *Psychological Science in the Public Interest*, *5*(1), 1-31.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D. W., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*, 143-156.

Ettema, D., Gärling, T., Olsson, L. E., & Friman, M. (2010). Out-of-home activities, daily travel, and subjective well-being. *Transportation Research Part A: Policy and Practice*, *44*(9), 723-732.

Gärling, T., & Gamble, A. (2017). Life satisfaction and Emotional Well-Being: Psychological, Economic and Social Factors. *Economic Psychology*, 405-420.

IEEE, (2022). The State of Well-being Metrics (An Introduction). Retrieved from https://standards.ieee.org/wp-content/uploads/import/documents/other/ead1e_state_wellbeing_metrics.pdf

International Transport Forum. (2021). ITF Transport Outlook 2021. Retrieved from https://www.itf-oecd.org/itf-transport-outlook-2021

Kaufmann, V., Bergman, M. M., & Joye, D. (2004). Motility: Mobility as capital. *International Journal of Urban and Regional Research*, *28*(4), 745-756.

Kitamura, R., Fujii, S., & Pas, E. I. (1997). Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies. *Transport Policy*, *4*(4), 225-235.

Lee, R. J., & Sener, I. N. (2016). Transportation planning and quality of life: Where do they intersect?. *Transport Policy*, *48*, 146-155.

Leonhardt, D. (2022). Covid and Race. Retrieved from https://www.nytimes.com/2022/06/09/briefing/covid-race-deaths-america.html

McMahan, E. A., & Estes, D. (2011). Measuring lay conceptions of well-being: The beliefs about well-being scale. *Journal of Happiness Studies*, *12*, 267-287.

Mokhtarian, P. L. (2019). Subjective well-being and travel: Retrospect and prospect. *Transportation*, *46*, 493-513.

Mokhtarian, P. L., Salomon, I., & Singer, M. E. (2015). What moves us? An interdisciplinary exploration of reasons for traveling. *Transport Reviews*, *35*(3), 250-274.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice*, *83*, 14-29.

Motte-Baumvol, B., & Nassi, C. D. (2012). Immobility in Rio de Janeiro, beyond poverty. *Journal of Transport Geography*, *24*, 67-76.

Nordbakke, S., & Schwanen, T. (2014). Well-being and mobility: A theoretical framework and literature review focusing on older people. *Mobilities*, *9*(1), 104-129.

Organisation for Economic Co-operation and Development. (2011). *How's life?: measuring well-being*. Paris: OECD.

Reardon, L., & Abdallah, S. (2013). Well-being and transport: Taking stock and looking forward. *Transport Reviews*, *33*(6), 634-657.

Russell, M., & Mokhtarian, P. (2015). How real is a reported desire to travel for its own sake? Exploring the 'teleportation' concept in travel behaviour research. *Transportation, 42*, 333-345.

Singleton, P. A. (2019). Walking (and cycling) to well-being: Modal and other determinants of subjective well-being during the commute. *Travel Behaviour and Society*, *16*, 249-261.

Stopher, P. R. (2005). Voluntary travel behavior change. In *Handbook of transport strategy, policy and institutions*. Emerald Group Publishing Limited.

UNDP. (2022). Human Development Index (HDI). Retrieved from https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

U.S. Department of Transportation - Federal Highway Administration. (2021). Highway Statistics 2021. Retrieved from https://www.fhwa.dot.gov/policyinformation/statistics/2021/

Västfjäll, D., Friman, M., Gärling, T., & Kleiner, M. (2002). The measurement of core affect: A Swedish self-report measure derived from the affect circumplex. *Scandinavian Journal of Psychology*, *43*(1), 19-31.

Veenhoven, R. (2013). *Data-Book of Happiness: A Complementary Reference Work to 'Conditions of Happiness' by the Same Author*. Springer Science & Business Media.

Vickery, C. (1977). The time-poor: A new look at poverty. *Journal of Human Resources*, 27-48.

Voukelatou, V., Gabrielli, L., Miliou, I., Cresci, S., Sharma, R., Tesconi, M., & Pappalardo, L. (2021). Measuring objective and subjective well-being: dimensions and data sources. *International Journal of Data Science and Analytics*, *11*, 279-309.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063.

Welch, T. F., & Mishra, S. (2013). A measure of equity for public transit connectivity. *Journal of Transport Geography*, *33*, 29-41.

Williams, J. R., Masuda, Y. J., & Tallis, H. (2016). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*, 265-283.

CHAPTER 2

AN INTEGRATED MODEL OF ACTIVITY-TRAVEL BEHAVIOR AND SUBJECTIVE WELLBEING

1. 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 wellbeing (Ziems et al., 2010; Bergstad et al., 2011; Lee and Sener, 2016; Friman et al., 2017; De Vos et al., 2013). Measures of subjective wellbeing 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 wellbeing 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 wellbeing, it can be said that a healthy accumulation of positive feelings of wellbeing will contribute (over time) to a higher quality of life. To the extent that transportation can engender such positive feelings of wellbeing (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 wellbeing that people derive from their daily activity-travel and time use patterns. Armed with knowledge about the wellbeing implications of the activity-travel ecosystem, transportation professionals will be able to plan built environments, design mobility systems, and implement policies that enhance wellbeing – and consequently, quality of life.

However, transportation demand forecasting models do not output measures of wellbeing, and household travel surveys never collect information about feelings of wellbeing associated with various activity-travel episodes reported in a travel diary. In the absence of any knowledge or data about actual subjective feelings of wellbeing that are derived from activities and trips, inferences about wellbeing are often drawn based on time use patterns. 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 wellbeing and overall quality of life.

While a time-based definition of wellbeing (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 wellbeing 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 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 wellbeing 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 will 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 wellbeing, thus enabling planners to assess the wellbeing implications of the transportation system and alternative actions.

This chapter presents an integrated model of activity-travel behavior and subjective wellbeing that can essentially serve as a wellbeing 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 wellbeing 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 chapter presents a data fusion approach to help overcome the challenges. The first challenge is that travel surveys do not contain any information about subjective wellbeing, and hence the calibration of a model of wellbeing is difficult in the absence of data. To overcome this issue, wellbeing data from 2010, 2012, and 2013 editions of the American Time Use Survey (ATUS) data collected in the United States is used to estimate wellbeing scores as a function of activity engagement and time use allocation patterns in addition to socio-economic attributes. 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 wellbeing (or lack thereof). Hence, in-home time use allocation patterns need to be estimated so that appropriate wellbeing 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 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 wellbeing score; that accounts for the entire slate of activities pursued by an individual inside and outside the home. The chapter describes the model development and data fusion process and demonstrates the efficacy of the model by presenting the 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 chapter).

The remainder of this chapter 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.

2. Activity-Travel Behavior and Subjective Wellbeing

The field of transportation, along with various other fields, has shown significant interest in the concept of subjective wellbeing. As stated by the National Research Council (2013), subjective wellbeing can be defined as an individual's self-assessment of their life within specific domains and activities. subjective wellbeing can be assessed through a series of momentary states over time, encompassing multiple dimensions and emotions. It is crucial to recognize the role of different emotions in influencing subjective wellbeing. Negative emotions are more intricate to understand compared to positive emotions, necessitating additional measures to comprehend the underlying forces contributing to negative emotions. It is also important to note that negative emotions and positive emotions are not necessarily complete opposites but should be considered together when evaluating subjective wellbeing (National Research Council, 2013).

In the realm of transportation and planning, the primary goal behind efforts to enhance mobility, accessibility, efficiency, safety, and sustainability is ultimately to improve the quality of life (societal wellbeing). Wellbeing is a multifaceted phenomenon that can be evaluated through a broad range of subjective and objective measures, including health, welfare, emotion, satisfaction, engagement, relationships, accomplishments, and happiness (Forgeard et al., 2011). Existing research has explored different domains of wellbeing and developed theoretical frameworks that integrate these domains. In the concluding section of a review study encompassing the diverse domains of wellbeing, Forgeard et al. (2011) highlighted the indispensability of subjective measures. They noted that the presence of objective conditions related to wellbeing does not always guarantee subjective feelings of wellbeing, as evidenced by the high rates of Major Depressive Disorders in developed countries. Additionally, the existence of a statistical link between objective and subjective wellbeing, as demonstrated by Oswald and Wu (2010), suggests that studying one aspect can provide insights into the other, to some extent. Therefore, the application of subjective wellbeing data in this chapter in relation to activity-time use patterns can shed light on the impact of activity and mobility engagement on people's subjective wellbeing while accounting for their socio-economic and demographic factors.

A number of researchers have explored the connection between travel and subjective wellbeing. Travel can influence subjective wellbeing through various mechanisms. Mokhtarian and Pendyala (2018) identified five sources of influence that impact travel satisfaction: experiences during destination-oriented travel, activities during destination-oriented travel, trips where travel is the activity itself, travel-facilitated activity, and utility. Travel can have both negative and positive utility. The negative aspect of travel, which involves additional time and cost to access certain mandatory or non-mandatory activities, has long been the basis of travel demand modeling and is referred to as disutility. However, more recent studies have shown that travel itself can also have positive utility in two primary categories: travel activities (travel-based multitasking) and travel experiences (subjective wellbeing associated with travel). Singleton (2017) extensively explored the positive utility of travel and these two categories in his dissertation. Gärling (2019) proposed that positive and negative emotional responses are triggered by transient critical incidents (such as disruptions) and non-transient factors (such as noise) experienced during travel. Ettema et al. (2010) identified three sources of the impacts of travel on subjective wellbeing: positive and negative effects during travel, accessibility to activities through travel, and the influence of travel on the amount of stress associated with activities performed throughout the day. Lee and Sener (2016) conceptualized four dimensions of transportation-related quality of life: physical, mental, social, and economic. They identified three components of the transportation system that affect these four dimensions: mobility/accessibility, attributes of the built environment, and vehicular traffic volumes. Waygood et al. (2017) evaluated child wellbeing and found that transportation influences wellbeing through three mechanisms: as an access mechanism to destinations, through intrinsic features of the travel experience itself, and through external connections (e.g., transporting or being transported by others). Interestingly, Gao et al. (2017) discovered that satisfaction with travel had a relatively small effect on overall wellbeing after accounting for socio-economic and demographic characteristics and personality traits (self-discipline, impatience, easy-going nature, reservedness, and calmness).

There have been numerous studies documenting the association between subjective wellbeing and various modes of transportation. Delbosc (2012) highlighted that transit can enhance life satisfaction through physical mobility and accessibility to important activities. On the other hand, Friman et al. (2017) and Mokhtarian and Pendyala (2018) reported a lower level of subjective wellbeing associated with public transit, while active modes of transportation were linked to higher subjective wellbeing. Interestingly, Mokhtarian and Pendyala (2018) found that car passengers reported the most positive emotions. Conversely, Ferenchak and Katirai (2015) found a negative association between carpooling and public transportation modes with mental state, while driving alone to work showed a significant positive association. Despite the negative perception of public transit, Abou-Zeid and Fujii (2016) discovered that incentives to promote transit use hold promise not only for encouraging sustainable travel behavior but also for increasing people's satisfaction. Additionally, greater use of active commuting modes was associated with higher levels of physical wellbeing, regardless of time spent in other domains of physical activity (Humphreys et al., 2013). Reduced car use was found to contribute to reduced subjective wellbeing (Bergstad et al., 2011). In terms of commuting, Chatterjee et al. (2020) emphasized that stress can arise from a lack of control, congestion, crowding, and unpredictability during the commute journey, resulting in lower mood compared to other daily activities. Individuals who walk or cycle to work generally reported higher satisfaction with their commute compared to car or public transportation users (Chatterjee et al., 2020). The study also revealed that satisfaction decreases with longer commute durations and increases when traveling with company. On the other hand, transportation poverty, encompassing both affordability and accessibility, exhibits a negative relationship with subjective wellbeing (Churchill and Smyth, 2019). While it has been shown that car users generally have higher subjective wellbeing compared to transit users, it is important to consider unobserved factors. For instance, individuals with higher wellbeing may be more likely to own a car due to their success in life. Thus, this chapter aims to control for socio-economic factors to capture the isolated impacts of activities and travel attributes on subjective wellbeing as much as possible.

In addition to travel, socio-economic and demographic attributes of individuals have been found to influence subjective wellbeing. Archer et al. (2013) found that males tend to report lower subjective wellbeing for travel episodes compared to females. Low-income individuals, who face monetary constraints, report a wider range of emotions than high-income individuals, potentially due to other factors affecting their lives (Mokhtarian and Pendyala, 2018). Contrary to studies suggesting that 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 individuals report higher levels of happiness across all types of activities, including out-of-home activities, in-home activities, and travel episodes. Bergstad et al. (2011) also reported higher satisfaction with daily travel patterns among older people, possibly because they have fewer constraints and busy schedules compared to their younger counterparts. Ziems et al. (2010) discovered that older people derived higher utility from their time use patterns compared to other age groups. Shergold (2019) emphasizes the "Activity Theory," which highlights the importance of activity participation for older adults as a useful framework to explore the role of mobility in wellbeing assessment for this population. Although older people spend less time outside the home, the loss of utility due to fewer out-of-home activities seems to be compensated for by the utility derived from discretionary in-home activities.

Other factors that impact subjective wellbeing include perceptions gained from social interactions. For instance, Abou-Zeid and Ben-Akiva (2011) found that favorable comparisons to others can enhance commute satisfaction. Additionally, the time use pattern of activities is relevant when studying subjective wellbeing. Abou-Zeid and Ben-Akiva (2012) found that frequent engagement in activities is associated with higher levels of happiness and greater life satisfaction. Similarly, Mokhtarian and Pendyala (2018) observed that emotions tend to be more positive for out-of-home activities compared to similar in-home activities. The geographic context is also an important determinant of wellbeing. Archer et al. (2013) found that individuals residing 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) identified that the correlation between transportation disadvantage and wellbeing was consistently higher for rural residents outside major metropolitan areas. Ye and Titheridge (2017) noted that the built environment plays a significant role in shaping satisfaction through its influence on commute characteristics.

Given the connection between activity-travel patterns/choices and subjective wellbeing, there is a need for an integrated model system that directly links these dimensions. Such a system would provide value to policymakers, enabling them to assess the subjective wellbeing implications of their investments and actions. Several multidimensional 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 consider various dimensions of travel behavior (e.g., residential location, car ownership, travel amount by mode, mode choice, travel schedule, and destination choice), they do not establish a connection between activity-time use patterns and subjective wellbeing. Understanding this connection is crucial as communities strive to enhance the quality of life for their residents.

Undoubtedly, there have been few studies that have attempted to establish a connection between subjective wellbeing and daily activity-travel and time use patterns. Archer et al. (2013) discovered that subjective wellbeing is influenced by activity start time, activity duration, child accompaniment, and activity location. Ye et al. (2009) developed a time use utility measure based on activity engagement patterns, but did not explicitly consider measures of wellbeing, such as emotions, in defining the time use utility measure. Their effort was primarily focused on creating a time use utility measurement tool that could be applied as a post-processor for activity-based travel demand models to evaluate the utility people derive from their activity-travel and time use patterns. However, their tool did not adequately account for the wide range of in-home activities that individuals engage in on a daily basis. Therefore, there is a need for an integrated model system that tightly connects daily activity-time use patterns and wellbeing, explicitly accounting for in-home time use and activity engagement.

Defining wellbeing based on activity engagement, travel, and time use has its merits but may not fully capture the true emotions that people associate with their daily lives. In this chapter, retrospective reporting of wellbeing measures is used, where emotions related to each activity are collected after the activities have been completed. However, it is important to note that these retrospective measures may differ from real-time feelings and emotions experienced during and immediately after the activities. When comparing real-time and retrospective happiness measures (Raveau et al., 2016), two cognitive biases are observed: the Peak-End Rule and the Hedonic Treadmill Effect. Extreme real-time measures of "Very Unhappy" and "Very Happy" tend to persist over time, while less extreme measures tend to be remembered at more neutral levels (Kahneman et al., 1993; Brickman et al., 1971; Frederick and Loewenstein, 1999).

Krueger et al. (2009) note that interpreting subjective wellbeing based on activity engagement has limitations, as people are highly heterogeneous. Workaholics may derive great satisfaction from work, while others may dislike it. Similarly, some individuals may find happiness in shopping, while others may not enjoy it. Preferences for traveling and experiencing new destinations also vary among individuals, with some enjoying it and others preferring to stay at home. Therefore, it is crucial to directly model and assess individuals' reported measures of wellbeing. This data can be used to develop models of subjective wellbeing that link emotions to activity-travel and time use patterns, providing a more accurate assessment of the subjective wellbeing derived from daily lives.

The objective of this chapter is to develop such an integrated model system that allows the computation of subjective wellbeing measures for agents in an activity-based travel demand model. The model system should not only account for wellbeing derived from out-of-home activities and travel but also include wellbeing derived from in-home activities. Through the utilization of data from the ATUS dataset, the integrated model system presented in this chapter accomplishes this objective.

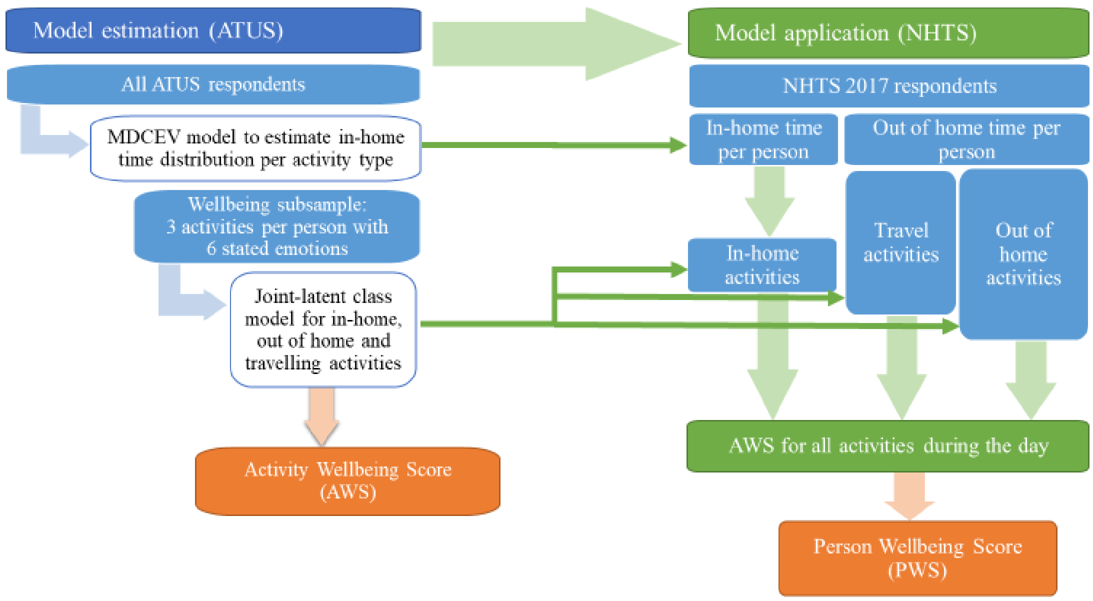
3. Conceptual Framework and Model Structure

This section presents the conceptual framework for the wellbeing estimation and analysis tool developed in this chapter. Figure 2-1 presents the framework to illustrate the components and steps that are involved in developing a wellbeing score for each individual in a synthetic population of agents. The fundamental premise underlying the conceptual framework is that wellbeing is determined by how people feel spending time traveling and engaging in different types of activities inside and outside the home.

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 the wellbeing of an individual. Therefore, to compute a person wellbeing 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 wellbeing score can be computed.

Figure 2-1

Summary of the Study Approach to Compute Daily Wellbeing Composite Score



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 for 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 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 ATUS data set that provides detailed information about in-home and out-of-home activity engagement and time use.

The data used in this chapter is presented in greater detail in the next section. In short, the ATUS 2010, 2012, and 2013 editions ATUS included a wellbeing 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.

Next, a latent joint estimation model system has been developed that relates the six emotions to people's socio-economic attributes and activity characteristics separately for in-home, travel, and out-of-home activities. In the model formulation, the wellbeing variable is defined as a latent variable (z^*), which cannot be directly observed but affects latent propensity functions ($\mathrm{y}_i{}^*$) and then determine the observed emotion levels (y_i) taking ordered values. Similar to the conventional factor analysis approach with a single factor, a list of models is formulated as:

$$\mathrm{y}_i{}^* = \mathrm{L}_i z^* + \varepsilon_i \tag{1}$$

In this chapter, the index variable “i” takes values from 1, 2, …,6, indicating six different emotions in total. There are 7 ordered values being denoted as 1,2,…,7 for each emotion level y_i. L_i is a scalar loading factor that quantifies the impact from the wellbeing variable on the latent propensity function y_i^*. The loading factor L_i can take either positive or negative value when y_i represents a positive or negative emotion. ε_i is an unobserved random error term following *i.i.d.* standard normal distribution. Based on each latent propensity function y_i^*, 8 ordered thresholds $\theta_{i,0}, \theta_{i,1}, \ldots \theta_{i,7}$ ($\theta_{i,0} < \theta_{i,1} \ldots < \theta_{i,7}$) are setup to determine the emotion level y_i. Among those thresholds, $\theta_{i,0} = -\infty$ and $\theta_{i,7} = +\infty$. When $\theta_{i,j-1} < y_i^* < \theta_{i,j}$, the emotion level takes the value "j" from the set {1,2,…,7}. Meanwhile, the wellbeing variable is modeled as a linear combination of explanatory variables in row vector "**x**" and their coefficients in column vector "β" plus a random error term as:

$$z^* = x\beta + \xi, \tag{2}$$

where ξ is assumed to follow the standard normal distribution.

For model estimation, one may replace the latent variable "z^*" in Equation (1) with the right part in Equation (2) and then obtain:

$$y_i^* = L_i(x\beta + \xi) + \varepsilon_i = L_i x\beta + L_i\xi + \varepsilon_i .$$

The random component $L_i\xi + \varepsilon_i$ can be converted into a new component η_i following a normal distribution with zero mean and standard deviation $\sqrt{1 + L_i^2}$. Between either pair of propensity functions y_i^* and y_k^*, the random error covariance can be expressed as $L_i L_k$ since all the new random components share the common random error ξ multiplied with a respective loading factor. Thus, all the model coefficients can be estimated in a multivariate ordered probit modeling framework after the propensity functions and thresholds are divided by the standard deviation $\sqrt{1+L_i^2}$ of random errors for normalization, as below:

$$\mathrm{y}_i{}^{*\prime} = \frac{\mathrm{y}_i{}^*}{\sqrt{1+L_i{}^2}} = \frac{\mathrm{L}_i x\beta}{\sqrt{1+L_i^2}} + \eta_i{}' \text{ and } \theta_{i,j}{}' = \frac{\theta_{i,j}}{\sqrt{1+L_i^2}},$$

where $\eta_i{}'$ follow the multivariate normal distribution with zero means and correlation matrix $\sum$, which can be expressed as:

$$\sum = \begin{bmatrix} 1 & \frac{\mathrm{L}_1\mathrm{L}_2}{\sqrt{1+L_1^2}\cdot\sqrt{1+L_2^2}} & \cdots & \frac{\mathrm{L}_1\mathrm{L}_6}{\sqrt{1+L_1^2}\cdot\sqrt{1+L_6^2}} \\ \frac{\mathrm{L}_2\mathrm{L}_1}{\sqrt{1+L_2^2}\cdot\sqrt{1+L_1^2}} & 1 & \cdots & \frac{\mathrm{L}_2\mathrm{L}_6}{\sqrt{1+L_2^2}\cdot\sqrt{1+L_6^2}} \\ \cdots & \cdots & 1 & \cdots \\ \frac{\mathrm{L}_6\mathrm{L}_1}{\sqrt{1+L_6^2}\cdot\sqrt{1+L_1^2}} & \frac{\mathrm{L}_6\mathrm{L}_2}{\sqrt{1+L_6^2}\cdot\sqrt{1+L_2^2}} & \cdots & 1 \end{bmatrix}. \tag{3}$$

CML (Composite Marginal Likelihood) estimation approach can be employed to consistently estimate model coefficients by maximizing the composite marginal log-likelihood function, as below:

$$\mathrm{LL}(\beta, L, \theta) = \sum_{i=1}^{5}\sum_{k=i+1}^{6}\sum_{j=1}^{7}\sum_{m=1}^{7}\{I(y_i = j)\cdot I(y_k = m)\cdot \ln\left[P(y_i = j, y_k = m)\right]\}. \tag{4}$$

In the composite log-likelihood function above, $I(y_i = j)$ and $I(y_k = m)$ are dummy variables indicating whether the motion levels y_i and y_k respectively take values of "j" and "m" while $P(y_i = j, y_k = m)$ represents the joint choice probability. As per the bivariate ordered probit model, $P(y_i = j, y_k = m) =$

$$= \Phi_2[\alpha_i(\theta_{i,j} - L_i x\beta), \alpha_k(\theta_{k,m} - L_k x\beta), \alpha_i \alpha_k L_i L_k]$$

$$-\Phi_2[\alpha_i(\theta_{i,j-1} - L_i x\beta), \alpha_k(\theta_{k,m} - L_k x\beta), \alpha_i \alpha_k L_i L_k]$$

$$-\Phi_2[\alpha_i(\theta_{i,j} - L_i x\beta), \alpha_k(\theta_{k,m-1} - L_k x\beta), \alpha_i \alpha_k L_i L_k]$$

$$+\Phi_2[\alpha_i(\theta_{i,j-1} - L_i x\beta), \alpha_k(\theta_{k,m-1} - L_k x\beta), \alpha_i \alpha_k L_i L_k],$$

where $\alpha_i = \frac{1}{\sqrt{1+L_i^2}}$ and $\alpha_k = \frac{1}{\sqrt{1+L_k^2}}$. (5)

Here, $\Phi_2[x, y, \rho]$ is the cumulative distribution function of the standard bivariate normal distribution. The composite log-likelihood function over a sample can be formulated as $\text{LL}_N(\beta, L, \theta) = \sum_{q=1}^{N} \text{LL}_q(\beta, L, \theta)$, where "$q$" is the index for observation in the sample, N represents the sample size and $\text{LL}_q(\beta, L, \theta)$ is the composite log-likelihood value for the observation "q" in the sample. It can be maximized to consistently estimate all the model coefficients in vectors β, L and θ.

Since the latent wellbeing variable $z^* = x\beta + \xi$, its conditional expectation $\text{E}(z^*|x) = x\beta \approx x\hat{\beta} = \hat{z}^*$, which can be used as a prediction of the wellbeing variable given an observed vector of explanatory variables x and the estimated vector of coefficients $\hat{\beta}$. Because the vector x contains several continuous and dummy variables associated with either positive or negative coefficients, the computed values of $x\hat{\beta}$ may take a positive or negative value. In order to obtain a score value falling to a reasonable non-negative range, one may convert the wellbeing variable into a wellbeing score by using the formula $\Phi\left[\frac{\hat{z}^*-E(\hat{z}^*)}{SD(\hat{z}^*)}\right]$, where $\Phi(\mathrm{x})$ represents the cumulative distribution function of the standard normal distribution, $E(\hat{z}^*)=\frac{\sum_{q=1}^{N}(x_q\hat{\beta})}{N}$ and $SD(\hat{z}^*)=\sqrt{\frac{\sum_{q=1}^{N}[x_q\hat{\beta}-E(\hat{z}^*)]^2}{N-1}}$. Through the conversion, the wellbeing scores obtained from different types of activities or travel can be normalized and ensured to fall into the range between 0 and 1.

In the end, the activity wellbeing scores (AWS) will be summed up over the 24-hour period for each individual consisting of in-home, travel, and out-of-home activity episodes and provide a single day-level Person Wellbeing Score (PWS) for each individual agent in the synthetic population of an activity-based travel demand model. The summation operation implies that the scores associated with various activities are additive and that wellbeing 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 reasonable. The right-hand side of Figure 2-1 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 PWS for synthetic agents. Because an activity-travel model output was not specifically available, the efficacy of the model is demonstrated in this chapter by applying it to a small random sample of records from the 2017 NHTS data set (the activity-travel records in the NHTS data set are very similar to a typical activity-travel model output).

4. Data Description

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 wellbeing 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 implies 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 2-1 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 for mandatory and non-mandatory activities. 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. People consistently reported significantly higher levels of happiness and meaningfulness for non-mandatory activities compared to mandatory activities across all three categories of activities. It appears that individuals are able to draw a more clear distinction in meaningfulness than in happiness. Higher percentages of people reported mandatory activities at the highest level of meaningfulness compared to happiness. For mandatory in-home and travel activities, the largest categories reported mid-level of happiness compared to the highest level of happiness for non-mandatory activities.

Table 2-1

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	Non-mandatory	4.83%	2.08%	5.30%	15.21%	17.59%	22.43%	32.56%
		Mandatory	6.17%	4.26%	11.20%	24.51%	20.11%	18.46%	15.28%
	Out of home activity	Non-mandatory	3.57%	1.69%	4.07%	12.08%	16.89%	24.43%	37.27%
		Mandatory	4.52%	2.67%	7.37%	20.15%	22.42%	22.65%	20.22%
	Travel activity	Non-mandatory	3.82%	1.76%	4.75%	14.09%	18.20%	24.00%	33.38%
		Mandatory	5.16%	2.87%	7.82%	21.87%	21.01%	21.50%	19.78%
	All activities		4.37%	2.02%	5.21%	14.91%	17.87%	22.90%	32.08%
Meaningfulness	In-home activity	Non-mandatory	8.46%	3.49%	6.46%	12.92%	12.31%	15.53%	39.51%
		Mandatory	3.68%	2.79%	6.98%	14.66%	15.80%	20.11%	35.85%
	Out of home activity	Non-mandatory	5.75%	2.60%	4.96%	11.48%	12.73%	16.80%	45.08%
		Mandatory	5.22%	2.23%	4.85%	13.24%	15.67%	21.52%	36.77%
	Travel activity	Non-mandatory	10.59%	4.08%	6.78%	13.07%	12.38%	14.37%	37.61%
		Mandatory	14.62%	5.72%	7.59%	14.82%	11.19%	13.11%	32.01%
	All activities		8.28%	3.42%	6.19%	12.78%	12.62%	15.88%	39.76%
Pain	In-home activity	Non-mandatory	65.76%	6.22%	6.82%	7.25%	6.08%	3.97%	3.57%
		Mandatory	67.58%	8.76%	8.31%	5.77%	5.27%	2.54%	1.65%
	Out of home activity	Non-mandatory	71.84%	6.33%	6.76%	5.91%	4.36%	2.60%	2.08%
		Mandatory	69.13%	7.37%	7.65%	6.56%	4.89%	2.47%	1.84%
	Travel activity	Non-mandatory	72.44%	6.41%	6.29%	5.69%	4.24%	2.69%	2.05%
		Mandatory	75.79%	7.15%	5.72%	5.39%	2.94%	1.59%	1.31%
	All activities		68.76%	6.41%	6.74%	6.57%	5.21%	3.28%	2.79%
Sadness	In-home activity	Non-mandatory	76.90%	5.81%	5.19%	4.82%	2.90%	2.02%	1.92%
		Mandatory	70.11%	10.15%	6.98%	6.35%	3.24%	1.71%	1.27%
	Out of home activity	Non-mandatory	80.52%	5.80%	4.46%	3.91%	2.08%	1.39%	1.63%
		Mandatory	72.66%	8.82%	7.71%	4.83%	2.92%	1.53%	1.36%
	Travel activity	Non-mandatory	79.05%	6.11%	4.92%	4.10%	2.39%	1.60%	1.55%
		Mandatory	74.44%	8.70%	5.96%	5.59%	2.53%	1.22%	1.47%
	All activities		77.60%	6.19%	5.19%	4.55%	2.64%	1.76%	1.74%
Stressfulness	In-home activity	Non-mandatory	58.01%	10.13%	10.55%	8.56%	5.67%	3.52%	3.22%
		Mandatory	27.28%	10.72%	16.12%	17.39%	13.32%	9.71%	5.39%
	Out of home activity	Non-mandatory	58.56%	10.87%	10.59%	8.28%	5.33%	3.39%	2.84%
		Mandatory	29.37%	10.90%	15.63%	17.25%	13.54%	7.75%	5.37%
	Travel activity	Non-mandatory	54.78%	11.18%	11.67%	9.09%	6.38%	3.68%	3.00%
		Mandatory	42.18%	12.58%	15.23%	13.11%	7.92%	5.27%	3.59%
	All activities		54.89%	10.60%	11.29%	9.38%	6.39%	3.92%	3.27%
Tiredness	In-home activity	Non-mandatory	32.08%	8.34%	12.96%	15.98%	13.90%	9.31%	7.02%
		Mandatory	24.37%	11.80%	14.21%	17.07%	14.97%	11.04%	6.35%
	Out of home activity	Non-mandatory	36.93%	10.12%	13.76%	15.35%	11.63%	7.30%	4.73%
		Mandatory	24.46%	10.28%	16.02%	19.18%	13.85%	9.46%	6.60%
	Travel activity	Non-mandatory	34.08%	9.65%	13.22%	15.66%	12.65%	8.52%	6.00%
		Mandatory	33.73%	13.31%	15.07%	15.43%	11.56%	5.92%	4.94%
	All activities		32.89%	9.24%	13.41%	15.98%	13.17%	8.71%	6.29%

Note: 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. In general, more individuals reported scores of zero for painfulness and sadness for non-mandatory activities compared to mandatory activities, except for in-home and travel activities which shows fewer scores of zero for pain for non-mandatory activities.

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 wellbeing (and consequently the 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. Non-mandatory activities consistently show significantly higher levels of zero-stressfulness and zero-tiredness compared to mandatory activities across the three groups.

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 wellbeing model system, an 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 twenty percent random sample of individuals is extracted from the ATUS database. The twenty 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 2-2 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 of 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 associate degree. About one-in-five individuals is a college graduate. The household income distribution shows a healthy spread across the various income categories with 23.3 percent reporting incomes greater than or equal to $100,000 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.

Table 2-2

Socio-Demographic Characteristics of ATUS and NHTS Samples

Variable	ATUS | Estimation Sample (N=5,069)	NHTS | Application Sample (N=9,700)	NHTS | Full Sample (N=230,778)
	%	%	%
Gender			
Female	55.9	53.4	53.1
Male	44.1	46.6	46.9
Age			
15-20 years	6.1	6.6	5.7
21-30 years	13.6	10.2	10.0
31-49 years	36.1	24.4	24.3
50-64 years	25.3	29.4	30.0
65 years or older	18.9	29.4	30.0
Educational attainment			
Less than a high school diploma	14.1	8.0	7.1
High school graduate or GED	25.9	19.5	19.9
Some college or associate degree	27.7	28.6	29.1
Bachelor's degree	20.1	24.1	23.4
Graduate or professional degree	12.2	19.8	20.5
Household income			
Less than $15,000	14.9	8.2	8.0
$15,000 to $34,999	23.3	15.7	16.3
$35,000 to $49,999	13.3	11.2	11.7
$50,000 to $74,999	19.1	18.3	18.0
$75,000 to $99,999	10.7	14.8	14.4
$100,000 and over	18.7	31.9	31.7
Household size			
1	26.0	16.9	17.3
2	26.6	45.1	45.6
3	16.9	16.8	16.3
4 or more	30.5	21.3	20.8

To demonstrate the efficacy of the wellbeing model system presented in this chapter, 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 chapter through an application to a small sample of records drawn from the 2017 National Household Travel Survey (NHTS) sample. A random sample of 10,000 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.

The resulting sample includes 9,700 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 percentage of older people (than ATUS) and a higher percentage 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. The attributes of the entire NHTS sample are also presented in Table 2-2 to show that the ransom subsample of NHTS is very similar to the entire unweighted NHTS national sample.

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 chapter. Model estimation time as well as the robustness of the estimates were considered in selecting the sample size to facilitate model estimation and application (i.e., sufficient sample sizes to perform analysis of wellbeing for various market segments). The two percent sample yielded usable estimation data set from ATUS (N=5,069) to have a reasonable estimation time with multiple iterations with robust results. For model application purposes, a larger sample from NHTS (N=9,700) has been used because only one application run is needed to get the final results. The next section of the chapter presents the model estimation results.

5. 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 for all the steps in the model estimation section, 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.

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).

It should be noted that the applied MDCEV method, which assigns activities to the time spent at home for each individual in the study, produces the associated activity durations for each activity type. The method, however, does not generate information about the sequence of activities and if the activity is undertaken in one unit of time or multiple units. This limitation of the MDCEV impacts the model output to be the same for people who spent multiple time episodes for one activity type compared to only spending a one-time episode for the same activity at home.

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). Since the model estimation outputs of the MDCEV component are lengthy and not essential to the primary focus of this chapter, they are excluded from discussion. However, for interested readers, the results of the model estimation are provided in Appendix A.

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 9,700 NHTS records were extracted (a 10,000 sample, further filtered and cleaned to remove missing data) 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 2-3. 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 include 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 include watching TV or other screen-based devices). The predictions are in 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 2-3

MDCEV Model Results for Average Time Spent at Home by Activity Category

Activity Category	Observed Time Allocation (ATUS)	MDCEV Model Replication (ATUS)	MDCEV Model Application (NHTS)
	N= 5,069		N= 9,700
	Average (min)	Average (min)	Average (min)
In-home - Sleep	531.8	527.6	508.5
In-home - Maintenance	185.3	188.6	178.9
In-home - Work	18.8	13.0	14.2
In-home - Education	6.5	5.8	5.1
In-home - Eating and drinking	42.7	65.5	65.9
In-home - Recreation/Social	248.5	233.0	231.8
In-home - Shopping	0.7	0.7	0.7
In-home - Religious	2.5	3.0	3.0
In-home - Other	15.6	15.8	15.8

Next, the model development process involved estimating the latent Activity Wellbeing Score (AWS) using the latent joint estimation approach. Table 2-4 illustrates the model estimation results separately for each of in-home, travel, and out-of-home activity categories. An underlying latent variable is assumed to represent AWS in all three models presented for in-home, travel, and out-of-home activities. This latent variable is considered to be a function of individual-level characteristics as well as activity-level attributes. It is also mapped to six indicators, each corresponding to one of the six wellbeing emotions reported by respondents in the ATUS wellbeing module (happiness, meaningfulness, painfulness, sadness, stressfulness, and tiredness). According to the results, the two positive emotions loaded positively, and the four negative emotions loaded negatively onto the AWS. Notably, happiness engenders more positive wellbeing than meaningfulness while sadness and stressfulness are more dominant indicators of negative wellbeing. Also, six threshold values were estimated for every indicator (emotion), but they are not included in this section and can be found in Appendix B.

The results presented in Table 2-4 suggest that the determinants of AWS have behaviorally intuitive interpretations. These determinants encompass both the socio-economic and demographic characteristics of the activity participants, as well as the attributes of the activities themselves. The activity attributes include activity or travel purpose, time and duration of activities, presence of accompaniments, travel modes, and some interaction terms with socio-economic attribute. The results suggest that striking a delicate balance was necessary when considering the inclusion of socio-economic and demographic characteristics alongside activity episode attributes. This is because activity attributes are strongly correlated with, and dependent upon, socio-economic and demographic characteristics. Consequently, when extensive sets of socio-economic and demographic variables were included in the models, the activity episode attributes often turned out to be statistically insignificant. However, since the primary objective of the integrated model system is to capture the wellbeing experienced by individuals in relation to their activity engagement and time use patterns, it was deemed crucial to retain as many attributes of the activity and travel episodes as possible, even if it meant compromising on the inclusion of socio-economic and demographic attributes. As a result, the model specifications include only a modest set of socio-economic variables. Furthermore, it is important to acknowledge the presence of endogeneity, which undoubtedly impacts the results of the model estimation.

The estimation results indicate that females are more likely to have lower AWS for in-home and travel activities, while their AWS during out-of-home activities does not differ significantly from that of males. On the other hand, the oldest age group consistently exhibits a higher degree of AWS for all three types of activities: in-home, travel, and out-of-home. While this can be attributed to the lower prevalence of work episodes among this age group in the case of out-of-home and travel activities, it can also be attributed to the fact that younger age groups are likely to experience more time constraints and stresses, resulting in lower wellbeing scores. The negative coefficient observed for the young age group (20-29 years old) in the context of travel episodes suggests that travel is often perceived as a burden, particularly for younger individuals who may face higher time constraints and pressures. Regarding household composition, individuals living alone report lower AWS for in-home activities, while those living in households with two or more members experience higher AWS for all three activity categories. Notably, income categories exhibit mild significance across the three estimated models. Mid-income individuals tend to have higher AWS for travel episodes, while high-income households show higher AWS for in-home activities and lower AWS for out-of-home activities (to delve deeper into the potential underlying reasons for these AWS differences, Appendix C provides time use patterns of these income groups). Lastly, it is worth mentioning that the presence of children in the household increases AWS for in-home and out-of-home activities, but it does not significantly impact AWS for travel episodes.

When examining the coefficients associated with activity purpose, it becomes evident that all purposes, except for in-home work, traveling to work, and out-of-home maintenance and shopping activities, have a positive impact on AWS. Essentially, all activities are generally regarded more favorably than work conducted at home and travel related to work. Regarding out-of-home activities, shopping and maintenance activities tend to result in lower AWS compared to other activities, while work does not exhibit significant impact. However, it is worth noting that traveling for shopping in the morning yields higher AWS compared to other activities. Recreational, social, eating, and drinking activities consistently demonstrate high AWS scores across in-home, travel, and out-of-home contexts. Notably, the highest coefficients associated with activity types are observed for religious activities when conducted out-of-home in the evening, particularly when individuals undertake such activities without any companions.

Table 2-4

Latent Joint Model Estimation Results for Activity Wellbeing Score

Variables	In-home		Travel		Out-of-home	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Socio-economics						
Female	-0.10	-7.39	-0.05	-2.35	na	na
Age ≥20, ≤29 years	na	na	-0.05	-1.58	na	na
Age ≥60 years	0.27	14.68	0.33	9.84	0.36	10.95
HH Size: 1	-0.11	-6.18	na	na	na	na
HH Size: 2	na	na	0.05	1.66	na	na
HH Size: 3 or more	0.01	1.23	0.07	2.44	0.13	3.69
Employed	0.15	9.73	na	na	-0.13	-4.67
Income >$35k, ≤$50k	na	na	0.12	3.88	na	na
Income >$50k, ≤$75k	na	na	0.06	2.29	na	na
Income >$75k, ≤$100k	0.08	4.27	na	na	na	na
Income >$100k	0.06	3.34	na	na	-0.01	-1.42
Presence of HH children (<18 Years)	0.10	4.18	na	na	0.04	1.14
Activity type/travel purposes						
Work	-0.37	-9.87	-0.11	-2.81	na	na
Maintenance	na	na	na	na	-0.10	-2.90
Recreational/Social	0.06	3.40	0.25	7.43	na	na
Eating/Drinking	0.14	8.13	0.28	6.92	0.20	6.24
Eating/Drinking in the evening	na	na	na	na	0.10	1.18
Shopping	na	na	na	na	-0.32	-5.87
Shopping in the morning	na	na	0.06	1.05		
Shopping by workers	na	na	na	na	0.24	3.80
Religious-alone	na	na	0.39	3.12	na	na
Religious in the evening	na	na	na	na	0.53	1.51
Activity/travel attributes						
Presence of accompaniment	na	na	0.05	1.79	na	na
Duration (in min divided by 100)	-0.04	-5.04	-0.15	-4.61	-0.07	-7.48
Morning	na	na	0.11	3.96	na	na
Evening	na	na	-0.09	-2.59	na	na
Night	na	na	-0.40	-4.13	na	na
Travel mode						
HOV Driver	na	na	0.22	7.39	na	na
HOV Passenger	na	na	0.12	3.46	na	na
Loading factors						
Happiness	0.58	47.05	0.67	25.13	0.76	29.41
Meaningfulness	0.25	24.61	0.29	15.29	0.35	18.07
Painfulness	-0.74	-43.36	-0.53	-21.85	-0.50	-23.03
Sadness	-1.42	-34.63	-1.01	-24.05	-0.97	-29.10
Stressfulness	-1.37	-35.11	-1.14	-24.95	-1.48	-20.22
Tiredness	-0.64	-50.17	-0.71	-25.23	-0.66	-34.31
Goodness-of-fit						
Sample size	34,000		14,000		13,000	
Lok-likelihood of full model	-1470156.6		-590205.0		-540088.9	
Log-likelihood of restricted model	-1473556.6		-592345.6		-542140.3	
K	12		19		12	
Rho squared	0.002		0.004		0.004	

Note: na=not applicable; "Base categories" encompass all categories that are not included for a particular attribute within the in-home, travel, and out-of-home models.

In addition to activity types, other activity attributes are also important. Notably, an increase in activity or travel duration consistently leads to a decrease in AWS for in-home, travel, and out-of-home activities. Interestingly, this effect is more pronounced for travel episodes compared to other activity types. Moreover, travel episodes occurring in the evening and in the middle of the night are generally perceived more negatively than morning episodes, whereas having companions (accompaniments) during travel enhances the wellbeing score. Additionally, it is worth highlighting that high-occupancy vehicle (HOV) travel modes are the only travel modes that exhibit a significant positive relationship with estimating AWS.

The Rho-squared values obtained from the models are relatively low, indicating that there is still a significant amount to learn about the factors influencing and explaining activity wellbeing scores. However, considering that these models were estimated using large, disaggregate person-level datasets, the Rho-squared values are not remarkably different from those commonly encountered in person-level models of activity-travel demand. Nonetheless, it is crucial for future research endeavors to focus on enhancing the model specifications by incorporating attributes that improve the accuracy in explaining and predicting AWS. This will contribute to a more comprehensive understanding of the factors that influence activity wellbeing scores.

6. Illustrative Application of the Model

The integrated wellbeing analysis and estimation model system was applied to a small sample of NHTS records (9,700 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 chapter, 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 wellbeing scores (PWSs) at the individual agent level 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 9,700 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 9,700 individuals. This step will yield a detailed in-home activity profile for each individual. In the next step of the application, the latent joint 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 the forecasting mode to the NHTS data set (which is being treated as equivalent to an activity-based travel model output). The application of the latent joint models will return AWSs (activity wellbeing scores) for each and every activity and travel episode pursued by an individual. Finally, all AWS values for each person are normalized and added up to create a daily person wellbeing score (PWS). This PWS is considered a measure of daily subjective wellbeing that considers the entire activity-travel pattern undertaken by an individual over the course of a day. Table 2-5 furnishes the average PWS for various demographic groups in the data set.

The results are quite intuitive, suggesting that the model system developed in this chapter could serve as a useful tool in assessing the feelings of wellbeing that people derive from their activity-travel patterns and in identifying subgroups of the population that are experiencing lower levels of daily wellbeing (although further investigations would need to be made to determine *why* these subgroups are experiencing lower wellbeing). The trends in the table suggest that females experience a lower degree of wellbeing. Females are generally spending more time inside the home taking care of household obligations and travel less, although they also spend more time with other household members (e.g., children) and engage in flexible and discretionary activities that add value (Cheng et al., 2019; Meloni et al., 2007).

Tenure status, education, income, and vehicle ownership are all correlating variables that undoubtedly impact PWS. 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 the pursuit of desirable leisure activities (McCabe, 2013), which all correspond to a higher average PWS. As educational attainment increases, PWS also increases. However, PWS increases with income from lower to mid-income value, and after that increases in income do not correspond to higher PWS. The findings related to income are consistent with the notion that “money can’t buy happiness” (Kahneman and Deaton, 2010). While wellbeing increases with income up to a certain level, wellbeing decreases after the $100,000 income level, suggesting that those in the high-income brackets have stresses and work-activity durations that decrease wellbeing (Gardner and Oswald, 2001; Kahneman and Deaton, 2010). Vehicle ownership is associated with higher levels of wellbeing, but there is drop in wellbeing at 3+ car ownership levels. This is likely reflecting a similar trend to income that 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 wellbeing (consistent with Bergstad, 2011), presumably due to lack of access to opportunities that come with zero-car ownership.

Table 2-5

Average PWS by Socio-Economic and Activity Attributes (N=9,700)

Attributes	Categories	PWS
Gender	Male	5.67
	Female	4.84
Tenure	Not homeowner	4.38
	Homeowner	5.45
Education	Less than a high school graduate	4.48
	High school graduate or GED	4.74
	Some college or assc. degree	5.05
	Bachelor’s degree	5.53
	Graduate or professional degree	5.90
Income	<$15K	3.78
	≥$15K, <$35K	4.68
	≥$35K, <$50K	5.56
	≥$50K, <$75K	5.41
	≥$75K, <$100K	5.65
	≥$100K	5.46
Household vehicles	0	3.19
	1	4.99
	2	5.54
	3 or more	5.21
Work status (last week)	Working	5.02
	Temporarily absent from a job	5.24
	Looking for work / unemployed	3.76
	A homemaker	4.96
	Going to school	4.15
	Retired	6.15
Age	15 to 20 years	4.35
	21 to 30 years	4.01
	31 to 49 years	4.80
	50 to 64 years	5.15
	65 years or older	6.27
Life cycle	one adult, no children	4.18
	2+ adults, no children	4.70
	one adult, youngest child 0-5	5.51
	2+ adults, youngest child 0-5	5.08
	one adult, youngest child 6-15	5.36
	2+ adults, youngest child 6-15	5.46
	one adult, youngest child 16-21	4.49
	2+ adults, youngest child 16-21	4.76
	one adult, retired, no children	5.24
	2+ adults, retired, no children	6.14

Attributes	Categories	PWS
Location	Urban	5.26
	Rural	5.12
Place of birth	Outside the U.S.	4.85
	U.S.	5.27
Hispanic origin	Hispanic	4.79
	Not Hispanic	5.27
Race	White	5.34
	Black or African American	4.71
	Asian	4.61
	Other	4.72
Driver status	Driver	5.40
	Not Driver	3.56
E-shopping (last month)	No	4.97
	At least once	5.43
Mode use	No walk trip	4.76
	At least one walk trip	5.41
	No bike trip	5.20
	At least one bike trip	5.59
	No transit use	5.26
	At least one transit trip	4.95
	No ridehailing trip	5.26
	At least one ridehailing trip	5.02
Medical condition	No	5.33
	Reduced day-to-day travel	4.41
	Asking others for rides	4.21
	Limiting driving to daytime	4.90
	Giving up driving	3.52
	Using transit less frequently	3.74
	Using special transportation services	3.28
	Using a reduced fare taxi	2.83
Opinion on health	Excellent	5.32
	Very good	5.43
	Good	5.26
	Fair	4.52
	Poor	3.60
Physical activity	None	4.31
	Moderate	5.23
	Vigorous	5.65

Work status indicating the primary activity of the individual during the last week of the survey has a high impact on the level of stated wellbeing. Students presumably experience a lower level of wellbeing because of participation in the education activity – a mandatory activity that is unlikely to be pleasant. Workers are found to experience lower wellbeing than people who are temporarily absent from a job (maybe due to vacation, maternity, or medical condition) and significantly lower than retired individuals. Unemployed individuals who are looking for a job have the lowest wellbeing score – suggesting that the wellbeing in retirement is not necessarily due solely to transition away from a work-oriented life. Homemakers (non-workers of non-retirement age who are taking care of household obligations and maintenance activities) may not have the income and time needed to engage in discretionary activities that offer positive emotions, and they are likely to have slightly lower incomes than workers but better financial situations than unemployed people who are actively looking for a job (Katz, 2015; Gaddis and Wadhwa, 2018).

The results with respect to age confirm that those who are in the retired age groups experience a higher sense of wellbeing. Although there is literature that speaks to the mobility limitations, social exclusion, and lower quality of life that the older adults experience (Glass et al., 2006; Liu et al., 2014), the results in this chapter and others (Archer et al., 2013; Ziems et al., 2010) show that the older adults are experiencing (on average) a high sense of wellbeing and quality of life relative to younger age groups. The breakpoint in the pattern is clearly seen at the age of 65, 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 wellbeing. Indeed, household structure categories show that individuals in retired households experience a higher level of wellbeing 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 wellbeing 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). For non-retired households, the presence of children, in general, corresponds to a higher level of wellbeing based on this chapter for both single and multiple adults in the household.

With respect to location, urban residents experience higher wellbeing than rural residents, presumably due to higher accessibility and mobility means to job opportunities, and various services, stores, and recreational places. However, congestion, pollution, and stresses in the urban ecosystem (Amato and Zuo, 1992) to some extent offset this positive aspect ending up with a small difference in PWS based on being in urban and rural locations.

Those not born in the USA (immigrants) experience lower levels of wellbeing, possibly due to their greater use of transit (Blumenberg 2009; Farber et al., 2018) and inability to afford to participate in discretionary activities that require monetary resources (Farber et al., 2018). Moreover, socio-economic opportunities such as job requirements or the presence of family members might not always be the same for people who are born inside the US compared to the immigrants. For similar reasons, Hispanic ethnic groups experience lower wellbeing levels compared to non-Hispanic people. Similarly, other races endure lower wellbeing levels compared to White people. This finding that race and ethnicity matter when it comes to stated wellbeing level warrants more research to differentiate between the pure impact and other collative attributes such as income and education.

Drivers experience a higher level of wellbeing, largely due to their ability to drive and engage in activities, and the non-driver group represents one of the very disadvantaged groups in this chapter in terms of PWS. This finding highlights that driving is still the key to mobility and accessibility. That being said, people who had at least one online shopping delivery in the last month experienced higher PWS compared to people with zero deliveries.

The auto mode has been found to engender more positive emotions for travel episodes (Mokhtarian and Pendyala, 2018), and the results in Table 2-4 illustrate that people who do not use transit at all during the survey day experience higher PWS compared to transit users. Those who walk and bike report a higher level of wellbeing, suggesting that walking (which might be undertaken for leisure purposes as well) is associated with a more positive lifestyle. On the other hand, the use of ridehailing services (which may be indicative of lower access to personal vehicles) is associated with lower degrees of wellbeing – suggesting that policies and investments are needed to improve the travel experience and destination accessibility for on-demand modes.

As expected, those with a disability experience a lower level of wellbeing, presumably due to mobility and activity engagement limitations. The amount and status of mobility limitation that accompanies medical conditions highly matter. People who have limited nighttime driving, reduced daily travel, and needed to ask others for rides represent higher WBS compared to people who are using transit less frequently, using special transportation services, and using the reduced fare taxi (the most disadvantaged group). Relative to the actual medical condition, the stated health level also correlates directly with PWS. As expected, those in poor health appear to experience lower wellbeing; 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). Lastly, people who participate in vigorous physical activities experience higher PWS compared to people with moderate and no exercise activity levels.

To further illustrate the wellbeing scores output by the model system, the distributions of wellbeing scores are shown in Figure 2-2. The entire sample of 9,700 respondents was divided into quintiles based on the sorting of wellbeing scores. The top quintile has the highest wellbeing scores, while the bottom quintile has the lowest. These five quintiles are labeled as having very positive to very negative wellbeing. The figure shows how each demographic group is distributed across the five bands of wellbeing quintiles. For example, consider work status; 18 percent of workers and 14 percent of retirees fall into the very negative category, but 46 percent of unemployed 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 2-5. The income relationship shows a pattern consistent with the notion that wellbeing increases with income up to a certain point but drops at the highest income levels. As age increases, the proportion of people with low wellbeing level decreases and the proportion of people with high wellbeing level increases steadily. More than half of people in 21 to 30 years are in very negative and negative wellbeing groups. The majority of people who do not drive and/or have medical conditions limiting their mobility or have zero vehicle ownership belong to very negative or negative wellbeing groups. This finding significantly highlights the impact of transportation on quality of life by providing accessibility and mobility means to various mandatory and non-mandatory destinations. New transportation technologies and services such as autonomous vehicles and Mobility-as-a-Service (MaaS) platforms have considerable potential to improve mobility and accessibility of medically and economically disadvantaged groups with proper planning and policy practices.

One of the major reasons why these patterns of wellbeing may be seen in Figure 2-2 is that time use patterns differ across groups. These distributions are shown in Figure 2-3. 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 the home and sleep can only be undertaken inside the home. These distributions should be viewed in the context of the wellbeing distributions shown in Figure 2-2.

Figure 2-2

Distribution of Demographic Groups by PWS Segment (N=9,700)

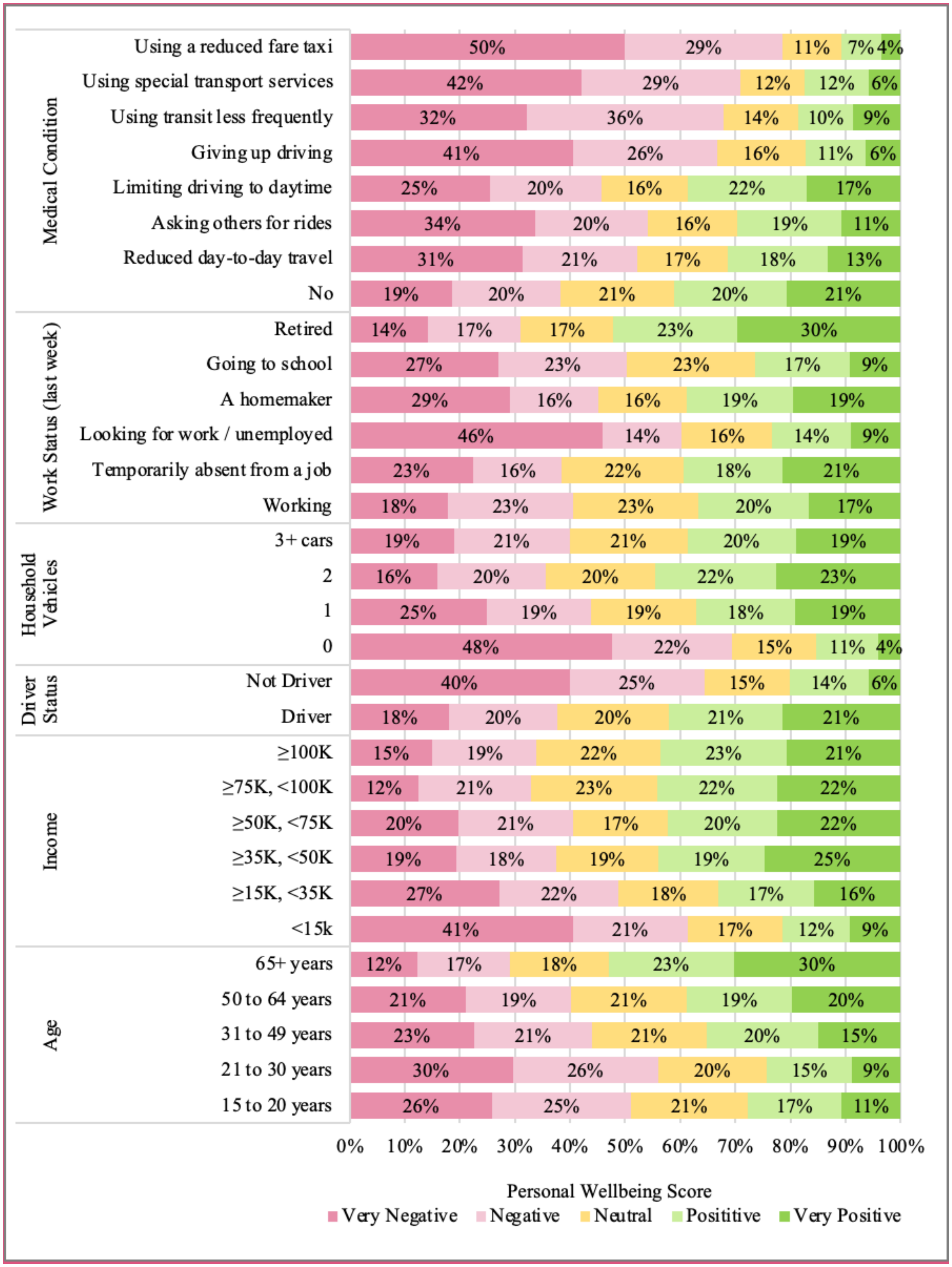
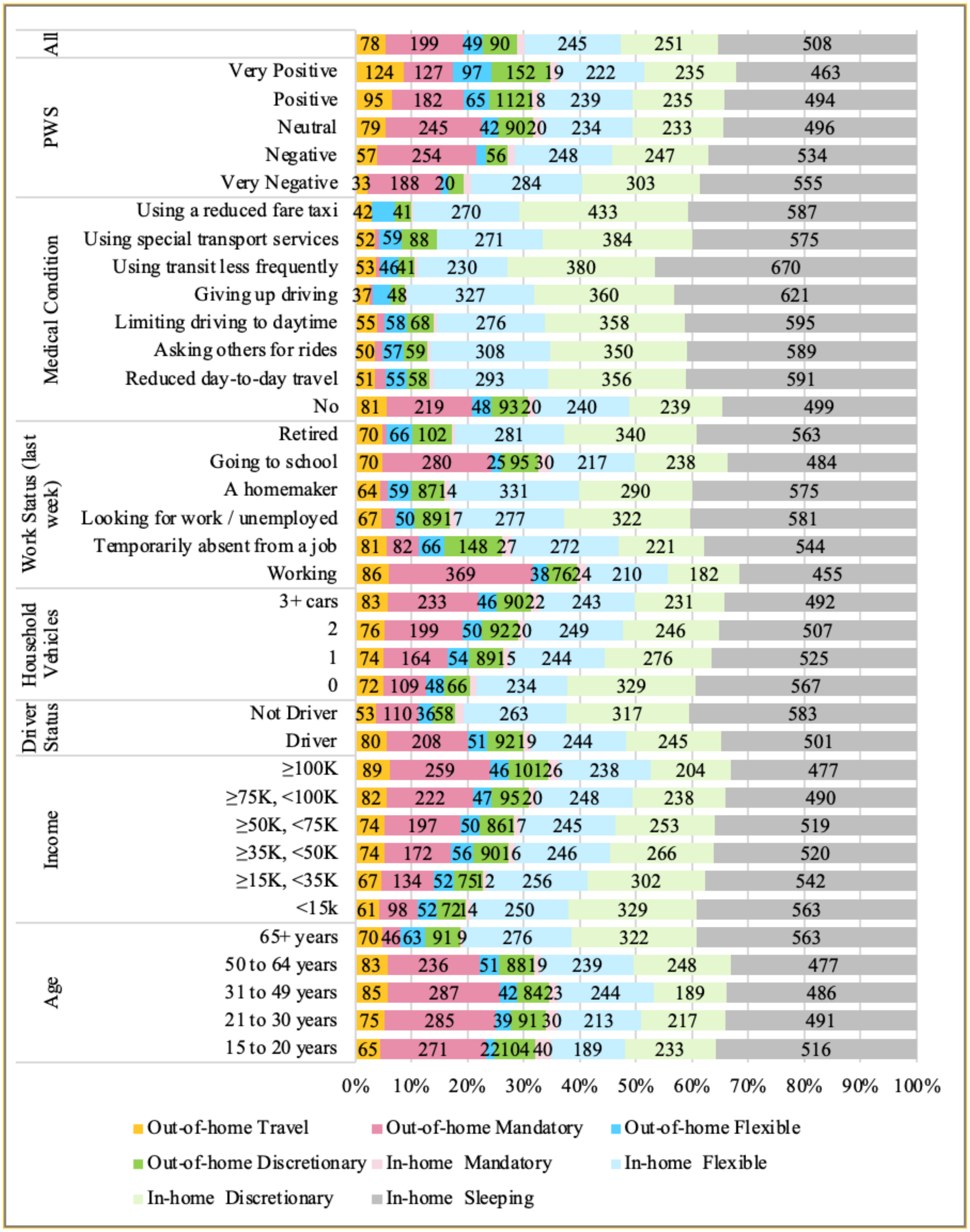


Figure 2-3

Distribution of Sample Groups by Time (min) Allocation to Activities (N=9,700)



Patterns of association between time use and wellbeing can be seen across the figures. For the sample as a whole, those in the very negative groups (top of Figure 2-3) spend a lot more time in-home, and a lot less time on travel and out-of-home flexible and discretionary activities. Those in the highest wellbeing quintile spend much less time on mandatory activities and a lot more time on travel and out-of-home discretionary activities. For older adults above 65 years, the dramatic drop in work duration is accompanied by longer sleep duration and significant increases in in-home flexible and discretionary activity durations. However, they are still making a good amount of travel similar to younger age groups more on flexible and discretionary activities. The highest-income individuals spend more time working and more time traveling, both of which contribute to a decrease in wellbeing. They do spend more time on out-of-home discretionary activities, but the dramatically lower time spent on in-home discretionary activities lowers wellbeing overall. Mobility constrained medical conditions, low vehicle ownership, and inability to drive clearly illustrate the negative impact on the amount of time individuals spend on out-of-home and travel activities. However, wellbeing is obviously not tied solely to activity and time use patterns. The retirees, homemakers, and unemployed people's time use patterns are very similar while their PWS distributions illustrate more complex relationships at play. Those unemployed do not enjoy a higher wellbeing score from staying at home and doing discretionary activities. Older individuals spend a lot more time in-home, but that is not necessarily leading to lower wellbeing because they are presumably relaxed, not saddled with household and child-rearing obligations, and able to engage in activities that they enjoy. On the other hand, students are spending a significant amount of time out-of-home on mandatory activity and experience a very low level of wellbeing. In other words, the ability to travel and undertake out-of-home activities independently significantly impacts the personal stated wellbeing level but does not explain the story and underlying dynamics of quality of life entirely.

7. Conclusions

Transportation and wellbeing 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 wellbeing and activity-travel patterns, little progress has been made in translating measures of activity-travel behavior into measures of wellbeing. As a result, the time use patterns themselves are often viewed as indicators of wellbeing 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 wellbeing 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 (wellbeing) impacts of alternative investments, technologies, and policies.

To fill this void, this chapter presents a comprehensive model system of wellbeing 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 wellbeing module of the American Time Use Survey (ATUS) to develop models of wellbeing scores as a function of socio-economic and activity-travel variables. One of the challenges associated with developing a comprehensive wellbeing 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 wellbeing 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, wellbeing scores can be computed for each individual using the model system developed in this chapter. The chapter 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 typical activity-based model output. The results are intuitive and consistent with the notion that being able to travel and participate in out-of-home flexible and discretionary activity engagement contributes positively to wellbeing.

A key finding that was derived from the analysis of the wellbeing module of the time use data set and the application of the wellbeing score models (to the random sample of NHTS records) is that wellbeing is dependent on out-of-home activity engagement and travel, but other factors are also important and can affect this relationship. Older individuals do not appear to be experiencing a lower quality of life by staying home; in fact, they appear to be experiencing the highest wellbeing, 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 wellbeing and time poverty (i.e., time devoted to discretionary activities) appears to be a stronger one, rather than the connection between wellbeing 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 wellbeing, degree of social exclusion, and quality of life. What is found is that those with poor health status, mobility constrained medical conditions, zero vehicle ownership, inability to drive, and low income (less than $15,000 annual household income) experience the lowest degrees of wellbeing, calling for greater interventions, investments, and policies that enable their participation in society and discretionary activities. While workers experience lower wellbeing, presumably due to suffering from time poverty as they spend a significant amount of time on work and commuting, unemployed individuals also experience lower wellbeing, despite having much fewer mandatory activities to allocate their time to. These individuals spend a lot more time sleeping (which yields diminishing returns rapidly above a certain threshold) and more time fulfilling in-home obligations and maintenance activities without enough chores to yield much in the way of wellbeing. For this group (unlike the older adult group), the substantial time spent in-home may indeed be leading to a lower quality of life; thus, the connection between wellbeing and out-of-home activity engagement (and travel) is much more nuanced and varies across demographic segments.

Overall, the model system developed in this chapter may be used in conjunction with activity-based travel models to assess the wellbeing implications of transportation investments and actions for different subgroups of the population. This is useful in the context of environmental justice and equity assessments. It may also provide insights into the planning directions of emerging autonomous and shared mobility systems, regarding how they can be effectively deployed to serve disadvantaged population groups in terms of mobility and quality of life. Future research should focus on enriching the models of wellbeing scores with additional attributes (such as attitudes and built environment variables) 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.

8. Acknowledgment

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9. References

Abou-Zeid, M., & Ben-Akiva, M. (2012). Well-being and activity-based models. *Transportation*, *39*, 1189-1207.

Abou-Zeid, M., & Ben-Akiva, M. (2011). The effect of social comparisons on commute well-being. *Transportation Research Part A: Policy and Practice*, *45*(4), 345-361.

Amato, P. R., & Zuo, J. (1992). Rural poverty, urban poverty, and psychological well-being. *The Sociological Quarterly*, *33*(2), 229-240.

American Time Use Survey. *Bureau of Labor Statistics*. Retrieved from https://www.bls.gov/tus/

Astroza, S., Pinjari, A. R., Bhat, C. R., & Jara-Díaz, S. R. (2017). A Microeconomic Theory–Based Latent Class Multiple Discrete–Continuous Choice Model of Time Use and Goods Consumption. *Transportation Research Record*, *2664*(1), 31-41.

Archer, M., Paleti, R., Konduri, K. C., Pendyala, R. M., & Bhat, C. R. (2013). Modeling the connection between activity-travel patterns and subjective well-being. *Transportation Research Record*, *2382*(1), 102-111.

Bergstad, C. J., Gamble, A., Gärling, T., Hagman, O., Polk, M., Ettema, D., ... & Olsson, L. E. (2011). Subjective well-being related to satisfaction with daily travel. *Transportation*, *38*, 1-15.

Blumenberg, E. (2009). Moving in and moving around: immigrants, travel behavior, and implications for transport policy. *Transportation Letters*, *1*(2), 169-180.

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological*, *42*(3), 274-303.

Brickman, P., & Campbell D.T. (1971). *Hedonic relativism and planning the good society. In Appley, M.H. (Ed.)*. Adaptation Level Theory: A Symposium, Academic Press, New York, 287-302.

Chatterjee, K., Chng, S., Clark, B., Davis, A., De Vos, J., Ettema, D., ... & Reardon, L. (2020). Commuting and wellbeing: a critical overview of the literature with implications for policy and future research. *Transport Reviews*, *40*(1), 5-34.

Cheng, L., Chen, X., Yang, S., Wu, J., & Yang, M. (2019). Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. *Transportation Letters*, *11*(6), 341-349.

Churchill, S. A., & Smyth, R. (2019). Transport poverty and subjective wellbeing. *Transportation Research Part A: Policy and Practice*, *124*, 40-54.

de Abreu e Silva, J., Martinez, L., & Goulias, K. (2012). Using a multi equation model to unravel the influence of land use patterns on travel behavior of workers in Lisbon. *Transportation Letters*, *4*(4), 193-209.

De Vos, J., Schwanen, T., Van Acker, V., & Witlox, F. (2013). Travel and subjective well-being: A focus on findings, methods and future research needs. *Transport Reviews*, *33*(4), 421-442.

Delbosc, A. (2012). The role of well-being in transport policy. *Transport Policy*, *23*, 25-33.

Delbosc, A., & Currie, G. (2011). The spatial context of transport disadvantage, social exclusion and well-being. *Journal of Transport Geography*, *19*(6), 1130-1137.

Duarte, A., Garcia, C., Limao, S., & Polydoropoulou, A. (2009). *Experienced and expected happiness in transport mode decision making process* (No. 09-2199).

Eluru, N., Pinjari, A., Pendyala, R., & Bhat, C. (2010). An econometric multi-dimensional choice model of activity-travel behavior. *Transportation Letters*, *2*(4), 217-230.

Ettema, D., Gärling, T., Olsson, L. E., & Friman, M. (2010). Out-of-home activities, daily travel, and subjective well-being. *Transportation Research Part A: Policy and Practice*, *44*(9), 723-732.

Farber, S., Mifsud, A., Allen, J., Widener, M. J., Newbold, K. B., & Moniruzzaman, M. (2018). Transportation barriers to Syrian newcomer participation and settlement in Durham Region. *Journal of Transport Geography*, *68*, 181-192.

Ferenchak, N. N., & Katirai, M. (2015). Commute mode and mental health in major metropolitan areas. *Transportation Letters*, *7*(2), 92-103.

Forgeard, M. J., Jayawickreme, E., Kern, M. L., & Seligman, M. E. (2011). Doing the right thing: Measuring wellbeing for public policy. *International Journal of Wellbeing*, *1*(1).

Fox, K. R. (1999). The influence of physical activity on mental well-being. *Public Health Nutrition*, *2*(3a), 411-418.

Frederick, S., & Loewenstein G. (1999). *Hedonic adaptation*. In Kahneman, D., E. Diener, and N. Schwarz (Eds.). Foundations of Hedonic Psychology: Scientific Perspectives on Enjoyment and Suffering. Russell Sage Foundation, New York, 302-329.

Frijters, P., & Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, *82*(2-3), 525-542.

Friman, M., Gärling, T., Ettema, D., & Olsson, L. E. (2017). How does travel affect emotional well-being and life satisfaction?. *Transportation Research Part A: Policy and Practice*, *106*, 170-180.

Gaddis, I. & Wadhwa D. (2018). *Poverty Lies Beyond the Unemployed*. World Bank Blogs. Retrieved from https://blogs.worldbank.org/opendata/poverty-lies-beyond-unemployed

Gao, Y., Rasouli, S., Timmermans, H., & Wang, Y. (2017). Understanding the relationship between travel satisfaction and subjective well-being considering the role of personality traits: A structural equation model. *Transportation Research Part F: Traffic Psychology and Behaviour*, *49*, 110-123.

Gardner, J., & Oswald, A. (2001). Does money buy happiness? A longitudinal study using data on windfalls. Retrieved from https://warwick.ac.uk/fac/soc/economics/staff/ajoswald/marchwindfallsgo.pdf.

Gärling, T. (2019). Travel-related feelings: review, theoretical framework, and numerical experiments. *Transportation Letters*, *11*(1), 54-62.

Glass, T. A., De Leon, C. F. M., Bassuk, S. S., & Berkman, L. F. (2006). Social engagement and depressive symptoms in late life: longitudinal findings. *Journal of Aging and Health*, *18*(4), 604-628.

Humphreys, D. K., Goodman, A., & Ogilvie, D. (2013). Associations between active commuting and physical and mental wellbeing. *Preventive Medicine*, *57*(2), 135-139.

Jensen, R. A., Kirkegaard Thomsen, D., O'Connor, M., & Mehlsen, M. Y. (2020). Age differences in life stories and neuroticism mediate age differences in subjective well-being. *Applied Cognitive Psychology*, *34*(1), 3-15.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, *107*(38), 16489-16493.

Katz, J (2015). How Nonemployed Americans Spend Their Weekdays: Men vs. Women. *The New York Times*. Retrieved from https://www.nytimes.com/interactive/2015/01/06/upshot/how-nonemployed-americans-spend-their-weekdays-men-vs-women.html

Krueger, A. B., Kahneman, D., Fischler, C., Schkade, D., Schwarz, N., & Stone, A. A. (2009). Time use and subjective well-being in France and the US. *Social Indicators Research*, *93*, 7-18.

Lee, R. J., & Sener, I. N. (2016). Transportation planning and quality of life: Where do they intersect?. *Transport Policy*, *48*, 146-155.

Liu, L., Gou, Z., & Zuo, J. (2016). Social support mediates loneliness and depression in elderly people. *Journal of Health Psychology*, *21*(5), 750-758.

Lucas, K. (2012). Transport and social exclusion: Where are we now?. *Transport Policy*, *20*, 105-113.

McCabe, B. J. (2013). Are homeowners better citizens? Homeownership and community participation in the United States. *Social Forces*, *91*(3), 929-954.

Meloni, I., E. Spissu, and M. Bez. A Model of the Dynamic Process of Time Allocation to Discretionary Activities. *Transportation Science*, 41(1), 2007, 15-28.

Mokhtarian, P.L. & Pendyala R.M. (2018). Travel Satisfaction and Well-being. In *Applying Quality of Life Research*, *Best Practices* (M. Friman, D. Ettema, and L. E. Olsson, ed.), Springer International Publishing AG., 17-39.

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation Research Part A: Policy and Practice*, *35*(8), 695-719.

National Research Council (2013). Subjective Well-being: Measuring Happiness, Suffering, and Other Dimensions of Experience. *The National Academies Press*.

National Household Travel Survey (2018). *Federal Highway Administration*. Retrieved from https://nhts.ornl.gov/

Schwanen, T., Lucas, K., Akyelken, N., Solsona, D. C., Carrasco, J. A., & Neutens, T. (2015). Rethinking the links between social exclusion and transport disadvantage through the lens of social capital. *Transportation Research Part A: Policy and Practice*, *74*, 123-135.

Oswald, A. J., & Wu, S. (2010). Objective confirmation of subjective measures of human well-being: Evidence from the USA. *Science*, *327*(5965), 576-579.

Sener, I., Bhat, C., & Pendyala, R. (2011). When, where, how long, and with whom are individuals participating in physically active recreational episodes?. *Transportation Letters*, *3*(3), 201-217.

Shergold, I (2020). Older people and out-of-home mobility: Is discretionary travel undervalued in current policy? (PhD Dissertation). University of the West of England. Retrieved from https://uwe-repository.worktribe.com/output/1491023.

Stutzer, A., & Frey, B. S. (2006). Does marriage make people happy, or do happy people get married?. *The Journal of Socio-Economics*, *35*(2), 326-347.

Singleton, P. A. (2020). Exploring the positive utility of travel and mode choice: subjective well-being and travel-based multitasking during the commute. In *Mapping the Travel Behavior Genome* (pp. 259-277).

Waygood, E. O. D., Friman, M., Olsson, L. E., & Taniguchi, A. (2017). Transport and child well-being: An integrative review. *Travel Behaviour and Society*, *9*, 32-49.

Williams, J. R., Masuda, Y. J., & Tallis, H. (2016). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*, 265-283.

Ye, X., Konduri, K., Pendyala, R. M., & Sana, B. (2009). Formulation of an Activity-Based Utility Measure of Time Use: Application to Understanding the Influence of Constraints. *Transportation Research Record*, *2135*(1), 60-68.

Ye, R., & Titheridge, H. (2017). Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. *Transportation Research Part D: Transport and Environment*, *52*, 535-547.

Ziems, S. E., Konduri, K. C., Sana, B., & Pendyala, R. M. (2010). Exploration of time use utility derived by older individuals from daily activity–travel patterns. *Transportation Research Record*, *2156*(1), 111-119.

CHAPTER 3

MOBILITY, TIME POVERTY, AND WELLBEING: HOW ARE THEY CONNECTED AND HOW MUCH DOES MOBILITY MATTER?

1. Introduction

Transportation systems – which enable people to travel, interact with others in person, and access destinations and economic opportunities – are viewed as critical to the vitality of a community, city, and country. The mobility afforded by transportation systems enables participation in society, accumulation of life experiences, and fulfillment of activities, all of which may be regarded as key determinants of quality of life. Investments in transportation infrastructure are therefore seen as investments in societal wellbeing because they ease the flow of goods and services and connect people and places.

In light of the connection that is often drawn between transportation and the ability to engage in societal functions, those who are mobility disadvantaged may experience a lower quality of life. A number of studies have drawn a connection between mobility limitations and quality of life, focusing particularly on the notion of social exclusion (Stanley et al., 2011; Delbosc and Currie, 2011). Several demographic groups including older adults, people with disabilities, low-income individuals, minorities, and those without access to a vehicle have generally been identified as being at risk of social exclusion because of their inability to use the transportation system and engage in (desirable) activities outside the home (Motte-Baumvol et al., 2012; Adeel et al., 2018; Corran et al., 2018). The inability to interact in person with the greater society outside the home may lead to isolation, depression, and other mental health issues (Windsor et al., 2007; Spinney et al., 2009; Stanley et al., 2011; Morris, 2015).

As a result of the seemingly important connection between mobility, participation in society, and quality of life, the literature has a number of examples and case studies that badge zero out-of-home activity-travel engagement as being representative of a poor quality of life (Kenyon et al., 2002; Spinney et al., 2009). While there is undoubtedly merit to the argument that an inability to travel (say, due to physiological or intellectual disabilities) may contribute to a lower quality of life, a systematic study that explicitly relates activity and time use patterns with measures of subjective wellbeing (which may be considered representative of quality of life, at least in the short term) would help establish and define the nature of the connection.

In the United States, the percent of individuals depicting daily activity-travel patterns characterized by zero trips (in the day) is on the rise. An analysis of the newest 2017 National Household Travel Survey data set shows that the percent of zero-trip makers is at the highest level since 2001 even though the data was collected at a time of relatively prosperous economic conditions characterized by record low unemployment rates. Why is zero-trip making on the rise? In the absence of explicit data to address this question, it is difficult to say for sure as to why the zero-trip making segment is rising over time. Some conjectures may be made, particularly in the context of the rapid evolution of technology and the workplace. Mobile technologies, ubiquitous connectivity, social media platforms, e-commerce, delivery-based services, streaming on-demand entertainment, and the internet of things have made it possible for individuals to work, study, play, shop, interact (virtually), and eat at home – essentially enjoying a high quality of life without setting foot outside the comforts of home.

It may be hypothesized that the zero-trip making segment is likely comprised of (at least) two broad segments; those who do not travel because they are truly mobility disadvantaged and those who do not want or need to travel because they can (happily) fulfill all of their activity needs from the comfort of their couch. While the former group is likely to experience a diminished sense of wellbeing (because they are not able to accomplish activities that they would like to undertake), the latter group may not necessarily be experiencing any diminished sense of wellbeing. In fact, they may be experiencing an elevated sense of wellbeing because they are accomplishing what they want to do at home and do not have to grapple with congestion, search for parking, wait for the bus, or be exposed to the elements. In other words, if travel is truly a disutility to be minimized and people are able to accomplish activities at home, then those who consciously choose not to travel are unlikely to be experiencing a lower quality of life – and may actually be experiencing a higher quality of life (as they eliminate the disutility of travel from their daily agenda).

A parallel stream of research in sociological literature has focused on the notion of "time poverty". This concept has been introduced as an alternative to the traditional notion of income poverty with a view to better understanding wellbeing and quality of life. Different researchers have suggested alternative definitions and criteria for defining time poverty, but the central idea underlying this notion is that those who spend less time on leisure activities (below a certain threshold) are said to experience time poverty (Vickery, 1977; Williams et al., 2016).

Although there is a body of literature devoted to time poverty and another devoted to activity-travel behavior and wellbeing, there is very little work that connects these strands of research. It is undoubtedly likely that time poverty and subjective wellbeing are closely related to one another. If subjective wellbeing is higher for those who pursue leisure activities, then those who experience time poverty will have a lower subjective wellbeing. One objective of this chapter is to determine the extent to which time poverty and subjective wellbeing are aligned with one another. This is accomplished by examining wellbeing and time use details in the 2017 version of the American Time Use Survey (ATUS) for which the wellbeing information was generated by reproducing the wellbeing data available in the 2010, 2012, and 2013 versions of ATUS which included wellbeing modules that collected data on emotional ratings for various activities and feelings (happiness, meaningfulness, sadness, painfulness, stress, and tiredness). The first preliminary objective of this chapter is to establish the connection between time poverty and feelings of wellbeing. It is hypothesized that there is a high degree of alignment between these two concepts.

The overarching goal of this chapter is to examine the extent to which transportation (mobility) contributes to time poverty and subjective wellbeing. As noted earlier, not all zero-mobility individuals are created equal; there are those who desire to travel, but are not able to do so, and then there are others who consciously choose not to travel because that is their intrinsic preference. In this chapter, detailed comparisons of time poverty and subjective wellbeing are conducted between zero-trip makers and trip makers. These comparisons are made for a variety of groups, including those that are generally considered mobility disadvantaged. The comparisons in time poverty and subjective wellbeing between zero-trip makers and trip makers will help in identifying the specific groups for which zero-trip making is actually resulting in a lower subjective wellbeing and a greater degree of time poverty.

The remainder of this chapter is organized as follows. The next section describes the data used in the chapter. The third section documents an analysis of wellbeing and time poverty based on the ATUS wellbeing data. The fourth section provides a comparison of zero-trip makers and trip makers with respect to their degree of time poverty and wellbeing scores, with a view to identifying the role of transport in shaping these quality-of-life measures. Finally, concluding thoughts are offered in the fifth section.

2. Data

This chapter primarily utilizes data from the 2017 American Time Use Survey (ATUS) data collected by the Bureau of Labor Statistics (BLS) in the United States. The 2017 ATUS provides detailed activity and time use data for a representative sample of 10,223 persons. The ATUS has individuals record all of their activities over the course of a day, including travel episodes. Because travel episodes are recorded, it is possible to identify individuals who did not engage in any travel on the survey day. However, because it is a time use survey as opposed to a travel survey, there may be concerns as to whether the time use survey adequately captured all travel episodes and provides an accurate depiction of the percentage of individuals who are zero-trip makers in various population groups.

As a first step aimed at vetting the ATUS data with respect to its data on travel episodes, statistical measures on zero-trip making obtained from the ATUS data were compared against those obtained from the National Household Travel Survey (NHTS) data set collected in the same year of 2017. The NHTS series is conducted by the US Department of Transportation to obtain detailed information about household and personal travel over the course of a 24-hour period (travel survey day). The 2017 edition of the survey obtained travel diary information from a sample of 264,234 individuals; although this is a very large sample, it is not necessarily representative of the general population because some states and jurisdictions were over-sampled at their request. Prior research has analyzed differences between travel surveys and time use surveys in terms of measures of travel and zero-trip making. Findings vary across studies. Some indicated time use surveys reporting higher levels of zero-trip making (Bose et al., 2005), while others reported that zero-trip makers appear higher in travel surveys (Aschauer et al., 2018; Yennamani and Srinivasan, 2008; Richardson, 2007). Therefore, in the context of this chapter, comparing NHTS and ATUS not only contributes to this strand of literature, but also enables an assessment of the appropriateness of using ATUS to draw inferences about travel and zero-trip making among various population groups.

A comparison of zero-trip makers and trip makers is presented in Tables 3-1 and 3-22. The samples were divided into four distinct and broad groups by day of week (weekday vs weekend) and employment status (worker vs non-worker) – excluding students. The four groups are tabulated with respect to their socio-economic characteristics in the context of zero-trip making and trip making. For comparison purposes, the analysis is limited to individuals of driving age, 15 years and over.

Table 3-1 shows the two weekday segments while Table 3-2 shows statistics for the two weekend segments. Overall, it can be seen that workers depict a low prevalence of zero-trip making on weekdays. Only 7.3 percent of workers are zero-trip makers on weekdays in the NHTS; the corresponding percentage in the ATUS is 5.6 percent. For non-workers, the prevalence of zero-trip making is much higher. While 27 percent of non-workers are identified as zero-trip makers on weekdays in the NHTS, the corresponding percentage in the ATUS is 28.6 percent. In other words, the two surveys provide rather equivalent measures of zero-trip making in the population. Note that all NHTS and ATUS statistics are based on weighted data to account for the oversampling and representativeness issues of the raw sample. However, all of the sample sizes are reported based on the raw sample so that the reader has a sense of the survey sample sizes for various groups.

The remainder of Table 3-1 provides a detailed picture of the composition of zero-trip makers and trip makers. In general, the statistics are consistent with expectations and mimic the presence of various demographic groups in the population. For example, a majority of non-workers in the population are females. Their presence is therefore higher in all four non-worker segments (NHTS and ATUS zero-trip makers and trip makers). However, there are subtle differences that suggest important demographic differences in the prevalence of zero-trip making. For example, consider the weekday-worker segment in the ATUS sample. The zero-trip maker subsample is about equally split between females and males (49.5 to 50.5 percent). The trip maker subsample has a higher proportion of males than females (54.7 percent males to 45.3 percent females). By combining the information contained in the two columns, it is possible to infer that females have a diminished level of trip making than males.

Overall, it can be seen that ATUS and NHTS are rather similar in the extent to which they portray zero-trip making among various population groups. A few differences are discernible, however. For example, consider the age distributions in the weekday-worker segment. In the NHTS, the age distributions between zero-trip makers and trip makers are rather similar (qualitatively speaking). However, the ATUS shows a marked difference in the distributions. Among zero-trip makers, 37.9 percent fall in the 51-65 year age category, and 8.9 percent fall in the 66+ year age category. Among trip makers, the corresponding percentages are 27.9 percent and 5.5 percent. Thus, in the ATUS it appears that zero-trip makers (in the weekday-worker segment) do skew towards older age groups when compared to trip makers. However, this skew is not seen in the NHTS, suggesting that there are subtle but important differences in the inferences drawn from different survey approaches. While the time use survey suggests that older people above the age of 50 comprise 46.8 percent of zero-trip makers, the travel survey suggests that older people above the age of 50 comprise only 31.9 percent of zero-trip makers (which is very close to the value of 31.7 percent for trip makers in the travel survey). These differences should be kept in mind when studying zero-trip making among different demographic groups. A few other differences emerge between NHTS and ATUS in the context of race, household location, and household size.

Table 3-1

Socio-Economic and Demographic Characteristics of the Weekday Samples (Weighted | N_{NHTS}=230,081, N_{ATUS}=9,560)

Person Characteristics		Segment 1: Weekday*Workers				Segment 2: Weekday*Non-workers			
		NHTS 2017 (N=78,685)		ATUS 2017 (N=2,282)		NHTS 2017 (N=64,522)		ATUS 2017 (N=1,532)	
Attribute	Categories	Zero-trip maker (7.3%)	Trip maker (92.7%)	Zero-trip maker (5.6%)	Trip maker (94.4%)	Zero-trip maker (27.0%)	Trip maker (73.0%)	Zero-trip maker (28.6%)	Trip maker (71.4%)
Gender	Female	48.7 (7.6)	46.6 (92.4)	49.5 (6.1)	45.3 (93.6)	60.5 (27.5)	59.0 (72.5)	62.8 (29.2)	61.1 (70.8)
	Male	51.3 (7.1)	53.4 (92.9)	50.5 (5.2)	54.7 (94.8)	39.5 (26.3)	41.0 (73.7)	37.2 (27.7)	38.9 (72.3)
Age	15–20	7.4 (11.6)	4.4 (88.4)	2.1 (6.6)	1.8 (93.4)	6.9 (25.4)	7.5 (74.6)	3.1 (10.3)	10.8 (89.7)
	21–30	20.4 (7.4)	20.2 (92.6)	7.8 (2.2)	20.2 (97.8)	12.9 (30.3)	10.9 (69.7)	6.1 (22.4)	8.5 (77.6)
	31–50	40.3 (6.8)	43.7 (93.2)	43.3 (5.4)	44.5 (94.6)	17.0 (25.0)	18.9 (75.0)	11.1 (20.0)	17.9 (80.0)
	51–65	26.0 (7.2)	26.5 (92.8)	37.9 (7.5)	27.9 (92.5)	23.6 (25.5)	25.5 (74.5)	28.7 (33. 9)	22.5 (66.1)
	66 or more	5.9 (8.2)	5.2 (91.8)	8.9 (8.6)	5.5 (91.4)	39.6 (28.3)	37.2 (71.7)	51.0 (33.6)	40.4 (66.4)
Educational attainment	Less than a high school diploma	5.0 (11.5)	3.1 (88.5)	15.8 (13.1)	6.2 (86.9)	15.1 (35.6)	10.1 (64.4)	20.1 (27.2)	21.5 (72.8)
	High school graduate or GED	26.2 (10.0)	18.7 (90.0)	24.9 (5.0)	28.2 (95.0)	35.4 (32.3)	27.4 (67.7)	41.0 (34.3)	31.5 (65.7)
	Some college or associates degree	31.4 (7.6)	30.4 (92.4)	19.6 (4.6)	23.9 (95.4)	29.0 (25.4)	31.4 (74.6)	19.4 (26.4)	21.7 (73.6)
	Bachelor's degree	21.2 (6.0)	26.4 (94.0)	25.5 (5.5)	25.8 (94.5)	12.5 (21.2)	17.2 (78.8)	13.3 (25.6)	15.5 (74.4)
	Graduate or professional degree	16.2 (5.6)	21.5 (94.4)	14.2 (5.0)	15.9 (95.0)	8.0 (17.6)	13.9 (82.4)	6.2 (20.3)	9.8 (79.7)
Race	White	69.9 (6.9)	74.6 (93.1)	73.5 (5.0)	82.2 (95.0)	70.0 (26.4)	72.1 (73.6)	76.0 (26.9)	82.7 (73.1)
	Black	12.9 (8.2)	11.5 (91.8)	20.6 (9.8)	11.3 (90.2)	14.7 (27.3)	14.5 (72.7)	18.4 (38.5)	11.8 (61.5)
	Asian	7.0 (9.3)	5.4 (90.7)	3.4 (4.5)	4.3 (95.5)	6.5 (33.2)	4.8 (66.8)	3.8 (35.3)	2.8 (64.7)
	Some other race	10.1 (8.6)	8.5 (91.4)	2.5 (6.1)	2.3 (93.9)	8.8 (27.5)	8.6 (72.5)	1.8 (21.0)	2.7 (79.0)
Annual household income	< $35K	26.8 (9.2)	20.7 (90.8)	18.6 (5.7)	18.1 (94.3)	48.5 (29.4)	42.6 (70.6)	56.0 (35.7)	40.4 (64.3)
	≥ $35K, < $50K	11.8 (7.3)	11.7 (92.7)	15.4 (6.7)	12.7 (93.3)	11.4 (25.5)	12.2 (74.5)	16.7 (29.6)	15.9 (70.4)
	≥ $50K, < $75K	17.3 (7.3)	17.2 (92.7)	16.3 (4.3)	21.3 (95.7)	15.0 (26.5)	15.3 (73.5)	11.4 (21.6)	16.6 (78.4)
	≥ $75K	44.2 (6.4)	50.3 (93.6)	49.6 (5.8)	47.8 (94.2)	25.1 (23.5)	29.9 (76.5)	15.9 (19.0)	27.1 (81.0)
Household size	1	8.9 (5.4)	12.3 (94.6)	13.0 (5.4)	13.3 (94.6)	16.1 (23.8)	19.1 (76.2)	23.7 (33.2)	19.1 (66.8)
	2	30.6 (7.4)	30.4 (92.6)	31.3 (5.1)	34.6 (94.9)	35.7 (25.9)	37.9 (74.1)	48.6 (32.6)	40.2 (67.4)
	3	22.3 (7.6)	21.5 (92.4)	22.7 (6.4)	19.6 (93.6)	18.2 (27.6)	17.7 (72.4)	11.3 (25.9)	13.0 (74.1)
	4 or more	38.1 (7.8)	35.7 (92.2)	33.1 (5.7)	32.5 (94.3)	32.5 (30.5)	30.0 (69.5)	16.4 (19.2)	27.7 (80.8)
Household location	Urban area	79.1 (6.9)	84.0 (93.1)	91.1 (5.9)	85.9 (94.1)	78.4 (26.1)	82.3 (73.9)	75.8 (26.8)	82.9 (73.2)
	Non-urban area	20.9 (9.3)	16.0 (90.7)	8.9 (3.6)	14.1 (96.4)	21.6 (31.1)	17.7 (68.9)	24.2 (36.2)	17.1 (63.8)

Table 3-2

Socio-Economic and Demographic Characteristics of the Weekend Samples (Weighted | N_{NHTS}=230,081, N_{ATUS}=9,560)

Person Characteristics		**Segment 3: Weekend*Workers**				**Segment 4: Weekend*Non-workers**			
		NHTS 2017 (N=47,914)		ATUS 2017 (N=3,462)		NHTS 2017 (N=38,960)		ATUS 2017 (N=2,284)	
Attribute	Categories	Zero-trip maker (12.9%)	Trip maker (87.1%)	Zero-trip maker (10.4%)	Trip maker (89.6%)	Zero-trip maker (29.0%)	Trip maker (71.0%)	Zero-trip maker (30.4%)	Trip maker (69.6%)
Gender	Female	45.7 (12.5)	47.0 (87.5)	45.2 (10.3)	45.5 (89.7)	59.4 (29.4)	58.4 (70.6)	61.1 (30.2)	61.9 (69.8
	Male	54.3 (13.1)	53.0 (86.9)	54.8 (10.4)	54.5 (89.6)	40.6 (28.6)	41.6 (71.4)	38.9 (30.9)	38.1 (69.1
Age	15–20	6.4 (17.2)	4.5 (82.8)	1.0 (6.0)	1.8 (94.0)	9.4 (37.2)	6.5 (62.8)	4.2 (15.6)	10.0 (84.4
	21–30	22.0 (13.7)	20.4 (86.3)	17.5 (9.8)	18.7 (90.2)	13.0 (34.9)	9.9 (65.1)	5.0 (21.0)	8.2 (79.0
	31–50	41.1 (12.3)	43.4 (87.7)	36.6 (8.5)	45.5 (91.5)	13.9 (23.2)	18.9 (76.8)	12.2 (22.9)	17.9 (77.1
	51–65	25.2 (12.1)	27.0 (87.9)	36.5 (12.8)	28.9 (87.2)	24.2 (27.7)	25.9 (72.3)	28.3 (36.7)	21.4 (63.3
	66 or more	5.3 (14.3)	4.7 (85.7)	8.3 (15.6)	5.2 (84.4)	39.5 (29.4)	38.8 (70.6)	50.2 (34.1)	42.5 (65.9
Educational attainment	Less than a high school diploma	4.4 (16.3)	3.3 (83.7)	9.3 (14.7)	6.2 (85.3)	14.3 (37.8)	9.6 (62.2)	23.0 (36.7)	17.3 (63.3
	High school graduate or GED	23.8 (16.7)	17.6 (83.3)	29.6 (11.0)	27.8 (89.0)	33.9 (32.6)	28.8 (67.4)	38.8 (35.1)	31.3 (64.9
	Some college or associates degree	33.9 (14.4)	29.6 (85.6)	25.7 (10.8)	24.6 (89.2)	31.3 (29.9)	30.2 (70.1)	21.1 (28.1)	23.6 (71.9
	Bachelor's degree	21.4 (10.4)	27.3 (89.6)	22.8 (9.4)	25.5 (90.6)	12.1 (22.2)	17.3 (77.8)	11.4 (21.9)	17.8 (78.1
	Graduate or professional degree	16.5 (9.9)	22.2 (90.1)	12.6 (8.5)	15.9 (91.5)	8.4 (19.6)	14.1 (80.4)	5.8 (20.2)	9.9 (79.8
Race	White	73.8 (12.5)	75.8 (87.5)	80.1 (10.4)	80.1 (89.6)	70.9 (28.8)	71.8 (71.2)	80.4 (30.1)	81.5 (69.9
	Black	12.3 (14.5)	10.6 (85.5)	15.7 (12.8)	12.4 (87.2)	14.9 (29.3)	14.7 (70.7)	15.7 (36.5)	11.9 (63.5
	Asian	6.0 (14.1)	5.4 (85.9)	2.1 (4.3)	5.5 (95.7)	5.3 (30.2)	5.1 (69.8)	2.8 (21.6)	4.5 (78.4
	Some other race	7.0 (12.4)	7.3 (87.6)	0.9 (10.7)	1.3 (89.3)	7.7 (29.9)	7.8 (70.1)	0.6 (17.7)	1.4 (82.3
Annual household income	< $35K	23.4 (15.2)	19.0 (84.8)	25.8 (14.0)	18.5 (86.0)	45.5 (31.4)	40.6 (68.6)	55.8 (38.9)	38.3 (61.1
	≥ $35K, < $50K	10.9 (12.4)	11.3 (87.6)	10.0 (8.1)	13.2 (91.9)	13.0 (28.7)	13.2 (71.3)	12.8 (26.8)	15.2 (73.2
	≥ $50K, < $75K	18.4 (13.1)	17.7 (86.9)	21.5 (11.1)	19.9 (88.9)	15.4 (27.9)	16.4 (72.1)	15.1 (27.1)	17.8 (72.9
	≥ $75K	47.3 (11.7)	52.0 (88.3)	42.7 (9.3)	48.5 (90.7)	26.0 (26.3)	29.9 (73.7)	16.3 (20.0)	28.7 (80.0
Household size	1 person	9.4 (10.3)	12.1 (89.7)	12.2 (9.6)	13.4 (90.4)	15.2 (24.3)	19.4 (75.7)	25.8 (37.5)	18.8 (62.5
	2 persons	29.0 (12.3)	30.5 (87.7)	42.1 (12.7)	33.7 (87.3)	34.7 (26.1)	40.2 (73.9)	44.7 (31.9)	41.9 (68.1
	3 persons	23.4 (13.8)	21.5 (86.2)	20.8 (10.7)	20.1 (89.3)	19.7 (34.1)	15.6 (65.9)	13.6 (29.5)	14.2 (70.5
	4+ persons	38.2 (13.6)	35.9 (86.4)	25.0 (8.1)	32.9 (91.9)	30.3 (33.4)	24.8 (66.6)	15.9 (21.7)	25.2 (78.3
Household location	Urban area	80.3 (12.5)	83.0 (87.5)	81.2 (9.8)	86.9 (90.2)	77.2 (28.3)	80.0 (71.7)	78.0 (29.1)	83.0 (70.9
	Non-urban area	19.7 (14.6)	17.0 (85.4)	18.8 (14.2)	13.1 (85.8)	22.8 (31.8)	20.0 (68.2)	22.0 (36.2)	17.0 (63.8)

Table 3-2 presents similar statistics, but for the weekend groups. According to the NHTS, 12.9 percent of employed individuals are zero-trip makers on weekends; the percentage for non-workers is considerably higher at 29 percent. It is not surprising to see that workers show a higher prevalence of zero-trip making on weekend days than weekdays. However, the percentages between weekdays and weekend days are not all that different for non-workers. Overall, it appears that nearly 30 percent of non-workers report zero travel, whether on a weekday or weekend day. These percentages are consistent between the NHTS and ATUS. Again, subtle differences in distributions are discernible, once again in the context of age, race, and household size.

Although there are some differences in the distributions as noted above between the NHTS and ATUS in terms of the incidence of zero-trip making for specific market segments, the overall distributions and the general patterns or trends are quite similar (qualitatively speaking). The ATUS is broadly offering measures of zero-trip making and distributions of various demographic groups in the zero-trip making and trip making segments that are in line with those seen in the NHTS. Given that the ATUS constitutes a representative sample of the nation, it may in fact give more accurate depictions of zero-trip making than the NHTS, whose statistics are derived from a weighted, but non-representative raw sample. As such, based on the information in Tables 3-1 and 3-2, using the ATUS data to measure and assess zero-trip making and the extent to which it impacts time poverty and wellbeing appears very appropriate.

3. Time Use and Time Poverty

As noted in the introduction, a number of previous studies in the transportation domain have linked zero-trip making with a diminished quality of life due to isolation, social exclusion, and non-participation in society at large (Spinney et al., 2009; Stanley et al., 2011; Lucas, 2012). Thus, transportation researchers have attempted to draw a linkage between mobility (out-of-home activity participation) and wellbeing. At the same time, sociologists and economists have been linking wellbeing to time use to define *time poverty*, similar to the notion of income-based poverty. A number of studies have attempted to define time poverty based on the time spent on discretionary leisure activities and identify the groups that are vulnerable to experiencing time poverty. In general, the literature has documented that women, parents with children, workers, and employed single parents with children are time poor, presumably because of the many obligations that they must fulfill – leaving limited time available to pursue desirable discretionary activities (Harvey and Mukhopadhyay, 2007; Bernardo et al., 2015; Kalenkoski et al., 2010; Qi and Dong, 2017).

A threshold value of available time for discretionary activities is used to classify whether a person is time poor. This threshold value has been conceptualized and measured in different ways across studies due to the subjective nature of the concept; and hence it appears that the field has not necessarily settled on a single definition for time poverty (Williams et al., 2016). Some studies define time poverty based on a fixed amount of time that should be available for the pursuit of discretionary activities (regardless of whether they are actually pursued or not). Vickery (1977) proposed a time threshold of 10 hours per week while Harvey and Mukhopadhyay (2007) used a time threshold of two hours per day in defining time poverty. They posited that individuals must have at least this amount of time available for pursuing discretionary activities to be identified as not being time poor.

More recently, a number of studies have pegged time poverty to the median time available for discretionary activities (Burchardt, 2008; Spinney and Millward, 2010). Using the American Time Use Survey data set, Kalenkoski et al. (2011) defined the time poverty threshold at various levels – the 50%, 60%, or 70% of median available discretionary time – and calculated time poverty rates for the US population and various subgroups of the population. Kalenkoski and Hamrick (2013) applied the "60% of the median available discretionary time" threshold to explore the relationship between time poverty, eating, and physical activity engagement. As there are a number of definitions that have been used to define time poverty, this chapter adopts the "60% of median" definition that has been used by Burchardt (2008) and Kalenkoski and Hamrick (2013). To define available discretionary time, Kalenkoski and Hamrick (2013) essentially subtracted the total necessary activity time and committed activity time from 1440 minutes. The median available discretionary time across the entire population was then multiplied by 0.6 to determine the threshold; those who had more discretionary time available were not time poor and vice versa. The activities were classified as follows:

- **Necessary activities**

  (1) Personal care (includes sleeping and grooming)

- **Committed activities**

  (1) Household activities (includes housework, food & drink preparation)

  (2) Caring for and helping household members, both children and adults

  (3) Work and work-related activities

- **Discretionary activities**

  (1) Caring for and helping non-household members

  (2) Education

  (3) Consumer purchases

  (4) Professional and personal care services (includes banking, paying for daycare, doctor's appointments, getting a haircut)

  (5) Household services (includes dropping off/picking up clothes from dry cleaner, hiring a plumber for home repair, waiting while a car is repaired)

  (6) Government services and civic obligations (includes using social services, getting a car inspected, serving on jury duty, voting)

  (7) Eating and drinking

  (8) Socializing, relaxing, and leisure (includes entertaining family and friends, watching television, computer use for leisure, attending performing arts events, gambling)

  (9) Sports, exercise, and recreation (includes participating in sports and attending a sporting event)

(10) Religious and spiritual activities

(11) Volunteer activities

(12) Telephone calls

It is undoubtedly possible to quibble with the categorization of activities presented above. For example, the transportation literature often treats education (school) as a mandatory (committed activity) as opposed to a discretionary activity. Nevertheless, in the interest of being consistent with the literature and the work of Kalenkoski and Hamrick (2013), who essentially used the same ATUS data to study time poverty, this exact same classification has been adopted in this chapter.

In this chapter, the ATUS sample was extensively analyzed to determine the percentage of individuals in various population subgroups that experience time poverty (based on the 60% of median definition). After computing the median of available discretionary time, the 60% value was determined to be *306 minutes* per day. Anybody having more time available for discretionary activities was considered not time poor. Table 3-3 shows the percentage of individuals in each subgroup that is time poor (i.e., they had less than 306 minutes of available discretionary time). The results offer a compelling narrative of the prevalence of time poverty according to the definition postulated in the literature.

Table 3-3

Percent of Individuals Experiencing Time Poverty by Subgroup (N=9,560)

Person characteristics	Weekday Worker	Weekday Non-worker	Weekend Worker	Weekend Non-worker
Gender				
Female	54.3%	13.8%	24.4%	12.7%
Male	51.5%	8.4%	22.3%	8.6%
Age				
15-20 years	32.6%	11.2%	10.0%	11.8%
21-30 years	46.1%	28.1%	25.8%	14.7%
31-50 years	61.7%	28.7%	26.1%	15.8%
51-65 years	50.3%	7.6%	19.7%	7.6%
65+ years	25.0%	4.9%	14.8%	5.3%
Educational attainment				
Less than a high school diploma	47.8%	10.5%	24.3%	9.5%
High school graduate or GED	52.2%	12.2%	23.4%	10.2%
Some college or associate degree	49.2%	14.6%	25.0%	8.9%
Bachelor's degree	54.7%	11.9%	22.6%	5.9%
Graduate or professional degree	58.1%	5.6%	20.7%	6.3%
Race				
White	52.6%	10.5%	23.2%	8.9%
Black or African American	53.9%	17.4%	20.8%	7.3%
Asian	58.5%	12.7%	30.6%	11.3%
Some other race	43.4%	17.2%	22.0%	7.0%
Household income				
< \$35K	49.2%	11.7%	27.4%	11.3%
≥ \$35K, < \$50K	49.2%	14.3%	21.3%	5.2%
≥ \$50K, < \$75K	51.6%	7.5%	27.4%	6.9%
≥ \$75K	55.6%	12.6%	20.3%	7.6%
Household size				
1	46.9%	6.9%	21.2%	6.2%
2	47.4%	7.0%	19.3%	6.1%
3	52.2%	18.1%	24.8%	15.3%
4+	61.1%	20.7%	27.4%	12.1%
Household location				
Urban area	53.2%	12.2%	23.5%	8.5%
Non-urban area	52.4%	10.0%	22.1%	9.0%
Segment average	**52.8%**	**11.7%**	**23.2%**	**8.8%**
Segment size	**N=2,282**	**N=1,532**	**N=3,462**	**N=2,284**

Color code: Each person characteristic category is separately color coded in a subgroup with percentages increasing from red to green.
Note: Sample is weighted

Considering the four segments (defined by employment status and day of week) it is found that 52.8 percent of workers are time poor on weekdays. This is not surprising as workers spend a considerable amount of time at work. Once work time and other necessary time (sleep and personal care) are subtracted from the 1440-minute time budget of a day, not much time is left for discretionary activities. Thus, workers have a high degree of time poverty. Does this mean that they have a lower quality of life? It is not entirely clear if that is indeed true. Only 11.7 percent of non-workers are time poor on weekdays. The corresponding percentages for weekend days are 23.2 percent for workers and just 8.8 percent for non-workers (including retirees). The extent of time poverty is lowest for 65+ year olds. Among workers, higher income individuals and individuals with higher level of education are more time poor than other groups, presumably because they spend more time working. Among non-workers, however, the most highly educated exhibit the lowest prevalence of time poverty. Non-workers do not have to spend long periods of time working, and those who are highly educated may be equipped to perform committed and necessary activities more efficiently, thus leaving more time available to discretionary activities. In general, females are more time poor than men, presumably because they shoulder the household obligations to a greater degree. Those in the middle age groups are more likely to be time poor, presumably due to lifecycle stage effects. Individuals in larger household sizes show a greater prevalence of time poverty due to higher level of household obligations.

4. Wellbeing, Time Poverty, and Zero-Trip Making

While the notion of time poverty is quite appealing and intuitive, the connection to wellbeing is not yet well-established. The following is a direct quote from Krueger et al. (2009), reproduced here because it states, very eloquently, the challenges associated with using the time poverty concept for assessing wellbeing:

> *" ... problems with this approach are that: (a) many people derive some pleasure from non-leisure activities; (b) not all leisure activities are equally enjoyable to the average person; (c) the nature of some activities changes over time; (d) people have heterogeneous emotional experiences during the same activities; and (e) emotional responses during activities are not unidimensional."*

In other words, not all activities are created equal, and not all people assess the activities in the same way. Accounting for this heterogeneity in the time poverty approach is extremely difficult because everybody is measured against the same discretionary time availability threshold. It is therefore necessary to more intricately connect the notion of time poverty with the notion of subjective wellbeing. Subjective wellbeing may be viewed as a composite representation of the emotional feelings of a person at any point in time or during an activity episode. Presumably, if the subjective wellbeing of an individual stays positive for an extended period of time, then the person is experiencing a high quality of life.

The challenge with connecting time use with wellbeing is that data on measures of wellbeing is virtually never available in travel and time use survey data sets. An exception is the American Time Use Survey (ATUS), when a special wellbeing module was administered in 2010, 2012, and 2013 to a sample of those who participated in the time use survey. The wellbeing module asked respondents to rate their emotional feelings for three randomly identified activities from their time use diary. The six emotions included happiness, meaningfulness, sadness, painfulness, tiredness, and stress. On each of these emotions, the respondents rated the intensity of the emotion on a scale of 0 through 6, with a higher number indicating a greater level of emotional intensity.

In order to connect zero-trip making, time poverty, and subjective wellbeing, a convenient measure or score of subjective wellbeing is needed. In prior research (Khoeini et al., 2019), a subjective wellbeing score for each individual in the ATUS data set was computed through a five-step approach. Full details are available in Khoeini et al. (2019), and only an outline of the procedure is described here. The steps involved in computing a person-level daily wellbeing score are:

1) Develop a joint-model framework to estimate a composite emotional score for each activity as a function of socio-economic and demographic variables as well as attributes of the activity or travel episode itself (duration, timing, purpose, and accompaniment). Deemed as the Activity Composite Wellbeing Score (ACWS), the score is defined as a latent variable, which is indicated by the six emotions in the framework.
2) Estimate three distinct regression equations for three different types of activities (in-home activities, out-of-home activities, and travel) using the developed joint-model framework.

3) Apply the regression equations to *all* of the activities in the entire ATUS data set of 2017 to compute an ACWS value for every activity and travel episode in the 2017 data set. The computed ACWS values are appended to every activity and travel episode record.
4) Normalize the ACWS values to fall into a reasonable non-negative range (that is between 0 and 1), as the computed ACWS values may take a positive or negative value.
5) Add the normalized ACWS values corresponding to all activities and trips undertaken by an individual to compute a person-daily composite wellbeing score (PCWS). The summation of individual activity wellbeing scores allows the computation of a single subjective wellbeing score for each person in the ATUS. A lower score signifies poorer wellbeing and vice versa.

Following the computation of the PCWS for each individual in the ATUS, a tabulation that relates time poverty, subjective wellbeing, and zero-trip making was developed with a view to establish the connections between them. The tabulation was developed to see how different demographic groups compared with respect to their wellbeing scores and time poverty levels. The time poverty literature considers the concept as binary in nature – either an individual is time poor or not. In order to provide a greater degree of granularity in the analysis, the time poor individuals are further disaggregated in this chapter into quartiles. The time poor individuals were sorted with respect to their available discretionary time, and those who are close to the threshold of 306 minutes are less time poor on the scale of time poverty than those whose time availability for discretionary activities is far removed from the threshold value. The results of this exercise are presented in Table 3-4. It should be noted that the numeric value of the subjective wellbeing score does not have an interpretation per se. However, differences represent the extent to which individuals experience higher or lower subjective wellbeing.

A number of interesting trends emerge when connecting time poverty to subjective wellbeing. Note that the subjective wellbeing score is based on what people have directly reported as their emotional feelings for different activity episodes. In other words, the subjective wellbeing score reflects what people are feeling as they undertake activities and travel. What is immediately discernible is that there are reasonably strong correspondence and alignment between subjective wellbeing and time poverty. The degree of time poverty increases as one goes from left to right in the table. It is found that, with a few exceptions, the subjective wellbeing score decreases (on average) as time poverty level increases. This trend is fairly consistent across the board for all demographic groups considered in this table. The table includes a number of demographic groups that are traditionally considered mobility disadvantaged and at risk of social exclusion (Delbosc and Currie, 2011) – besides the four segments defined by employment status and day of week. A few notable exceptions in the alignment between time poverty and average subjective wellbeing score are worth exploring further.

Table 3-4

Average Wellbeing Scores Across Selected Population Segments by Time Poverty Level (Weighted | N=9,560)

Segment	Avg. SWB Score[1]	Trip making	Sample size	Row Avg.	Time poverty levels[3]				
					Non-time poor	Low	Mid-low	Mid-high	High
Full sample	9.59	trip maker	7,843	10.13	10.89	9.18	8.60	8.88	6.85
		zero-trip maker	1,717	6.69	6.79	6.66	7.22	6.82	4.64
Weekday worker	9.47	trip maker	2,144	9.57	10.56	9.64	8.61	9.09	7.28
		zero-trip maker	138	7.75	7.87	7.25	8.17	10.26	5.18
Weekday non-worker	9.91	trip maker	1,086	11.21	11.71	7.88	7.19	7.31	6.05
		zero-trip maker	446	6.64	6.85	5.33	4.99	6.67	4.52
Weekend worker	9.51	trip maker	3,059	9.81	10.30	8.72	9.16	8.68	5.96
		zero-trip maker	403	6.88	6.87	8.90	7.68	5.78	5.68
Weekend non-worker	9.56	trip maker	1,554	11.03	11.34	6.40	8.03	7.19	4.34
		zero-trip maker	730	6.21	6.40	6.08	7.56	3.17	2.91
Low-income (< $35K)	8.01	trip maker	2,233	8.89	9.55	7.69	7.29	7.88	5.24
		zero-trip maker	854	5.47	5.71	4.95	3.61	4.84	2.39
Non-metropolitan	9.59	trip maker	1,098	10.45	11.12	8.31	9.71	9.54	6.76
		zero-trip maker	343	6.43	6.45	4.80	6.65	8.15	4.91
Age: 75+	12.44	trip maker	653	14.37	14.44	9.88	12.87	17.49	21.88
		zero-trip maker	352	8.61	8.50	10.57	13.78	10.45	6.74
Female	9.22	trip maker	4,198	9.87	10.49	9.10	8.32	9.17	6.91
		zero-trip maker	1,012	6.18	6.23	5.76	6.57	6.87	4.57
Minority	8.35	trip maker	1,578	8.93	9.43	9.88	7.78	7.98	6.73
		zero-trip maker	414	5.81	5.94	3.93	9.43	6.66	2.53
Foreign-born non-citizen	7.87	trip maker	671	8.15	8.65	7.81	8.33	7.80	5.76
		zero-trip maker	89	5.32	6.33	3.62	10.14	3.11	2.72

[1]Color coded: Avg. SWB (subjective wellbeing) score increases from red to green between segments.
[2]Color coded: The higher of the trip maker and zero-trip maker in each segment is colored green while the lower is colored red.
[3]Color coded: Avg. SWB score within time poverty levels increases from red to green in each row.

For example, consider the demographic group aged 75 years or older. The subjective wellbeing score is found to be the highest for this group, presumably because they do not spend time working and spend more time engaged in enjoyable discretionary activities – whether inside the home or outside the home. In other words, their feelings of wellbeing have not diminished with age; in fact, they have been amplified, suggesting that they are not necessarily experiencing a diminished quality of life in their older years. For trip makers, it is found that the average subjective wellbeing is higher than for non-travelers; this is largely due to the fact that they are engaging in discretionary activities outside the home, and such activities engender the most positive emotional feelings among all activity types. Among trip makers, the wellbeing score reaches the highest level for the most time poor subgroup. This is rather counter-intuitive. A deep dive into the data shows that these individuals are time poor because they are taking care of household members – both children and adults; according to the time poverty definition, these individuals are time poor. However, these individuals are engaging in care-taking and companionship activities that they find very meaningful and bring them happiness. They are taking care of family members, enjoying time with children and grandchildren, going out to places with family members, and experiencing a high level of positive emotions through such activities. In other words, it is difficult to define the emotional state of an individual based solely on their time use patterns.

Another key finding is that trip makers are almost always experiencing a higher level of subjective wellbeing than zero-trip makers. Trip makers gain subjective wellbeing by traveling and engaging in activities out-of-home, largely because they are pursuing activities that engender positive emotions. Although the technological advancements such as social network platforms, online streaming services, and video games enable the pursuit of numerous discretionary activities in home, the variety of discretionary activities that zero-trip makers can pursue are still limited. Also, some activities such as sports, exercise, and recreational that are categorized as discretionary by definition may not equally increase subjective wellbeing when performed in home. This expectedly leads to a lower level of subjective wellbeing for zero-trip makers. The relationship between mobility and higher subjective wellbeing is persistent for all demographic groups in the table, including the low-income, non-metropolitan, older adults (75+ year-old), female, minority, and immigrant groups.

Furthermore, a detailed look through the lens of time poverty shows some contradictory patterns about the contribution of mobility to subjective wellbeing. For example, consider the worker group on weekdays, where the subjective wellbeing score is higher for trip makers. In this group, when time poverty is accounted for, it is found that trip making is not associated with higher subjective wellbeing for those who are time poor at mid-high level. That is, time poor individuals in this group report higher subjective wellbeing when they do not undertake any trip during the day – supposedly because they utilize the time saved from traveling to pursue discretionary activities, which amplifies their wellbeing. Overall, although almost all groups depict higher subjective wellbeing scores for trip makers, the noticeable exceptions imply that not all zero-trip makers are created equal and that zero-trip makers do not necessarily suffer from lack of mobility at certain time poverty levels. Based on this analysis, it appears that there are distinct groups of zero-trip makers with varying levels of wellbeing. Appendix D provides an additional analysis that separates zero-trip makers into two groups. In one group, zero-trip makers have higher average wellbeing compared to trip makers, while the other group consists of zero-trip makers with lower average wellbeing than trip makers. This further highlights the wellbeing disparities between these two distinct groups of zero-trip makers in terms of their socio-economic and demographic characteristics.

5. Discussions and Conclusions

This chapter attempts to bridge two streams of literature that address the role of activity engagement in influencing wellbeing and quality of life. In the transportation literature, an absence of travel and out-of-home activity engagement is often viewed as leading to a diminished quality of life due to the risk of social exclusion, isolation, and disengagement from society. Many mobility disadvantaged groups, such as older adults, people with disabilities, low-income, carless, and minorities, are viewed as potentially at risk of social exclusion and diminished quality of life due to lower access to mobility options. In the sociological and economic literature, the notion of time poverty has been used to assess wellbeing and quality of life. People who do not have available discretionary activity time that exceeds a certain threshold are viewed as experiencing time poverty – and hence a diminished quality of life.

Due to an absence of data, notions of wellbeing and time poverty have not been adequately related to one another. In addition, the role of mobility in influencing wellbeing for different demographic groups has not been studied in detail. This chapter utilizes data from the American Time Use Survey (ATUS) to assess the extent to which wellbeing and time poverty are correlated with one another. It is found that time poverty (availability of discretionary activity time) and subjective wellbeing align with each other quite well, with those experiencing high degrees of time poverty also experiencing a lower subjective wellbeing. A couple of exceptions to this pattern are discernible, such as the case of 75+ year old individuals. Activities that are considered as contributing to time poverty are actually activities that 75+ year olds rate very positively. Thus, for some, the definition of time poverty established in the literature does not correspond well with subjective wellbeing.

As emphasized in the literature, the time poverty concept is associated with some challenges in assessing wellbeing and it may not be able to account for heterogeneity in the population (Krueger et al. 2009). This chapter not only showed that time poverty is associated with diminished wellbeing but also suggested that using the subjective wellbeing concept is an effective way to account for the heterogeneity present in the population where time poverty concept falls short to recognize.

The analysis revealed that mobility appears to be a key factor in contributing to higher levels of wellbeing. The chapter includes a detailed analysis of the level of zero-trip making among various demographic groups and finds that non-workers generally exhibit much higher levels of zero-trip making than workers – conforming the findings in the literature (Richardson, 2007; Motte-Baumvol et al., 2012; Corran et al., 2018). When subjective wellbeing is considered, however, non-workers overall report higher levels of wellbeing than workers, presumably because work episodes do not engender positive emotional feelings. Furthermore, it is found that trip makers have a higher subjective wellbeing score than zero-trip makers for virtually all demographic groups (including those traditionally considered mobility disadvantaged). The chapter contributes to the long-established strand of literature between mobility and enhanced life-quality by confirming this connection using the subjective wellbeing concept.

Although trip making is found to be an important factor contributing to higher levels of wellbeing, the analysis also shows that zero-trip makers are not entirely a homogeneous group in this respect. The inclusion of time poverty to this nexus between mobility and wellbeing points to the heterogeneity present among the zero-trip makers. For example, the mid-high time poor workers reporting zero-trips on weekdays have higher subjective wellbeing scores than their trip maker counterparts. This suggests that trip making does not enhance the wellbeing of those in this group when they are at mid-high time poverty level. Again, using the subjective wellbeing concept appears as an effective way to account for the heterogeneity present in the population.

This chapter shows that wellbeing and quality of life cannot always be viewed in terms of mobility alone. It should also be viewed in terms of time spent pursuing activities that engender positive emotions. Transportation improvements and land use policies that save time for, and increase access to, discretionary activity opportunities would increase wellbeing by making it possible for people to pursue leisure activities more easily. However, because there is heterogeneity in how people associate emotional feelings with different types of activities, there is a need for a model of wellbeing that computes wellbeing scores as a function of activity and travel attributes, attitudes and lifestyle preferences, and socio-demographic characteristics. Such a model would help transportation planners more accurately assess the wellbeing implications of their actions.

6. Acknowledgement

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7. References

Adeel, M., & Yeh, A. G. (2018). Gendered immobility: influence of social roles and local context on mobility decisions in Pakistan. *Transportation Planning and Technology*, *41*(6), 660-678.

Bureau of Labor Statistics (2017). American Time Use Survey. Retrieved from https://www.bls.gov/tus/

Aschauer, F., Hössinger, R., Schmid, B., & Gerike, R. (2018). Reporting quality of travel and non-travel activities: A comparison of three different survey formats. *Transportation Research Procedia*, *32*, 309-318.

Bernardo, C., Paleti, R., Hoklas, M., & Bhat, C. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A: Policy and Practice*, *76*, 71-91.

Bose, J., & Sharp, J. (2005, December). Measurement of travel behavior in a trip-based survey versus a time use survey–A comparative analysis of travel estimates using the 2001 National Household Travel Survey and the 2003 American Time Use Survey. In *American Time Use Survey Early Results Conference*.

Burchardt, T. (2008). Time and income poverty.

Corran, P., Steinbach, R., Saunders, L., & Green, J. (2018). Age, disability and everyday mobility in London: An analysis of the correlates of 'non-travel'in travel diary data. *Journal of Transport & Health*, *8*, 129-136.

Delbosc, A., & Currie, G. (2011). Exploring the relative influences of transport disadvantage and social exclusion on well-being. *Transport Policy*, *18*(4), 555-562.

Harvey, A. S., & Mukhopadhyay, A. K. (2007). When twenty-four hours is not enough: Time poverty of working parents. *Social Indicators Research*, 57-77.

Kalenkoski, C. M., & Hamrick, K. S. (2013). How does time poverty affect behavior? A look at eating and physical activity. *Applied Economic Perspectives and Policy*, *35*(1), 89-105.

Kalenkoski, C. M., Hamrick, K. S., & Andrews, M. (2011). Time poverty thresholds and rates for the US population. *Social Indicators Research*, *104*, 129-155.

Kenyon, S., Lyons, G., & Rafferty, J. (2002). Transport and social exclusion: investigating the possibility of promoting inclusion through virtual mobility. *Journal of Transport Geography*, *10*(3), 207-219.

Khoeini, S., Pendyala, R. M., da Silva, D. C., & Sharda, S. (2019). *An Integrated Model of Activity-Travel Behavior and Subjective Well-being* (No. 69A3551747116). Center for Teaching Old Models New Tricks (TOMNET).

Krueger, A. B., Kahneman, D., Schkade, D., Schwarz, N., & Stone, A. A. (2009). National time accounting: The currency of life. In *Measuring the subjective well-being of nations: National accounts of time use and well-being* (pp. 9-86). University of Chicago Press.

Morris, E. A. (2015). Should we all just stay home? Travel, out-of-home activities, and life satisfaction. *Transportation Research Part A: Policy and Practice*, *78*, 519-536.

Motte-Baumvol, B., & Nassi, C. D. (2012). Immobility in Rio de Janeiro, beyond poverty. *Journal of Transport Geography*, *24*, 67-76.

U.S. Department of Transportation - Federal Highway Administration. (2019). National Household Travel Survey.

Qi, L., & Dong, X. Y. (2018). Gender, low-paid status, and time poverty in urban China. *Feminist Economics*, *24*(2), 171-193.

Richardson, T (2007). Immobility in urban travel surveys. *30th Australasian Transport Research Forum*.

Spinney, J. E., Scott, D. M., & Newbold, K. B. (2009). Transport mobility benefits and quality of life: A time-use perspective of elderly Canadians. *Transport Policy*, *16*(1), 1-11.

Spinney, J., & Millward, H. (2010). Time and money: a new look at poverty and the barriers to physical activity in Canada. *Social Indicators Research*, *99*, 341-356.

Stanley, J. K., Hensher, D. A., Stanley, J. R., & Vella-Brodrick, D. (2011). Mobility, social exclusion and well-being: Exploring the links. *Transportation Research Part A: Policy and Practice*, *45*(8), 789-801.

Vickery, C. (1977). The time-poor: A new look at poverty. *Journal of Human Resources*, 27-48.

Williams, J. R., Masuda, Y. J., & Tallis, H. (2016). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*, 265-283.

Windsor, T. D., Anstey, K. J., Butterworth, P., Luszcz, M. A., & Andrews, G. R. (2007). The role of perceived control in explaining depressive symptoms associated with driving cessation in a longitudinal study. *The Gerontologist*, *47*(2), 215-223.

Yennamani, R., Srinivasan, S., Yennamani, R., & Srinivasan, S. (2008). Disaggregate comparison of travel reported by two American surveys, the NHTS and the ATUS. In *8th International Conference on Survey Methods in Transport, May, Annecy, France*.

CHAPTER 4

THE INFLUENCE OF MODE USE ON LEVEL OF SATISFACTION WITH DAILY TRAVEL ROUTINE: A FOCUS ON AUTOMOBILE DRIVING IN THE UNITED STATES

This chapter is substantially drawn from the following journal article:

Magassy, T. B., Batur, I., Mondal, A., Asmussen, K. E., Khoeini, S., Pendyala, R. M., & Bhat, C. R. (2022). Influence of mode use on level of satisfaction with daily travel routine: a focus on automobile driving in the United States. *Transportation Research Record*, 2676(10), 1-15.

1. Introduction

Transportation planning agencies around the world are investing in sustainable modes of transportation such as transit and bicycle/walk infrastructure, besides implementing a variety of voluntary behavior change programs, in an effort to render the transportation ecosystem more sustainable and livable. Voluntary behavior change programs include – but are not limited to – the provision of free or subsidized transit passes, implementation of ridesharing programs, construction of high-occupancy vehicle lanes (to promote carpooling), provision of incentives and use of gamified platforms to encourage use of alternative modes of transportation, and investments in bicycle lanes and pedestrian paths.

Despite all of the efforts being made to stem the tide of automobile use, why does it continue to grow and be the dominant mode of transportation in jurisdictions across the US? To what extent does automobile mode use impact the level of satisfaction that people derive from their daily travel routine? Is automobile use largely due to the unavailability of competitive sustainable transportation alternatives, and do people use the automobile simply because they have to – even though automobile use contributes nothing to (and possibly takes away from) the level of satisfaction they derive from their daily travel routine? How does the extent of automobile use affect the level of satisfaction that people derive from their daily travel routine, after controlling for many other attributes, including socio-economic and demographic characteristics, attitudinal factors, and lifestyle proclivities and preferences? These are the research questions that this chapter attempts to answer, in the quest to better understand why it is proving to be a formidable challenge to stem the growing use of the private automobile in cities worldwide.

There is considerable prior research connecting mode use and the level of satisfaction derived from daily travel. The literature has shown that this relationship tends to be somewhat context specific and sensitive to the way in which survey questions are asked. In some contexts, it is clear that riding public transit is seen as more burdensome and less preferred when compared to using the automobile, largely due to poor public transit service, concerns about safety and security, exposure to the elements, access/egress and waiting times (out-of-vehicle travel time) that tend to be perceived as onerous, and poor reliability (De Vos et al., 2016; Molin et al., 2016). On the other hand, walking and bicycling are often viewed quite positively and associated with a higher level of travel satisfaction, particularly in social-recreational contexts (Singleton, 2019; De Vos et al., 2016; Ye and Titheridge, 2017; Mondal et al., 2021). In most studies of mode use and travel satisfaction, however, it has been found that automobile use is associated with positive levels of reported travel satisfaction (Ory and Mokhtarian, 2005; Ettema et al., 2011).

Despite the evidence in the literature to date, the extent to which automobile use affects one's level of satisfaction with daily travel routine remains a question worthy of exploration, particularly because the connection between these dimensions – after controlling for a host of socio-economic and demographic variables and attitudinal and lifestyle preference variables – is not fully understood. In this chapter, data collected from four automobile-dominated metropolitan regions in the United States (Phoenix, Austin, Atlanta, and Tampa) are used to assess the impact of the amount of driving that individuals undertake on the level of satisfaction that they derive from their daily travel routine. Unlike previous studies, a holistic and comprehensive modeling framework is adopted in this research effort, recognizing the presence of endogeneity when modeling multiple behavioral phenomena of interest and the role that latent attitudinal constructs reflecting lifestyle proclivities and preferences may play in shaping the association between the frequency of automobile driving and satisfaction with daily travel routine. In the modeling framework adopted in this chapter, the relative frequency of driving (alone or with passengers on a weekly basis) and the self-reported level of satisfaction with daily travel routine are treated as endogenous variables with an error covariance that accounts for correlated unobserved attributes that jointly influence both of these endogenous variables. In addition, the model structure incorporates a host of latent attitudinal constructs (besides the usual socio-economic and demographic variables), and hence the influence of driving on daily travel routine satisfaction is modeled while controlling for all of the many other confounding relationships that may be at play. The model system is estimated in one step using the Generalized Heterogeneous Data Model (GHDM) methodology developed by Bhat (2015).

The remainder of this chapter is organized as follows. The next section presents a detailed description of the data and the endogenous variables of interest. The third section presents the modeling framework and methodology. The fourth section presents detailed model estimation results. The fifth section offers a discussion of the study implications and concluding thoughts.

2. Data Description

This section of the chapter presents a brief overview of the dataset used in this chapter. The section furnishes a description of the survey and a descriptive statistic of the survey sample. A presentation of socio-economic and demographic characteristics is provided first, and a more in-depth examination of the endogenous variables and latent attitudinal constructs is presented second.

Overview of Survey and Sample Characteristics

The data set used in this chapter is derived from the 2019 TOMNET – D-STOP Transformative Technologies in Transportation (T4) survey conducted in four major metropolitan regions of the United States. The four regions are Phoenix, Austin, Atlanta, and Tampa. These are four regions in warmer climates that are very automobile-centric in their transportation ecosystem. Transit services are generally limited and poor, and modal shares for transit and other modes of transportation are very low. A comprehensive survey instrument was deployed in Fall 2019. The survey was administered by sending hundreds of thousands of email invitations and a few tens of thousands of mail invitations to addresses purchased from a commercial vendor. A total of 3,465 responses were received. Complete information about the survey design, content, and administration and sampling methodology is available elsewhere (Khoeini, 2020). The data set was filtered and cleaned of obviously erroneous data and records with missing data. The final analysis sample consisted of 3,365 records.

Table 4-1 depicts the socio-economic and demographic characteristics of the sample of 3,365 respondents. The survey collected very detailed information about respondent characteristics and their attitudes, perceptions, and preferences related to new and emerging transportation technologies and mobility services, including ridehailing services, micromobility, and autonomous vehicles. In addition, the survey included a battery of attitudinal statements that aimed to capture the general values, preferences, and perceptions of individuals in the sample. The sample offers a rich variation in socio-economic and demographic characteristics, thus rendering the dataset appropriate for a modeling effort of the type undertaken in this chapter.

Table 4-1

Socio-Economic and Demographic Sample Characteristics

Individual characteristics (N = 3,365)		*Household characteristics (N = 3,365)*	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Female	58.3	Less than $25,000	11.1
Male	41.7	$25,000 to $49,999	15.7
Age category		$50,000 to $74,999	18.6
18-30 years	26.3	$75,000 to $99,999	15.5
31-40 years	11.5	$100,000 to $149,999	20.4
41-50 years	14.8	$150,000 to $249,999	12.6
51-60 years	16.6	$250,000 or more	6.1
61-70 years	16.1	**Household size**	
71+ years	14.7	One	21.3
Driver's license possession		Two	38.6
Yes	93.4	Three or more	40.1
No	6.6	**Housing unit type**	
Employment status		Stand-alone home	70.1
Student (part-time or full-time)	10.2	Condo/apartment	20.6
Worker (part-time or full-time)	52.1	Other	9.3
Both worker and student	11.1	**Home ownership**	
Neither worker nor student	26.6	Own	68.1
Education attainment		Rent	26.2
High school or less	9.4	Other	5.7
Some college or technical school	29.4	**Vehicle ownership**	
Bachelor's degree(s)	36.7	Zero	4.0
Graduate degree(s)	24.5	One	23.7
Race		Two	40.0
Asian or Pacific Islander	9.6	Three or more	32.3
Black or African American	7.9	**Location**	
Multi race	3.9	Atlanta, GA	29.7
Native American	0.6	Austin, TX	32.5
Other	1.8	Phoenix, AZ	30.5
White or Caucasian	76.3	Tampa, FL	7.4
Endogenous Variables			
Satisfaction with daily travel routine	**%**	**Proportion of driving for non-commute trips**	**%**
Very dissatisfied	4.5	Less than 20%	12.2
Dissatisfied	12.3	≥ 20% and < 40%	5.9
Neutral	15.2	≥ 40% and < 60%	12.9
Satisfied	48.9	≥ 60% and < 80%	19.7
Very satisfied	19.0	≥ 80%	49.4

The respondent sample is slightly skewed in favor of females, who comprise just over 58 percent of the sample. About 26 percent of the sample is in the young age group of 18-30 years. There is a healthy representation of every age group in the sample. Just over 93 percent of respondents have a driver's license, about 52 percent are part- or full-time workers, and 26.6 percent are neither workers nor students. The sample exhibits a high level of educational attainment, with 36.7 percent having a Bachelor's degree and 24.5 percent having a graduate degree. Just under 10 percent have a high school diploma or less. More than three-quarters of the sample is White, just under 10 percent is Asian, and nearly eight percent are Black, reflecting a reasonable level of racial diversity in the respondent sample.

The sample depicts the full range of annual household income, with 11.1 percent earning less than $25,000 per year and 18.7 percent earning $150,000 or more per year. It is found that 40.1 percent of the respondents reside in households with three or more people, suggesting that household sizes are rather high in this respondent sample relative to the general population. Only four percent reside in households with no vehicles; this distribution is not surprising, given the very automobile-oriented nature of the four metropolitan regions. The sample is rather evenly distributed across Atlanta, Austin, and Phoenix, with a smaller share in Tampa. Overall, the sample depicts the variability that is desired for modeling behavioral choices.

Endogenous Variables

Table 4-1 also shows the distribution of the endogenous variables of interest in this chapter. Two endogenous variables are of interest here; first, the proportion of automobile driving (alone or with a passenger) that an individual undertakes in a week for non-commute trips, and second, the level of satisfaction that an individual self-reports for their typical daily travel routine. Among the battery of attitudinal statements is a statement requesting individuals to indicate their level of agreement with the statement, "My daily travel routine is generally satisfactory". Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree. The proportion of automobile driving is computed based on a question requesting individuals to indicate the weekly frequency of use for different modes of transportation. The responses to this question were converted to a numeric scale and then used to compute a relative proportion of automobile driving (alone or with a passenger). This fraction varied from zero to one; a value of zero meant that the individual did not engage in automobile driving at all, while a value of one implies that the individual used only the automobile-driving mode and did not report using any other mode of transportation at all. The question was asked separately for commute and non-commute purposes, thus enabling the calculation of this proportion for non-commute travel.

The question regarding the frequency of mode use for non-commute trips was asked for 12 modes: (1) drive private vehicle, alone; (2) drive private vehicle, with passengers; (3) ride in private vehicle, with others; (4) carsharing services (e.g., Zipcar); (5) bus; (6) light rail; (7) Uber/Lyft/ridehailing service; (8) taxi; (9) bicycle (including bikesharing); (10) e-scooter (e.g., Bird/Lime); (11) walk; (12) other mode. For each mode, respondents could choose among the following frequency categories: not available; available but never use it; less than one day a month; 1-3 days a month; 1-2 days a week; and 3 or more days a week. As these response options did not directly lend themselves to calculating a relative amount of driving, they were converted into numeric frequency values representing the number of days that various travel modes were used on a weekly basis. For instance, someone that reported using a bicycle 1-2 times a week was considered to have an average frequency of 1.5 days per week. Similarly, a respondent who drives alone less than one day a month was assumed to use the mode every other month (which translates to 0.125 days per week). This assumption was considered appropriate, given the automobile-centric nature of the survey areas. The response categories were converted to numeric weekly frequency scores as follows:

0, if *'not available'* was selected;

0, if *'available but never use it'* was selected;

0.125, if *'less than one day a month'* was selected;

0.5, if *'1-3 days a month'* was selected;

1.5, if *'1-2 days a week'* was selected; and

5, if *'3 or more days a week'* was selected.

The relative proportion of driving could then be computed as a share of the total weekly mode usage pattern. For example, suppose a respondent reported using four travel modes for his/her non-commute trips: driving alone 3 or more days a week, driving with passengers 1-3 times a month, e-scooter less than one day a month, and walk 1-3 times a month (clearly, drive alone is the dominant mode). The proportion of driving for non-commute trips for this respondent would be calculated as follows:

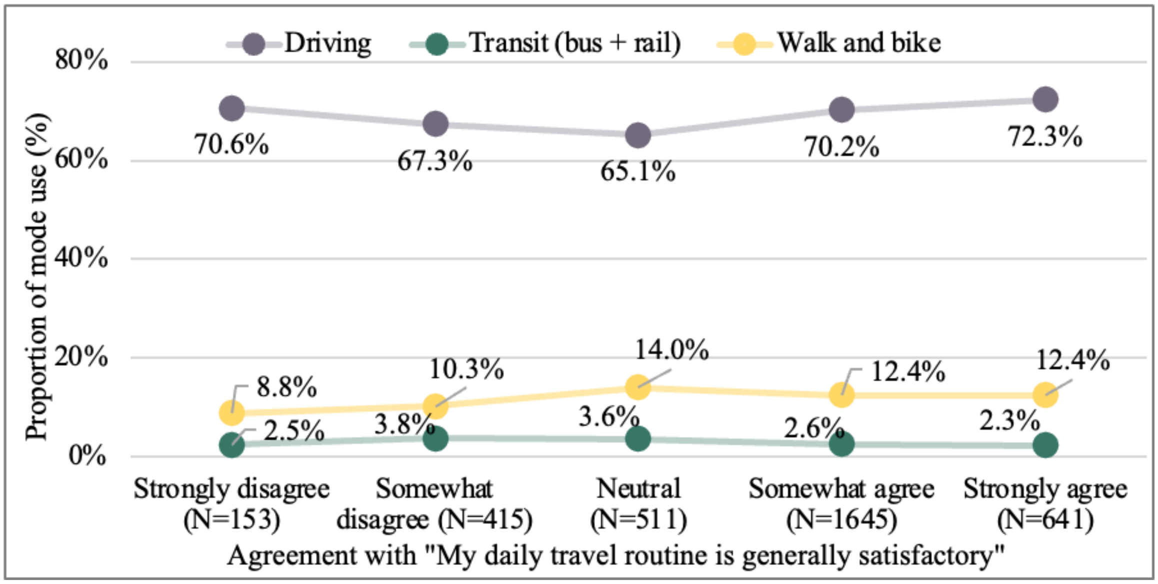
$$\frac{5+0.5}{5+0.5+0+0+0+0+0+0+0+0.125+0.5+0}=\frac{5.5}{6.125}=0.898=89.8\%$$

Most individuals deem their daily travel routine satisfactory. Table 4-1 shows that 19 percent strongly agree that their daily travel routine is generally satisfactory; another 49 percent somewhat agree with this statement. The distribution for the relative proportion of automobile driving for non-commute trips is also shown in Table 4-1. It is seen that nearly one-half of the sample have a relative driving proportion between 0.8 and 1, and at the other end of the spectrum, only 12.2 percent of individuals have a relative driving proportion less than 0.2.

Figure 4-1 constitutes a chart depicting the average proportion of driving for non-commute trips (in the form of a dot) for respondents in each Likert scale category of the daily travel satisfaction statement. For example, the purple dot corresponding to the strongly agree category is at 72.3 percent. This means that the 641 individuals in this category drive, on average, 72.3 percent of the time on a weekly basis. Other values on the figure can be interpreted similarly. The figure shows that the average relative driving proportion value does not seem to vary much across the Likert scale categories; there is only a minimal variance in the average relative driving proportion value across the Likert scale categories. To examine whether a similar pattern exists for other modes, Figure 4-1 also displays the average proportion of transit and walk/bike usage for non-commute trips. Once again, the relationships between satisfaction with daily travel routine and transit and walk/bike usage show very modest variation across the Likert scale categories.

Figure 4-1

Average Proportions of Driving, Transit, and Walk/Bike Usage for Non-Commute Trips Across Likert Scale Categories of Daily Travel Satisfaction Statement (N = 3,365)



As the bivariate relationship between average proportion of driving for non-commute trips and the daily travel satisfaction appears somewhat unclear, possibly due to many confounding factors, an econometric modeling framework capable of shedding light on the direct relationship between the relative proportion of driving and level of satisfaction with daily travel routine (while controlling for all other factors) is estimated in this chapter. This framework takes into account various factors that could potentially impact travel behavior (such as socio-demographic characteristics, built-environment attributes, attitudes, perceptions, and lifestyles) and isolates the impact of the average proportion of driving on the satisfaction with daily travel routine. The details of the modeling framework are provided in the Modeling Framework section of the chapter.

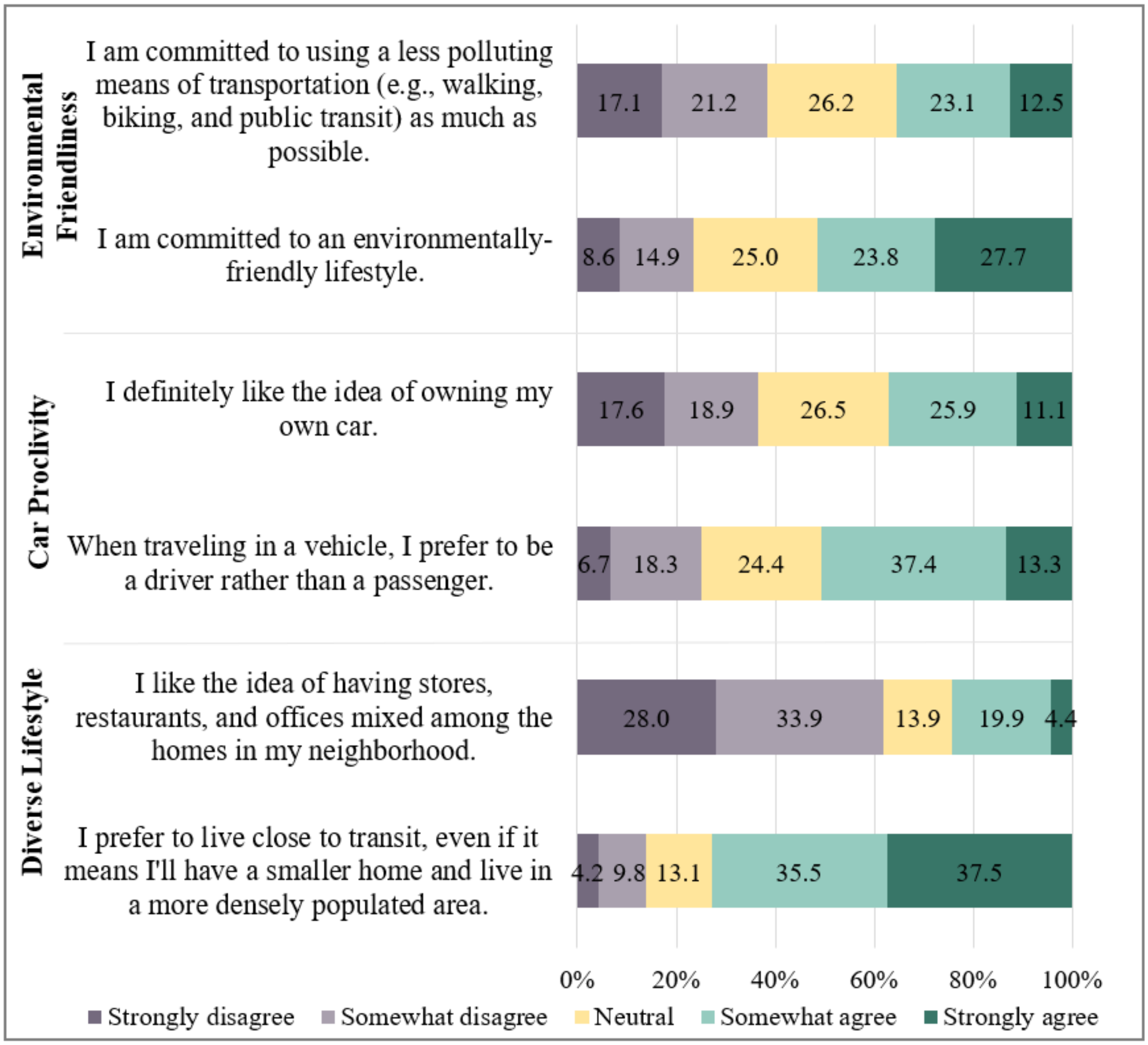
Attitudinal Indicators

The aim of the chapter is to understand the relationship between automobile-driving frequency and feeling of satisfaction with the daily travel routine while explicitly accounting for socio-economic variables as well as other attitudinal variables. To support such a modeling effort, three attitudinal constructs are defined and used in this chapter. Each latent (unobserved) attitudinal construct is mapped to two attitudinal statements or indicators from the survey. These attitudinal factors and the statements to which they are mapped are depicted in Figure 4-2.

The latent construct representing environmental friendliness is mapped to two indicators, one measuring an individual's commitment to using a less polluting means of transportation and the other measuring the commitment to an environmentally friendly lifestyle. The second latent construct encapsulating car proclivity is represented by attitudinal statements on the extent to which an individual likes the idea of owning his or her own car and the extent to which an individual prefers to be the driver over being a passenger when traveling in a car. Finally, the third latent construct is representative of a diverse lifestyle proclivity. This construct is mapped to two indicators as well – one representing the extent to which an individual likes having stores and restaurants mixed among the homes in the neighborhood and the other measuring the degree to which an individual prefers living close to transit, even if it involves compromising on the size of home. The distributions on the six attitudinal statements are depicted in the figure.

Figure 4-2

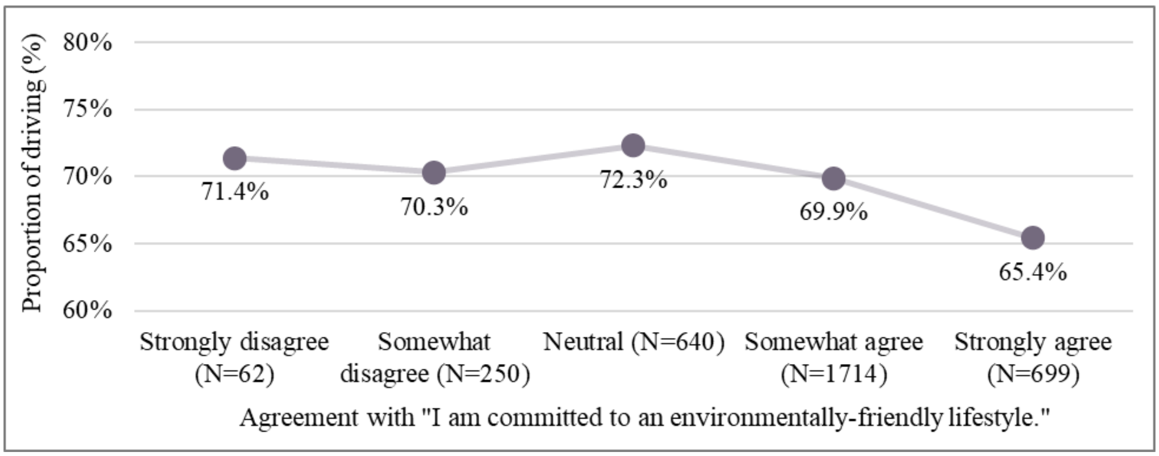
Distribution of Attitudinal Indicators of Latent Factors (N = 3,365)



The distributions of the attitudinal indicators, as shown in Figure 4-2, provide the variation necessary to use them in a modeling exercise that integrates latent attitudinal constructs. However, in order to gain a more detailed understanding of their relationships with the endogenous variables of the chapter, a select attitudinal statement representing each latent construct is further analyzed in this section. By examining these relationships more closely, the findings from the model estimation can be better contextualized and understood, and the complex and nuanced relationships between many confounding factors that may affect the relationship between the satisfaction with daily travel routine and proportion of driving can be revealed.

Figure 4-3

Average Proportion of Driving for Non-Commute Trips Across the Likert Scale Categories of Environmentally-Friendly Lifestyle Statement (N = 3,365)



The attitudinal statement "I am committed to an environmentally-friendly lifestyle" is chosen to represent the latent construct of *Environmental Friendliness* for further analysis. The relationships between this statement and the endogenous variables of the study are presented in Figures 4-3 and 4-4. Figure 4-3 indicates that individuals who agree that they are committed to an environmentally friendly lifestyle tend to drive less, highlighting the sustainability concerns associated with car usage. Figure 4-4, however, shows a less distinct relationship between being committed to an environmentally friendly lifestyle and satisfaction with daily travel routine. For instance, among those who strongly agreed that their daily travel routine is satisfactory, 75.2 percent agreed that they are committed to an environmentally friendly lifestyle, which is the same percentage among those who strongly disagreed with their daily travel routine being satisfactory. Thus, it appears that there is no straightforward relationship between being environmentally friendly and having higher or lower travel satisfaction.

Figure 4-4

Bivariate Relationship between Likert Scale Categories of Daily Travel Satisfaction and Environmentally-Friendly Lifestyle Statements (N = 3,365)

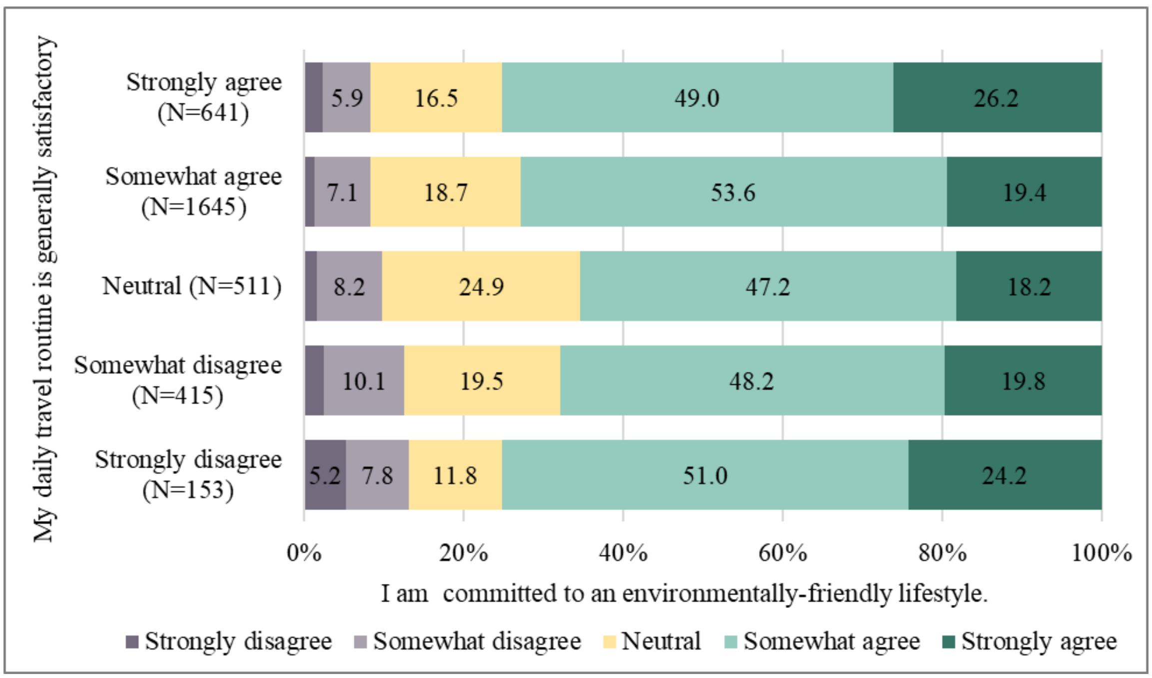
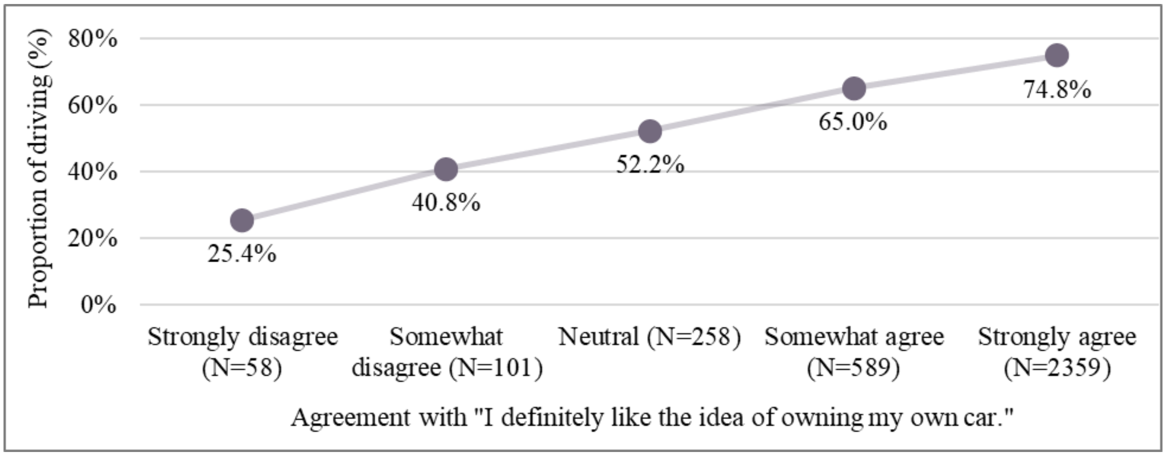


Figure 4-5

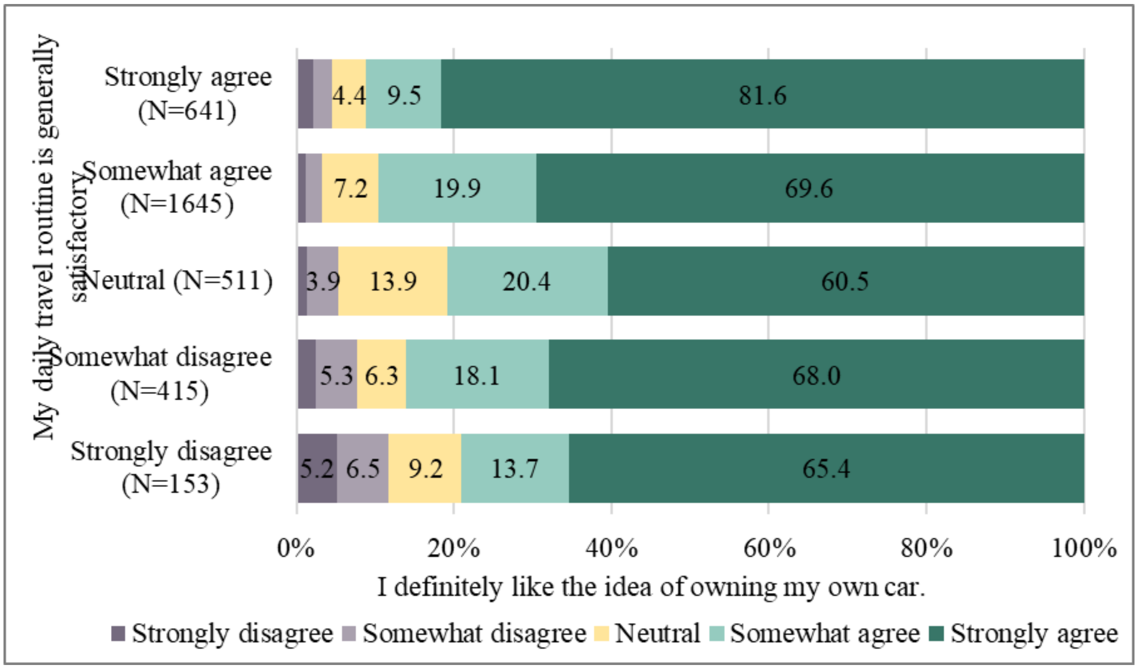
Average Proportion of Driving for Non-Commute Trips Across the Likert Scale Categories of Car-Owning Proclivity Statement (N = 3,365)



To analyze the latent construct of *Car Proclivity*, the attitudinal statement "I definitely like the idea of owning my own car" is selected. The relationship between this statement and the endogenous variables of the study are illustrated in Figures 4-5 and 4-6. Figure 4-5 depicts a clear pattern between this statement and the average proportion of driving, with a three-fold increase from 25.4 percent to 74.8 percent between those who strongly disagree and strongly agree with this statement. Similarly, Figure 4-6 indicates that individuals who like owning their own car tend to have higher satisfaction with their daily travel routine. Similarly, Figure 4-6 reveals that individuals who like owning their own car tend to have higher satisfaction with their daily travel routine. Specifically, among those who strongly disagreed that their daily travel routine is satisfactory, approximately 70 percent expressed liking the idea of owning their own car. In contrast, among those who strongly agreed that their daily travel routine is satisfactory, over 90 percent expressed liking the idea of owning their own car. This suggests a strong correlation between having a higher car proclivity and greater travel satisfaction.

Figure 4-6

Bivariate Relationship between Likert Scale Categories of Daily Travel Satisfaction and Car-Owning Proclivity Statement (N = 3,365)



Lastly, to analyze the latent construct of *Diverse Lifestyle*, the attitudinal statement "I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood" is selected. The relationship between this statement and the endogenous variables of the study are depicted in Figures 4-7 and 4-8. Figure 4-7 reveals a noticeable correlation between this statement and the average proportion of driving, with a nearly 10 percent decrease from 74.7 percent to 65 percent between those who strongly disagree and strongly agree with the statement. This implies that individuals who prefer mixed-use land patterns in their neighborhoods tend to drive less. However, the association between satisfaction with daily travel routine and liking mixed-use neighborhoods is less apparent. Figure 4-8 illustrates that among those who strongly agreed with the statement of liking mixed-use neighborhoods, 66 percent indicated their daily travel routine being satisfactory, while this percentage is only slightly higher among those who strongly disagreed, at 70 percent. Thus, although there is a 10 percent decrease in the proportion of driving among individuals who prefer mixed-use neighborhoods, those who do not live in such neighborhoods exhibit a nearly 5 percent increase in their travel satisfaction with their daily routines. This may also be attributable to the above finding that as the proportion of driving decreases, so does travel satisfaction.

Figure 4-7

Average Proportion of Driving for Non-Commute Trips Across the Likert Scale Categories of Mixed-Use Residential Location Preference Statement (N = 3,365

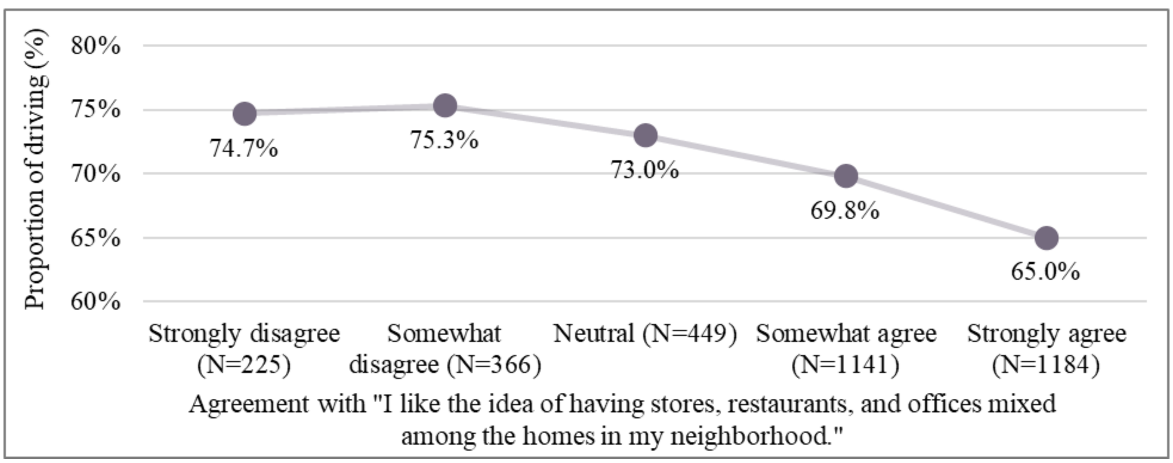
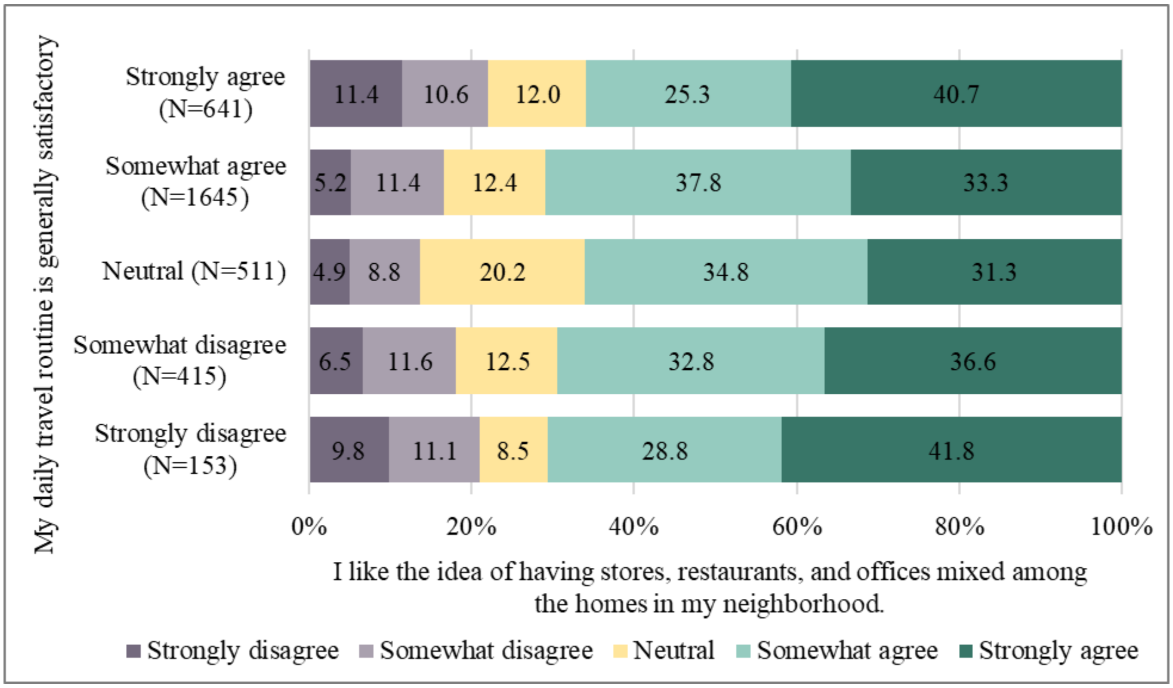


Figure 4-8

Bivariate Relationship between Likert Scale Categories of Daily Travel Satisfaction and Mixed-Use Residential Location Preference Statements (N = 3,365)



3. Modeling Framework

This section presents the model structure and the model formulation and estimation methodology. The model structure is capable of accommodating multiple endogenous variables and multiple stochastic latent constructs that are endogenous themselves. First, an overview of the model structure is furnished, and second, a brief description of the model formulation and estimation methodology is presented.

Model Structure

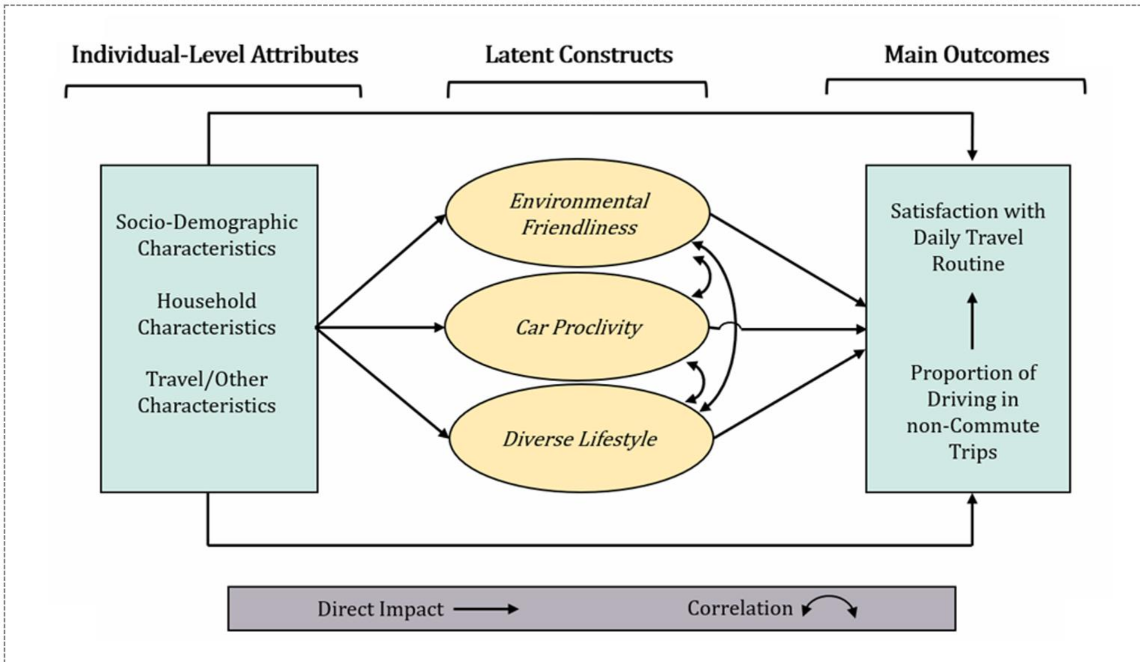
A simplified version of the model structure is shown in Figure 4-9. A host of socio-economic and demographic characteristics, household characteristics, and routine travel and mobility characteristics (that may be treated as exogenous for purposes of this study) serve as exogenous variables. The two endogenous variables include the proportion of driving for non-commute trips and the level of agreement that the daily travel routine is generally satisfactory. The proportion of driving for non-commute trips is a continuous variable, while the level of agreement is an ordered discrete variable that ranges from strongly disagree to strongly agree. Whether the proportion of driving for non-commute trips significantly affects satisfaction with the daily travel routine is the hypothesis that is being tested in this modeling exercise.

The host of latent attitudinal constructs act as intermediaries between the exogenous variables and the behavioral outcomes of interest. Exogenous socio-economic and demographic variables may affect the behavioral outcome variables directly or indirectly through the mediating influence of latent attitudinal constructs. The three latent attitudinal constructs are themselves endogenous and hence influenced by exogenous variables. At the same time, they influence the two behavioral outcome variables. The latent attitudinal constructs are stochastic and incorporate an error term. Thus, it is possible to compute error correlations between the latent constructs; by virtue of the stochastic nature of the constructs, an implied error correlation between the two behavioral outcome variables is realized and can be computed as well. Thus, the model structure accounts for endogeneity, the stochastic nature of latent constructs, and error correlations between latent constructs and between the two endogenous variables of interest. The entire model structure is estimated in a single step using the Generalized

Heterogeneous Data Model (GHDM) framework. The model formulation and estimation methodology are presented next.

Figure 4-9

Model Structure and Framework



Model Estimation Methodology

Consider the case of an individual $q \in \{1, 2, ..., Q\}$. However, for the ease of presentation, we will suppress the index q for decision-makers and assume that all error terms are independent and identically distributed across decision-makers. Let l be an index for latent variables (l=1,2,…,L). Consider the latent variable z_l^* and write it as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l'\boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(\tilde{D} \times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(\tilde{D} \times 1)$ vector of coefficients, and η_l is a random error term assumed to be standard normally distributed for identification purpose. Next, define the $(L \times \tilde{D})$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \ldots, \eta_L)'$. we allow an multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is $(L \times L)$ correlation matrix. In matrix form, we may write Equation (1) as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}. \tag{2}$$

Let there be H continuous outcomes $(y_1, y_2, ..., y_H)$ with an associated index h $(h = 1, 2, ..., H)$. Let $y_h = \boldsymbol{\gamma}_h'\boldsymbol{x} + \boldsymbol{d}_h'\boldsymbol{z}^* + \varepsilon_h$ in the usual linear regression fashion, where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant), $\boldsymbol{\gamma}_h$ is a coefficient vector, $\boldsymbol{d}_h$ is an $(L \times 1)$ vector of latent variable loadings on the h^{th} continuous outcome, and ε_h is a normally distributed measurement error term. Stack the H continuous outcomes into an $(H \times 1)$ vector $\boldsymbol{y}$, and the H error terms into another $(H \times 1)$ vector $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_H)'$. Also, let $\boldsymbol{\Sigma}$ be the covariance matrix of $\boldsymbol{\varepsilon}$, which is restricted to be diagonal. This helps in identification. Define the $(H \times A)$ matrix $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, ...\gamma_H)'$ and the $(H \times L)$ matrix of latent variable loadings $\boldsymbol{d} = (\boldsymbol{d_1}, \boldsymbol{d_2}, ..., \boldsymbol{d_H})'$. Then, one may write, in matrix form, the following measurement equation for the continuous outcomes:

$$\boldsymbol{y} = \boldsymbol{\gamma x} + \boldsymbol{d z}^* + \boldsymbol{\varepsilon}. \tag{3}$$

Now, consider N ordinal outcomes (indicator variables and main outcomes) for the individual, and let n be the index for the ordinal outcomes $(n = 1, 2, ..., N)$. Also, let J_n be the number of categories for the n^{th} ordinal outcome $(J_n \geq 2)$ and let the corresponding index be j_n $(j_n = 1, 2, ..., J_n)$. Let $\tilde{y}_n^*$ be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the n^{th} ordinal variable. Assume that the individual under consideration chooses the a_n^{th} ordinal category. Then, in the usual ordered response formulation, for the individual, we may write:

$$\tilde{y}_n^* = \tilde{\boldsymbol{\gamma}}_{\boldsymbol{n}}' \boldsymbol{x} + \tilde{\boldsymbol{d}}_n' \boldsymbol{z}^* + \tilde{\varepsilon}_n, \text{ and } \tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}, \tag{4}$$

where $\boldsymbol{x}$ is a vector of exogenous variables (including a constant) and observed values of other endogenous continuous variables or other endogenous ordinal variables (although only in a recursive fashion). $\tilde{\boldsymbol{\gamma}}_{\boldsymbol{n}}$ is a corresponding vector of coefficients to be estimated, $\tilde{\boldsymbol{d}}_{\boldsymbol{n}}$ is an $(L \times 1)$ vector of latent variable loadings on the n^{th} underlying continuous propensity, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_n$ is the standard normal random error for the n^{th} ordinal outcome. For each ordinal outcome, $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} ... < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$; $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. For later use, let $\tilde{\boldsymbol{\psi}}_{\boldsymbol{n}} = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3} ..., \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_{\boldsymbol{1}}', \tilde{\boldsymbol{\psi}}_{\boldsymbol{2}}', ..., \tilde{\boldsymbol{\psi}}_{\boldsymbol{N}})'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into another

$(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define $\tilde{\boldsymbol{\gamma}} = (\tilde{\boldsymbol{\gamma}}_1, \tilde{\boldsymbol{\gamma}}_2, ..., \tilde{\boldsymbol{\gamma}}_H)'$ [$(N \times A)$ matrix] and $\tilde{\boldsymbol{d}} = (\tilde{\boldsymbol{d}}_{\mathbf{1}}, \tilde{\boldsymbol{d}}_{\mathbf{2},}, ..., \tilde{\boldsymbol{d}}_N)$ [$(N \times L)$ matrix], and let $\mathbf{IDEN_N}$ be the identity matrix of dimension N representing the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$ (so, $\tilde{\boldsymbol{\varepsilon}} \sim MVN_N(\mathbf{0}_N, \mathbf{IDEN_N})$; again, this is for identification purposes, given the presence of the unobserved $\boldsymbol{z}^*$ vector to generate covariance. Finally, stack the lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}(n = 1, 2, ..., N)$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{\boldsymbol{low}}$ and the upper thresholds $\tilde{\psi}_{n,a_n}(n = 1, 2, ..., N)$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes (indicators) for the decision-maker may be written as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{\boldsymbol{low}} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{\boldsymbol{up}}. \tag{5}$$

Let $E = (H + N)$. Define $\ddot{\boldsymbol{y}} = \left(\boldsymbol{y}', \left[\tilde{\boldsymbol{y}}^*\right]'\right)'$ [$E \times 1$ vector], $\ddot{\boldsymbol{\gamma}} = (\boldsymbol{\gamma}', \tilde{\boldsymbol{\gamma}}')'$ [$E \times A$ matrix], $\ddot{\boldsymbol{d}} = (\boldsymbol{d}', \tilde{\boldsymbol{d}}')'$ [$E \times L$ matrix], and $\ddot{\boldsymbol{\varepsilon}} = (\boldsymbol{\varepsilon}', \tilde{\boldsymbol{\varepsilon}}')'$ ($E \times 1$ vector), Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vech}(\boldsymbol{\Sigma}), \text{Vech}(\ddot{\boldsymbol{\gamma}}), \text{Vech}(\ddot{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}]$, where the operator "Vech(.)" vectorizes all the non-zero elements of the matrix/vector on which it operates.

With the matrix definitions above, the continuous components of the model system may be written compactly as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}, \tag{6}$$

$$\ddot{\boldsymbol{y}} = \ddot{\boldsymbol{\gamma}}\boldsymbol{x} + \ddot{\boldsymbol{d}}\boldsymbol{z}^* + \ddot{\boldsymbol{\varepsilon}}, \text{ with Var}(\ddot{\boldsymbol{\varepsilon}}) = \ddot{\boldsymbol{\Sigma}} = \begin{bmatrix} \boldsymbol{\Sigma} & \mathbf{0} \\ \mathbf{0} & \mathbf{IDEN_N} \end{bmatrix} \ (E \times E \text{ matrix}), \tag{7}$$

To develop the reduced form equations, replace the right side of Equation (6) for $\boldsymbol{z}^{*}$ in Equation (7) to obtain the following system:

$$\vec{\boldsymbol{y}} = \vec{\boldsymbol{\gamma}}\boldsymbol{x} + \vec{\boldsymbol{d}}\boldsymbol{z}^{*} + \vec{\boldsymbol{\varepsilon}} = \vec{\boldsymbol{\gamma}}\boldsymbol{x} + \vec{\boldsymbol{d}}(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \vec{\boldsymbol{\varepsilon}} = \vec{\boldsymbol{\gamma}}\boldsymbol{x} + \vec{\boldsymbol{d}}\boldsymbol{\alpha w} + \vec{\boldsymbol{d}}\boldsymbol{\eta} + \vec{\boldsymbol{\varepsilon}}\,, \tag{8}$$

Now, consider

$$\boldsymbol{B} = \vec{\boldsymbol{\gamma}}\boldsymbol{x} + \vec{\boldsymbol{d}}\boldsymbol{\alpha w} \quad \text{and} \quad \boldsymbol{\Omega} = \vec{\boldsymbol{d}}\boldsymbol{\Gamma}\vec{\boldsymbol{d}}' + \vec{\boldsymbol{\Sigma}}\,. \tag{9}$$

Then $\vec{\boldsymbol{y}} \sim \boldsymbol{MVN}_{\boldsymbol{E}}(\boldsymbol{B},\boldsymbol{\Omega})$.

For the purpose of estimation, partition the vector $\boldsymbol{B}$ into components that correspond to the mean of the vectors $\boldsymbol{y}$ (for the continuous variables) and $\left[\tilde{\boldsymbol{y}}^{*}\right]'$ $[N \times 1$ vector], (for the ordinal outcomes), and the matrix $\boldsymbol{\Omega}$ into the corresponding variances and covariances:

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{B}_{y} \\ \boldsymbol{B}_{\tilde{y}^{*}} \end{bmatrix} (E) \times 1 \text{vector and } \boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\Omega}_{y} & \boldsymbol{\Omega}_{y\tilde{y}^{*}} \\ \boldsymbol{\Omega}'_{y\tilde{y}^{*}} & \boldsymbol{\Omega}_{\tilde{y}^{*}} \end{bmatrix} (E) \times (E) \text{ matrix.} \tag{10}$$

Then, conditional distribution of $\left[\tilde{\boldsymbol{y}}^{*}\right]'$, given $\boldsymbol{y}$, is MVN with mean $\vec{\boldsymbol{B}}_{\tilde{y}^{*}} = \boldsymbol{B}_{\tilde{y}^{*}} + \boldsymbol{\Omega}'_{y\tilde{y}^{*}}\boldsymbol{\Omega}_{y}^{-1}\left(\boldsymbol{y} - \boldsymbol{B}_{y}\right)$ and variance $\vec{\boldsymbol{\Omega}}_{\tilde{y}^{*}} = \boldsymbol{\Omega}_{\tilde{y}^{*}} - \boldsymbol{\Omega}'_{y\tilde{y}^{*}}\boldsymbol{\Omega}_{y}^{-1}\boldsymbol{\Omega}_{y\tilde{y}^{*}}$.

Then the likelihood function may be written as:

$$L(\boldsymbol{\delta}) = f_{H}(\boldsymbol{y} \mid \boldsymbol{B}_{y}, \boldsymbol{\Omega}_{y}) \times \Pr\left[\tilde{\boldsymbol{\psi}}_{low} \le \tilde{\boldsymbol{y}}^{*} \le \tilde{\boldsymbol{\psi}}_{up}\right], \tag{11}$$

$$= f_{H}(\boldsymbol{y} \mid \boldsymbol{B}_{y}, \boldsymbol{\Omega}_{y}) \times \int_{D_r} f_{N}(\boldsymbol{r} \mid \vec{\boldsymbol{B}}_{\tilde{y}^{*}}, \vec{\boldsymbol{\Omega}}_{\tilde{y}^{*}})\,dr,$$

where the integration domain $D_{r} = \{\boldsymbol{r} : \tilde{\boldsymbol{\psi}}_{low} \le \boldsymbol{r} \le \tilde{\boldsymbol{\psi}}_{up}\}$ is simply the multivariate region of the elements of the $\tilde{\boldsymbol{y}}^{*}$ vector determined by the observed ordinal indicator and main outcomes. $f_H(\boldsymbol{y} \,|\, \boldsymbol{B}_y, \boldsymbol{\Omega}_y)$ is the MVN density function of dimension H with a mean of $\boldsymbol{B}_y$ and a covariance of $\boldsymbol{\Omega}_y$, and evaluated at $\boldsymbol{y}$. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.

Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, we used the One-variate Univariate Screening technique proposed by Bhat (2018) for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

4. Model Estimation Results

The key contribution of this chapter, relative to the body of literature that has strived to document the relationship between mode use and level of satisfaction with (or wellbeing derived from) the daily travel routine, is that the relationship is being studied here while controlling for attitudinal factors that may mediate and influence the nature and strength of the relationship. This section presents estimation results for the integrated model system, which was estimated using the GHDM methodology. The estimation results are presented in two parts – first for the latent construct components and second, for the endogenous outcomes of interest.

Latent Construct Model Components

Table 4-2 presents results for the latent construct model components. In this chapter, three attitudinal constructs were developed based on a set of six indicators (two indicators per factor). All three latent constructs are significantly correlated with one another; as expected, environmental friendliness is negatively correlated with car proclivity and positively correlated with a diverse lifestyle preference. The factor representing diverse lifestyle preference is negatively correlated with the car proclivity factor.

The table shows that socio-economic and demographic variables significantly influence all three latent constructs. It is found that the younger age group (18-30 years old) are less likely to be environmentally friendly than older generations. This is a somewhat surprising finding as there is evidence to suggest that younger individuals are more environmentally conscious; however, there is also evidence to suggest that environmental consciousness is less about age and more about awareness, knowledge, and information (Otto and Kaiser, 2014). On the other hand, those 65 years and older are clearly more car-oriented, reflecting decades of dependency on the automobile for meeting mobility needs (KRC Research, 2018). Race is also significant. Whites are more car-oriented, Blacks embrace a more diverse lifestyle, and Native Americans are more environmentally friendly. These findings are consistent with those reported in the literature (e.g., Polzin et al., 1999; Rentziou et al., 2012; Polzin et al., 2014) and the finding about Native Americans reflects their sensitivity to preserving their lands and ecosystem (Vickery, 2016). Hispanics are also found to embrace a more diverse lifestyle, consistent with previous research (Parker et al., 2018).

Table 4-2

Determinants of Latent Variables and Loadings on Indicators (N = 3,365)

Explanatory variables (base category)	Latent Construct Model					
	Environmental friendliness		Car proclivity		Diverse lifestyle	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Age (*)						
18-30 years	-0.13	-5.93	—	—	—	—
65 years or older	—	—	0.21	11.10	—	—
Race (*)						
White	—	—	0.27	16.55	—	—
Black	—	—	—	—	0.34	11.34
Native American	0.41	4.79	—	—	—	—
Ethnicity (not Hispanic)						
Hispanic	—	—	—	—	0.24	9.32
Employment (*)						
Student	0.34	14.82	—	—	—	—
Worker	—	—	—	—	0.23	13.21
Education (*)						
Some college or technical school	-0.20	-12.74	—	—	—	—
At least some college or technical school	—	—	0.21	8.61	—	—
Household income (*)						
Less than $25,000	—	—	-0.40	-16.97	—	—
$50,000 to $150,000	—	—	—	—	-0.20	-11.84
Correlations between latent constructs						
Environmental friendliness	1.00	—	-0.33	-4.04	0.78	6.78
Car proclivity			1.00	—	-0.49	-2.66
Diverse lifestyle					1.00	—
Attitudinal Indicators	**Loadings of Latent Variables on Indicators (Measurement Equation Model Component)**					
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	1.34	32.55				
I am committed to an environmentally-friendly lifestyle.	0.64	29.97				
I definitely like the idea of owning my own car.			0.97	26.72		
When traveling in a vehicle, I prefer to be a driver rather than a passenger.			1.03	27.05		
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.					0.56	27.73
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.					0.92	29.82

**Base category is all other complementary categories for that variable.*

Employment, education level, and income are all socio-economic variables that affect latent attitudinal constructs. Students are more environmentally friendly (due to greater exposure to information and greater awareness) and workers embrace a more diverse lifestyle, presumably for greater access to jobs and opportunities. Those with at least some college education are less environmentally friendly and more car-oriented, reflecting their greater dependence on and use of the automobile to access jobs, destinations, and opportunities. These findings are consistent with those reported in the literature (e.g., Durr et al., 2017; Blazanin et al., 2021). Finally, low-income individuals are less car-oriented, while those in the middle-income bracket are less prone to embracing a diverse lifestyle. Those in the middle-income bracket are more likely to embrace affordable suburban living where lifestyle is less diverse (De Vos and Witlox, 2016; Sultana et al., 2019; Wells, 2012). Low-income individuals are less car-oriented by virtue of their greater alternative mode use (Molin et al., 2016; Conway et al., 2018).

Bivariate Model of Behavioral Outcomes

The bivariate model in this chapter takes the form of a discrete-continuous model with endogenous latent factors that account for complex interrelationships driving behavioral dimensions of interest. Results are shown in Table 4-3. The key finding is that, after controlling for the influence of latent attitudinal factors and all socio-economic and demographic variables in the data set, the proportion of driving for non-commute trips (on a weekly basis) significantly and positively impacts level of satisfaction with daily travel routine. The coefficient is positive and significant and suggests that – all other things being equal – the higher proportion of private automobile use (as a driver) is associated with a higher level of satisfaction with the daily travel routine. Note that this effect may be considered a "true" causal effect after accommodating the spurious unobserved correlation between the two variables engendered by the stochastic latent construct effects. Although the reverse or even the bidirectional relationship may be true and has been explored by other scholars (Kroesen et al., 2017, Kroesan and Chorus, 2018), the literature supports the current hypothesis that behaviors shape more attitudes than the other way around (Sharda et al., 2019). Thus, the proposed methodology is more plausible.

It should be recognized that this relationship holds true in the context of this sample, which is drawn from four sprawling metropolitan regions of the United States that are very auto-oriented and lack good transit service. This finding is consistent with results reported in the literature; in metro regions that are sprawled and auto-oriented, the finding that driving is associated with a higher level of satisfaction with the daily travel routine is not surprising and reinforces the notion that bringing about noticeable shifts in mode choice (away from auto use) remains a formidable challenge in such contexts (Mouratidis et al., 2019; De Vos and Witlox, 2016). To gain further insights into the generalizability and applicability of this finding to other geographical areas and contexts, particularly transit-rich metropolitan areas in the US, an additional analysis based on the wellbeing modules of the American Time Use Survey is presented in Appendix E.

Table 4-3

Estimation Results of the Joint Model of Driving Proportion and Satisfaction with Daily Travel Routine (N=3,365)

Explanatory variables (base category)	Main Outcome Variables			
	Satisfaction with daily travel routine (five-point Likert scale: strongly disagree to strongly agree)		**Proportion of driving in non-commute trips** (continuous, ranging from 0 to 1)	
	Coef.	**t-stat**	**Coef.**	**t-stat**
Endogenous variable				
Proportion of driving in non-commute trips	0.31	4.38	—	—
Latent constructs				
Environmental friendliness	-0.12	-4.02	-0.04	-7.57
Car proclivity	—	—	0.09	16.17
Diverse lifestyle	0.10	3.41	—	—
Age (31 years or older)				
18-30 years	-0.21	-9.67	-0.10	-17.57
Education (more than high school)				
High school or less	—	—	-0.09	-15.38
Employment (not a student)				
Student	—	—	-0.09	-16.72
Household income ($25,000 or more)				
Less than $25,000	-0.20	-7.22	-0.08	-13.79
Household size (less than 3)				
3 or more	-0.08	-5.60	—	—
Tenure status (not a homeowner)				
Homeowner	—	—	0.05	10.40
Commute distance (*)				
Less than 5 miles	—	—	-0.04	-8.50
10 miles or more	-0.61	-37.03	—	—
Population density (≥ 3,000 people/sq mile)				
Low density (< 3,000 people/sq mile)	-0.07	-4.77	0.05	12.76
Constant	—	—	0.68	122.75
Thresholds				
1|2	-1.89	-37.79	—	—
2|3	-1.12	-22.48	—	—
3|4	-0.59	-11.87	—	—
4|5	0.82	15.83	—	—
Correlation				
Proportion of driving for non-commute trips	0.08	—	—	—
Normalizing scale	—	—	0.26	123.36
Data Fit Measures	**GHDM model**		**Independent model**	
Log-likelihood at convergence	-4935.22		-4956.3	
Log-likelihood at constants	-5455.78			
Number of parameters	82		32	
Likelihood ratio test	0.045		0.039	

**Base category is all other complementary categories for that variable.*

When it comes to the influence of latent constructs, the findings are quite intuitive. Those who are environmentally friendly exhibit a lower level of driving (relative to the use of other modes) and a lower level of satisfaction with the daily travel routine – suggesting that they are still driving more than they would like. Those who are auto-oriented exhibit a greater level of proportion of driving. Individuals who embrace a diverse lifestyle express a greater level of satisfaction with their daily travel routine. This is because these individuals have consciously self-selected themselves to reside in neighborhoods that are diverse, dense, and well served by transit (e.g., Bhat et al., 2013; De Vos and Witlox, 2016; Schwanen and Mokhtarian, 2005; Cao and Ettema 2014). By virtue of self-selecting themselves into such neighborhoods, they are able to live and move according to their preferences and hence have a high level of satisfaction. The same does not necessarily apply to those who are environmentally friendly; many environmentally friendly individuals reside in low density auto-oriented environments, thus resulting in a level of driving dependency that is out of sync with their preferences and approach to sustainability.

Among socio-economic and demographic characteristics, it is clear that the youngest age group (18-30 years) has a lower proportion of driving and a tendency to report a lower level of satisfaction with their daily travel routine. The degree to which the dissatisfaction directly stems from the lower level of driving is uncertain and merits further investigation in future research. Nevertheless, the correlation is undeniable. Those with a lower educational attainment and students exhibit lower proportions of driving. Similarly, lower income individuals drive less and exhibit a propensity towards lower levels of daily travel satisfaction, reflecting a correlation between driving proportion and daily travel satisfaction. Home ownership is associated with a higher level of driving, consistent with the notion that home ownership tends to be higher in suburban areas where automobile dependence is higher (Bagley and Mokhtarian, 2002; Cao et al., 2007; Bhat et al., 2013). Residing in larger households (which generally have more complex activity-travel patterns) is associated with lower levels of satisfaction with the daily travel routine.

As expected, those with short commutes have a lower proportion of driving even for non-commute trips (as non-commute trips are often chained to longer commutes and tend to be auto-oriented). Individuals with longer commutes are likely to express a lower level of satisfaction with their daily travel routine; this finding is consistent prior research showing long commutes are generally deemed less desirable (Ory and Mokhtarian, 2005; Ye and Titheridge, 2017). Individuals residing in low density areas drive more and have a higher probability of being less satisfied with their daily travel routine. This finding may appear counterintuitive but is in fact consistent with expectations. Some (but not all) individuals reside in low-density areas for the sake of affordability, large yards and homes, and quality of schools. They end up driving more than they would like and hence end up unhappy with their daily travel routine. Such lifestyle relationships and outcomes have been reported previously in the literature and this chapter corroborates earlier findings (De Vos et al., 2016; Mouratidis et al., 2019).

5. Study Implications and Conclusions

The ability to access destinations and pursue activities that are distributed in time and space has been shown to impact a person's wellbeing and quality of life. However, there is limited evidence on how daily mode use affects an individual's level of satisfaction with his or her daily travel routine. This chapter attempts to fill this critical gap in the literature by analyzing the relationship between the degree (frequency) of automobile driving that an individual typically undertakes in a week and the degree to which an individual considers the daily travel routine satisfactory. Does an individual who drives more feel less satisfaction or more? Do individuals in automobile-oriented cities (with poor transit service, sprawled land use patterns) experience low levels of satisfaction with their daily travel routine (due to the high levels of driving required)? Or is a high level of driving associated with a high level of satisfaction with the daily travel routine due to the generally superior performance, convenience, and comfort of the personal automobile mode relative to other modes of transportation? Insights on these questions may help inform policy directions and future transportation investments. If people in automobile-oriented cities are unhappy with their daily travel routine (and drive a lot) and there is a clear negative effect from increased driving on daily travel routine satisfaction, then it is clear that municipalities should and could invest in alternative modes of transportation – such investments are likely to yield benefits and result in mode shifts away from the automobile. On the other hand, if people in automobile-oriented cities are generally happy and satisfied with their daily travel routine, and the amount of driving has a positive effect on daily travel satisfaction, then it would appear that bringing about a mode shift would be extremely challenging in the absence of policies that strongly disincentivize driving.

In this chapter, the relationship between the relative amount of weekly driving for non-commute trips and the level of satisfaction associated with the daily travel routine is explored. A joint model that considers the relationship between these two endogenous variables is estimated. The joint model explicitly incorporates the effects of latent attitudinal factors that capture people's preferences, values, and perceptions. These latent attitudinal factors are themselves endogenous and influenced by exogenous variables. The entire model system is estimated jointly in a Generalized Heterogeneous Data Model (GHDM) framework to assess the true effect of amount of driving on level of daily travel satisfaction, after controlling for all other variables. The joint model is found to offer a statistically superior goodness-of-fit than a corresponding independent model that ignores jointness and endogeneity in the model structure.

The joint model, by virtue of its ability to control for many confounding variables, reveals that the relative amount of weekly driving for non-commute trips positively and significantly impacts the level of satisfaction that an individual associates with his or her daily travel routine. The data reveal that 68 percent of survey respondents find their daily travel routine to be satisfactory and only 17 percent deem their daily travel routine unsatisfactory. Model estimation results show that latent attitudinal factors representing an environmentally friendly lifestyle, a proclivity towards car ownership and driving, and a desire to live close to transit and in diverse land use neighborhoods affect both endogenous variables, namely, relative frequency of auto-driving for non-commute trips and degree of agreement that the daily travel routine is satisfactory. Even after controlling for these latent attitudinal factors, the effect of driving on daily travel routine satisfaction is positive and significant.

The findings suggest that auto driving mode use is not necessarily an undesirable activity that leads to diminished satisfaction. In fact, it appears to contribute positively to satisfaction. In areas that have poor transit service and sprawled land use patterns, it is very difficult for other modes of transportation to compete effectively with the automobile. However, based on the findings in this chapter, mere investments in alternative modes of transportation and improvements to their level of service (as explored by Eriksson et al., 2008, 2013, for instance) are not necessarily going to draw people away from the automobile if the use of the auto-driving mode is itself associated with higher levels of satisfaction. The only way to bring about noticeable shifts in mode use would entail the application of strong disincentives to automobile mode use. One of the interesting findings is that those who prefer living close to transit and in the midst of shops and restaurants are more likely to report higher levels of satisfaction with the daily travel routine. These individuals likely self-select into such neighborhoods and pursue a lifestyle that is consistent with their preferences. At the same time, it is found that those who have an environmentally friendly attitude are relatively dissatisfied with their daily travel routine even though they drive less than those who do not have an environmentally friendly attitude, presumably due to poor service. It is this group of dissatisfied environmentally friendly individuals that may be motivated to drive less and shift more to alternative modes if investments were made to upgrade service. Alternatively, they need to be provided the amenities they seek (affordable housing, good schools, open spaces) in areas well served by transit and other modes of transportation. By offering alternative residential lifestyle options, it may be possible to draw these dissatisfied, environmentally friendly individuals to a more non-automobile centric mode use pattern. Future research efforts should aim to characterize this market segment so that targeted interventions can be done. Also, future modeling efforts should account for the role of daily time use, the amount of driving in mileage and time, and activity participation (at trip destinations) in determining level of satisfaction with daily travel routine.

It is also noteworthy that this study has limitations. Measuring overall daily travel routine satisfaction is rather complex, and there is not a single well-established way of doing so. While we use a unidimensional scale in the form of an attitudinal statement to quantify it (similar to Susilo and Cats, 2014 and Mao et al., 2016), many scholars have used multidimensional scales, and sometimes even more sophisticated methodologies, to quantify travel satisfaction (Cao and Ettema, 2014, De Vos et al., 2016, and Friman et al., 2013). Furthermore, special care should be taken before generalizing results. As stated before, the sample is comprised of survey respondents from four U.S. automobile-oriented metropolitan areas (Phoenix, Austin, Atlanta, and Tampa); further research should explore different geographical characteristics, such as transit-oriented cities and rural areas. In addition, it is worth recognizing that a variety of other factors could affect travel satisfaction. For instance, physical activity levels, some personality traits, or disability status could be included in the modeling effort and tested to determine whether they have a significant effect on satisfaction with daily travel routine. However, due to model fitting limitations and data availability, additional latent constructs and person characteristics are not considered in the estimated model. Alternative modeling frameworks with the inclusion of new latent constructs and person characteristics may also be considered in future research endeavors.

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7. References

Bagley, M. N., & Mokhtarian, P. L. (2002). The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *The Annals of Regional Science*, *36*, 279-297.

Bhat, C. R. (2015). A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B: Methodological*, *79*, 50-77.

Bhat, C. R. (2018). New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B: Methodological*, *109*, 238-256.

Bhat, C. R., Paleti, R., Pendyala, R. M., Lorenzini, K., & Konduri, K. C. (2013). Accommodating immigration status and self-selection effects in a joint model of household auto ownership and residential location choice. *Transportation Research Record*, *2382*(1), 142-150.

Blazanin, G., Mondal, A., Asmussen, K. E., & Bhat, C. R. (2022). E-scooter sharing and bikesharing systems: An individual-level analysis of factors affecting first-use and use frequency. *Transportation Research Part C: Emerging Technologies*, *135*, 103515.

Cao, X. J., & Ettema, D. F. (2014). Satisfaction with travel and residential self-selection: How do preferences moderate the impact of the Hiawatha Light Rail Transit line?. *Journal of Transport and Land Use*, *7*(3), 93-108.

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2007). Cross-sectional and quasi-panel explorations of the connection between the built environment and auto ownership. *Environment and Planning A*, *39*(4), 830-847.

Conway, M. W., Salon, D., & King, D. A. (2018). Trends in taxi use and the advent of ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Science*, *2*(3), 79.

De Vos, J., & Witlox, F. (2016). Do people live in urban neighbourhoods because they do not like to travel? Analysing an alternative residential self-selection hypothesis. *Travel Behaviour and Society*, *4*, 29-39.

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V., & Witlox, F. (2016). Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. *Transportation*, *43*, 771-796.

Durr, E., Bilecki, J., & Li, E. (2017). Are beliefs in the importance of pro-environmental behaviors correlated with pro-environmental behaviors at a college campus?. *Sustainability: The Journal of Record*, *10*(3), 204-210.

Eriksson, L., Friman, M., & Gärling, T. (2008). Stated reasons for reducing work-commute by car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *11*(6), 427-433.

Eriksson, L., Friman, M., & Gärling, T. (2013). Perceived attributes of bus and car mediating satisfaction with the work commute. *Transportation Research Part A: Policy and Practice*, *47*, 87-96.

Ettema, D., Gärling, T., Eriksson, L., Friman, M., Olsson, L. E., & Fujii, S. (2011). Satisfaction with travel and subjective well-being: Development and test of a measurement tool. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(3), 167-175.

Friman, M., Fujii, S., Ettema, D., Gärling, T., & Olsson, L. E. (2013). Psychometric analysis of the satisfaction with travel scale. *Transportation Research Part A: Policy and Practice*, *48*, 132-145.

Khoeini, S., Pendyala, R. M., da Silva, D. C., Batur, I., Magassy, T. B., & Sharda, S. (2020). Attitudes Towards Emerging Mobility Options and Technologies–Phase 3: Survey Data Compilation, and Analysis.

KRC Research (2018). Transportation Needs and Assessment: Survey of Older Adults, People with Disabilities, and Caregivers. Retrieved from http://www.krcresearch.com/wp-content/uploads/2018/12/KRC-nadtc-Survey-Report-120718-FINAL_for-web.pdf

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190-202.

Kroesen, M., & Chorus, C. (2018). The role of general and specific attitudes in predicting travel behavior–A fatal dilemma?. *Travel Behaviour and Society*, *10*, 33-41.

Mao, Z., Ettema, D., & Dijst, M. (2016). Commuting trip satisfaction in Beijing: Exploring the influence of multimodal behavior and modal flexibility. *Transportation Research Part A: Policy and Practice*, *94*, 592-603.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice*, *83*, 14-29.

Mouratidis, K., Ettema, D., & Næss, P. (2019). Urban form, travel behavior, and travel satisfaction. *Transportation Research Part A: Policy and Practice*, *129*, 306-320.

Mondal, A., Bhat, C. R., Costey, M. C., Bhat, A. C., Webb, T., Magassy, T. B., ... & Lam, W. H. K. (2021). How do people feel while walking? A multivariate analysis of emotional well-being for utilitarian and recreational walking episodes. *International Journal of Sustainable Transportation*, *15*(6), 419-434.

Ory, D. T., & Mokhtarian, P. L. (2005). When is getting there half the fun? Modeling the liking for travel. *Transportation Research Part A: Policy and Practice*, *39*(2-3), 97-123.

Otto, S., & Kaiser, F. G. (2014). Ecological behavior across the lifespan: Why environmentalism increases as people grow older. *Journal of Environmental Psychology*, *40*, 331-338.

Parker, K., Horowitz J., Brown A., Fry R., Cohn D.V., & Igielnik R. (2018). What Unites and Divides Urban, Suburban and Rural Communities. Retrieved from https://www.pewresearch.org/social-trends/2018/05/22/demographic-and-economic-trends-in-urban-suburban-and-rural-communities/

Polzin, S. E., Chu, X., & Godfrey, J. (2014). The impact of millennials' travel behavior on future personal vehicle travel. *Energy Strategy Reviews*, *5*, 59-65.

Polzin, S. E., Chu, X., & Rey, J. R. (1999). *Mobility and mode choice of people of color for non-work travel*. Center for Urban Transportation Research.

Rentziou, A., Gkritza, K., & Souleyrette, R. R. (2012). VMT, energy consumption, and GHG emissions forecasting for passenger transportation. *Transportation Research Part A: Policy and Practice*, *46*(3), 487-500.

Schwanen, T., & Mokhtarian, P. L. (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?. *Journal of Transport Geography*, *13*(1), 83-99.

Sharda, S., Astroza, S., Khoeini, S., Batur, I., Pendyala, R. M., & Bhat, C. R. (2019, March). Do attitudes affect behavioral choices or vice-versa: Uncovering latent segments within a heterogeneous population. In *Transportation Research Board 98th Annual Meeting Compendium of Papers, Washington DC, January*.

Singleton, P. A. (2019). Walking (and cycling) to well-being: Modal and other determinants of subjective well-being during the commute. *Travel Behaviour and Society*, *16*, 249-261.

Sultana, S., Salon, D., & Kuby, M. (2019). Transportation sustainability in the urban context: A comprehensive review. *Urban Geography*, *40*(3), 279-308.

Susilo, Y. O., & Cats, O. (2014). Exploring key determinants of travel satisfaction for multi-modal trips by different traveler groups. *Transportation Research Part A: Policy and Practice*, *67*, 366-380.

Vickery, J., & Hunter, L. M. (2016). Native Americans: Where in environmental justice research?. *Society & Natural Resources*, *29*(1), 36-52.

Wells, M. (2010). Resilience in older adults living in rural, suburban, and urban areas. *Online Journal of Rural Nursing and Health Care*, *10*(2), 45-54.

Ye, R., & Titheridge, H. (2017). Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. *Transportation Research Part D: Transport and Environment*, *52*, 535-547.

CHAPTER 5

AN ANALYSIS OF CHANGES IN TIME USE AND ACTIVITY PARTICIPATION IN RESPONSE TO THE COVID-2019 PANDEMIC IN THE UNITED STATES: IMPLICATIONS FOR WELLBEING

This chapter is substantially drawn from the following journal article:

Batur, I., Dirks, A. C., Bhat, C. R., Polzin, S. E., Chen, C., & Pendyala, R. M. (2023). Analysis of changes in time use and activity participation in response to the COVID-19 pandemic in the United States: implications for well-being. *Transportation Research Record*, 03611981231165020.

1. Introduction

The COVID-19 pandemic brought about significant changes in human activity-travel patterns, time use, and activity modalities. Due to the length of the pandemic, individuals have adopted new routines and habits, and organizations have adopted new operating procedures and implemented changes in how they interface with employees and customers. Professionals who engage in forecasting future travel demand and planning future transportation systems are grappling with much more uncertainty about the future than in the pre-COVID era. There is considerable uncertainty on the extent to which people will return to pre-COVID behaviors and the degree to which the new normal (in a post-pandemic period) will resemble the pre-COVID conditions (Currie et al., 2021).

Presumably, many changes in lifestyles, activity engagement, and time use brought about by the pandemic impacted peoples' quality of life and wellbeing. For example, work from home (WFH) has been embraced by workers during the pandemic, and many workers are resisting a full-time return to the office. This is likely because the WFH modality provided individuals the ability to enjoy a higher quality of life, have greater control of their time, put their commuting time to more productive and enjoyable uses that enhanced wellbeing, and take advantage of the flexibility that WFH offers in terms of being able to juggle multiple work responsibilities and household/ personal/childcare obligations. In other words, WFH, rather than commuting, likely enhanced wellbeing and is therefore likely to persist well into the post-pandemic era.

On the other hand, there may have been changes in pandemic-era activity-travel patterns that resulted in decreased wellbeing. These were generally induced by health and safety concerns and in response to lockdowns, business closures, and stay-at-home orders promulgated by jurisdictions and organizations. Any changes in activity-travel patterns resulting in reduced wellbeing are likely to be short-lived in nature; people are likely to abandon those changes and revert to pre-pandemic behaviors (or adopt entirely new behaviors) once the pandemic is history.

During the height of the pandemic, many public health precautions resulted in dramatic reductions in travel. Concerns about the spread of the contagion and the rapid adoption of technological platforms that enabled virtual transactions, WFH, online shopping and delivery of goods, meals, and services, and online education led to a substantial reduction in physical travel and in-person activity engagement (Eliasson, 2022). In communities around the world, dramatic reductions in traffic were reported, together with substantial improvements in air quality in some of the most polluted cities in the world (Adams et al., 2021). While there were significant concerns related to the health and safety of frontline workers, survival of small businesses, hollowing out of vibrant downtowns, and ability to sustain transit services, many reports emphasized the benefits of reduced traffic, greater flexibility and accessibility resulting from embracing virtual activity engagement and the elimination of the stressful commute (Calvert, 2021; Parker et al., 2022).

However, as the pandemic faded in the latter half of 2021 and into 2022, the traffic rebound has been fast and furious. Even though WFH has persisted, and hybrid work patterns have been embraced by many organizations (Parker et al., 2022), there has been a substantial recovery in traffic as measured by vehicle miles of travel (VMT), number of trips, and air travel (Markezich, 2021; BTS, 2022; TSA, 2022). The trends show that transit recovery remains tepid (BTS, 2022; Magassy et al., 2023), and office occupancy rates in many cities are subdued (Kastle Systems, 2022). On average, across the US, transit patronage is currently about 60 percent of pre-pandemic levels; office occupancy rates also exhibit a similar recovery pattern. However, virtually all other measures of travel and in-person activity engagement have recovered or even surpassed pre-pandemic levels (FHWA, 2022).

The recovery of travel and in-person activity engagement has likely been dramatic due to a reduction in wellbeing during the height of the pandemic when travel levels were substantially lower than pre-pandemic times. Indeed, many articles documented mental health issues during the pandemic, struggling with isolation, inability to interact with family, friends, and co-workers, and inability to engage in familiar routines and favorite activities (e.g., going to the gym, dining at a favorite restaurant) (Nochaiwong, 2021).

While the ability to work, learn, shop, play, and order meals from home may have increased flexibility, discretionary time, and convenience in accessing goods and services, the inability to travel and engage in physical activities and social interactions has taken a toll on the human psyche (Cudjoe and Kotwal, 2020; Nochaiwong, 2021).

This essentially means that there is a strong connection between physical activity-travel engagement and human wellbeing; indeed, there is an abundant body of literature that speaks to wellbeing implications of activity-travel patterns and mode use (Batur et al., 2019). Much of the literature related to wellbeing implications of transportation has focused on the effects of the commute (Hensher et al., 2022; Hook et al., 2021), influence of activity and time use patterns (Schwanen and Wang, 2014), use of different modes of transportation (De Vos et al., 2016), and role of situational context as described by the built environment in which an individual engages in activities (Van Acker et al., 2010). While the literature provides valuable insights, there has been little research on the wellbeing impacts of a disruption characterized by rapid adoption and implementation of virtual/online technology platforms. Virtually no research has examined how wellbeing changes as a result of changes in the transportation ecosystem in the wake of a severe and prolonged disruption.

To understand changes in wellbeing that resulted from changes in activity-travel patterns, this chapter presents a comprehensive wellbeing analysis of daily activity-travel patterns before and during the pandemic. The chapter utilizes American Time Use Survey (ATUS) data from 2019 and 2020. Because the pandemic started in March 2020, time use records for May through November of 2019 and 2020 are extracted for year-to-year comparisons (December was omitted to control for holiday period effects, and April was omitted because no data was collected in April 2020). The daily time use records in these respective years are utilized to compute wellbeing scores for all individuals in the survey samples, based on the methodology in Khoeini et al. (2018). The wellbeing analysis is also done using the time poverty approach to assess the degree to which this approach may explain the change in individuals' wellbeing. Time poverty is defined by the time available (or unavailable) to pursue leisure activities (Williams et al., 2016). By applying two different wellbeing analysis methods, this paper explores how different approaches explain activity-travel impacts on wellbeing. More importantly, the paper aims to provide deep insights on why there has been such a fast and furious rebound in travel, in an era when many have touted the benefits of reduced travel and embraced virtual platforms for activity engagement. The paper aims to identify population groups most vulnerable to disruption through a detailed analysis of wellbeing. Such insights will help public and private entities implement appropriate strategies and deploy much-needed resources to help mitigate the disruptive impacts of an extreme event.

2. Data Description

The chapter utilizes data from the 2019 and 2020 editions of the American Time Use Survey (ATUS). The ATUS is a federally administered annual time use survey conducted by the Bureau of Labor Statistics (BLS) in the United States since 2003. The survey aims to measure how people spend their time in life, encompassing activities related to personal care, household maintenance, work, education, shopping, travel, volunteering, errands, telephone calls, and child and elder care. The survey provides detailed information about time spent on all these activities both in-home and out-of-home, with the total time allocated across all activity purposes adding to 1440 minutes (the day for which time use diary is completed goes from 4 AM to 4 AM). The ATUS does not have a provision for recording multiple activities in the same time slot; thus, it does not capture multitasking when individuals may engage in primary, secondary, and tertiary activities simultaneously. Nevertheless, the ATUS is a very rich source of information to study activity-travel and time use patterns for a representative sample of the United States. The COVID pandemic offers an opportunity to study the impacts of a significant and prolonged disruption on activity and time use patterns, and the implications of such impacts for human wellbeing and time poverty.

The 2019 and 2020 ATUS editions provide detailed activity and time use data for a representative sample of 9,435 and 8,782 individuals, respectively. Because children generally depend on adults for their care and activity engagement, the analysis subsample used in this chapter is limited to those 18 years or older. The investigation in this paper is heavily oriented towards understanding the effects of alternative work modalities (work-from-home, commute to workplace) and comparing activity and time use patterns between non-workers and workers (adopting different modalities). Respondents who reported being part-time workers were removed from the analysis subsample. Part-time workers are certainly an important demographic segment, but it is difficult to decipher whether a day with no work episodes constitutes a working day in which they chose not to work (e.g., took a vacation day) or a non-working day due to their part-time work status. Therefore, a more well-informed comparison could be made by limiting the analysis subsample to non-workers and *full-time* workers.

The pandemic took effect in the US in March 2020. As a result of the immediate shutdowns and serious public health concerns, ATUS data collection was suspended in April 2020. In order to compare pre-COVID to during-COVID activity and time use patterns, all records corresponding to May through November of 2019 and 2020 were extracted and used for analysis. Records collected in December were excluded because of the unique nature of the holiday season. This filtering resulted in final sample sizes of 4,534 for 2019 and 5,120 for 2020. Table 5-1 depicts the socio-economic and demographic characteristics of the ATUS subsamples analyzed in this chapter. All statistics are based on an analysis of the weighted survey sample. In the interest of brevity, only a few highlights are mentioned here.

In general, the two subsamples (2019 versus 2020) are similar in overall profile. For each year, four distinct subsamples are defined based on work status. Non-workers are those who indicated that they were not participating in the labor force. Workers are those who are employed *full-time*. Workers with zero work correspond to the subsample that reported no work activity in the time use diary. In-home only workers include those who reported working exclusively from home with absolutely no out-of-home work activity. Finally, commuters are those who reported at least some out-of-home work activity in the time use diary; commuters may have also engaged in in-home work episodes. The ATUS respondent samples are distributed across all days of the week. Even though there are more weekdays than weekend days, the respondent sample exhibits a different profile, with a larger share of respondents providing data for weekend days. Further filtering to exclude weekend days from the analysis would have resulted in sample sizes being too small to facilitate robust, statistically valid computations. The inclusion of weekend days in the analysis does render interpretation of certain statistics challenging; most notably, the group labeled “workers with zero work” presents considerable ambiguity as zero work may have been due to it being a non-work (weekend) day or due to the worker taking the day off (e.g., vacation or sick day). Caution must be exercised when viewing the statistics for this specific subgroup as it represents a mix of two phenomena at play.

Overall, the samples are nearly equally split between females and males, with 30 percent aged 65 years or over, 17 percent with a graduate or professional degree, 80 percent White, 30 percent residing in single-person households, more than 70 percent having no child present, and more than 80 percent residing in an urban area. In general, the sample characteristics provide the variation needed to conduct the analysis undertaken in this paper.

Table 5-1

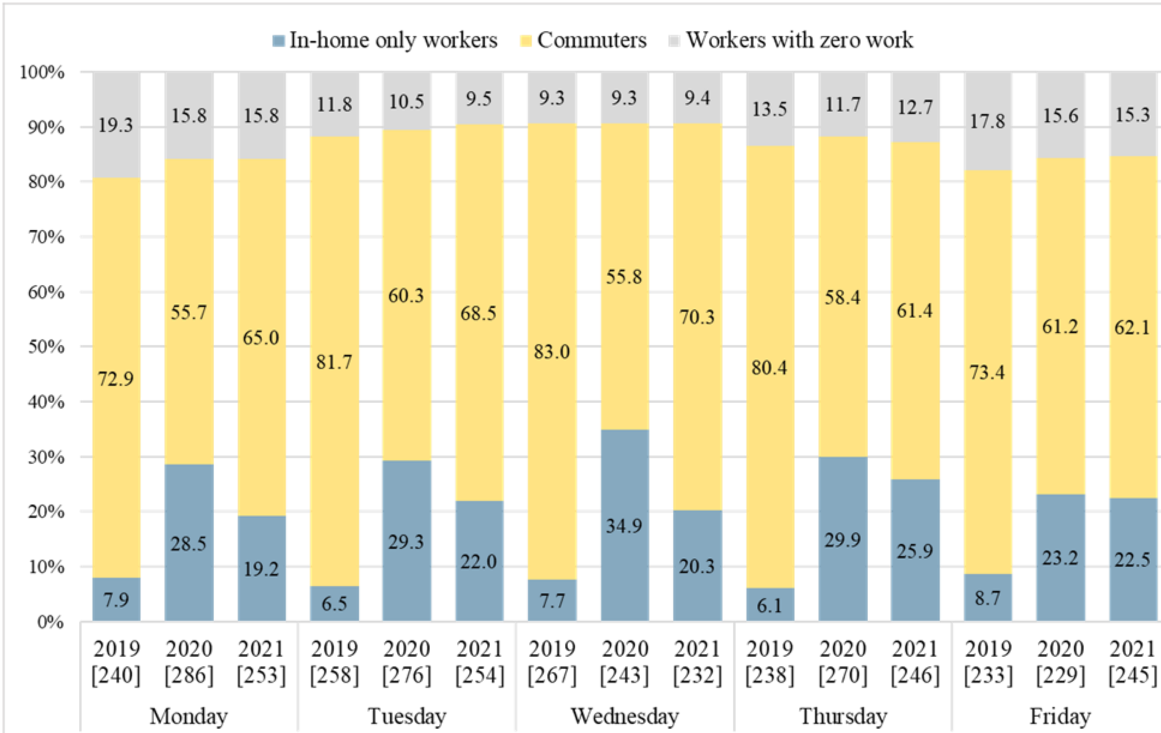
Socio-Economic and Demographic Characteristics of the ATUS Subsamples

Attribute	Category	Non-workers		Workers with zero work		In-home only workers		Commuters		All	
		2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
Sample size		1,949	2,398	1,026	1,100	302	655	1,257	967	4,534	5,120
Gender	Female	63.1	61.8	50.0	45.9	47.7	50.4	41.9	39.5	53.2	52.7
	Male	36.9	38.2	50.0	54.1	52.3	49.6	58.1	60.5	46.8	47.3
Age	18 to 25	3.2	4.4	5.1	5.0	3.0	2.3	5.3	4.7	4.2	4.3
	26 to 35	6.4	6.6	21.5	22.8	14.6	18.9	22.4	20.1	14.8	14.2
	36 to 50	9.1	11.0	37.5	36.5	41.1	41.7	37.0	36.4	25.4	25.2
	51 to 65	20.5	19.5	30.4	31.9	33.1	29.5	30.5	33.1	26.4	26.0
	65 or more	60.8	58.5	5.5	3.8	8.3	7.6	4.7	5.8	29.2	30.3
Educational attainment	Less than a high school diploma	12.5	11.6	5.4	4.5	3.0	1.1	5.5	6.1	8.3	7.7
	High school graduate or GED	30.0	27.9	19.2	20.4	11.3	6.7	21.0	27.0	23.8	23.4
	Some college or associates degree	28.8	28.2	27.6	26.1	15.9	16.3	27.0	28.5	27.2	26.3
	Bachelor's degree	16.9	20.0	28.0	30.4	37.4	39.1	26.6	23.8	23.5	25.4
	Graduate or professional degree	11.9	12.3	19.9	18.7	32.5	36.8	19.9	14.6	17.3	17.2
Race	White	79.6	80.4	81.3	80.9	82.8	78.9	80.8	80.6	80.5	80.4
	Black	15.5	14.0	11.6	9.6	6.6	9.0	12.0	12.8	13.1	12.2
	Asian	2.4	3.6	5.8	6.4	7.0	10.2	5.2	3.9	4.2	5.1
	Some other race	2.5	2.0	1.4	3.1	3.6	1.8	2.0	2.7	2.2	2.3
Employment	Employed full-time	0.0	0.0	100.0	100.0	100.0	100.0	100.0	100.0	57.0	53.2
	Unemployed	4.8	8.4	0.0	0.0	0.0	0.0	0.0	0.0	2.1	3.9
	Not in labor force	95.2	91.6	0.0	0.0	0.0	0.0	0.0	0.0	40.9	42.9
Household income	< $35K	44.4	39.0	15.0	12.4	10.9	7.3	18.7	16.6	28.4	25.0
	≥ $35K, < $50K	14.2	15.4	12.9	12.2	8.6	5.5	11.8	11.6	12.8	12.7
	≥ $50K, < $75K	17.4	17.8	18.0	20.5	15.6	16.0	20.0	23.0	18.2	19.1
	≥ $75K, < $100 K	9.9	10.0	15.3	15.5	16.6	15.0	14.8	16.8	12.9	13.1
	≥ $100K, <150K	7.5	9.7	21.1	19.5	15.2	21.4	17.1	18.3	13.7	14.9
	≥ $150K	6.7	8.0	17.7	20.0	33.1	34.8	17.7	13.8	14.0	15.1
Household size	1	39.5	34.5	23.1	21.4	19.9	19.4	23.4	21.6	30.0	27.3
	2	38.4	39.9	26.7	32.1	30.8	31.8	28.3	32.8	32.4	35.9
	3 or more	22.1	25.5	50.2	46.5	49.3	48.9	48.3	45.6	37.5	36.8
Child presence in household	Child present	12.1	13.6	43.5	37.6	40.1	44.0	40.3	36.9	28.9	27.0
	No child present	87.9	86.4	56.5	62.4	59.9	56.0	59.7	63.1	71.1	73.0
Household location	Urban area	81.2	81.9	86.0	86.4	88.7	92.2	85.3	84.6	83.9	84.7
	Not an urban area	18.8	18.1	14.0	13.6	11.3	7.8	14.7	15.4	16.1	15.3

In view of the mix of weekends and weekdays that characterize the sample descriptions presented in Table 5-1, a specific weekday-based analysis of work modalities was conducted separately. This analysis also incorporated the 2021 ATUS data (for the same months of May through November) to examine the extent to which pandemic-era behaviors in 2020 may have faded in 2021. Figure 5-1 depicts work modalities for full-time workers by weekday. The figure patterns are consistent with expectations. In 2019, the percentage of workers who worked exclusively at home varied between six and nine percent. This percentage surged in 2020 at the height of the pandemic, varying between 20 and 35 percent. Interestingly, the highest percent of in-home work only occurs on Wednesday and the lowest on Friday, suggesting that workers following a hybrid schedule are likely to favor a mid-week break from the workplace instead of creating three-day weekends by working at home on Fridays. In 2021, the percentage reporting in-home work only varied between 19.2 and 26 percent, suggesting that some recovery of commuting to the workplace happened by May through November of 2021. The in-home work shift is largest for Wednesday, with Thursday and Friday depicting modest changes in in-home work shares. The percentage of workers reporting zero work is largest on Mondays and Fridays, possibly as a result of individuals trying to combine a non-workday with the weekend.

Figure 5-1

Share of In-Home Only Workers, Commuters, and Workers with Zero Work by Weekday in 2019, 2020, and 2021 (Weighted)



3. A Descriptive Comparison of Time Use Patterns

This section presents a comparison of time use patterns between 2019 and 2020. In the interest of brevity, only very select comparisons will be presented here. Because there is considerable interest in understanding the time use and wellbeing implications of alternative work modalities, the tabulations and charts in this paper largely use these dimensions for comparison purposes. Table 5-2 presents a color-coded tabulation of time use (in minutes per day) for various activities in 2019 and 2020, offering a comparison along multiple dimensions.

The pandemic took a toll on out-of-home activity engagement. The last row of the table (corresponding to totals) shows a distinct pattern of increased in-home time use and reduced out-of-home time use across the board, with the greatest decrease in out-of-home time use for full-time workers on weekdays. This is clearly because of the substantial increase in time spent working at home, from 49.7 minutes per day in 2019 to 152.9 minutes per day in 2020. In general, all groups show a modest increase in sleep time, which appears to have been facilitated by a rather substantial decrease in travel and out-of-home activity time.

The time spent traveling reduced considerably for all groups during the pandemic, suggesting that public health concerns, lockdowns and closures, and stay-at-home orders significantly impacted out-of-home activity engagement. Time spent on personal care decreased, echoing the findings of Restrepo and Zeballos (2022), whereas time spent on household activities (chores) and caring for household members increased. Time spent in-home for eating and drinking showed a substantial increase, with a corresponding decrease in time spent on this activity out-of-home. More time was also devoted to in-home telephone calls, suggesting that telecommunications significantly replaced in-person interactions and communication.

Table 5-2

Time Use (Average Minutes per Day) in 2019 and 2020 (Weighted)

Activity type	Location	Worker				Non-worker			
		Weekday		Weekend		Weekday		Weekend	
		2019	2020	2019	2020	2019	2020	2019	2020
Sample size		1,273	1,339	1,312	1,383	953	1,216	996	1,182
Sleeping	In-home	482.5	489.1	557.6	566.1	551.7	562.6	568.2	578.8
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	47.8	40.7	41.9	37.2	45.4	38.7	45.7	41.2
	Out-of-home	0.2	0.0	0.1	0.1	0.6	0	0.2	0.0
Household activities	In-home	63.6	69.1	124.0	143.9	154.8	158.9	125.7	147.0
	Out-of-home	5.5	6.2	12.5	12.6	7.8	7.5	13.6	8.1
Helping household members	In-home	18.6	20.9	21.6	26.5	21.7	25.8	12.0	14.4
	Out-of-home	6.7	2.9	6.9	4.3	5.2	3.3	4.1	3.6
Helping non-household members	In-home	1.7	1.6	1.8	1.7	6.8	6.5	2.7	3.8
	Out-of-home	3.0	4.2	5.8	5.9	8.5	7.2	5.1	5.9
Work & work-related activities	In-home	49.7	152.9	21.0	28.4	0.0	0.0	0.0	0.0
	Out-of-home	379.7	287.6	104.7	74.0	0.0	0.0	0.0	0.0
Education	In-home	2.5	4.5	4.3	4.8	6.6	14.8	7.5	9.4
	Out-of-home	0.8	1.9	0.5	0.9	8.3	4.8	2.2	1.0
Consumer purchases	In-home	0.6	0.8	1.0	1.7	0.6	1.4	0.5	1.4
	Out-of-home	11.2	8.0	31.2	26.5	24.3	18.6	24.1	14.6
Personal care services	In-home	0.1	0.2	0.2	0.1	0.9	1.0	0.1	0.8
	Out-of-home	4.2	2.8	3.1	2.1	8.8	9.0	2.6	3.0
Household services	In-home	0.2	0.2	0.1	0.2	1.1	1.1	0.4	0.5
	Out-of-home	0.4	0.3	0.8	0.6	0.6	0.8	0.1	0.2
Government services & civic obligations	In-home	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.1
	Out-of-home	0.3	0.1	0.1	0.2	0.2	0.1	0.0	0.1
Eating and drinking	In-home	31.1	42.5	40.1	50.2	51.7	59.5	47.2	58.8
	Out-of-home	28.6	18.6	28.6	18.7	15.3	7.8	20.5	9.5
Socializing, relaxing, leisure	In-home	151.2	173.5	210.6	256.0	354.1	377.1	364.9	411.8
	Out-of-home	29.1	18.5	70.7	56.5	37.2	26.6	58.8	33.0
Sports, exercise, recreation	In-home	2.0	4.2	3.9	6.5	4.1	7.6	3.3	6.1
	Out-of-home	14.5	12.2	28.9	26.9	21.6	18.2	16.8	15.0
Religious and spiritual activities	In-home	1.2	1.9	0.7	3.9	3.7	4.8	4.1	7.4
	Out-of-home	1.3	0.2	10.2	5.2	2.3	1.2	18.9	5.0
Volunteer activities	In-home	0.6	1.1	1.6	1.0	3.4	4.1	3.0	3.6
	Out-of-home	3.0	1.7	5.9	2.2	7.2	4.9	6.4	0.9
Telephone calls	In-home	3.4	4.9	4.0	6.7	8.7	14	5.8	9.7
	Out-of-home	1.6	0.9	0.5	0.5	0.2	0.4	0.4	0.1
Traveling	Total	84.5	55.0	82.2	58.5	61.7	37.5	58.7	32.5
	To/from work	36.2	26.4	8.1	6.9	0.0	0.0	0.0	0.0
Data codes (other)	In-home	5.9	8.2	10.5	8.2	11.5	13.1	14.3	11.9
	Out-of-home	2.5	2.3	2.5	1.4	3.6	1.1	1.9	0.8
Total	In-home	863.4	1017.8	1045.4	1143.8	1227.4	1291.8	1206.2	1308.2
	Out-of-home	576.6	422.2	394.6	296.2	212.6	148.2	233.8	131.8

Note: The table is color coded, with red indicating statistically significant decreases at a 95% confidence level, green indicating statistically significant increases, and yellow indicating statistically insignificant change from 2019.

Every group depicted reduced time spent shopping (consumer purchases) outside the home, presumably due to the adoption of online shopping platforms and the fear of contagion (Jacobsen and Jacobsen, 2020). Time spent on out-of-home socializing, relaxing, and leisure also dropped considerably for all groups, presumably because of the closures of many establishments such as gyms and theaters (Zhuo and Zacharias, 2020). Given that such out-of-home leisure activities are likely to be enjoyable in nature, this decrease in out-of-home recreational time is likely to diminish wellbeing. It is unclear whether the increased in-home time use for socializing/relaxing/leisure activities sufficiently compensates for the loss of out-of-home leisure activity engagement. This paper aims to shed light on the net effects of such substitution patterns on subjective wellbeing and time poverty.

4. A Focus on Temporal Dynamics by Work Status

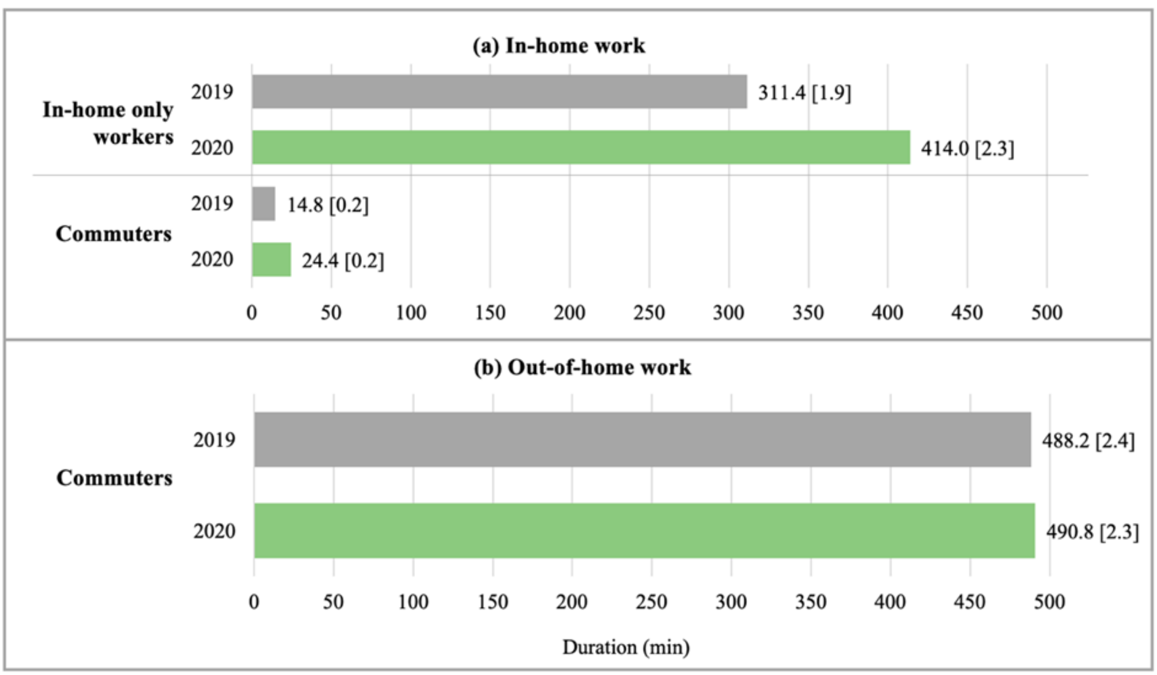
Time use is inevitably about quantifying and understanding temporal patterns of behavior, including both the *amount of time* devoted to activities and individual episodes as well as the *scheduling* (timing) of activity episodes throughout the day. This section offers a more detailed look at these temporal dimensions through the lens of work modality/status.

Activity Duration by Work Modality

Figures 5-2 and 5-3 show the average daily activity durations for selected purposes at aggregated (individual) daily level. The number of activities per day per person is also provided in square brackets next to each average activity duration. Note that corresponding sample sizes for each worker group are presented in Table 5-1. In both figures, the 2020 bars are color-coded, with red indicating statistically significant decreases, green indicating statistically significant increases, and yellow indicating statistically insignificant changes from 2019. The comparisons are shown for different worker subgroups, although – as noted earlier – caution should be exercised when viewing statistics for "workers with zero work". The comparisons cover all days of the week.

Figure 5-2

Average Daily Work Duration and Frequency by Commute Status in 2019 and 2020 (Weighted)



Workers who reported only in-home work in 2019 are most likely self-employed workers, contract workers, or other types of freelance workers who have greater degrees of flexibility and freedom in setting their work schedules. In 2020, however, in-home only workers included many hitherto regular commuters who pivoted to work-from-home during the pandemic. These workers experienced the elimination of the commute and may have substituted telecommunications for many in-person interactions but otherwise experienced no other changes in their work routines. These differences in the make-up of the in-home only worker group are likely to have contributed to the substantial increase in daily time spent (by this worker subgroup) for work (311.4 minutes to 414.0 minutes) as well as in the number of daily work episodes (1.9 activities to 2.3 activities). Commuters, on the other hand, show a steady amount of time dedicated to out-of-home work (488.2 minutes in 2019 and 490.8 minutes in 2020), consistent with the notion that these individuals experienced no substantial changes in their work modalities (the increase is statistically significant but numerically modest). It is interesting to note, however, that commuters depicted an increase in their in-home work time (14.8 minutes in 2019 to 24.4 in 2020).

Figure 5-3

Average Daily Shopping and Social-Recreational Activity Durations and Frequencies by Work Status in 2019 and 2020 (Weighted)

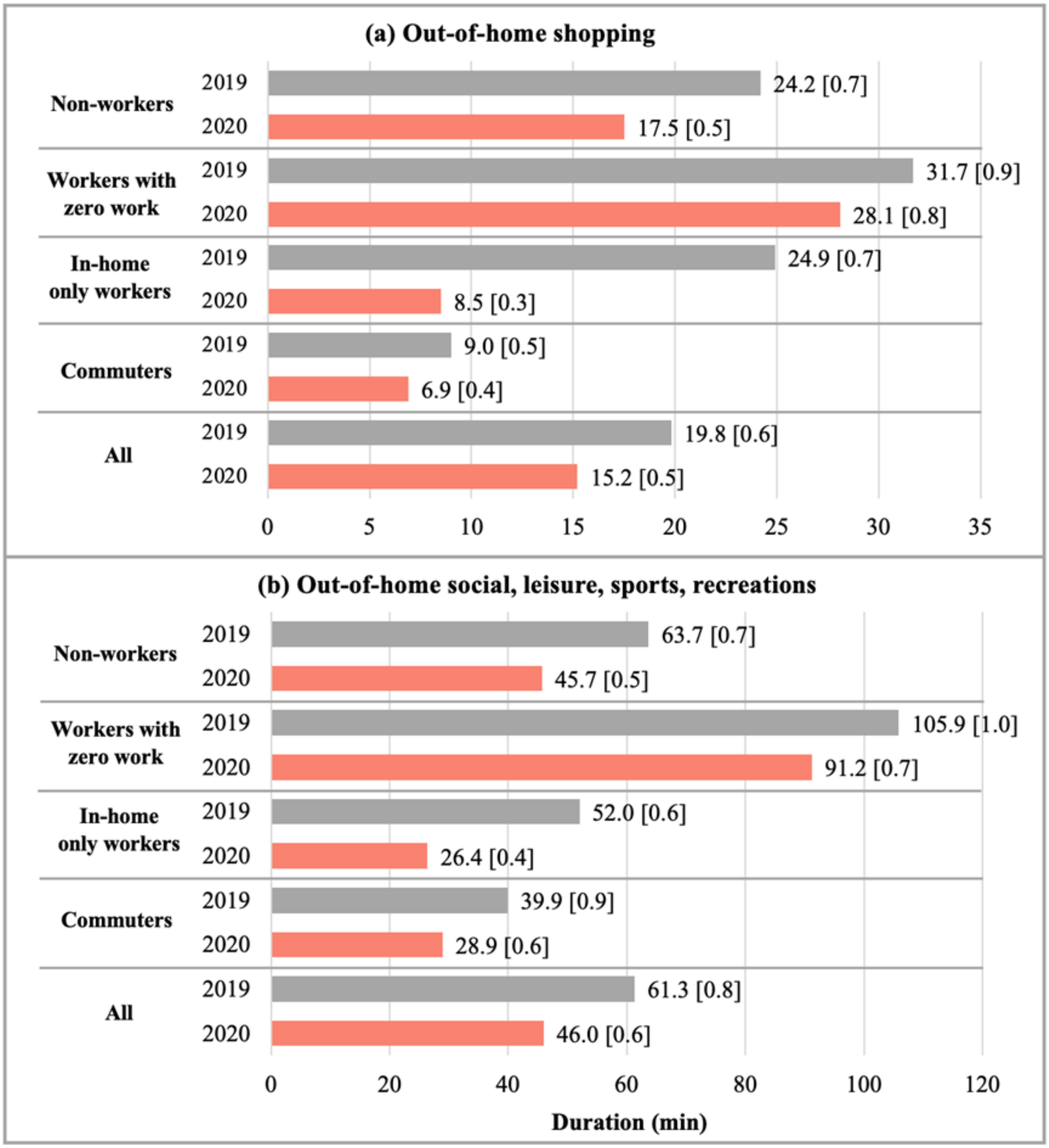


Figure 5-3 shows that all groups have decreased their daily time spent on out-of-home shopping. However, the decrease is greatest for the in-home only workers (from 24.9 minutes in 2019 to 8.5 in 2020). This is likely because shopping trips that were previously chained to the commute were eliminated (Harrington and Hadjiconstantinou, 2022). On the other hand, commuters experienced a much more modest decrease in out-of-home shopping duration (and episode frequency). The key finding in this figure is that time spent on social, leisure, sports, and recreational activities dropped substantially for all worker subgroups – including non-workers. In-home only workers, in particular, show a duration in 2020 that is just one-half of the duration in 2019; again, this is partly due to the change in makeup of this segment, but also due to the many closures and restrictions during the pandemic. Also, the elimination of the commute reduced opportunities to chain leisure activities to the commute trip. There is also some evidence to suggest that in-home only workers struggled to maintain a healthy work-life balance during the pandemic; the absence of a boundary between work and home may have contributed to diminished levels of participation in out-of-home leisure and social activities (Palumbo et al., 2021).

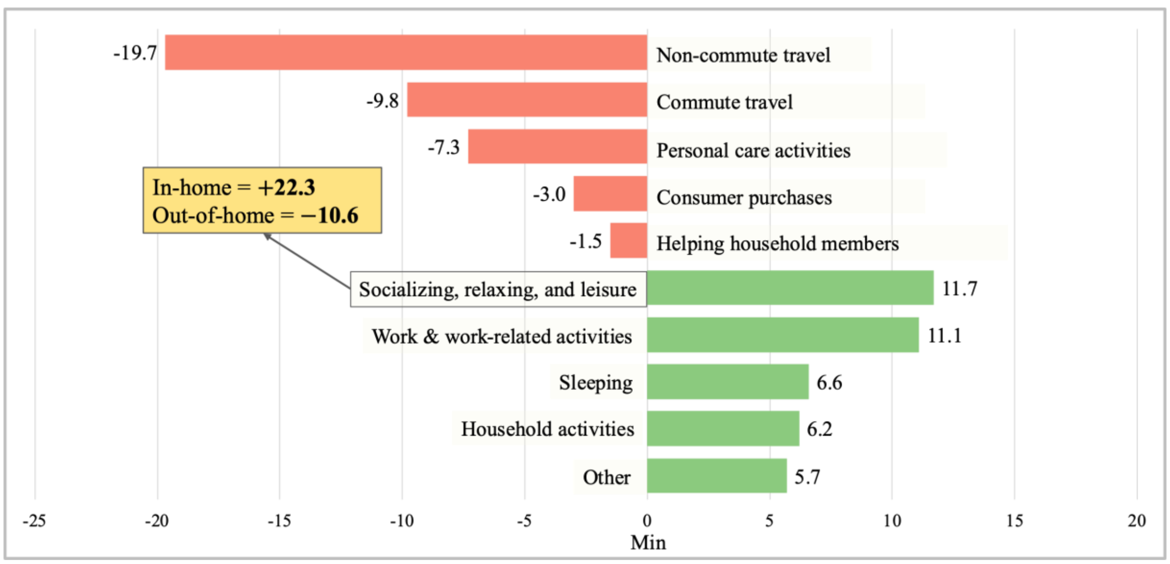
Reallocation of Travel Time Savings

As noted earlier in the context of Table 5-2, the elimination of the commute results in considerable time savings for many full-time workers during the pandemic. Moreover, the pandemic resulted in a decrease in non-work travel as well (due to restrictions and closures, and elimination of opportunities to chain non-work travel to the commute). Full-time workers show a net reduction of 30.6 minutes in daily travel time expenditure on weekdays, in addition to modest reductions in other out-of-home activity durations. The key question is: how and where are these time savings (re)allocated during the pandemic?

Figure 5-4 depicts how full-time workers redeployed these time savings on weekdays. It is found that the time savings were largely reallocated to socializing, relaxing, and leisure, work/work-related activities, sleeping, and household activities (besides other miscellaneous activities). Savings in commute travel amount to about 10 minutes, whereas the increase in time spent working is 11.1 minutes, suggesting that a similar share of the eliminated commute time is redeployed to work.

Figure 5-4

Reallocation of Time Savings for Full-time Workers on Weekdays (Weighted)



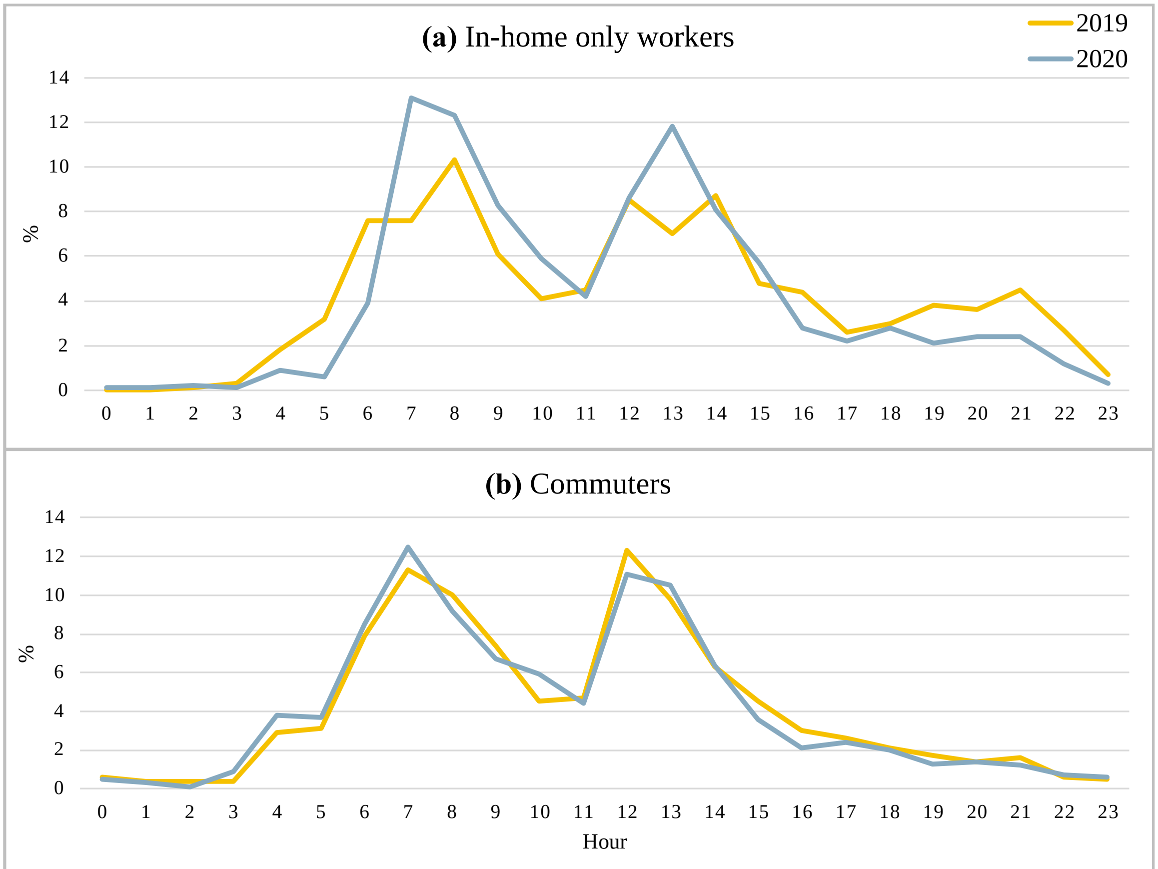
The greatest increase in time allocation is seen for socializing, relaxing, and leisure activities. However, this time redeployment is not well-balanced between in-home and out-of-home in the context of a pandemic. In fact, in-home socializing, relaxing, and leisure experienced an increase of 22.3 minutes, while out-of-home socializing, relaxing, and leisure experienced a *decrease* of 10.6 minutes. In other words, much of the time savings was channeled to in-home leisure activities (such as watching television) with a concomitant decrease in out-of-home leisure pursuits, suggesting that the pandemic-era shifts in work modalities did not allow employees to engage in out-of-home activities that would potentially elevate wellbeing.

Temporal Distribution of Work Activity Episodes

It is often argued that workers are resisting the return to office, not only because they would like to avoid the dreaded commute, but also because work-from-home affords a high degree of schedule flexibility (thus enabling individuals to achieve a better work-life balance and tend to household needs more effectively). To examine the extent to which this notion holds true, a comparison of work activity start times is presented in Figure 5-5. All work activity episodes of in-home only workers and commuters are considered in generating this graphic.

Figure 5-5

Start Time Distribution of Work Episodes for In-home Only Workers and Commuters in 2019 and 2020 (Weighted)



Sample size	Number of activities		Number of individuals	
	2019	**2020**	**2019**	**2020**
(a) In-home only workers	513	1,436	302	655
(b) Commuters	3,244	2,413	1,257	967

An examination of the temporal distribution of work episodes for *commuters* shows that there is very little difference between 2019 and 2020 distributions. Both distributions show a similar pattern, overlap considerably, and depict the typical dual peak (morning and post-lunch work episode start times). For in-home only workers, the distributions change considerably, with the distribution in 2020 showing a pattern similar to commuters. This is understandable given that in-home only workers in 2019 are largely comprised of flexible, freelance, self-employed individuals whereas this group in 2020 comprises many past commuters working from home during the pandemic. These workers are likely to have fixed work schedules and reporting obligations (to managers) and are used to a certain work schedule rhythm. Behavioral inertia (habit persistence) for these workers is likely to have played a major role in retaining the dual peak work schedule even during the pandemic era.

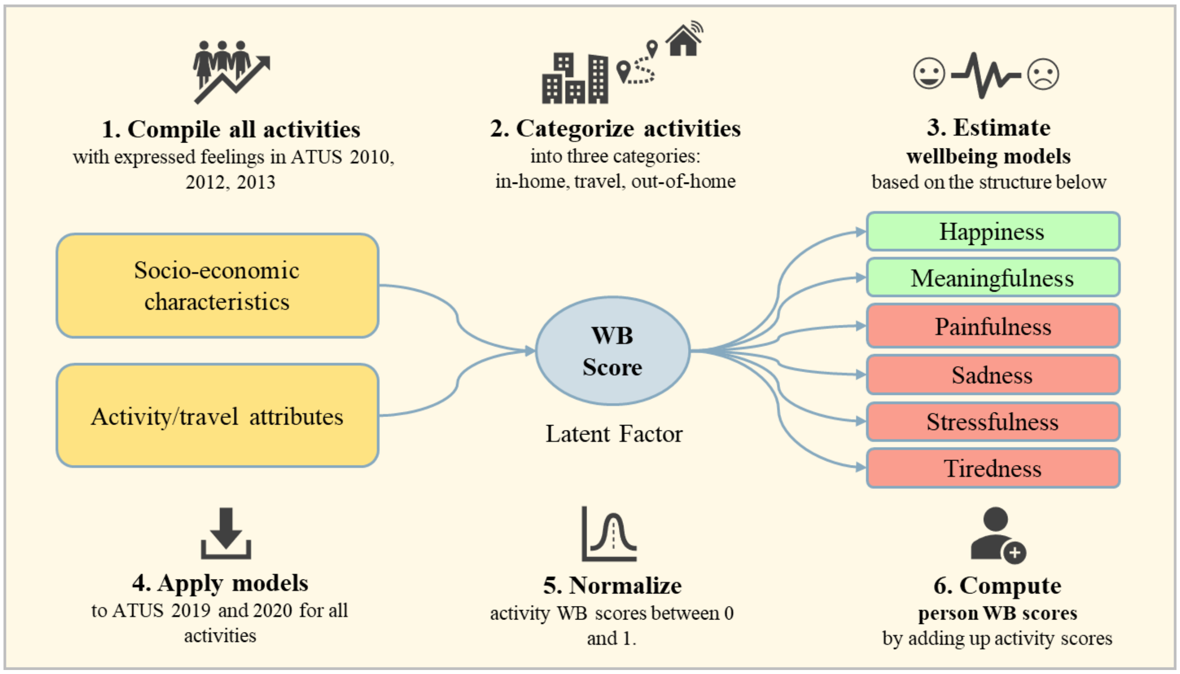
Overall, it is found that the elimination of the commute and the widespread adoption of work-from-home did not necessarily engender activity time reallocation patterns or temporal activity schedules that would suggest an enhanced state of wellbeing during the pandemic. The next section checks this hypothesis through rigorous wellbeing and time poverty analysis.

5. Analysis of Daily Wellbeing and Time Poverty

The focus of this section is to understand and evaluate the wellbeing impacts of the changes in activity/travel and time use patterns brought about by the pandemic. This analysis aimed to determine how wellbeing changed for different socio-economic and demographic groups. Through such an analysis, it will be possible to determine *winners* and *losers* and identify population groups who experienced the greatest adversity (reduction in wellbeing) during the pandemic. Both, an enhanced wellbeing scoring methodology (Khoeini, et. al., 2018) and time poverty analysis methodology (Kalenkoski and Hamrick, 2013) are employed for this purpose. Multiple methods are applied here to examine their similarities and differences in analyzing the wellbeing implications of changes in activity and time use patterns.

Figure 5-6

Person Daily Wellbeing (WB) Score Estimation Methodology



The wellbeing scoring methodology adopted for this paper constitutes an enhanced version of the original methodology documented in Khoeini et al. (2018). The methodology was developed based on ATUS data and is therefore suitable for application in this chapter. The steps of the enhanced methodology are presented in Figure 5-6. Additionally, since the wellbeing scoring method adopted in this chapter is developed based on the ATUS wellbeing module data gathered in 2010, 2012, and 2013, there is some uncertainty as to whether wellbeing data collected a decade ago is appropriate to investigate changes in wellbeing during the pandemic (given that wellbeing triggers may have been different during the pandemic). However, previously established key determinants of subjective wellbeing were found to still be important predictors of wellbeing during the pandemic (Ng and Khang, 2022). Also, activities perceived as favorable/pleasant prior to the pandemic (e.g., volunteering, exercising, or spending time in nature) continued to be perceived as favorable/pleasant during the pandemic, and vice versa (Aknin et al., 2022). This implies that the contribution (positive or negative) of daily activity patterns to individual wellbeing has remained largely stable even during the pandemic. As a result, the wellbeing method used in this chapter may be considered suitable for achieving chapter objectives, although future research would benefit from more up-to-date wellbeing data.

A detailed exposition of the methodology is not provided here in the interest of conciseness; however, the steps may be summarized as follows:

- <u>Step 1:</u> The 2010, 2012, and 2013 editions of the ATUS included a comprehensive wellbeing module in which respondents were asked to indicate how they felt on six measures of subjective wellbeing (happiness, meaningfulness, tiredness, sadness, painfulness, and stress) for three randomly selected activities in their time use diary. For each measure, individuals indicated their feelings on a scale of 0 to 6, with 0 representing a lack of any intensity for a particular emotion and a 6 indicating a very strong level of intensity for a particular emotion. All the activities for which emotion scores are available (from all three years) were compiled into an integrated database.

- Step 2: All activities were categorized into three groups based on location: in-home, travel, and out-of-home. This aimed at differentiating the locational influence on feelings.
- Step 3: The six emotions, taken together, are assumed to define an unobserved (latent) wellbeing score. This wellbeing score is not explicitly measured. Hence, a latent joint model system simultaneously considering all six emotions is formulated. This model system relates the latent propensity functions (underlying the emotional measures) to an unobserved latent wellbeing score that is assumed to be a function of socio-demographic characteristics as well as activity-travel attributes. Through this formulation, it is possible to estimate a joint wellbeing model for each category of in-home, out-of-home, and travel activity episodes. Thus, three joint models are estimated.
- Step 4: The three wellbeing score models are then applied to the 2019 and 2020 ATUS records extracted for this chapter. The model application process computes a wellbeing score for each activity in the data sets.
- Step 5: The activity-specific wellbeing scores are normalized so that they take a value between zero and one.
- Step 6: Although somewhat simplistic, it is assumed that the daily wellbeing score is an additive accumulation of all activity-level wellbeing scores computed in the prior step. The normalized activity episode wellbeing scores for each individual are summed to compute a person-level daily wellbeing score. Although these scores do

not have a straightforward numeric interpretation, they can be used to conduct comparisons and assess improvements or degradations in wellbeing.

The second methodology employed in this paper to study changes in wellbeing is based on the notion of time poverty. This concept is often used to describe individuals who do not have enough time to engage in discretionary activities that presumably enhance wellbeing. Similar to income-based poverty, time poverty is linked to poorer wellbeing. Previous studies have typically used a threshold value to flag time poor people based on their available discretionary time (Williams et al., 2016). This paper employs a similar threshold value methodology consistent with established approaches to defining time poverty. The methodology is implemented as follows. For each individual, the time spent on necessary and committed activities is computed. The total time spent on these activities is subtracted from the daily available total of 1440 minutes. The remaining time is treated as being available for discretionary activities. The necessary and committed activities include personal care (including sleeping and grooming), household activities (including housework and food preparation), caring for and helping household members (both children and adults), and work activities. All other activities shown in Table 5-2 are treated as discretionary activities. It is possible to question this categorization of activities. For example, the transportation literature often treats education as a mandatory (committed activity) as opposed to a discretionary activity. Nevertheless, in the interest of being consistent with the sociological literature, the activity classification scheme in Kalenkoski and Hamrick (2013), who used the same ATUS data to study time poverty, is adopted in this work.

After computing the discretionary time available for each individual in the data set, the median discretionary time is computed for the entire sample. The threshold value for determining time poverty is set to be 60 percent of median discretionary time. If an individual has at least as much discretionary time as this threshold value, then the individual is deemed *not* time poor (and vice versa). The 60 percent median discretionary time was found to be *279 minutes* for 2019 and *288 minutes* for 2020; these values were then used to identify time poor respondents in the respective years.

Table 5-3 presents the results of the wellbeing and time poverty analysis. The table presents average wellbeing scores and the percent of individuals designated as time poor for different population groups of interest, subclassified by worker status (work modality). First and foremost, the contrast in results between the two approaches is striking. For virtually all subgroups, the *wellbeing score decreases* from 2019 to 2020 (Chen and Wang, 2021). On the other hand, it is found that the *time poverty status improves* for a vast majority of the subgroups. These findings are not all that surprising or counterintuitive. These measures are fundamentally representing and capturing different concepts. The time poverty concept singularly focused on the increase or decrease in discretionary time availability. It does not consider the plethora of activity episode attributes that engender emotional feelings. Feelings associated with activity engagement are influenced by whether the activity is done alone, who the activity is done with, the time allocated to the activity, and the location and time of day of the activity (Archer et al., 2013).

Table 5-3

Average Subjective Wellbeing (SWB) Scores and Time Poverty Percentages (Weighted)

Segment		Sample size		SWB Score		Time Poverty (%)	
		2019	2020	2019	2020	2019	2020
All	Non-workers	1,949	2,398	9.6	8.4	9.1	7.5
	Workers with zero work	1,026	1,100	8.9	8.1	11.6	10.9
	In-home only workers	302	655	8.8	7.8	28.6	41.7
	Commuters	1,257	967	8.3	7.8	64.9	58.2
	All	4,534	5,120	9.0	8.1	31.7	26.0
Female	Non-workers	1,230	1,482	9.5	8.2	11.9	10.4
	Workers with zero work	513	505	8.8	7.5	13.9	13.0
	In-home only workers	144	330	8.6	7.1	37.1	46.3
	Commuters	527	382	7.7	7.1	69.1	62.5
	All	2,414	2,699	8.8	7.7	31.3	25.7
Male	Non-workers	719	916	9.7	8.6	4.8	3.2
	Workers with zero work	513	595	9.0	8.7	9.3	9.2
	In-home only workers	158	325	9.0	8.6	21.8	36.8
	Commuters	730	585	8.8	8.2	62.0	55.6
	All	2,120	2,421	9.1	8.5	32.1	26.2
Age 18 to 30	Non-workers	120	197	5.2	4.8	9.3	7.3
	Workers with zero work	175	191	7.3	5.9	9.0	7.1
	In-home only workers	28	67	6.2	5.9	15.6	33.7
	Commuters	222	154	6.1	6.7	62.7	54.4
	All	545	609	6.2	5.8	34.1	25.6
Age 65+	Non-workers	1,185	1,402	12.0	11.1	4.7	3.9
	Workers with zero work	56	42	14.2	12.6	21.2	8.0
	In-home only workers	25	50	13.6	11.4	14.2	30.0
	Commuters	59	56	14.9	13.5	49.9	42.0
	All	1,325	1,550	12.3	11.2	7.6	6.6
Low-income (< $35K)	Non-workers	865	936	7.8	6.8	8.8	9.5
	Workers with zero work	154	136	7.2	6.0	12.8	8.0
	In-home only workers	33	48	4.7	5.0	53.8	29.2
	Commuters	235	161	7.0	6.0	67.6	58.2
	All	1,287	1,281	7.4	6.5	26.2	18.2
High-income (≥ $100K)	Non-workers	276	426	11.1	9.3	9.0	8.3
	Workers with zero work	398	435	9.8	9.2	11.7	9.0
	In-home only workers	146	368	9.9	8.3	23.7	46.5
	Commuters	437	310	9.6	8.6	69.4	56.1
	All	1,257	1,539	10.0	8.8	38.2	30.9
White	Non-workers	1,552	1,928	10.0	8.8	9.0	7.7
	Workers with zero work	834	890	9.2	8.1	11.0	10.4
	In-home only workers	250	517	8.8	8.0	30.1	42.8
	Commuters	1,016	779	8.5	8.0	63.7	56.2
	All	3,652	4,114	9.2	8.4	31.2	25.6
Non-white	Non-workers	397	470	8.0	6.6	9.6	6.9
	Workers with zero work	192	210	7.8	8.1	13.6	12.9
	In-home only workers	52	138	8.5	7.4	21.2	37.9
	Commuters	241	188	7.9	6.8	69.9	66.2
	All	882	1,006	7.9	7.0	33.6	27.4

Note: The table is color coded, with red indicating statistically significant decreases at a 95% confidence level, green indicating statistically significant increases, and yellow indicating statistically insignificant change from 2019.

The wellbeing models developed and estimated for this chapter explicitly account for all these dimensions (and these attributes are found to significantly impact emotional intensities). On the contrary, time poverty does not account for the myriad attributes that engender feelings of wellbeing. The wellbeing scores show a decrease across the board because the attributes that contribute positively to wellbeing largely disappeared during the height of the pandemic. Wellbeing is positively impacted by companionship (doing activities with family and friends, for example), activity location (out-of-home activities are associated with greater levels of positive emotions than in-home activities, (see Appendix F), and temporal dimensions (the influence of activity duration and timing is dependent on the nature of the activity). Given that the pandemic drastically reduced the ability to engage in social, leisure, and recreational activities outside the home with family and friends, the significant drop in wellbeing scores is consistent with expectations. More importantly, these findings are consistent with the literature pointing to significant levels of mental health issues during the pandemic (Killgore et al., 2021) and the rapid recovery in roadway and air traffic as the pandemic waned, primarily due to people's desire to enhance their wellbeing through the pursuit of discretionary activities and travel whose attributes contribute to positive emotions. There are a few exceptions, however; younger commuters and low-income workers who reported only in-home work experienced enhanced wellbeing. Not surprisingly, low-income workers who were able to work from home during the pandemic valued the time and cost savings that resulted from eliminating their commute, and the added flexibility and freedom that work-from-home offers.

The time poverty analysis shows that most subgroups gained discretionary time during the pandemic. As such, many subgroups appear to have experienced diminished time poverty, which is generally a positive outcome. However, this improvement in time poverty did not translate into improvements in wellbeing because individuals could not use the additional discretionary time to pursue activities that would elevate wellbeing. Individuals were not able to engage in social, leisure, and relaxing activities with family and friends outside the home (at favorite recreational destinations, eating places, theaters, and sporting arenas). In general, however, there is no question that people value time savings and the increased availability of discretionary time. For this reason, workers are reluctant to return to the workplace and are embracing hybrid work schedules that provide both flexibility and work-based social interactions. Note, however, that female in-home only workers experienced worse time poverty, largely because they shoulder greater household obligations and childcare responsibilities. It would be of value to identify women-friendly workplace policies that also translate to home-based work contexts. Note that his pattern is observed for *all in-home only workers*. Employees working from home exclusively are possibly doing more housework and caring for family members. These activity categories are considered committed activities, and hence there is a decrease in available discretionary time for in-home only workers. Furthermore, they are working long(er) hours, potentially struggling to create a separation between home and work. Policies that help ameliorate these detrimental effects of work-from-home should be implemented to ensure employee wellbeing.

6. Conclusions

This paper presents a comprehensive time use analysis of pandemic-era activity-travel patterns and presents a detailed comparison of 2019 (pre-pandemic) and 2020 (during-pandemic) patterns. The analysis is performed using May through November records of the 2019 and 2020 ATUS data sets. Through such comparison, the chapter aims to shed light on the potential underlying reasons for some of the phenomena that the transportation and workplace ecosystems have witnessed. Roadway traffic and air travel have shown a very strong and rapid recovery as the pandemic has waned. At the same time, workers are embracing work-from-home and hybrid work modalities and resisting a full-scale return to the workplace. Understanding the potential underlying reasons for these phenomena is critical to planning for the future.

Through the use of a comprehensive wellbeing score computation methodology, this paper assesses the change in wellbeing experienced by society between the pre-pandemic 2019 year and the during-pandemic 2020 year. The results show that virtually every subgroup of the population experienced significant reductions in wellbeing. This happened despite significant improvements in time poverty between 2019 and 2020. The increase in available discretionary time (or reduced time poverty) did not lead to greater wellbeing because people were not able to undertake enjoyable activities with family and friends in desirable locations. Many pandemic-era restrictions and closures, coupled with fear of contagion, prevented individuals from engaging in activities in a manner that enhanced wellbeing. This explains why roadway traffic and air travel recovery have been strong and robust, despite many logistical challenges. People seek to re-engage in activities that enhance their wellbeing. Commuting to work is not, however, one of those activities. While many are embracing a hybrid work modality to enjoy some workplace-based social interactions, the flexibility and time savings that result from the elimination of the commute are clearly valued.

The findings of this chapter have important implications for policy and planning. Clearly, hybrid and home-based work modalities are here to stay, and transportation planning and modeling processes need to adapt to this new normal. Changes in commute patterns will have secondary and tertiary impacts on spatiotemporal characteristics of activities and trips. At the same time, the demand for travel and engaging in in-person activities that enhance wellbeing will likely continue to grow unabated, particularly as the effects of the pandemic further fade in the rear-view mirror. People do not thrive in isolation (especially for extended periods) and crave the accumulation of life experiences that are garnered through travel and social interactions (Polzin, 2016; Bomey, 2022). As such, future transportation infrastructure investments should no longer be centered around accommodating the work commute but rather around enabling individuals to pursue and accomplish fulfilling life experiences in appealing places.

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8. References

Adam, M. G., Tran, P. T., & Balasubramanian, R. (2021). Air quality changes in cities during the COVID-19 lockdown: A critical review. *Atmospheric Research*, *264*, 105823.

Aknin, L. B., De Neve, J. E., Dunn, E. W., Fancourt, D. E., Goldberg, E., Helliwell, J. F., ... & Ben Amor, Y. (2022). Mental health during the first year of the COVID-19 pandemic: A review and recommendations for moving forward. *Perspectives on Psychological Science*, *17*(4), 915-936.

Archer, M., Paleti, R., Konduri, K. C., Pendyala, R. M., & Bhat, C. R. (2013). Modeling the connection between activity-travel patterns and subjective well-being. *Transportation Research Record*, *2382*(1), 102-111.

Batur, I., Sharda, S., Kim, T., Khoeini, S., Pendyala, R. M., & Bhat, C. R. (2019). Mobility, Time Poverty, and Well-Being: How Are They Connected and How Much Does Mobility Matter?. *Technical paper, Arizona State University*.

Bomay, N. (2022). What Amex Tells Us About Consumer Spending. *Axios*. Retrieved from https://www.axios.com/2022/07/22/american-express-second-quarter-earnings-economy.

BTS (Bureau of Transportation Statistics). (2022). Latest Weekly COVID-19 Transportation Statistics. Retrieved from https://www.bts.gov/covid-19/week-in-transportation#combined.

Calvert, S (2021). Covid-19 Pandemic Likely Improved Your Commute to Work. *The Wall Street Journal*. Retrieved from https://www.wsj.com/articles/covid-19-pandemic-likely-improved-your-commute-to-work-11609669801.

Chen, D. T. H., & Wang, Y. J. (2021). Inequality-Related health and social factors and their impact on well-being during the COVID-19 pandemic: findings from a national survey in the UK. *International Journal of Environmental Research and Public Health*, *18*(3), 1014.

Cudjoe, T. K., & Kotwal, A. A. (2020). “Social distancing” amid a crisis in social isolation and loneliness. *Journal of the American Geriatrics Society*, *68*(6), E27.

Currie, G., Jain, T., & Aston, L. (2021). Evidence of a post-COVID change in travel behaviour–Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice*, *153*, 218-234.

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V., & Witlox, F. (2016). Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. *Transportation*, *43*, 771-796.

Delbosc, A., & Currie, G. (2011). Exploring the relative influences of transport disadvantage and social exclusion on well-being. *Transport Policy*, *18*(4), 555-562.

Eliasson, J. (2022). Will we travel less after the pandemic?. *Transportation Research Interdisciplinary Perspectives*, *13*, 100509.

FHWA (Federal Highway Administration) (2022). Traffic Volume Trends. Retrieved from https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm on Aug 1, 2022.

Harrington, D. M., & Hadjiconstantinou, M. (2022). Changes in commuting behaviours in response to the COVID-19 pandemic in the UK. *Journal of Transport & Health*, *24*, 101313.

Hensher, D. A., Beck, M. J., & Balbontin, C. (2022). Time allocation of reduced commuting time during COVID-19 under working from home. *Journal of Transport Economics and Policy (JTEP)*, *56*(4), 399-428.

Hook, H., De Vos, J., Van Acker, V., & Witlox, F. (2021). Do travel options influence how commute time satisfaction relates to the residential built environment?. *Journal of Transport Geography*, *92*, 103021.

Jacobsen, G. D., & Jacobsen, K. H. (2020). Statewide COVID-19 stay-at-home orders and population mobility in the United States. *World Medical & Health Policy*, *12*(4), 347-356.

Kalenkoski, C. M., & Hamrick, K. S. (2013). How does time poverty affect behavior? A look at eating and physical activity. *Applied Economic Perspectives and Policy*, *35*(1), 89-105.

Kastle Systems (2022). Back to Work Barometer. Retrieved from https://www.kastle.com/safety-wellness/getting-america-back-to-work/.

Khoeini, S., Pendyala, R. M., da Silva, D. C., & Sharda, S. (2018). *An Integrated Model of Activity-Travel Behavior and Subjective Well-being* (No. 69A3551747116). Center for Teaching Old Models New Tricks (TOMNET).

Killgore, W. D., Cloonan, S. A., Taylor, E. C., & Dailey, N. S. (2021). Mental health during the first weeks of the COVID-19 pandemic in the United States. *Frontiers in Psychiatry*, *12*, 561898.

Magassy, T. B., Batur, I., Mondal, A., Asmussen, K. E., Bhat, C. R., Salon, D., ... & Pendyala, R. M. (2023). Evolution of Mode Use During the COVID-19 Pandemic in the United States: Implications for the Future of Transit. *Transportation Research Record*, 03611981231166942.

Markezich, A (2021). Downtown Trips Begin to Recover while Metro Area Surpasses Pre-COVID Levels. *INRIX*. Retrieved from https://inrix.com/blog/downtown-trips-recovering/.

Ng, W., & Kang, S. H. (2022). Predictors of well-being during the COVID-19 pandemic: The importance of financial satisfaction and neuroticism. *Journal of Community Psychology*, *50*(7), 2771-2789.

Nochaiwong, S., Ruengorn, C., Thavorn, K., Hutton, B., Awiphan, R., Phosuya, C., ... & Wongpakaran, T. (2021). Global prevalence of mental health issues among the general population during the coronavirus disease-2019 pandemic: a systematic review and meta-analysis. *Scientific Reports*, *11*(1), 1-18.

Palumbo, R., Manna, R., & Cavallone, M. (2021). Beware of side effects on quality! Investigating the implications of home working on work-life balance in educational services. *The TQM Journal*, *33*(4), 915-929.

Parker, K., J.M. Horowitz, & R. Minkin, R (2022). COVID-19 Pandemic Continues to Reshape Work in America. *Pew Research Center*. Retrieved from https://www.pewresearch.org/social-trends/2022/02/16/covid-19-pandemic-continues-to-reshape-work-in-america/.

Polzin, S.E (2016). So Much for Peak VMT. Planetizen. Retrieved from https://www.planetizen.com/node/84877/so-much-peak-vmt.

Restrepo, B. J., & Zeballos, E. (2022). Work from home and daily time allocations: evidence from the coronavirus pandemic. *Review of Economics of the Household*, *20*(3), 735-758.

Schwanen, T., & Wang, D. (2014). Well-being, context, and everyday activities in space and time. *Annals of the Association of American Geographers*, *104*(4), 833-851.

TSA (Transportation Security Administration) (2022). TSA checkpoint travel numbers (current year versus prior year(s)/same weekday). Retrieved from https://www.tsa.gov/travel/passenger-volumes.

Van Acker, V., Van Wee, B., & Witlox, F. (2010). When transport geography meets social psychology: toward a conceptual model of travel behaviour. *Transport Reviews*, *30*(2), 219-240.

Williams, J. R., Masuda, Y. J., & Tallis, H. (2016). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*, 265-283.

Zhuo, K., & Zacharias, J. (2021). The impact of out-of-home leisure before quarantine and domestic leisure during quarantine on subjective well-being. *Leisure Studies*, *40*(3), 321-337.

CHAPTER 6

RESEARCH APPLICATION

This dissertation introduces three wellbeing indicators that are based on individual activity-travel and time use patterns. These indicators include a subjective wellbeing score, time poverty rate, and zero-trip making status. To facilitate the application of this knowledge, an online, open-source tool called the TOMNET Wellbeing Platform has been developed. This online tool uses ATUS data sets from 2003 onwards to apply the three wellbeing indicators and allows for tracking changes in wellbeing among different population groups on a year-to-year basis. Each indicator serves a unique purpose and offers a distinct perspective on individual wellbeing stemming from activity and time use patterns. By integrating these indicators into a single platform, the aim is to provide policymakers, researchers, practitioners, and the public with a comprehensive tool to assess changes in wellbeing over time and place for different population subgroups. In doing so, the platform may be used to potentially uncover racial, economic, and other forms of social disparities prevalent in society.

1. TOMNET Wellbeing Platform

The TOMNET Wellbeing Platform comprises three distinct sections, each dedicated to one of the three wellbeing indicators. The first section, called *WBEAT* (**W**ell-**B**eing **E**stimator for **A**ctivities and **T**ravel), utilizes the subjective wellbeing scoring method introduced in the second chapter of the dissertation. The second section, *Time Poverty Analysis*, focuses on time poverty rates, while the third section, *Mobility Analysis*, looks at individuals' zero-trip making status. Each section features three modules with identical functionalities. The first module in each section illustrates changes in wellbeing over time for the entire nation and user-defined subpopulations, based on the wellbeing indicator considered in that section. The second module allows users to investigate changes in wellbeing within various socio-demographic and economic categories for a specific year. Lastly, the third module displays a heatmap of how wellbeing varies across states based on the household locations of respondents for a chosen year, and also shows the best and worst-performing states in that year. For the sake of brevity, only the modules in the first section will be explained in the rest of this chapter as the modules in each section share identical functionalities.

Module 1 – Wellbeing over the years

This first module utilizes a graph visualization function that displays how wellbeing (based on the subjective wellbeing scoring method) has evolved over time for any subpopulation group in society. This function enables users to track wellbeing changes over time in society. By default, the graph displays the wellbeing average for the entire sample. However, users can create their own population subgroups and compare them to the overall average and/or other subgroups, using the "add a profile” function. This function allows users to select from a set of attributes, including gender, age, educational attainment, race, employment status, household income, household location, the main mode of transportation, time poverty status, and trip making status, to create (up to three) profiles. The full categories of these attributes are presented in Table 6-1.

Table 6-1

Individual and Household-level Attributes Included in Module 1

Attribute	Category	Attribute	Category
Gender	Female	Employment Status	Employed
	Male		Unemployed
Age	15 to 19 years	Household Income	Less than $35,000
	20 to 29 years		$35,000 to $49,999
	30 to 49 years		$50,000 to $74,999
	50 to 64 years		$75,000 to $99,999
	65 years or older		$100,000 or more
Education Attainment	Less than high school	Household Location	Urban
	High school		Rural
	Some college degree	Main Mode of Transportation	Car
	Bachelor's degree		Other
	Graduate degree(s)	Trip Making Status	Zero trip
Race	Asian		One or more trips
	Black	Time Poverty Status	Time poor
	White		Not time poor
	Other	--	--

To calculate the wellbeing scores in this module, the platform uses the 2003 level of the national average as a reference point, which is assumed to be 100. As a result, the wellbeing scores for the national average in all years (excluding 2003) and all user-created profiles in all years (including 2003) are calculated relative to this number. As an example, Figure 6-1 displays three profiles created in Module 1 along with the overall average (*All*), which represents the annual average for the entire sample. To ensure completeness and enable more meaningful comparisons, the module also presents sample sizes for each profile for each year in a tabular format, as illustrated in the bottom of Figure 6-1. As depicted in the figure, Profile 1 consists of Black females, while Profile 2 consists of low-income individuals (earning less than $35,000 annually) who reported zero out-of-home trips on the survey day. Additionally, Profile 3 comprises highly educated and employed males. The figure shows that Profiles 1 and 2, both traditionally viewed as vulnerable populations, have lower wellbeing than the national average between 2003 and 2021, while Profile 3 individuals have higher wellbeing than the national average. The figure reveals that the disruptions between 2003 and 2021 (i.e., the 2008 Global Financial Crisis and the COVID-19 Pandemic) led to a decline in wellbeing. The 2008 recession, which resulted in widespread job losses, reduced household incomes, and a general decline in economic activity, had a significant impact on individual wellbeing, which is not surprising. Similarly, during the pandemic, people were compelled to isolate themselves at home, which impacted their activity-travel patterns and overall wellbeing. However, unlike the nation's average and Profiles 1 and 3, Profile 2 individuals experienced a slight increase in wellbeing during the pandemic in 2020 and 2021. This could be attributed to the fact that low-income workers who were able to work from home during the pandemic appreciated the time and cost savings from eliminating their commute, as well as the additional flexibility and freedom provided by remote work. The module can be used to make similar observations for various groups in society.

Figure 6-1

Evolution of Wellbeing for Select Profiles Between 2003-2021 in Module 1

Wellbeing over the years

The graph below shows the evolution of wellbeing over time since 2003. The wellbeing average for the entire sample is displayed by default. You can create your own population subgroups by adding profiles and compare them to the overall average and/or other subgroups. *Note that the wellbeing scores over the years were computed relative to the 2003 level, for which average wellbeing is assumed to be 100.*

Add profile

All

Profile 1
Female
Black

Profile 2
<$35K
Zero trip

Profile 3
Male
Graduate degree(s)
Employed

Sample sizes

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
All	20,720	13,973	13,038	12,943	12,248	12,723	13,133	13,260	12,479	12,443	11,385	11,592	10,905	10,493	10,223	9,593	9,435	8,782	9,087
Profile 1	1,496	979	988	1,018	983	1,058	1,135	1,209	1,145	1,163	1,051	965	1,008	923	891	783	727	654	676
Profile 2	1,345	883	820	834	770	863	879	848	1,099	1,129	986	988	861	868	885	837	745	901	839
Profile 3	822	569	534	553	505	602	519	574	539	577	498	576	495	521	519	518	521	445	507

Module 2 – Wellbeing within years

The module allows users to examine changes in wellbeing across different socio-economic and demographic categories within a specific year. It presents two drop-down menus, where users can choose an attribute from a selection of gender, age, educational attainment, race, and household income in one menu, and a year between 2003 and 2021 in the other. The module then displays a bar chart that illustrates the average wellbeing score for each category of the selected attribute, calculated relative to the 2003 reference point. This provides users with a quick and easy way to display the wellbeing of subpopulation groups within a specific socio-demographic category for a given year. The use of the module is exemplified in Figure 6-2, which includes two instances: one for the household income categories in 2015, and another for the racial groups in 2006. The depicted patterns in the figure are highly consistent and meaningful for these two instances. The bar chart on the left of the figure shows that as income rises, wellbeing increases up to a certain point beyond which additional income does not generate additional wellbeing, likely because people become more time poor and unable to pursue desired discretionary activities, beyond the income bracket of $75,000 to $100,000 (Dolan et al., 2008; Giurge et al., 2020; Sharif et al., 2021). Additionally, the bar chart on the right of the figure also reveals that racial minorities have lower wellbeing scores compared to White individuals, which aligns with prior expectations (Blanchflower & Oswald, 2004). This module can be used to make similar comparisons for other groups and years, providing valuable insights into societal wellbeing.

Figure 6-2

Demonstrating Module 2 for Two Instances: (a) Wellbeing of Income Groups in 2015; (b) Wellbeing of Racial Groups in 2006

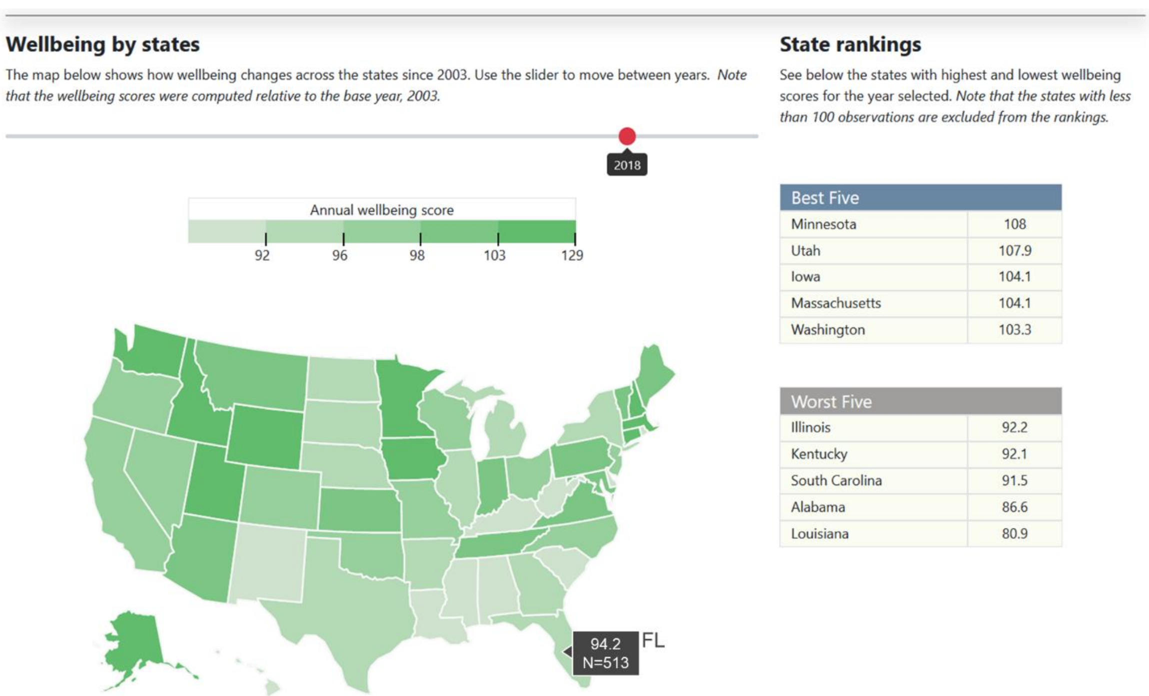
Module 3 – Wellbeing by states and states rankings

This module offers insight into how wellbeing varies across states by displaying average relative wellbeing scores on a heatmap for each state based on the household locations of respondents for a selected year. The heatmap shades indicate the level of wellbeing, with lighter shades representing lower scores and darker shades representing higher scores. When the mouse pointer is placed over a state, the average wellbeing score and sample size for that state are also provided. Furthermore, the module presents the five best and worst states, for which at least 100 observations are available in the selected year. Figure

6-3 illustrates the module for the year 2018, with a dark diagonal box displaying the average wellbeing score and sample size for Florida as an example. The figure also lists the five best and worst states for that year, along with their average wellbeing scores, on the right. This module, thus, provides a spatiotemporal perspective of how wellbeing changes across different states over time and can be used to generate similar maps and rankings for every year between 2003 and 2021.

Figure 6-3

Demonstration of Module 3 for the Year, 2018



Overall, the subjective wellbeing section's examples above illustrate how the TOMNET Wellbeing Platform effectively captures nuanced aspects of societal wellbeing. The platform thus demonstrates the practical application of this dissertation's findings in real-world situations, as it enables the identification and monitoring of various forms of social disparities over time. This highlights the broad potential for these wellbeing indicators, especially when used in combination, to understand the impact of various factors on individual wellbeing.

2. References

Blanchflower, D. G., & Oswald, A. J. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics*, *88*(7-8), 1359-1386.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, *29*(1), 94-122.

Giurge, L. M., Whillans, A. V., & West, C. (2020). Why time poverty matters for individuals, organisations and nations. *Nature Human Behaviour*, *4*(10), 993-1003.

Sharif, M. A., Mogilner, C., & Hershfield, H. E. (2021). Having too little or too much time is linked to lower subjective well-being. *Journal of Personality and Social Psychology*, *121*(4), 933.

CHAPTER 7

CONCLUSIONS

The connection between transportation and individual wellbeing has gained widespread recognition in the transportation field and beyond, which led to the notion that transportation systems must be designed to contribute to equity and quality of life. Transportation planners and policymakers strive to achieve this by developing policies and directing investments in ways that enable mobility for all, improve access to destinations and opportunities, and enhance quality of life. However, planners and policymakers often lack the necessary information to make informed decisions about policy actions and investment decisions due to the absence of appropriate wellbeing tools that can translate activity-travel behavior measures into wellbeing measures. In such cases, proxies of wellbeing, such as accessibility, time poverty, and zero-trip making, are used to assess the impact of policies and investments on wellbeing. Although these measures have some utility in making assessments about wellbeing, they also have limitations that must be addressed to provide a more accurate and nuanced understanding of individual wellbeing and its relationship to activity-travel and time use. This dissertation aimed to address this issue by exploring and modeling the nexus of mobility, time poverty, and wellbeing across its five main chapters. Four of these chapters address specific research questions, while the fifth introduces a web-based wellbeing platform that translates the knowledge generated in this dissertation into a practical real-world application for the use of the public, policymakers, professionals, and academics. The findings of each chapter are discussed in detail in their respective chapters; thus, this chapter only highlights their main objectives, contributions, and key findings, along with their implications for future research.

1. Chapter Summaries

Chapter 2 – This chapter focuses on the development of a model system that connects measures of activity-travel behavior to measures of wellbeing, with an ultimate goal that it can be used assess the impact of alternative transportation policies and investments on the quality of life. The American Time Use Survey (ATUS) Wellbeing Modules were used to develop models of wellbeing scores based on socio-economic and activity-travel variables. Additionally, a multiple discrete-continuous extreme value (MDCEV) model of in-home activity engagement and time allocation was estimated to predict in-home time use patterns for each individual in a synthetic population. The estimated MDCEV model allows the developed wellbeing model system to be used as a post-processor of activity-based travel models outputs to evaluate the wellbeing implications of transportation investments and policies for different subgroups of the population.

The model systems for wellbeing, along with the MDCEV component for estimating in-home time allocation, were demonstrated in a case study. This involved applying the model systems to a random sample from the 2017 National Household Survey to generate average daily wellbeing scores for all individuals in the sample. These scores were then used to evaluate the wellbeing of various subgroups of the population while taking into account their daily activity-travel and time use patterns. The case study results showed that wellbeing is affected by out-of-home activity engagement and travel, as well as in-home discretionary activity engagement. Older individuals have the highest wellbeing, presumably due to their discretionary activity engagement inside the home. Those with poor health status, mobility-constrained medical condition, zero vehicle ownership, not being able to drive, and being in the lowest income bracket are associated with the lowest degrees of wellbeing, indicating a need for greater interventions and policies to enable their participation in society and discretionary activities.

To summarize, this chapter introduces a wellbeing model system that can be used as a post-processor of activity-based travel model outputs and highlights its effectiveness through a case study. The developed model system allows for making assessments on the impacts of different transportation investments and actions on various subgroups of the population, particularly the mobility and quality-of-life disadvantaged groups. This has important implications for equity analyses, environmental justice, and planning for new autonomous and shared mobility systems to better serve disadvantaged populations. Moreover, the chapter highlights the importance of future research that explicitly connects activity-travel behavior to measures of wellbeing and enriches wellbeing models with additional attributes, such as built environment variables. The future research can also test the model system developed in a real-world setting by applying it to a full-fledged activity-based travel model output of millions of agents.

Chapter 3 – This chapter explores the relationship between zero-trip making, time poverty, and subjective wellbeing in an attempt to provide empirical evidence for the extent to which mobility poverty (zero-trip making) and time poverty can be considered as indicators of poor wellbeing. It examines the rates of zero-trip making from two datasets, namely National Household Travel Survey and American Time Use Survey and identifies the rates of time poverty experienced by different socio-demographic groups in the latter dataset. Then, it compares zero-trip makers and time poor individuals to trip makers and non-time poor individuals, respectively, using a subjective wellbeing scoring method that is developed in the second chapter. The chapter finds that time poverty and subjective wellbeing align with each other, with those experiencing high degrees of time poverty also experiencing a lower subjective wellbeing. However, for some groups, such as 75+ year old individuals, the definition of time poverty established in the literature does not correspond well with subjective wellbeing. The chapter also confirms the connection between mobility and enhanced life-quality, showing that trip making contributes to higher levels of wellbeing across all population groups considered in the analysis. However, the analysis reveals that zero-trip makers are not entirely a homogeneous group, and there is heterogeneity present among them. The chapter results suggest that transportation improvements and land use policies that save time for, and increase access to, discretionary activity opportunities would increase wellbeing in society by making it possible for people (especially mobility-disadvantaged groups) to pursue leisure activities more easily.

In summary, this chapter offers valuable insights into the relationship between mobility poverty, time poverty, and subjective wellbeing, along with the circumstances and degree to which the former two can serve as measures of wellbeing. It identifies the groups that are most vulnerable to diminished wellbeing resulting from mobility poverty and time poverty, and offers opportunities for targeted interventions and the development of transportation policies to address these challenges. The chapter also highlights the importance of considering the emotional feelings associated with daily activity-travel patterns, attitudes, lifestyle preferences, and socio-demographic characteristics when assessing wellbeing and quality of life. Using a model of wellbeing developed in the second chapter of this dissertation, which computes wellbeing scores as a function of these factors, can help transportation planners more accurately assess the impact of transportation policies on wellbeing.

Chapter 4 – This chapter makes a significant contribution by examining the relationship between automobile use, wellbeing, and satisfaction with daily travel routines. It aimed at understanding why automobile use continues to remain unabated and be the dominant mode of transportation in many parts of the developed countries and its impact on people's overall wellbeing. The chapter uses data from four automobile-dominated metropolitan areas in the United States to analyze the influence of individuals' relative amount of driving in non-commute trips on their satisfaction with their daily travel routines. The research acknowledges the presence of endogeneity and incorporates latent attitudinal factors that shape the relationship between mobility choices and satisfaction. The Generalized Heterogeneous Data Model (GHDM) is employed to estimate the model and unravel the impact of relative amount of driving on daily travel satisfaction.

According to the results, individuals who engage in a greater amount of driving for non-commute trips in comparison to other modes tend to have higher satisfaction (thus, wellbeing) from their daily travel routines. The chapter indicates that there is a correlation between the relative amount of driving and the level of satisfaction experienced by people. This suggests that in automobile-oriented cities with limited transit options and sprawled land use patterns, alternative modes of transportation may struggle to compete with the convenience and comfort of personal automobiles. Simply investing in alternative modes may not be sufficient to shift people away from automobiles unless strong disincentives are introduced against the use and acquisition of personal vehicles. The chapter also highlights the importance of factors such as living close to transit and preferring diverse neighborhoods, which positively influence satisfaction with daily travel routines. Future research should focus on understanding specific market segments and considering additional factors such as daily time use and activity participation in modeling satisfaction with travel routines. Overall, this chapter provides valuable insights into the relationship between automobile use, satisfaction with daily travel routines, and wellbeing, laying the foundation for further investigations in this field and offering important implications for policy formulations aimed at creating sustainable and equitable transportation systems.

Chapter 5 – This chapter investigates the impact of changes in daily activity patterns during the COVID-19 pandemic on individual wellbeing, using the wellbeing scoring method developed in the second chapter and time poverty. The chapter compares data from the 2019 and 2020 American Time Use Survey to identify winners and losers during the pandemic and sheds light on two notable phenomena that emerged during the pandemic. First, the chapter explains why there was a rapid resurgence in travel and non-essential activities outside the home following the development of vaccines and the slowdown of virus spread. Second, the chapter explores why many workers opted to continue working remotely from home instead of returning to the workplace. The chapter suggests that subjective wellbeing and time poverty offer important perspectives to understand these phenomena. It also offers strategies to mitigate adverse consequences for vulnerable groups in future disruptions.

It is found that virtually every subgroup of the population experienced significant reductions in wellbeing during the pandemic, despite significant improvements in time poverty. The increase in available discretionary time did not lead to greater wellbeing because individuals were not able to undertake enjoyable activities with family and friends in desirable locations due to pandemic-era restrictions and closures. The chapter findings suggest that transportation planning and modeling processes need to adapt to the new normal of hybrid and home-based work modalities. Future transportation infrastructure investments should no longer focus solely on accommodating the work commute but should also enable individuals to pursue and accomplish fulfilling life experiences in appealing places.

In summary, this chapter provides insights into the impact of changes in daily activity patterns during the pandemic on individual wellbeing, identifies winners and losers during the pandemic, and offers strategies to mitigate adverse consequences for vulnerable groups in future disruptions. The chapter emphasizes the importance of considering subjective wellbeing and time poverty indicators in transportation planning and modeling processes and suggests that future transportation infrastructure investments should focus on enabling individuals to pursue fulfilling life experiences.

2. Limitations and Implications for Future Research

While chapter-specific limitations and implications for future research are presented at the end of each chapter, the overarching limitations and implications for future research that can be derived from this dissertation are listed below.

- This dissertation has primarily focused on modeling the relationship between individual wellbeing and activity/travel patterns, assuming a one-way causal relationship where daily activity/travel patterns influence individual wellbeing. However, it is important to note the possibility of a two-way relationship, where individual wellbeing can also influence the types of activities and associated modalities pursued in a given day. For instance, a person experiencing happiness at the start of the day may choose to engage in more out-of-home activities, use active modes of transportation, and dedicate less time to household chores. Conversely, if an individual begins the day feeling relatively unhappy, they may engage in different activities, such as spending more time at home and participating less in social and recreational activities. In this scenario, the wellbeing derived from daily activity patterns at the end of the day on both happy and unhappy days is influenced by the initial emotional/wellbeing state at the beginning of the day. Future research should explore this duality and investigate the extent to which the initial wellbeing (or overall wellbeing) influences the types of activities individuals seek throughout the day, and how that relates to the experienced wellbeing at the end of the day.

- Another limitation of this dissertation arises from the concept of “opportunity cost” per se. The conclusions drawn in this study are based on the assumption that individuals with similar socioeconomic and household characteristics are assumed to have the same level of wellbeing if they exhibit identical activity and time use patterns in a day. Yet, it is possible that individuals with identical person characteristics and activity/travel patterns may still experience different levels of wellbeing if their preferred activities and associated modalities differ. For instance, let us consider two individuals who have identical trips in a day (using the same travel mode, say car). According to the assumption adopted in this dissertation, the contribution of these trips to their daily wellbeing would be equal. However, one person may prefer traveling by car as their mode of transportation, while the other person may favor biking. Consequently, the preference for biking would likely result in reduced wellbeing from these travel activities, thereby impacting individuals’ daily wellbeing. Another example pertains to two identical workers with the same activity and time use patterns, focusing on their first work episodes of the day. The wellbeing experienced from these work episodes depends on the alternative activities each worker would have engaged in. If one worker prefers attending a sports event with friends, whereas the other worker would have chosen to stay at home and sleep, this "opportunity cost" in terms of alternative preferred activities would influence the level of wellbeing experienced by each worker during that specific work episode. Future research should consider these preferences and account for the concept of "opportunity cost" in order to gain a deeper understanding of its impact on wellbeing.

- This dissertation has further limitations regarding the consideration of the impact of activity scheduling on the wellbeing experienced at the activity level. It is important to recognize that the wellbeing experienced during a specific activity or travel is influenced by the activities that precede (as well as succeed) it. For instance, engaging in discretionary activities like watching TV or exercising after a long work episode would likely result in a different level of wellbeing compared to conducting the same activity following another discretionary activity. In the former situation, individuals may experience higher wellbeing. This suggests that individuals following a specific schedule for their daily activities may experience varying levels of wellbeing compared to when they follow a different schedule for the same activities. Therefore, future research should also investigate the impact of activity scheduling on daily individual wellbeing, as well as the experienced wellbeing during an activity and its relationship with preceding and succeeding activities.
- Attitudes, lifestyles, values, and personality traits may all have an impact on wellbeing. For instance, Chapter 3 shows that individuals who do not engage in any out-of-home activities during the day, known as zero-trip makers, exhibit varying levels of experienced wellbeing. This variation is likely influenced not only by the types of activities they engage in within their homes but also by their personalities,

attitudes, values, and lifestyles. Extroverted individuals, for example, may experience heightened diminished wellbeing if they are unable to participate in out-of-home activities. Additionally, these factors can also shape the relationship between time poverty and wellbeing. Given that working long hours is a common cause of time poverty, it is reasonable to assume that individuals who have a strong inclination towards work, often labeled as "workaholics", may derive higher levels of wellbeing from work activities compared to others, thereby this personality trait resulting in different levels of experienced wellbeing. Therefore, it is crucial to consider the impacts of attitudes, lifestyles, values, and personalities on individual wellbeing. Future efforts should prioritize investigating this avenue of research.

- In future research examining the relationship between attitudes, lifestyles, values, preferences, and wellbeing, it is also important to distinguish between intrinsic and extrinsic attitudes. This differentiation holds significance because many policies are designed to shape individual attitudes. Therefore, it is crucial to identify the impact of intrinsic and extrinsic attitudes on daily individual wellbeing and satisfaction with travel activities. For instance, people's inclination towards car ownership is often shaped during their childhood, representing an intrinsic attitude that is challenging to change through external influences. On the other hand, attitudes towards the environment, such as environmental consciousness, can be considered extrinsic and may be influenced by awareness campaigns. In such cases, increasing individuals' awareness of environmental issues can alter their environmental consciousness, which in turn may lead to behavioral changes favoring sustainable transportation modes. Consequently, future research should investigate the roles of intrinsic and extrinsic attitudes in shaping activity and travel patterns as well as choices.

- Lastly, other areas for future research are as follows. Throughout this dissertation, the daily activity patterns were derived from the American Time Use Survey, which has a limitation in that it only captures information about the main activity when individuals engage in multitasking. For instance, if individuals are driving to work while listening to a podcast, only the travel activity is reported, omitting the additional activity. Therefore, future research should strive to collect data that accounts for multitasking activities and analyze their impact on wellbeing. Furthermore, in Chapter 2, the developed activity-wellbeing model system involved estimating an MDCEV model to ensure the transferability of the system to situations where in-home time allocation data is unavailable, such as in national household surveys. However, this method does not consider the scheduling of in-home activities, resulting in an incomplete representation of individuals' allocation of time at home. To address this shortcoming, future research should focus on developing novel methods that provide a more accurate estimation of in-home time allocation patterns.

BIBLIOGRAPHY

Abou-Zeid, M., & Ben-Akiva, M. (2011). The effect of social comparisons on commute well-being. *Transportation Research Part A: Policy and Practice*, *45*(4), 345-361.

Abou-Zeid, M., & Ben-Akiva, M. (2012). Well-being and activity-based models. *Transportation*, *39*, 1189-1207.

Adam, M. G., Tran, P. T., & Balasubramanian, R. (2021). Air quality changes in cities during the COVID-19 lockdown: A critical review. *Atmospheric Research*, *264*, 105823.

Adeel, M., & Yeh, A. G. (2018). Gendered immobility: influence of social roles and local context on mobility decisions in Pakistan. *Transportation Planning and Technology*, *41*(6), 660-678.

Aknin, L. B., De Neve, J. E., Dunn, E. W., Fancourt, D. E., Goldberg, E., Helliwell, J. F., ... & Ben Amor, Y. (2022). Mental health during the first year of the COVID-19 pandemic: A review and recommendations for moving forward. *Perspectives on Psychological Science*, *17*(4), 915-936.

Alkire, S. (2002). Dimensions of human development. *World Development*, *30*(2), 181-205.

Amato, P. R., & Zuo, J. (1992). Rural poverty, urban poverty, and psychological well-being. *The Sociological Quarterly*, *33*(2), 229-240.

Batur, I. (2015). *Social behavioral change for sustainable urban transportation under TDM concept: A case study of Istanbul* (Master's thesis, Istanbul Sehir University).

Bureau of Labor Statistics (2017). American Time Use Survey. Retrieved from https://www.bls.gov/tus/.

Bureau of Labor Statistics (2022). American Time Use Survey. Retrieved from https://www.bls.gov/tus/.

Archer, M., Paleti, R., Konduri, K. C., Pendyala, R. M., & Bhat, C. R. (2013). Modeling the connection between activity-travel patterns and subjective well-being. *Transportation Research Record*, *2382*(1), 102-111.

Aschauer, F., Hössinger, R., Schmid, B., & Gerike, R. (2018). Reporting quality of travel and non-travel activities: A comparison of three different survey formats. *Transportation Research Procedia*, *32*, 309-318.

Astroza, S., Pinjari, A. R., Bhat, C. R., & Jara-Díaz, S. R. (2017). A Microeconomic Theory–Based Latent Class Multiple Discrete–Continuous Choice Model of Time Use and Goods Consumption. *Transportation Research Record*, *2664*(1), 31-41.

Bagley, M. N., & Mokhtarian, P. L. (2002). The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *The Annals of Regional Science*, *36*, 279-297.

Batur, I., Sharda, S., Kim, T., Khoeini, S., Pendyala, R. M., & Bhat, C. R. (2019). Mobility, Time Poverty, and Well-Being: How Are They Connected and How Much Does Mobility Matter?. *Technical paper, Arizona State University*.

Bergstad, C. J., Gamble, A., Gärling, T., Hagman, O., Polk, M., Ettema, D., ... & Olsson, L. E. (2011). Subjective well-being related to satisfaction with daily travel. *Transportation*, *38*, 1-15.

Bernardo, C., Paleti, R., Hoklas, M., & Bhat, C. (2015). An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A: Policy and Practice, 76*, 71-91.

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological*, *42*(3), 274-303.

Bhat, C. R. (2015). A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B: Methodological*, *79*, 50-77.

Bhat, C. R. (2018). New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B: Methodological*, *109*, 238-256.

Bhat, C. R., Paleti, R., Pendyala, R. M., Lorenzini, K., & Konduri, K. C. (2013). Accommodating immigration status and self-selection effects in a joint model of household auto ownership and residential location choice. *Transportation Research Record*, *2382*(1), 142-150.

Blanchflower, D. G., & Oswald, A. J. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics*, *88*(7-8), 1359-1386.

Blazanin, G., Mondal, A., Asmussen, K. E., & Bhat, C. R. (2022). E-scooter sharing and bikesharing systems: An individual-level analysis of factors affecting first-use and use frequency. *Transportation Research Part C: Emerging Technologies*, *135*, 103515.

Blumenberg, E. (2009). Moving in and moving around: immigrants, travel behavior, and implications for transport policy. *Transportation Letters*, *1*(2), 169-180.

Bomay, N (2022). What Amex Tells Us About Consumer Spending. *Axios*. Retrieved from https://www.axios.com/2022/07/22/american-express-second-quarter-earnings-economy.

Bose, J., & Sharp, J. (2005, December). Measurement of travel behavior in a trip-based survey versus a time use survey–A comparative analysis of travel estimates using the 2001 National Household Travel Survey and the 2003 American Time Use Survey. In *American Time Use Survey Early Results Conference*.

Brickman, P., & Campbell D.T. (1971). *Hedonic relativism and planning the good society. In Appley, M.H. (Ed.)*. Adaptation Level Theory: A Symposium, Academic Press, New York, 287-302.

BTS (Bureau of Transportation Statistics) (2022). Latest Weekly COVID-19 Transportation Statistics. Retrieved from https://www.bts.gov/covid-19/week-in-transportation#combined.

Burchardt, T. (2008). Time and income poverty.

Calvert, S (2021). Covid-19 Pandemic Likely Improved Your Commute to Work. *The Wall Street Journal*. Retrieved from https://www.wsj.com/articles/covid-19-pandemic-likely-improved-your-commute-to-work-11609669801.

Cao, X. J., & Ettema, D. F. (2014). Satisfaction with travel and residential self-selection: How do preferences moderate the impact of the Hiawatha Light Rail Transit line?. *Journal of Transport and Land Use*, *7*(3), 93-108.

Cao, X., Mokhtarian, P. L., & Handy, S. L. (2007). Cross-sectional and quasi-panel explorations of the connection between the built environment and auto ownership. *Environment and Planning A*, *39*(4), 830-847.

Chatterjee, K., Chng, S., Clark, B., Davis, A., De Vos, J., Ettema, D., ... & Reardon, L. (2020). Commuting and wellbeing: a critical overview of the literature with implications for policy and future research. *Transport Reviews*, *40*(1), 5-34.

Chen, D. T. H., & Wang, Y. J. (2021). Inequality-Related health and social factors and their impact on well-being during the COVID-19 pandemic: findings from a national survey in the UK. *International Journal of Environmental Research and Public Health*, *18*(3), 1014.

Cheng, L., Chen, X., Yang, S., Wu, J., & Yang, M. (2019). Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. *Transportation Letters*, *11*(6), 341-349.

Churchill, S. A., & Smyth, R. (2019). Transport poverty and subjective wellbeing. *Transportation Research Part A: Policy and Practice*, *124*, 40-54.

Cohen, P. (2020). Recession With a Difference: Women Face Special Burden. Retrieved from https://www.nytimes.com/2020/11/17/business/economy/women-jobs-economy-recession.html.

Conway, M. W., Salon, D., & King, D. A. (2018). Trends in taxi use and the advent of ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. *Urban Science*, *2*(3), 79.

Corran, P., Steinbach, R., Saunders, L., & Green, J. (2018). Age, disability and everyday mobility in London: An analysis of the correlates of 'non-travel'in travel diary data. *Journal of Transport & Health*, *8*, 129-136.

Cudjoe, T. K., & Kotwal, A. A. (2020). "Social distancing" amid a crisis in social isolation and loneliness. *Journal of the American Geriatrics Society*, *68*(6), E27.

Currie, G., Jain, T., & Aston, L. (2021). Evidence of a post-COVID change in travel behaviour–Self-reported expectations of commuting in Melbourne. *Transportation Research Part A: Policy and Practice*, *153*, 218-234.

de Abreu e Silva, J., Martinez, L., & Goulias, K. (2012). Using a multi equation model to unravel the influence of land use patterns on travel behavior of workers in Lisbon. *Transportation Letters*, *4*(4), 193-209.

De Vos, J., & Witlox, F. (2016). Do people live in urban neighbourhoods because they do not like to travel? Analysing an alternative residential self-selection hypothesis. *Travel Behaviour and Society*, *4*, 29-39.

De Vos, J., Mokhtarian, P. L., Schwanen, T., Van Acker, V., & Witlox, F. (2016). Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. *Transportation*, *43*, 771-796.

De Vos, J., Schwanen, T., Van Acker, V., & Witlox, F. (2013). Travel and subjective well-being: A focus on findings, methods and future research needs. *Transport Reviews*, *33*(4), 421-442.

Delbosc, A. (2012). The role of well-being in transport policy. *Transport Policy*, *23*, 25-33.

Delbosc, A., & Currie, G. (2011). Exploring the relative influences of transport disadvantage and social exclusion on well-being. *Transport Policy*, *18*(4), 555-562.

Delbosc, A., & Currie, G. (2011). The spatial context of transport disadvantage, social exclusion and well-being. *Journal of Transport Geography*, *19*(6), 1130-1137.

Delbosc, A., Kroesen, M., Van Wee, B., & de Haas, M. (2020). Linear, non-linear, bi-directional? Testing the nature of the relationship between mobility and satisfaction with life. *Transportation*, *47*(4), 2049-2066.

Diener, E., & Seligman, M. E. (2004). Beyond money: Toward an economy of well-being. *Psychological Science in the Public Interest*, *5*(1), 1-31.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D. W., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*, 143-156.

Dolan, P., Peasgood, T., & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology*, *29*(1), 94-122.

Duarte, A., Garcia, C., Limao, S., & Polydoropoulou, A. (2009). *Experienced and expected happiness in transport mode decision making process* (No. 09-2199).

Durr, E., Bilecki, J., & Li, E. (2017). Are beliefs in the importance of pro-environmental behaviors correlated with pro-environmental behaviors at a college campus?. *Sustainability: The Journal of Record*, *10*(3), 204-210.

Eliasson, J. (2022). Will we travel less after the pandemic?. *Transportation Research Interdisciplinary Perspectives*, *13*, 100509.

Eluru, N., Pinjari, A., Pendyala, R., & Bhat, C. (2010). An econometric multi-dimensional choice model of activity-travel behavior. *Transportation Letters*, *2*(4), 217-230.

Eriksson, L., Friman, M., & Gärling, T. (2008). Stated reasons for reducing work-commute by car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *11*(6), 427-433.

Eriksson, L., Friman, M., & Gärling, T. (2013). Perceived attributes of bus and car mediating satisfaction with the work commute. *Transportation Research Part A: Policy and Practice*, *47*, 87-96.

Ettema, D., Gärling, T., Eriksson, L., Friman, M., Olsson, L. E., & Fujii, S. (2011). Satisfaction with travel and subjective well-being: Development and test of a measurement tool. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*(3), 167-175.

Ettema, D., Gärling, T., Olsson, L. E., & Friman, M. (2010). Out-of-home activities, daily travel, and subjective well-being. *Transportation Research Part A: Policy and Practice*, *44*(9), 723-732.

Farber, S., Mifsud, A., Allen, J., Widener, M. J., Newbold, K. B., & Moniruzzaman, M. (2018). Transportation barriers to Syrian newcomer participation and settlement in Durham Region. *Journal of Transport Geography, 68*, 181-192.

Ferenchak, N. N., & Katirai, M. (2015). Commute mode and mental health in major metropolitan areas. *Transportation Letters, 7*(2), 92-103.

FHWA (Federal Highway Administration) (2022). Traffic Volume Trends. Retrieved from https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm on Aug 1, 2022.

Forgeard, M. J., Jayawickreme, E., Kern, M. L., & Seligman, M. E. (2011). Doing the right thing: Measuring wellbeing for public policy. *International Journal of Wellbeing*, *1*(1).

Fox, K. R. (1999). The influence of physical activity on mental well-being. *Public Health Nutrition*, *2*(3a), 411-418.

Frederick, S., & Loewenstein G. (1999). *Hedonic adaptation*. In Kahneman, D., E. Diener, and N. Schwarz (Eds.). Foundations of Hedonic Psychology: Scientific Perspectives on Enjoyment and Suffering. Russell Sage Foundation, New York, 302-329.

Frijters, P., & Beatton, T. (2012). The mystery of the U-shaped relationship between happiness and age. *Journal of Economic Behavior & Organization*, *82*(2-3), 525-542.

Friman, M., Fujii, S., Ettema, D., Gärling, T., & Olsson, L. E. (2013). Psychometric analysis of the satisfaction with travel scale. *Transportation Research Part A: Policy and Practice, 48*, 132-145.

Friman, M., Gärling, T., Ettema, D., & Olsson, L. E. (2017). How does travel affect emotional well-being and life satisfaction?. *Transportation Research Part A: Policy and Practice*, *106*, 170-180.

Gaddis, I. & Wadhwa D. (2018). *Poverty Lies Beyond the Unemployed*. World Bank Blogs. Retrieved from https://blogs.worldbank.org/opendata/poverty-lies-beyond-unemployed.

Gao, Y., Rasouli, S., Timmermans, H., & Wang, Y. (2017). Understanding the relationship between travel satisfaction and subjective well-being considering the role of personality traits: A structural equation model. *Transportation Research Part F: Traffic Psychology and Behaviour*, *49*, 110-123.

Gardner, J., & Oswald, A. (2001). Does money buy happiness? A longitudinal study using data on windfalls. Retrieved from https://warwick.ac.uk/fac/soc/economics/staff/ajoswald/marchwindfallsgo.pdf.

Gärling, T. (2019). Travel-related feelings: review, theoretical framework, and numerical experiments. *Transportation Letters*, *11*(1), 54-62.

Gärling, T., & Gamble, A. (2017). Life satisfaction and Emotional Well-Being: Psychological, Economic and Social Factors. *Economic Psychology*, 405-420.

Giurge, L. M., Whillans, A. V., & West, C. (2020). Why time poverty matters for individuals, organisations and nations. *Nature Human Behaviour*, *4*(10), 993-1003.

Glass, T. A., De Leon, C. F. M., Bassuk, S. S., & Berkman, L. F. (2006). Social engagement and depressive symptoms in late life: longitudinal findings. *Journal of Aging and Health*, *18*(4), 604-628.

Harrington, D. M., & Hadjiconstantinou, M. (2022). Changes in commuting behaviours in response to the COVID-19 pandemic in the UK. *Journal of Transport & Health*, *24*, 101313.

Harvey, A. S., & Mukhopadhyay, A. K. (2007). When twenty-four hours is not enough: Time poverty of working parents. *Social Indicators Research*, 57-77.

Hensher, D. A., Beck, M. J., & Balbontin, C. (2022). Time allocation of reduced commuting time during COVID-19 under working from home. *Journal of Transport Economics and Policy (JTEP)*, *56*(4), 399-428.

Hook, H., De Vos, J., Van Acker, V., & Witlox, F. (2021). Do travel options influence how commute time satisfaction relates to the residential built environment?. *Journal of Transport Geography*, *92*, 103021.

Humphreys, D. K., Goodman, A., & Ogilvie, D. (2013). Associations between active commuting and physical and mental wellbeing. *Preventive Medicine*, *57*(2), 135-139.

IEEE. (2022). The State of Well-being Metrics (An Introduction). Retrieved from https://standards.ieee.org/wp-content/uploads/import/documents/other/ead1e_state_wellbeing_metrics.pdf.

International Transport Forum. (2021). ITF Transport Outlook 2021. Retrieved from https://www.itf-oecd.org/itf-transport-outlook-2021.
Jacobsen, G. D., & Jacobsen, K. H. (2020). Statewide COVID-19 stay-at-home orders and population mobility in the United States. *World Medical & Health Policy*, *12*(4), 347-356.

Jensen, R. A., Kirkegaard Thomsen, D., O'Connor, M., & Mehlsen, M. Y. (2020). Age differences in life stories and neuroticism mediate age differences in subjective well-being. *Applied Cognitive Psychology*, *34*(1), 3-15.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, *107*(38), 16489-16493.

Kalenkoski, C. M., & Hamrick, K. S. (2013). How does time poverty affect behavior? A look at eating and physical activity. *Applied Economic Perspectives and Policy*, *35*(1), 89-105.

Kalenkoski, C. M., Hamrick, K. S., & Andrews, M. (2011). Time poverty thresholds and rates for the US population. *Social Indicators Research*, *104*, 129-155.

Kastle Systems (2022). Back to Work Barometer. Retrieved from https://www.kastle.com/safety-wellness/getting-america-back-to-work/ on Aug 1, 2022.

Katz, J (2015). How Nonemployed Americans Spend Their Weekdays: Men vs. Women. *The New York Times*. Retrieved from https://www.nytimes.com/interactive/2015/01/06/upshot/how-nonemployed-americans-spend-their-weekdays-men-vs-women.html.

Kaufmann, V., Bergman, M. M., & Joye, D. (2004). Motility: Mobility as capital. *International Journal of Urban and Regional Research*, *28*(4), 745-756.

Kenyon, S., Lyons, G., & Rafferty, J. (2002). Transport and social exclusion: investigating the possibility of promoting inclusion through virtual mobility. *Journal of Transport Geography*, *10*(3), 207-219.

Khoeini, S., Pendyala, R. M., da Silva, D. C., & Sharda, S. (2018). *An Integrated Model of Activity-Travel Behavior and Subjective Well-being* (No. 69A3551747116). Center for Teaching Old Models New Tricks (TOMNET).

Khoeini, S., Pendyala, R. M., da Silva, D. C., Batur, I., Magassy, T. B., & Sharda, S. (2020). Attitudes Towards Emerging Mobility Options and Technologies–Phase 3: Survey Data Compilation, and Analysis.

Killgore, W. D., Cloonan, S. A., Taylor, E. C., & Dailey, N. S. (2021). Mental health during the first weeks of the COVID-19 pandemic in the United States. *Frontiers in Psychiatry*, *12*, 561898.

Kitamura, R., Fujii, S., & Pas, E. I. (1997). Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies. *Transport Policy*, *4*(4), 225-235.

KRC Research (2018). Transportation Needs and Assessment: Survey of Older Adults, People with Disabilities, and Caregivers. Retrieved from http://www.krcresearch.com/wp-content/uploads/2018/12/KRC-nadtc-Survey-Report-120718-FINAL_for-web.pdf.

Kroesen, M., & Chorus, C. (2018). The role of general and specific attitudes in predicting travel behavior–A fatal dilemma?. *Travel Behaviour and Society*, *10*, 33-41.

Kroesen, M., Handy, S., & Chorus, C. (2017). Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, *101*, 190-202.

Krueger, A. B., Kahneman, D., Fischler, C., Schkade, D., Schwarz, N., & Stone, A. A. (2009). Time use and subjective well-being in France and the US. *Social Indicators Research*, *93*, 7-18.

Krueger, A. B., Kahneman, D., Schkade, D., Schwarz, N., & Stone, A. A. (2009). National time accounting: The currency of life. In *Measuring the subjective well-being of nations: National accounts of time use and well-being* (pp. 9-86). University of Chicago Press.

Lee, R. J., & Sener, I. N. (2016). Transportation planning and quality of life: Where do they intersect?. *Transport Policy*, *48*, 146-155.

Leonhardt, D. (2022). Covid and Race. Retrieved from https://www.nytimes.com/2022/06/09/briefing/covid-race-deaths-america.html.

Liu, L., Gou, Z., & Zuo, J. (2016). Social support mediates loneliness and depression in elderly people. *Journal of Health Psychology*, *21*(5), 750-758.

Lucas, K. (2012). Transport and social exclusion: Where are we now?. *Transport Policy*, *20*, 105-113.

Magassy, T. B., Batur, I., Mondal, A., Asmussen, K. E., Bhat, C. R., Salon, D., ... & Pendyala, R. M. (2023). Evolution of Mode Use During the COVID-19 Pandemic in the United States: Implications for the Future of Transit. *Transportation Research Record*, 03611981231166942.

Mao, Z., Ettema, D., & Dijst, M. (2016). Commuting trip satisfaction in Beijing: Exploring the influence of multimodal behavior and modal flexibility. *Transportation Research Part A: Policy and Practice*, *94*, 592-603.

Markezich, A (2021). Downtown Trips Begin to Recover while Metro Area Surpasses Pre-COVID Levels. *INRIX*. Retrieved from https://inrix.com/blog/downtown-trips-recovering/.

McCabe, B. J. (2013). Are homeowners better citizens? Homeownership and community participation in the United States. *Social Forces*, *91*(3), 929-954.

McMahan, E. A., & Estes, D. (2011). Measuring lay conceptions of well-being: The beliefs about well-being scale. *Journal of Happiness Studies*, *12*, 267-287.

Meloni, I., E. Spissu, and M. Bez. A Model of the Dynamic Process of Time Allocation to Discretionary Activities. *Transportation Science*, 41(1), 2007, 15-28.

Mokhtarian, P. L. (2019). Subjective well-being and travel: Retrospect and prospect. *Transportation*, *46*, 493-513.

Mokhtarian, P. L., & Salomon, I. (2001). How derived is the demand for travel? Some conceptual and measurement considerations. *Transportation Research Part A: Policy and Practice*, *35*(8), 695-719.

Mokhtarian, P. L., Salomon, I., & Singer, M. E. (2015). What moves us? An interdisciplinary exploration of reasons for traveling. *Transport Reviews*, *35*(3), 250-274.

Mokhtarian, P.L. & Pendyala R.M. (2018). Travel Satisfaction and Well-being. In *Applying Quality of Life Research*, *Best Practices* (M. Friman, D. Ettema, and L. E. Olsson, ed.), Springer International Publishing AG., 17-39.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. *Transportation Research Part A: Policy and Practice*, *83*, 14-29.

Morris, E. A. (2015). Should we all just stay home? Travel, out-of-home activities, and life satisfaction. *Transportation Research Part A: Policy and Practice*, *78*, 519-536.

Mondal, A., Bhat, C. R., Costey, M. C., Bhat, A. C., Webb, T., Magassy, T. B., ... & Lam, W. H. K. (2021). How do people feel while walking? A multivariate analysis of emotional well-being for utilitarian and recreational walking episodes. *International Journal of Sustainable Transportation*, *15*(6), 419-434.

Motte-Baumvol, B., & Nassi, C. D. (2012). Immobility in Rio de Janeiro, beyond poverty. *Journal of Transport Geography*, *24*, 67-76.

Mouratidis, K., Ettema, D., & Næss, P. (2019). Urban form, travel behavior, and travel satisfaction. *Transportation Research Part A: Policy and Practice*, *129*, 306-320.

National Research Council (2013). Subjective Well-being: Measuring Happiness, Suffering, and Other Dimensions of Experience. *The National Academies Press*.

Ng, W., & Kang, S. H. (2022). Predictors of well-being during the COVID-19 pandemic: The importance of financial satisfaction and neuroticism. *Journal of Community Psychology*, *50*(7), 2771-2789.

Nochaiwong, S., Ruengorn, C., Thavorn, K., Hutton, B., Awiphan, R., Phosuya, C., ... & Wongpakaran, T. (2021). Global prevalence of mental health issues among the general population during the coronavirus disease-2019 pandemic: a systematic review and meta-analysis. *Scientific Reports*, *11*(1), 1-18.

Nordbakke, S., & Schwanen, T. (2014). Well-being and mobility: A theoretical framework and literature review focusing on older people. *Mobilities*, *9*(1), 104-129.

Organisation for Economic Co-operation and Development. (2011). *How's life?: measuring well-being*. Paris: OECD.

Ory, D. T., & Mokhtarian, P. L. (2005). When is getting there half the fun? Modeling the liking for travel. *Transportation Research Part A: Policy and Practice*, *39*(2-3), 97-123.

Oswald, A. J., & Wu, S. (2010). Objective confirmation of subjective measures of human well-being: Evidence from the USA. *Science*, *327*(5965), 576-579.

Otto, S., & Kaiser, F. G. (2014). Ecological behavior across the lifespan: Why environmentalism increases as people grow older. *Journal of Environmental Psychology*, *40*, 331-338.

Palumbo, R., Manna, R., & Cavallone, M. (2021). Beware of side effects on quality! Investigating the implications of home working on work-life balance in educational services. *The TQM Journal*, *33*(4), 915-929.

Parker, K., Horowitz J., Brown A., Fry R., Cohn D.V., & Igielnik R. (2018). What Unites and Divides Urban, Suburban and Rural Communities. Retrieved from https://www.pewresearch.org/social-trends/2018/05/22/demographic-and-economic-trends-in-urban-suburban-and-rural-communities/.

Parker, K., J.M. Horowitz, & R. Minkin, R (2022). COVID-19 Pandemic Continues to Reshape Work in America. *Pew Research Center*. Retrieved from https://www.pewresearch.org/social-trends/2022/02/16/covid-19-pandemic-continues-to-reshape-work-in-america/.

Polzin, S. E., Chu, X., & Godfrey, J. (2014). The impact of millennials' travel behavior on future personal vehicle travel. *Energy Strategy Reviews*, *5*, 59-65.

Polzin, S. E., Chu, X., & Rey, J. R. (1999). *Mobility and mode choice of people of color for non-work travel*. Center for Urban Transportation Research.

Polzin, S.E (2016). So Much for Peak VMT. Planetizen. Retrieved from https://www.planetizen.com/node/84877/so-much-peak-vmt on Aug 1, 2022.

Qi, L., & Dong, X. Y. (2018). Gender, low-paid status, and time poverty in urban China. *Feminist Economics*, *24*(2), 171-193.

Reardon, L., & Abdallah, S. (2013). Well-being and transport: Taking stock and looking forward. *Transport Reviews*, *33*(6), 634-657.

Rentziou, A., Gkritza, K., & Souleyrette, R. R. (2012). VMT, energy consumption, and GHG emissions forecasting for passenger transportation. *Transportation Research Part A: Policy and Practice*, *46*(3), 487-500.

Restrepo, B. J., & Zeballos, E. (2022). Work from home and daily time allocations: evidence from the coronavirus pandemic. *Review of Economics of the Household*, *20*(3), 735-758.

Richardson, T (2007). Immobility in urban travel surveys. *30th Australasian Transport Research Forum*.

Russell, M., & Mokhtarian, P. (2015). How real is a reported desire to travel for its own sake? Exploring the 'teleportation' concept in travel behaviour research. *Transportation*, *42*, 333-345.

Schwanen, T., & Mokhtarian, P. L. (2005). What affects commute mode choice: neighborhood physical structure or preferences toward neighborhoods?. *Journal of Transport Geography*, *13*(1), 83-99.

Schwanen, T., & Wang, D. (2014). Well-being, context, and everyday activities in space and time. *Annals of the Association of American Geographers*, *104*(4), 833-851.

Schwanen, T., Lucas, K., Akyelken, N., Solsona, D. C., Carrasco, J. A., & Neutens, T. (2015). Rethinking the links between social exclusion and transport disadvantage through the lens of social capital. *Transportation Research Part A: Policy and Practice, 74*, 123-135.

Sener, I., Bhat, C., & Pendyala, R. (2011). When, where, how long, and with whom are individuals participating in physically active recreational episodes?. *Transportation Letters*, *3*(3), 201-217.

Sharda, S., Astroza, S., Khoeini, S., Batur, I., Pendyala, R. M., & Bhat, C. R. (2019, March). Do attitudes affect behavioral choices or vice-versa: Uncovering latent segments within a heterogeneous population. In *Transportation Research Board 98th Annual Meeting Compendium of Papers, Washington DC, January*.

Sharif, M. A., Mogilner, C., & Hershfield, H. E. (2021). Having too little or too much time is linked to lower subjective well-being. *Journal of Personality and Social Psychology*, *121*(4), 933.

Shergold, I (2020). Older people and out-of-home mobility: Is discretionary travel undervalued in current policy? (PhD Dissertation). University of the West of England. Retrieved from https://uwe-repository.worktribe.com/output/1491023.

Singleton, P. A. (2019). Walking (and cycling) to well-being: Modal and other determinants of subjective well-being during the commute. *Travel Behaviour and Society*, *16*, 249-261.

Singleton, P. A. (2020). Exploring the positive utility of travel and mode choice: subjective well-being and travel-based multitasking during the commute. In *Mapping the Travel Behavior Genome* (pp. 259-277).

Spinney, J. E., Scott, D. M., & Newbold, K. B. (2009). Transport mobility benefits and quality of life: A time-use perspective of elderly Canadians. *Transport Policy*, *16*(1), 1-11.

Spinney, J., & Millward, H. (2010). Time and money: a new look at poverty and the barriers to physical activity in Canada. *Social Indicators Research*, *99*, 341-356.

Stanley, J. K., Hensher, D. A., Stanley, J. R., & Vella-Brodrick, D. (2011). Mobility, social exclusion and well-being: Exploring the links. *Transportation Research Part A: Policy and Practice, 45*(8), 789-801.

Stopher, P. R. (2005). Voluntary travel behavior change. In *Handbook of transport strategy, policy and institutions*. Emerald Group Publishing Limited.

Stutzer, A., & Frey, B. S. (2006). Does marriage make people happy, or do happy people get married?. *The Journal of Socio-Economics*, *35*(2), 326-347.

Sultana, S., Salon, D., & Kuby, M. (2019). Transportation sustainability in the urban context: A comprehensive review. *Urban Geography*, *40*(3), 279-308.

Susilo, Y. O., & Cats, O. (2014). Exploring key determinants of travel satisfaction for multi-modal trips by different traveler groups. *Transportation Research Part A: Policy and Practice*, *67*, 366-380.

TSA (Transportation Security Administration) (2022). TSA checkpoint travel numbers (current year versus prior year(s)/same weekday). Retrieved from https://www.tsa.gov/travel/passenger-volumes.

UNDP. (2022). Human Development Index (HDI). Retrieved from https://hdr.undp.org/data-center/human-development-index#/indicies/HDI.

U.S. Department of Transportation - Federal Highway Administration. (2018). National Household Travel Survey.

U.S. Department of Transportation - Federal Highway Administration. (2021). Highway Statistics 2021. Retrieved from https://www.fhwa.dot.gov/policyinformation/statistics/2021/.

Van Acker, V., Van Wee, B., & Witlox, F. (2010). When transport geography meets social psychology: toward a conceptual model of travel behaviour. *Transport Reviews*, *30*(2), 219-240.

Västfjäll, D., Friman, M., Gärling, T., & Kleiner, M. (2002). The measurement of core affect: A Swedish self-report measure derived from the affect circumplex. *Scandinavian Journal of Psychology*, *43*(1), 19-31.

Veenhoven, R. (2013). *Data-Book of Happiness: A Complementary Reference Work to 'Conditions of Happiness' by the Same Author*. Springer Science & Business Media.

Vickery, C. (1977). The time-poor: A new look at poverty. *Journal of Human Resources*, 27-48.

Vickery, J., & Hunter, L. M. (2016). Native Americans: Where in environmental justice research?. *Society & Natural Resources*, *29*(1), 36-52.

Voukelatou, V., Gabrielli, L., Miliou, I., Cresci, S., Sharma, R., Tesconi, M., & Pappalardo, L. (2021). Measuring objective and subjective well-being: dimensions and data sources. *International Journal of Data Science and Analytics*, *11*, 279-309.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063.

Waygood, E. O. D., Friman, M., Olsson, L. E., & Taniguchi, A. (2017). Transport and child well-being: An integrative review. *Travel Behaviour and Society*, *9*, 32-49.

Welch, T. F., & Mishra, S. (2013). A measure of equity for public transit connectivity. *Journal of Transport Geography*, *33*, 29-41.

Wells, M. (2010). Resilience in older adults living in rural, suburban, and urban areas. *Online Journal of Rural Nursing and Health Care*, *10*(2), 45-54.

Williams, J. R., Masuda, Y. J., & Tallis, H. (2016). A measure whose time has come: Formalizing time poverty. *Social Indicators Research*, *128*, 265-283.

Windsor, T. D., Anstey, K. J., Butterworth, P., Luszcz, M. A., & Andrews, G. R. (2007). The role of perceived control in explaining depressive symptoms associated with driving cessation in a longitudinal study. *The Gerontologist*, *47*(2), 215-223.

Ye, R., & Titheridge, H. (2017). Satisfaction with the commute: The role of travel mode choice, built environment and attitudes. *Transportation Research Part D: Transport and Environment*, *52*, 535-547.

Ye, X., Konduri, K., Pendyala, R. M., & Sana, B. (2009). Formulation of an Activity-Based Utility Measure of Time Use: Application to Understanding the Influence of Constraints. *Transportation Research Record*, *2135*(1), 60-68.

Yennamani, R., Srinivasan, S., Yennamani, R., & Srinivasan, S. (2008). Disaggregate comparison of travel reported by two American surveys, the NHTS and the ATUS. In *8th International Conference on Survey Methods in Transport, May, Annecy, France*.

Zhuo, K., & Zacharias, J. (2021). The impact of out-of-home leisure before quarantine and domestic leisure during quarantine on subjective well-being. *Leisure Studies*, *40*(3), 321-337.

Ziems, S. E., Konduri, K. C., Sana, B., & Pendyala, R. M. (2010). Exploration of time use utility derived by older individuals from daily activity–travel patterns. *Transportation Research Record*, *2156*(1), 111-119.

APPENDIX A

MDCEV MODEL ESTIMATION RESULTS FOR IN-HOME ACTIVITY TIME ALLOCATIONS

The table below presents the model estimation results for the MDCEV component of Chapter 2, including translation parameters and goodness of fit statistics at the bottom.

Table A-1

MDCEV Model Estimation Results for In-home Activity Time Allocations

Activity type	Explanatory variables (base category)		Coef.	t-stat
Maintenance	Constant		-4.07	-96.94
	Gender (not male)	Male	-0.62	-32.82
	Age (<31 years | > 64 years)	31 to 49 years	0.2	6.97
		50 to 64 years	0.1	3.19
	Household income ($15K to $75K)	Less than $15K	-0.06	-2.45
		$75K to $100K	0.08	2.75
		Over $100K	0.05	1.85
	Educational attainment (high school degree or less)	Some college or assc. degree	0.07	3.17
		Bachelor's degree	0.1	3.66
		Graduate degree(s)	0.06	1.54
	Household size (up to 3)	4 or more	0.12	4.53
	Tenure status (not homeowner)	Homeowner	0.17	7.4
	Place of birth (outside of U.S.)	U.S.	-0.05	-1.62
	Student status (not student)	Student	-0.51	-9.82
	Employment status (unemployed)	Employed	-0.07	-2.66
	# of hh. children under 14 (up to 3)	4 or more	0.26	5.26
Work	Constant		-10.57	-117.5
	Gender (not male)	Male	0.19	5.31
	Age (<21 years | > 64 years)	21 to 30 years	0.22	2.86
		31 to 49 years	0.47	7.2
		50 to 64 years	0.56	8.19
	Household income (<$15K | $35K to $100K)	$15K to $35K	-0.12	-2.27
		Over $100K	0.26	6.44
	Educational attainment (high school degree or less)	Some college or assc. degree	0.45	8.03
		Bachelor's degree	1.03	18.62
		Graduate degree(s)	1.37	22.41
	Place of birth (outside of U.S.)	U.S.	0.25	4.61
	Employment status (unemployed)	Employed	1.13	20.45

Table A-1 (Continued)

Activity type	Explanatory variables (base category)		Coef.	t-stat
Education	Constant		-7.85	-77.61
	Gender (not male)	Male	-0.24	-3.9
	Age (<31 years)	31 to 49 years	-1.22	-14.96
		50 to 64 years	-2.27	-17.46
		65 years or older	-3.62	-16.72
	Household income (over $35K)	Less than $15K	-0.29	-3.37
		$15K to $35K	-0.17	-2.37
	Place of birth (outside of U.S.)	U.S.	-0.22	-2.67
	Student status (not student)	Student	1.09	14.29
	Employment status (unemployed)	Employed	-0.72	-10.81
	# of hh. children under 14 (up to 3)	4 or more	-0.20	-1.61
Shopping	Constant		-10.72	-59.79
	Gender (not male)	Male	-0.35	-3.69
	Age (64 years or younger)	65 years or older	-0.46	-3.53
	Household income (over $35K)	$15K	-0.34	-2.13
		$15K to $35K	-0.16	-1.34
	Educational attainment (high school degree or less)	Some college or assc. degree	0.37	3.03
		Bachelor's degree	0.43	3.33
		Graduate degree(s)	0.47	3.19
	Place of birth (outside of U.S.)	U.S.	0.44	2.87
	Student status (not a student)	Student	-0.77	-2.86
Eating and drinking	Constant		-5.13	-123.9
	Age (<31 years)	31 to 49 years	0.16	5.17
		50 to 64 years	0.24	6.93
		65 years or older	0.4	12.3
	Household income (less than $75K)	$75K to $100K	0.06	2.13
		Over $100K	0.11	4.13
	Educational attainment (high school or less)	Graduate degree(s)	0.05	1.68
	Household size (up to 3)	4	0.11	3.92
		5 or more	0.14	3.94
	Tenure status (not homeowner)	Homeowner	0.11	4.95
	Place of birth (outside of U.S.)	U.S.	-0.24	-8.12
	Student status (not student)	Student	-0.29	-5.72
	Employment status (unemployed)	Employed	-0.26	-9.62
	# of hh. children under 14 (up to 3)	4 or more	0.06	1.19
Social and recreational	Constant		-4.73	-106.36
	Gender (not male)	Male	0.17	8.84
	Age (<31 years | > 64 years)	31 to 49 years	-0.1	-3.29
		50 to 64 years	0.06	1.62
	Household income (over $35K)	$15K	0.09	3.19
		$15K to $35K	0.05	2.21
	Educational attainment (high school degree or less)	Some college or assc. degree	-0.1	-4.35
		Bachelor's degree	-0.16	-5.84
		Graduate degree(s)	-0.22	-6.28
	Household size (up to 3)	4	-0.18	-6.33
		5 or more	-0.08	-2.22
	Tenure status (not homeowner)	Homeowner	0.08	3.3
	Place of birth (outside of U.S.)	U.S.	0.14	4.49
	Student status (not a student)	Student	-0.48	-9.27
	Employment status (unemployed)	Employed	-0.39	-13.58
	# of hh. children under 14 (up to 3)	4 or more	-0.22	-4.15

Table A-1 (Continued)

Activity type	Explanatory variables (base category)		Coef.	t-stat
Religious	Constant		-8.95	-85.36
	Gender (not male)	Male	-0.52	-8.83
	Age (30 to 50 years)	15 to 20 years	-0.6	-2.44
		21 to 30 years	-0.6	-4.8
		50 to 64 years	0.5	6.57
		65 years or older	0.71	8.68
	Household income (over $35K)	$15K	0.36	4.6
		$15K to $35K	0.22	3.33
	Household size (up to 4)	5 or more	0.53	6.36
	Tenure status (not homeowner)	Homeowner	-0.16	-2.5
	Place of birth (outside of U.S.)	Born in US	-0.38	-5.38
	Student status (not a student)	Student	-0.46	-1.76
	Employment status (unemployed)	Employed	-0.28	-4.14
Other	Constant		-7.22	-192.37
	Gender (not male)	Male	-0.46	-17.7
	Age (49 years or younger)	50 to 64 years	0.13	3.52
		65 years or older	0.18	4.59
	Household income (<$100K)	$100K or more	0.09	2.62
	Educational attainment (less than high school degree | some college or assc. degree | graduate degree)	High school degree	-0.2	-6.55
		Bachelor's degree	0.06	1.79
	Household size (up to 3)	4 or more	-0.12	-3.41
	Student status (not a student)	Student	-0.24	-3.48
	Employment status (unemployed)	Employed	-0.24	-7.13
	# of hh. children under 14 (up to 3)	4 or more	0.21	3.33
Translation parameters				
Sleeping			0	na
Maintenance			15.17	56.32
Work			94.73	30.28
Education			146.55	12.74
Eating			10.99	55.76
Recreational			47.97	57.48
Shopping			23.43	11.63
Religious			36.03	15.43
Other			32.51	41.34
Sigma			1	na
Goodness of fit statistics				
Log-Likelihood of base model			-692418.6	
Degrees of freedom of base model			16	
Log-Likelihood of final model at convergence			-686106.5	
Degrees of freedom of final model			111	
Likelihood ratio			12624.2	
Chi-Squared (95,0.01)			129.9	

Note: na=not applicable.

APPENDIX B

THRESHOLDS FOR THE LATENT JOINT MODEL ESTIMATION RESULTS

The table below presents the threshold values corresponding to each emotion for the latent joint model estimated in Chapter 2.

Table B-1

Latent Joint Model Estimation Results: Threshold Values for Each Activity Type

Thresholds	In-home		Travel		Out-of-home	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Happiness						
1|2	-1.84	0.020	-1.98	0.035	-2.21	0.070
2|3	-1.62	0.019	-1.77	0.031	-1.97	0.067
3|4	-1.24	0.017	-1.36	0.027	-1.57	0.064
4|5	-0.59	0.016	-0.64	0.025	-0.85	0.059
5|6	-0.04	0.015	-0.02	0.026	-0.23	0.058
6|7	0.64	0.016	0.73	0.031	0.55	0.057
Meaningful						
1|2	-1.38	0.012	-1.21	0.017	-1.68	0.034
2|3	-1.17	0.011	-1.00	0.016	-1.48	0.033
3|4	-0.88	0.010	-0.72	0.016	-1.19	0.031
4|5	-0.45	0.009	-0.32	0.015	-0.71	0.029
5|6	-0.11	0.009	0.02	0.016	-0.30	0.028
6|7	0.31	0.009	0.40	0.017	0.19	0.028
Stressfulness						
1|2	0.38	0.019	0.58	0.021	0.60	0.039
2|3	0.61	0.019	0.82	0.022	0.83	0.039
3|4	0.89	0.019	1.10	0.023	1.13	0.040
4|5	1.26	0.020	1.43	0.025	1.48	0.041
5|6	1.69	0.022	1.82	0.029	1.86	0.043
6|7	2.17	0.026	2.26	0.035	2.28	0.048
Tiredness						
1|2	1.07	0.038	0.92	0.039	1.10	0.074
2|3	1.45	0.041	1.26	0.042	1.46	0.076
3|4	1.87	0.046	1.63	0.046	1.86	0.078
4|5	2.41	0.053	2.06	0.053	2.32	0.082
5|6	2.91	0.062	2.43	0.060	2.69	0.086
6|7	3.48	0.072	2.85	0.070	3.07	0.093

Table B-1 (Continued)

Thresholds	In-home		Travel		Out-of-home	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Sadness						
1|2	1|2	1|2	1|2	1|2	1|2	1|2
2|3	2|3	2|3	2|3	2|3	2|3	2|3
3|4	3|4	3|4	3|4	3|4	3|4	3|4
4|5	4|5	4|5	4|5	4|5	4|5	4|5
5|6	5|6	5|6	5|6	5|6	5|6	5|6
6|7	6|7	6|7	6|7	6|7	6|7	6|7
Painful						
1|2	1|2	1|2	1|2	1|2	1|2	1|2
2|3	2|3	2|3	2|3	2|3	2|3	2|3
3|4	3|4	3|4	3|4	3|4	3|4	3|4
4|5	4|5	4|5	4|5	4|5	4|5	4|5
5|6	5|6	5|6	5|6	5|6	5|6	5|6
6|7	6|7	6|7	6|7	6|7	6|7	6|7

APPENDIX C

TIME USE PATTERNS OF INCOME GROUPS

In order to offer a more detailed insight into the impact of income on activity-level wellbeing scores, this appendix presents the time use patterns of the income groups analyzed during the model estimation process outlined in Chapter 2. The corresponding information is displayed in Tables C-1 and C-2 below, respectively for weekday and weekend samples. It is important to note that this table is generated using the combined data sets of the American Time Use Survey (ATUS) from the years 2010, 2012, and 2013, and the time use patterns presented are based on a weighted sample.

Table C-1

Weekday Time Use Patterns of Income Groups (Average Minutes per Day) (Weighted)

Activity type	**Location**	**Annual Household Income**				
		≤$35K	$35K-$50K	$50K-$75K	$75K-$100K	≥$100K
Sample size		*5,006*	*1,875*	*2,452*	*1,542*	*2,462*
Sleeping	In-home	537.6	511.6	500.2	495.2	482.2
	Out-of-home	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	47.2	47.9	46.3	46.0	46.1
	Out-of-home	0.1	0.0	0.7	0.1	0.1
Household activities	In-home	108.9	99.2	91.7	85.5	78.9
	Out-of-home	7.1	5.9	5.4	6.5	6.2
Helping household members	In-home	20.4	21.5	22.8	22.6	24.4
	Out-of-home	5.3	5.1	5.2	5.6	6.7
Helping non-household members	In-home	2.7	2.9	2.2	2.9	2.3
	Out-of-home	5.7	5.4	4.5	5.7	3.9
Work & work-related activities	In-home	12.5	22.4	24.4	31.4	36.9
	Out-of-home	150.8	216.0	256.7	266.4	275.6
Education	In-home	8.6	10.0	8.5	9.4	11.9
	Out-of-home	22.3	20.5	23.2	24.0	35.1
Consumer purchases	In-home	0.5	0.4	0.5	0.4	0.4
	Out-of-home	17.5	18.6	18.7	15.3	17.5
Personal care services	In-home	0.5	0.5	0.4	0.2	0.1
	Out-of-home	6.7	5.9	4.6	4.8	4.8
Household services	In-home	0.2	0.2	0.3	0.9	0.5
	Out-of-home	0.4	0.6	0.7	0.3	0.3
Government services & civic obligations	In-home	0.0	0.0	0.0	0.0	0.0
	Out-of-home	0.6	0.6	1.0	0.6	0.4
Eating and drinking	In-home	43.1	42.8	40.4	40.2	38.3
	Out-of-home	18.1	22.4	24.7	27.8	28.8
Socializing, relaxing, leisure	In-home	269.8	226.9	202.0	182.5	165.1
	Out-of-home	39.4	32.8	33.5	36.0	36.0
Sports, exercise, recreation	In-home	2.6	2.7	2.7	3.9	3.6
	Out-of-home	12.1	14.4	15.7	20.1	17.5
Religious and spiritual activities	In-home	3.4	2.6	1.5	1.8	1.2
	Out-of-home	3.0	3.3	2.0	1.5	1.3
Volunteer activities	In-home	1.4	1.0	2.8	2.2	2.1
	Out-of-home	4.5	5.7	5.2	6.5	6.9
Telephone calls	In-home	6.8	6.3	6.0	4.2	5.1
	Out-of-home	0.4	0.3	0.5	0.4	0.6
Traveling	Total	61.9	67.6	73.7	76.4	83.9
	To/from work	14.1	19.0	22.0	25.7	28.6
Data codes (other)	In-home	11.5	9.3	7.9	7.9	8.1
	Out-of-home	6.2	6.7	3.4	4.9	7.4
Total	In-home	1078.5	1009.1	961.0	938.0	907.6
	Out-of-home	361.5	430.9	479.0	502.0	532.4

Table C-2

Weekend Time Use Patterns of Income Groups (Average Minutes per Day) (Weighted)

Activity type	Location	Annual Household Income				
		≤$35K	$35K-$50K	$50K-$75K	$75K-$100K	≥$100K
Sample size		*7,612*	*2,807*	*3,684*	*2,339*	*3,762*
Sleeping	In-home	560.6	539.5	533.9	521.8	522.0
	Out-of-home	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	46.0	46.8	44.5	44.2	43.5
	Out-of-home	0.6	0.0	0.1	0.0	0.0
Household activities	In-home	106.3	102.7	109.3	108.1	107.5
	Out-of-home	8.0	9.8	9.3	8.1	8.2
Helping household members	In-home	17.9	13.5	18.0	19.9	22.2
	Out-of-home	4.7	5.1	4.5	6.8	8.2
Helping non-household members	In-home	3.1	3.5	3.4	2.2	1.8
	Out-of-home	6.3	6.3	6.7	6.5	5.2
Work & work-related activities	In-home	9.2	9.9	17.4	17.2	27.5
	Out-of-home	84.7	119.0	125.1	131.5	122.1
Education	In-home	7.5	8.6	6.8	6.5	7.4
	Out-of-home	7.3	7.2	8.7	7.7	13.3
Consumer purchases	In-home	0.6	0.4	0.8	0.9	1.0
	Out-of-home	23.3	27.7	26.9	27.5	31.0
Personal care services	In-home	0.2	0.1	0.3	0.3	0.2
	Out-of-home	3.0	2.9	3.3	3.0	3.2
Household services	In-home	0.1	0.2	0.2	0.1	0.6
	Out-of-home	0.5	0.5	0.3	0.5	0.8
Government services & civic obligations	In-home	0.1	0.0	0.0	0.0	0.0
	Out-of-home	0.1	0.2	0.3	0.4	0.9
Eating and drinking	In-home	43.2	40.5	42.0	41.5	44.4
	Out-of-home	21.2	29.1	30.4	33.7	37.2
Socializing, relaxing, leisure	In-home	302.9	256.9	237.0	228.5	210.4
	Out-of-home	61.0	67.7	67.4	62.8	61.6
Sports, exercise, recreation	In-home	2.8	2.8	4.4	4.3	3.8
	Out-of-home	14.1	19.6	19.5	24.2	27.5
Religious and spiritual activities	In-home	3.1	2.3	1.2	1.3	1.2
	Out-of-home	14.2	14.5	12.5	11.2	10.1
Volunteer activities	In-home	1.7	1.9	2.0	3.1	2.5
	Out-of-home	5.8	5.7	8.8	10.5	9.7
Telephone calls	In-home	5.9	6.8	4.5	3.7	5.2
	Out-of-home	0.3	0.3	0.5	0.2	0.2
Traveling	Total	59.2	71.5	75.8	84.3	85.5
	To/from work	7.6	10.5	11.7	13.4	11.2
Data codes (other)	In-home	10.3	10.7	8.6	10.7	9.8
	Out-of-home	4.4	5.6	5.8	6.9	4.1
Total	In-home	1122.1	1047.8	1035.0	1015.1	1011.8
	Out-of-home	317.9	392.2	405.0	424.9	428.2

APPENDIX D

SEGMENT CHARACTERISTICS: HAPPY VS UNHAPPY ZERO-TRIP MAKERS

Chapter 4 highlights a significant finding that not all individuals who do not undertake any trips during a day consistently experience lower wellbeing in comparison to those who do make trips. To delve deeper into this observation, an additional analysis is conducted to provide further insights into the characteristics of zero-trip makers. This analysis involves dividing the zero-trip makers into two distinct groups: the first group consists of zero-trip makers who, on average, have higher wellbeing than trip makers (referred to as "happy zero-trip makers"), while the second group comprises zero-trip makers who have lower wellbeing than trip makers (referred to as "unhappy zero-trip makers"). The wellbeing scores are computed based on the subjective wellbeing scoring method introduced in Chapter 2. It is important to note that this analysis is not limited to the 2017 edition of American Time Use Survey (ATUS); instead, it examines a pooled dataset of zero-trip makers from all ATUS years spanning from 2003 to 2019 (excluding 2020 and 2021 to isolate the impacts of the COVID-19 pandemic). Table D-1 presents the results of this analysis, illustrating the socio-economic and demographic characteristics of each of these two segments and their relative sample sizes. Furthermore, in order to shed light on potential factors contributing to the differences in wellbeing between happy and unhappy zero-trip makers, Table D-2 provides insights into the time use patterns of these two distinct groups across numerous sociodemographic categories.

Table D-1

Segment Characteristics: Happy vs. Unhappy Zero-Trip Makers (Weighted)

Attribute	Category	Happy zero-trip makers	Unhappy zero-trip makers	All*
Sample size		*6,106*	*26,753*	*210,586*
Gender	Female	55.9	56.6	51.6
	Male	44.1	43.4	48.4
Age	15 to 19 years	0.4	6.9	8.5
	20 to 29 years	4.3	12.0	17.2
	30 to 49 years	16.7	25.3	33.9
	50 to 64 years	20.8	26.7	23.5
	65 years or older	57.8	29.0	17.0
Race	White	86.7	77.4	81.7
	Black	7.8	16.7	12.1
	Asian	4.0	3.5	3.9
	Other	1.5	2.5	2.4
Educational attainment	Less than high school	14.2	24.6	17.1
	High school	32.1	36.7	29.2
	Some college or assc. degree	23.3	21.9	25.0
	Bachelor's degree	17.8	11.3	18.3
	Graduate degree(s)	12.6	5.5	10.4
Employment status	Worker	35.4	31.9	60.8
	Non-worker	64.6	68.1	39.2
Household income	Up to $34,999	32.7	46.1	29.9
	$35,000 to $49,999	13.8	13.1	13.2
	$50,000 to $74,999	15.7	15.0	18.1
	$75,000 to $99,999	14.5	7.4	12.6
	$100,000 or more	16.4	10.9	19.1
Household size	One	9.9	22.3	14.8
	Two	53.9	35.3	33.2
	Three or more	36.3	42.3	52.0
Household location	Metropolitan area	80.4	81.9	85.3
	Non-metropolitan area	19.6	18.1	14.7
Time poverty status	Time poor	12.0	17.1	26.4
	Non-time poor	88.0	82.9	73.7
Trip making status	Zero-trip maker	100.0	100.0	14.1
	Trip maker	0.0	0.0	85.9

Note: (1) All* includes all trip makers and zero-trip makers, representing the full sample; (2) The table is color-coded to highlight the comparison between the happy and unhappy groups, with green indicating the larger share and red indicating the smaller share within each row.

Table D-2

Time Use Patterns of Happy vs Unhappy Zero-Trip Makers (Average Minutes per Day) (Weighted)

Activity type	**Location**	**Male**		**Income up to $35K**		**Age 65 years or older**	
		Happy	Unhappy	Happy	Unhappy	Happy	Unhappy
Sample size		*2,603*	*10,340*	*2,048*	*13,592*	*3,197*	*9,089*
Sleeping	In-home	535.7	594.2	542.1	603.1	540.4	578.4
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	38.9	35.5	43.0	47.1	47.0	46.8
	Out-of-home	0.5	0.2	0.5	0.4	0.2	0.6
Household activities	In-home	193.6	125.0	213.7	156.4	218.8	167.3
	Out-of-home	5.0	2.2	4.9	1.7	4.8	1.5
Helping household members	In-home	33.0	9.6	29.4	20.8	10.8	3.3
	Out-of-home	0.8	0.3	0.7	0.4	0.6	0.0
Helping non-household members	In-home	5.5	3.5	4.8	5.6	5.8	4.6
	Out-of-home	0.2	0.6	0.9	0.6	1.2	0.6
Work & work-related activities	In-home	34.0	49.7	11.8	17.8	13.5	12.9
	Out-of-home	13.6	31.0	2.5	7.5	3.5	3.2
Education	In-home	1.3	11.5	1.8	7.7	0.5	0.5
	Out-of-home	0.2	0.6	0.0	0.3	0.0	0.0
Consumer purchases	In-home	0.7	0.5	0.7	0.6	0.9	0.3
	Out-of-home	0.1	0.4	0.0	0.1	0.1	0.2
Personal care services	In-home	1.3	0.3	1.0	0.6	1.5	1.0
	Out-of-home	0.3	0.2	0.2	0.1	0.1	0.0
Household services	In-home	2.0	0.9	0.6	0.4	2.1	0.9
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Government services & civic obligations	In-home	0.0	0.0	0.0	0.0	0.1	0.0
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Eating and drinking	In-home	84.6	58.1	74.2	55.0	82.2	65.5
	Out-of-home	1.6	2.9	1.7	1.1	1.5	1.0
Socializing, relaxing, leisure	In-home	435.7	472.6	443.6	472.4	444.3	511.9
	Out-of-home	5.0	8.9	8.6	6.4	6.5	4.1
Sports, exercise, recreation	In-home	8.5	6.0	6.4	3.2	6.4	2.7
	Out-of-home	7.6	6.3	5.5	4.2	5.5	3.5
Religious and spiritual activities	In-home	4.1	1.7	7.7	3.9	6.2	5.0
	Out-of-home	0.1	0.1	0.2	0.1	0.4	0.0
Volunteer activities	In-home	3.7	1.8	4.6	2.0	6.5	4.0
	Out-of-home	0.9	0.2	0.8	0.2	0.3	0.3
Telephone calls	In-home	5.4	3.9	12.0	7.9	11.1	7.3
	Out-of-home	0.1	0.1	0.3	0.0	0.2	0.0
Traveling	In-home	0.7	0.6	0.3	0.4	0.4	0.2
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Data codes (other)	In-home	14.8	9.7	15.2	10.9	16.5	11.3
	Out-of-home	0.4	1.3	0.5	0.9	0.3	1.0
Total	In-home	1403.6	1384.9	1412.7	1415.9	1414.9	1423.9
	Out-of-home	36.4	55.1	27.3	24.1	25.1	16.1

Table D-2 (Continued)

Activity type	Location	Household size 2		Non-metropolitan		Non-worker	
		Happy	Unhappy	Happy	Unhappy	Happy	Unhappy
Sample size		*2,641*	*7,544*	*1,075*	*4,722*	*3,491*	*17,982*
Sleeping	In-home	532.6	586.3	534.2	587.7	535.9	596.9
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Personal care activities	In-home	43.9	46.2	36.7	45.4	46.8	46.6
	Out-of-home	0.3	0.5	0.9	0.6	0.4	0.4
Household activities	In-home	230.6	172.1	242.8	175.8	220.3	160.6
	Out-of-home	4.4	2.7	5.5	1.4	5.0	1.9
Helping household members	In-home	14.0	6.5	36.1	17.8	27.2	22.5
	Out-of-home	1.0	0.3	0.2	0.5	1.4	0.4
Helping non-household members	In-home	8.3	8.2	6.8	6.3	7.1	5.7
	Out-of-home	1.0	0.6	1.4	0.5	1.0	0.4
Work & work-related activities	In-home	22.2	43.6	25.1	34.8	2.7	10.4
	Out-of-home	5.5	16.0	9.1	22.9	0.6	1.2
Education	In-home	0.8	7.3	1.5	5.0	0.8	12.2
	Out-of-home	0.0	0.1	0.0	0.1	0.1	0.3
Consumer purchases	In-home	1.0	0.8	0.6	0.5	1.0	0.6
	Out-of-home	0.1	0.4	0.1	0.3	0.1	0.1
Personal care services	In-home	1.3	0.4	1.5	0.3	1.3	0.6
	Out-of-home	0.0	0.1	0.5	0.2	0.2	0.1
Household services	In-home	1.7	0.8	1.8	0.7	1.6	0.7
	Out-of-home	0.1	0.0	0.0	0.0	0.1	0.0
Government services & civic obligations	In-home	0.0	0.0	0.0	0.1	0.0	0.0
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Eating and drinking	In-home	82.5	61.2	77.0	60.5	80.2	59.4
	Out-of-home	1.5	1.8	1.9	2.3	1.8	0.9
Socializing, relaxing, leisure	In-home	428.6	446.4	401.0	438.2	440.6	475.5
	Out-of-home	5.6	5.9	8.3	5.2	8.1	5.9
Sports, exercise, recreation	In-home	6.5	3.3	6.8	6.0	6.5	4.5
	Out-of-home	6.2	5.1	3.9	3.6	6.3	4.4
Religious and spiritual activities	In-home	5.1	2.4	3.9	2.2	6.2	3.7
	Out-of-home	0.2	0.1	0.2	0.1	0.3	0.0
Volunteer activities	In-home	7.4	2.7	4.0	2.2	6.4	2.6
	Out-of-home	0.2	0.2	1.3	0.1	0.8	0.2
Telephone calls	In-home	10.6	5.8	9.8	6.2	11.8	8.5
	Out-of-home	0.1	0.1	0.0	0.0	0.2	0.1
Traveling	In-home	0.3	0.3	1.0	0.3	0.4	0.3
	Out-of-home	0.0	0.0	0.0	0.0	0.0	0.0
Data codes (other)	In-home	16.4	10.9	15.6	10.9	16.3	11.4
	Out-of-home	0.3	1.2	0.6	1.3	0.4	1.0
Total	In-home	1413.8	1405.0	1406.2	1400.8	1413.3	1422.7
	Out-of-home	26.2	35.0	33.8	39.2	26.7	17.3

APPENDIX E

AVERAGE EMOTION SCORES ASSOCIATED WITH TRAVEL MODES BY TRIP PURPOSE AND LOCATION IN THE ATUS WELLBEING MODULE

The key finding in Chapter 5 reveals a positive relationship between the proportion of driving in non-commute trips and increased satisfaction with daily travel routines. However, it is important to note that this finding is derived from a sample collected in four southern metropolitan regions of the United States that are heavily automobile-oriented and have limited transit service coverage. Consequently, there is uncertainty about the generalizability of this finding to other contexts, particularly transit-rich metropolitan areas within the country. To address this concern, this Appendix presents an additional analysis utilizing the American Time Use Survey (ATUS) Wellbeing Module.

Within the ATUS Wellbeing Module, participants were asked to express their emotional experiences related to six specific emotions (happiness, meaningfulness, stress, painfulness, tiredness, and sadness) for three randomly chosen activities recorded in their time-use diary during the years 2010, 2012, and 2013. These emotions were rated on a scale ranging from 0 to 6, with higher numbers indicating a greater intensity of emotion. Using this module, average emotional scores were calculated for all travel activities based on the mode of transportation used. This computation was performed for overall trips as well as for commute and non-commute trips across the country. The resulting findings of this analysis are presented in Table E-1.

Next, a similar analysis is conducted to examine the potential influence of geographical factors. The aim is to determine whether individuals who use public transit in transit-rich areas experience higher levels of positive emotions (or lower levels of negative emotions) compared to users of other modes of transportation, in contrast to the situation in transit-poor areas. Transit-rich metropolitan areas in the United States are characterized by well-established and extensive public transportation systems. These areas typically have extensive networks of subways, light rail systems, buses, and commuter trains, offering convenient and accessible transportation options for both residents and visitors. However, it is important to acknowledge that the availability and quality of transit can vary within each metropolitan area. While the classification of transit-rich areas may differ depending on specific criteria and data sources, the analysis in this study considers the metro areas below as transit-rich, while the remaining metro areas across the U.S. are regarded as transit-poor. The outcome of this analysis is presented in Table E-2.

1. New York-Newark-Jersey City, NY-NJ-PA
2. San Francisco-Oakland-Hayward, CA
3. Washington-Arlington-Alexandria, DC-VA-MD-WV
4. Boston-Cambridge-Newton, MA-NH
5. Chicago-Naperville-Elgin, IL-IN-WI
6. Philadelphia-Camden-Wilmington, PA-NJ-DE-MD
7. Seattle-Tacoma-Bellevue, WA
8. Los Angeles-Long Beach-Anaheim, CA
9. Portland-Vancouver-Hillsboro, OR-WA
10. Denver-Aurora-Lakewood, CO

Table E-1

Average Emotion Scores by Travel Mode and Trip Purpose in the ATUS Wellbeing Module

Emotion	Trip Purpose	Travel Mode						
		SOV	HOV Driver	HOV Passenger	Walking	Bicycle	Bus and Rail	Other
Happy	Commute	4.05	4.32	4.18	4.03	4.76	3.87	4.12
	Non-commute	4.25	4.61	4.63	4.37	4.36	4.12	4.38
	All	4.18	4.60	4.59	4.32	4.45	4.01	4.33
Meaningful	Commute	3.61	3.88	3.89	3.66	3.62	3.42	3.75
	Non-commute	3.80	4.33	4.17	3.97	4.10	3.78	3.94
	All	3.74	4.31	4.15	3.92	4.00	3.63	3.91
Pain	Commute	0.73	0.77	0.89	0.74	1.05	0.73	1.03
	Non-commute	0.80	0.63	0.90	0.97	1.00	0.71	0.86
	All	0.77	0.63	0.90	0.93	1.01	0.72	0.89
Stressful	Commute	1.66	1.65	1.60	1.59	1.52	1.66	1.80
	Non-commute	1.19	1.21	1.09	1.21	0.87	1.32	1.34
	All	1.35	1.22	1.13	1.28	1.01	1.47	1.43
Tired	Commute	2.41	2.30	2.79	2.26	1.86	2.85	2.71
	Non-commute	1.90	1.94	2.22	2.15	1.99	2.27	2.15
	All	2.07	1.96	2.26	2.17	1.96	2.52	2.25
Sad	Commute	0.63	0.44	0.76	0.70	0.67	0.75	0.84
	Non-commute	0.59	0.43	0.57	0.70	0.74	0.71	0.66
	All	0.60	0.43	0.59	0.70	0.72	0.73	0.69
Sample size	Commute	3,670	255	324	196	21	226	157
	Non-commute	7,075	6,086	3,660	968	77	304	655
	All	10,745	6,341	3,984	1,164	98	530	812

Note: The table is color-coded, with green indicating a higher level of positive emotion and red representing a higher level of negative emotion.

Table E-2

Average Emotion Scores by Travel Mode and Location in the ATUS Wellbeing Module

Emotion	Location	Travel Mode						
		SOV	HOV Driver	HOV Passenger	Walking	Bicycle	Bus and Rail	Other
Happy	Transit-rich	4.12	4.53	4.52	4.21	4.45	3.90	4.23
	Transit-poor	4.19	4.61	4.60	4.39	4.45	4.14	4.38
Meaningful	Transit-rich	3.67	4.20	4.19	3.82	3.50	3.66	3.66
	Transit-poor	3.75	4.33	4.14	3.98	4.13	3.60	4.01
Pain	Transit-rich	0.72	0.51	0.82	0.87	1.00	0.73	0.80
	Transit-poor	0.78	0.65	0.91	0.97	1.01	0.71	0.93
Stressful	Transit-rich	1.44	1.29	1.15	1.37	0.75	1.59	1.52
	Transit-poor	1.34	1.21	1.12	1.21	1.08	1.33	1.39
Tired	Transit-rich	2.11	1.95	2.27	2.23	1.55	2.70	2.34
	Transit-poor	2.07	1.96	2.26	2.13	2.06	2.31	2.22
Sad	Transit-rich	0.63	0.47	0.53	0.76	0.75	0.83	0.70
	Transit-poor	0.60	0.42	0.60	0.66	0.72	0.61	0.69
Sample size	Transit-rich	1,626	884	590	468	20	279	235
	Transit-poor	9,119	5,457	3,394	696	78	251	577

Note: The table is color-coded, with green indicating a higher level of positive emotion and red representing a higher level of negative emotion.

APPENDIX F

AVERAGE EMOTION SCORES BY ACTIVITY TYPE IN THE ATUS WELLBEING MODULE

In the ATUS Wellbeing Module, the ATUS respondents (in 2010, 2012, and 2013) indicated their feelings on six emotions for three randomly selected activities in their time-use diary. The six emotions included happiness, meaningfulness, stress, painfulness, tiredness, and sadness. On each of these emotions, the respondents rated the intensity of the emotion on a scale of 0 through 6, with a higher number indicating a greater level of emotional intensity. The table below shows average emotion scores for each activity category based on where the activity was undertaken (i.e., in-home or out-of-home). It is observed from the table that respondents reported experiencing more positive feelings for virtually all activities when performed outside the home. The table is color coded, with green indicating a more positive emotional score and red indicating a worse emotional score for out-of-home activities compared to their corresponding in-home counterparts. The sample sizes for each activity type are also presented in the last two columns of the table. No statistical significance (in the differences) is implied through the color-coding scheme.

Table F-1

Average Emotion Scores by Activity Type in the ATUS Wellbeing Module

Activity Type	Happy		Meaningful		Painful		Stressful		Tired		Sad		N	
	In	*Out*	*In*	*Out*	*In*	*Out*	*In*	*Out*	*In*	*Out*	*In*	*Out*	*In*	*Out*
Personal care activities	3.06	3.39	3.88	4.26	3.19	2.52	2.22	1.65	3.50	3.57	1.67	1.26	586	23
Household activities	4.13	4.45	4.13	4.42	1.12	0.92	1.24	1.14	2.22	2.11	0.63	0.56	16,586	1,304
Caring for household members	4.78	4.58	5.21	4.92	0.66	0.59	1.38	1.40	2.77	2.13	0.35	0.50	4060	1,062
Caring for non-household members	5.15	4.62	5.37	4.75	0.88	0.86	1.28	1.26	2.14	2.07	0.41	0.68	280	770
Work & work-related activities	3.75	3.99	4.42	4.42	0.94	0.89	2.16	2.22	2.30	2.40	0.70	0.70	1,310	5,376
Education	3.22	3.88	4.19	4.44	0.65	0.49	2.70	2.14	2.82	2.83	0.74	0.54	446	411
Consumer purchases	4.01	4.18	3.63	3.88	0.56	0.86	1.48	1.34	1.83	1.96	0.71	0.56	94	3,820
Professional & personal care services	3.74	3.72	4.42	4.31	2.32	1.44	2.65	1.88	2.84	2.18	1.13	0.98	31	521
Household services	4.26	3.52	4.24	3.81	0.91	1.01	1.41	1.56	1.44	1.80	0.62	0.47	34	75
Government services & civic obligations	2.50	3.97	3.83	4.97	0.67	0.50	0.83	2.25	1.00	1.34	0.50	0.84	6	32
Eating/drinking	4.45	4.69	4.26	4.49	1.01	0.64	1.06	1.04	2.10	1.87	0.61	0.41	11,780	4,304
Socializing/relaxing/leisure	4.26	4.73	3.74	4.57	1.09	0.75	1.04	0.98	2.28	1.94	0.70	0.53	15,599	4,315
Sports, exercise, recreation	4.59	4.88	5.02	4.88	1.37	1.09	0.91	0.83	2.06	2.03	0.41	0.35	409	1,405
Religious/spiritual activities	4.95	5.01	5.59	5.55	1.03	0.72	0.82	0.71	1.80	1.33	0.66	0.61	348	862
Volunteer activities	4.34	4.98	4.70	5.32	0.98	0.79	1.57	1.00	1.88	1.79	0.39	0.26	215	521
Telephone calls	4.39	4.14	4.76	4.56	1.02	1.22	1.33	2.18	1.96	2.39	0.86	0.86	1,004	108
Traveling	–	4.37	–	3.97	–	0.77	–	1.28	–	2.10	–	0.56	–	23,674
Other	4.16	4.46	4.28	4.53	1.05	0.82	1.49	1.40	2.38	2.11	0.72	0.53	646	491

Note: In = In-home location; Out = Out-of-home location; N = Sample size (number of activities)

APPENDIX G

PUBLICATION STATEMENT

Chapters 2 to 5 have been reproduced and included in this dissertation with the consent of the co-authors involved.