Multidimensional Models to Understand Travel Behavior Implications for

Transport and Household Energy Use

by

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ABSTRACT

To reduce the environmental burden of transport, previous studies have resorted on solutions that accentuate towards techno-economical pathways. However, there is growing evidence that transport behaviors, lifestyle choices, and the role of individuals' attitudes/perceptions are considered influential factors in shaping households' engagement with sustainable technologies in the face of environmental crises. The objective of this dissertation is to develop multidimensional econometric model systems to explore complex relationships that can help us understand travel behaviors' implications for transport and household energy use. To this end, the second chapter of this dissertation utilizes the latent segmentation approach to quantify and unravel the relationship between attitudes and behaviors while recognizing the presence of unobserved heterogeneity in the population. It was found that two-thirds of the population fall in the causal structure where behavioral experiences are shaping attitudes, while for one-third attitudes are shaping behaviors. The findings have implications on the energy-behavior modeling paradigm and forecasting household energy use. Building on chapter two, the third chapter develops an integrated modeling framework to explore the factors that influence the adoption of on-demand mobility services and electric vehicle ownership while placing special emphasis on attitudes/perceptions. Results indicated that attitudes and values significantly affect the use of on-demand transportation services and electric vehicle ownership, suggesting that information campaigns and free trials/demonstrations would help advance towards the sustainable transportation future and decarbonizing the transport sector. The integrated modeling framework is enhanced, in chapter four, to explore the interrelationship between transport and residential energy

consumption. The findings indicated the existence of small but significant net complimentary relationships between transport and residential energy consumption. Additionally, the modeling framework enabled the comparison of energy consumption patterns across market segments. The resulting integrated transport and residential energy consumption model system is utilized, in chapter fifth, to shed light on the overall household energy footprint implications of shifting vehicle/fuel type choices. Results indicated that electric vehicles are driven as much as gasoline vehicles are. Interestingly, while an increase in residential energy consumption was observed with the wide-scale adoption of electric vehicles, the total household energy use decreased, indicating benefits associated with transportation electrification.

DEDICATION

This dissertation is wholeheartedly dedicated to the memory of my beloved mother, Late Mrs. Adarsh Sharda. Taking this opportunity, mother, it was your tremendous hard work and vision that led me to stand at this juncture; without your enormous sacrifices and unconditional love, I would have never been able to become the individual that I am today. Thank you for providing me strength and balance in my life. I am missing you always!

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1. INTRODUCTION

The modal composition, per-capita activity level, and pace of activity growth has resulted in steep rise of household energy use. Transportation accounts for about one-third of the total energy use in the United States which has major implications on energy security and sustainability (U.S. EIA, 2020). With the advent of rapid advancement in technology of alternative fuels (e.g., electric vehicles), automation, and information technologies, recent studies have projected a radical change in transport energy use (Muratori, 2021; Shaheen et al, 2018; McCollum et al, 2014).

To reduce the environmental burden of transport, previous studies have focused on solutions that accentuate towards techno-economical pathways. In other words, these studies considered vehicle technological efficiency gains and fuel switching as the central mitigation strategies to decarbonize transport sector (Kobashi and Yarime, 2019; Anable et al, 2012). However, there is growing evidence that transport behaviors, lifestyle choices, and role of individuals attitudes and perceptions are considered influential factors in shaping society's engagement with sustainable technological opportunities in the face of environmental crisis (Brand et al, 2019; Sekar et al, 2018; Stern et al, 2016; Anable et al, 2012; Allcott and Mullainathan, 2010). For instance, Brand et al (2019) found that lifestyle changes alone (without an EV transition) have a similar effect on transport carbon emission and air quality index than a transition to EVs with no lifestyle change. Sekar et al (2018) studied the impact of changes in activity time use on energy consumption. The authors find that lifestyle changes caused by technology contribute to shifts in energy use across sectors.

Clearly, environmental sustainability of communities, neighborhoods, and cities are critically tied to the energy consumption associated with transport behaviors/attitudes. In the energy-behavior modeling paradigm, it is often assumed that the direction of influence in a causal structure is in a logical single direction (e.g., Gokasar et al, 2017; Yan et al, 2015). In other words, transport behaviors/attitude (e.g., mode choice, pro-environmental attitude) affect energy use or well-being or health outcomes, for example. But it could be argued that the reverse causal direction may be equally plausible in some instances, or the causality may be bidirectional in nature where the two phenomena of interest affect each other. For example, consider the relationship between residential location choice and transport energy use. It can indeed be argued that households and individuals locate themselves in neighborhoods, and then based on neighborhoods attributes (e.g., proximity to bus/transit stop) determine their energy consumption behaviors (Biying et al, 2012; Lindsey et al, 2011). However, the reverse may be true for some people. An individual who is pro-environment, may self-select to settle down in areas where there is good transit service or availability of sustainable modes (e.g., e-scooters, bike sharing) to pursue their energy saving lifestyle – suggesting that a different causal structure is at play for this individual.

The existence of bidirectional causal relationship is not limited to travel behavior domain, similar phenomena may also exist in the context of building energy use. For instance, consider the relationship between housing unit type and residential energy use. It is often noted that housing unit type (e.g., apartments, detached housing) influence building energy use (US Energy Information Administration, 2013). For some individual, however, the relationship might be reverse. In other words, occupants looking to pursue energy saving lifestyle may self-select to reside in housing unit type which provides the opportunity to conserve energy.

Perhaps there is a cyclical bidirectional relationship between behaviors and energy use. In other words, the multiple behavioral dimensions of interest may be inter-related with each other (Kitamura et al, 1996; Pendyala and Bhat, 2004) in complex ways. To put this in the context, let us say, households that are not auto-oriented may choose to live closer to transit or in a pedestrian-friendly neighborhood. The presence of good transit service may, in turn, structurally influence the mode choice behavior of households.

To account for the multitude of relationships among behavioral choices, the profession has heavily gravitated towards the development, estimation, specification, and implementation of simultaneous equation model systems. For instance, Paleti et al (2011) considered six activity-travel choice dimensions (long-term choices [e.g., residential location choice, work location choice], medium-term choices [e.g., automobile ownership], and short-term choices [e.g., number of stops on commute]) in a simultaneous modeling framework and found a direct relationship among the choice dimensions and across unobserved factors (through error correlations). Several other studies in the simultaneous equation modeling paradigm included those of Konduri et al (2011), Eluri et al (2011), Pinjari et al (2011), Lavieri et al (2017), Astroza et al (2018), and Dias et al (2020). However, in the above studies, it was assumed that the entire population follows the same causal structure (in a simultaneous equation model system) which might not be true in reality. Virtually, all the activity-based travel demand forecasting model systems in practice assumes the same causal structure relating various activity-travel variables (even if coefficients within models vary across market segments). But heterogeneity in a population may not simply be limited to differences in coefficients (which represents different levels of sensitivity or elasticities). Heterogeneity may manifest itself in the form of different underlying causal structures at play within the same population across various population segments. In a heterogenous population, the presence of different causal structures is entirely possible and neglecting or ignoring the presence of different causal structures might lead to erroneous energy use forecasts and poor policy decisions. In order to uncover the presence of multiple causal structures in the population, the ***second chapter*** of this dissertation utilizes a latent segment-based approach to help reveal the presence of multiple (unobserved) market segments in the population following different causal structures. Specifically, this chapter deals with three endogenous variables such as residential location choice, frequency of transit usage, and attitude towards transit as an outcome of interest. The findings of this research have major implications on sustainable transport development and policy implications, especially in the scenarios of emerging transport technologies. For instance, if attitudes are shaped by behaviors, information campaigns (on adoption and utilization of sustainable transport technologies) may not be all that effective and it would be important to provide individuals with opportunities to experience sustainable transport modes to bring a change in energy use. While the reverse causality is also possible indicating that attitudes might influence behavior. However, it should be noted that the ***second chapter*** does not attempt to quantify the household energy use but rather highlight the existence of structural heterogeneity in consumer decision-making processes which might help in accurately forecasting energy use and design policy interventions. In other words, the findings of this research will help energy-behavior analysts who are increasingly trying to assess the relationship between human attitudes and perceptions on the one hand and behavioral choices on the other. From a travel demand forecasting perspective, there is interest in exploring the possibility of using attitudinal variables and constructs to better explain and more accurately predict travel demand (and in turn household energy use) under a variety of scenarios, particularly in the context of the emerging transport technologies. Lastly, from a sustainable transportation policy development perspective, there is interest in influencing attitudes of people (say, through information campaigns) to bring about more sustainable activity-travel behaviors. Overall, the study makes an important contribution in unraveling and quantifying the relationship between traveler attitudes and behaviors. Results from this study indicates that there is considerable heterogeneity in the population with the contemporaneous causal structures in which behaviors shape attitudes more prevalent than those in which attitudes affect choice behaviors. Thus, clearly indicating that special emphasis should be placed on attitudes/perceptions while explaining a behavioral phenomenon of interest.

Building on the causal segmentation research, which provides deeper insights on the relationship between attitude and behaviors, the ***third chapter*** explores the factors that influence the adoption of on-demand mobility services and electric vehicle ownership while placing *special emphasis* on *attitudes, perceptions, and preferences*. The rapid advancement in sustainable transport technologies has provided technical pathways to decarbonize transport sector but the adoption and utilizations of these technologies remains a challenge. To advance the adoption and utilization mechanism of these technologies, it is important to understand the role played by attitudes, perceptions, and preferences in consumer decision-making processes. Overall, the role of socio-technical factors in concomitant with understanding consumer decision-making processes may yield effective interventions strategies to decarbonize the transport sector. Because the prediction of on-demand transportation usage and adoption of electric vehicles is the phenomenon of interest in ***chapter three***, a single structure is used (no heterogeneity in causal structures) in view of the desire to identify the factors that influence the utilization and adoption of these transportation innovations. To this end, the next chapter of this dissertation explores the following question:

Do Attitudes, Perceptions, and Preferences Play a Role in Adoption and Utilization of Sustainable Transport Technology in India?

India has experienced a surge in middle class population due to rapid and consistent economic development over the past few decades that has fueled the growth in vehicle ownership and use. Transportation accounts for 11 percent of all India's greenhouse gas (GHG) emissions, one-third of particulate matter (PM) pollution, and an even higher proportion of nitrogen oxides - all of which are harmful to human health (Kumar, 2021; Guttikunda, 2015). This has motivated the search for sustainable transport solutions to ensure environment and social sustainability. One solution constitutes the ride hailing services, which are expected to reduce car ownership and provide affordable means of transportation. Another key solution is the rise of electric vehicles (EVs), which are expected to reduce greenhouse gas emission and address the growing demand for sustainable urban mobility.

Several research studies have explored the factors that influence car ownership and use in India (Zhou et al, 2020; Srinivasan et al, 2017; Verma, 2015; Dash et al, 2013). Srinivasan et al (2017) found that if the car holding among peers, friends or collegues is significant, the tendency to own a car increases. Also, car ownership increases with household size and economic standard of households as noted by Dash et al (2013). Further, Verma et al (2015) indicated that lower interest rate on car loan is fueling the adoption of gasoline cars among young adults in India.

According to recent articles by the International Council on Clean Transportation (ICCT), it is imperative that the nation embraced emerging vehicular technologies to reverse the growth in India's road transport emissions. One such mobility option is transportation electrification which can reduce the negative externalities caused due to growth in road transportation. Sen et al (2021) studied the "Ambitious EV (without tighten power plant emission and decarbonize strategies)" scenarios between 2020 and 2040 and found that vehicle electrification could alone lead to a significant improvement in air quality and health benefits in India. Besides identifying individuals who are more likely to adopt EVs (Dua et al, 2021; Shalender and Sharma, 2020; Nazari et al, 2019; Hardman et al, 2016; Langbroek, 2016), studies have also found that vehicle price, vehicle type, vehicle performance, federal and state tax incentives, HOV lane access, proximity to charging unit, and operational cost associated with EVs impacts EV adoption and utilization patterns

(Chakraborty et al, 2019; Jenn et al, 2020; Hardman et al, 2019; Gass et al, 2014; Tal and Nicholas, 2013).

Another mobility option that is expected to soften the impact of private automobile use is ridehailing or ridesharing services (Singh, 2019). In India, two of the most popular ridehailing services are Ola and Uber. Ridehailing services are expected to reduce the growing car ownership in India, as they offer door-to-door mobility services via a smartphone app that can be used to summon the ride in real-time. However, Devaraj et al (2017) found that ridehailing adoption decreases with increase in vehicle ownership per worker. The rich body of literature has indicated that ridehailing services are generally used by individuals who are younger, more highly educated, employed and residing in urban areas (Malik, 2021; Wadud, 2020; Lavieri and Bhat, 2019; Alemi, 2018).

Despite extensive research on ridehailing usage and electric vehicle adoption, there is very little research that explicitly explores the interaction between these transportation innovations - particularly in developing countries such as India. Thus, this chapter fills an important gap in the literature and sheds new light on the adoption of promising new transportation technologies in the Indian context, while explicitly accounting for attitudinal variables within a *holistic integrated modeling framework*. The findings indicated that attitudes and values significantly affect the use of on-demand transportation services and EV ownership, suggesting that information campaigns and free trials/demonstrations would help advance the adoption of sustainable transportation modes. Further, the integrated modeling framework provided a good fit to the dataset indicating the need to advance towards holistic integrated approaches as big data continues to emerge. In other words, a holistic integrated modeling framework provides the capability to fully assess and understand the interrelationships among multiple behavioral phenomena of interest which is otherwise not accounted. The integrated modeling paradigm will assist in holistically assessing the implications of alternative policy interventions, built environment conditions, and technology advances on energy consumption footprints.

The technological, social, and environmental shift warrants the adoption of a ***holistic integrated modeling frameworks*** to solve the energy challenges and explore pathways to a low carbon future. Due to phenomenal growth in energy demand and corresponding human and environmental impacts, it is critical for communities and cities to explore pathways to simultaneously manage household's transportation and residential energy consumption patterns to advance economic vitality, wellbeing, and environmental sustainability of the region. Holistic integrated modeling frameworks present an opportunity to develop, analyze, and model these connections which may be desired for analyzing alternative energy future and policy scenarios.

Human activities/behaviors and energy use are intrinsically connected (Schipper et al, 1989; Li and Zhao, 2012). Despite a clear connection among energy constituents, prior research efforts aimed at characterizing and estimating energy footprints have been largely aggregated in their approach. In other words, they do not sufficiently account for attributes, attitudes, and behaviors of individuals, households, and organizations at the agent level, which is critical to forecast the energy consumption patterns in different scenarios (Stern et al, 2016). Further, most of the energy use computations are unidimensional in nature, focusing on a single energy component (Muratori et al, 2020), thus limiting the ability of modeling frameworks to quantify the total household energy footprint in response to changes in population characteristics, built environment conditions, technology, and public policies. Because, the multiple behavioral dimensions of interest are interconnected to each other, integrated modeling framework will provide the capability to assess following scenarios (but not only limited to this):

An individual working from home (even for few days of the week) is likely to travel less, and spend more time at home, thus simultaneously affecting energy use in transport and residential sectors. How do we account for such inter-dependencies in a holistic energy analysis framework?

To develop these connections among different components of interest, a data fusion across multiple datasets is required as different dataset contains different pieces of information. For instance, the *National Household Travel Survey (NHTS)* contains detailed information about household and person level socio-demographic characteristics, activity-travel characteristics, vehicles owned or leased by the household, and other trip characteristics. The *Residential Energy Consumption Survey (RECS)* data set contains detailed information about socio-demographic characteristics and residential energy consumption details. The *American Time Use Survey (ATUS)*, ATUS Well-being module, and ATUS Eating, and Health module contains detailed information about people's use of time, well-being measures, eating habits, health outcomes, and socio-demographic characteristics. Thus, utilizing the information present in each of these datasets and fusing it across the datasets will help us to develop more comprehensive computational model systems that reflect relationships between the components of interest. The developed comprehensive model system will then make it possible to view the patterns in a holistic manner and assess the impact of transport behaviors and transport policies/decisions on other societal outcomes.

Therefore, the ***fourth chapter*** develops an integrated transport and residential energy consumption model system that explores the interrelationship between the transport and residential energy consumption under the hypothesis that, *if people travel more (and spend more time outside home), they may consume more transport energy, but less in-home residential energy*. To explore this relationship, the information from the NHTS is fused with the RECS to develop a comprehensive computational modeling framework within an agent-based microsimulation environment that can be used to characterize and quantify the spatiotemporal dynamics of the components of household energy footprint. The characterization and quantification of spatio-temporal dynamics will enable us to track how transport and residential energy changes over time as different users carry out their daily activities in space and time. The findings from the previous chapter indicated the importance of attitudes and values in explaining a behavioral phenomenon of interest. However, due to non-availability of attributes related to attitudes and value, chapter four does not account for attitudes, perceptions, and values. Future, research endeavors should explore pathways to impute attitudes and value for households in NHTS and RECS dataset which will help in developing a robust model system. The findings from this study indicate the existence of small but significant net complementary relationships between transport and residential energy consumption. Additionally, the modeling framework enabled the identification and comparison of energy consumption patterns across market segments.

Further, the resulting integrated transport and residential energy consumption model system can be utilized to assess the overall household energy footprint implications of shifting vehicle/fuel type choices (e.g., electric vehicles).

One of the mobility fuel type choices that is expected to dominate the household vehicle fleet composition is the adoption and utilization of electric vehicles. Many countries have formulated policies to encourage electric vehicle (EV) adoption so that EVs will account for an increased share of future vehicle fleets. Various incentives, rebates, improvements in battery technology and cost, advancements in charging infrastructure units, and new compelling electric car models in the market have collectively stimulated the adoption of EVs, but the market share of EVs remains very small in most contexts. The current estimates indicate that about 2 million battery electric vehicles have been sold in the U.S. since 2010 (Argonne, 2021) and the forecasts suggests that EVs will account for about 60 percent of new car sales in US by 2040 (Electric Vehicle Outlook, 2021). Transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which different vehicles in the households are driven. Although there have been a number of surveys aimed at understanding factors that influence adoption of EVs, there is little work focusing on ownership and utilization of EVs among households that actually own one or more EVs. Most household travel surveys have few, if any, records of households that own EVs, thus rendering it difficult to analyze the usage of EVs relative to gasoline vehicles. Thus, the ***fifth chapter*** of this dissertation attempts to fill this critical gap by presenting a comprehensive comparison of the utilization patterns of electric vehicles relative to gasoline vehicles and its implications on household energy footprint.

If electric vehicles were to be utilized more than gasoline vehicles, this may negate some of the benefits associated with transition to an EV future. It is expected that EVs will yield lower energy consumption per mile which will, in turn, decrease carbon emissions from the transport sector. However, wide scale adoption and utilization of electric vehicles could significantly increase total electricity demand (Moon et al, 2018) as about 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021). To account for these inter-relationships and tradeoffs (as part of ***chapter five***), an integrated transport and residential energy consumption model system, developed in *chapter four*, is used to shed light on the overall household energy footprint implications of shifting vehicle/fuel type choices.

Overall, the objective of this dissertation is to significantly contribute to the existing literature by developing multidimensional statistical and econometric model systems to explore complex relationships that can help us understand travel behaviors implication for transport household energy use. These efforts involve the use of novel data sets, and in one endeavor, involve the fusion of information across disparate data sets. More specifically, the ***second chapter*** utilizes the dataset from 2014 Who's on Board Mobility Attitudes Survey (Transit Center, 2014), an online survey administered to a sample residing in 46 diverse metropolitan areas in the United States. The ***third chapter*** utilizes a comprehensive survey effort undertaken in India by the Ola Mobility Institute as part of its Ease of Moving Index framework in 2018. The survey was conducted across 20 cities in India (with a collective population of 90 million). To explore the interrelationship between transport and residential energy consumption as part of ***fourth chapter***, the 2017 National Household

Travel Survey and 2015 Residential Energy Consumption Survey Dataset were utilized. The National Household Travel Survey (NHTS) data set is derived from a large-scale travel survey conducted about every 8-10 years by the US Department of Transportation. The Residential Energy Consumption Survey (RECS) data set is derived from a large-scale energy consumption survey that is conducted about every six years. The 2017 NHTS and 2015 RECS are further used in the ***fifth and final chapter,*** to explore the household energy footprint implications of shifting vehicle/fuel type choices. Thus, the dissertation effort contains four distinct chapters with the following objectives:

Chapter Two: Do Attitudes Affect Behavioral Choices or Vice-Versa: Quantifying and Uncovering Latent Segments Within a Population

The aim of this study is to quantify and unravel the relationship between attitudes and behaviors while recognizing the presence of unobserved heterogeneity in the population. This study presents a simultaneous equations model of attitudes and behaviors that explicitly recognizes the joint nature of the relationship between them.

Chapter Three: Accounting for the Influence of Attitudes and Perceptions in Modeling the Adoption of Emerging Transportation Services and Technologies in India

This paper attempts to shed light on the factors that affect adoption of on-demand transportation services and electric vehicles (EVs) in India. Specifically, not only does this paper consider the socio-economic and demographic variables that affect these behavioral choices, but the holistic integrated modeling framework developed in this study places a special emphasis on representing the important role played by attitudes, values, and perceptions in determining adoption of on-demand transportation services and EVs.

Chapter 4: Development of an Integrated Transport and Residential Energy Consumption Model System

This study aims to develop a comprehensive integrated model system and energy analysis tool that can be used to quantify the total household energy footprint, including separate transport and residential energy consumption components. The tool involves computing only operational energy consumption and does not consider embodied energy footprint.

Chapter 5: Modeling Impacts of Electric Vehicles (EV) Adoption and Utilization on Household Energy Consumption

The goal of this research effort is to explore the differences in utilization pattern of electric vehicles relative to gasoline vehicles and its implication on household energy footprint. This research has implications on travel patterns, charging infrastructure location, energy consumption, and social sustainability- as EVs become prevalent in the population.

The remainder of the dissertation is organized as follows. The next sections provide the detailed description of the chapters. Within each chapter, introduction, background, dataset description, modeling framework, results and conclusions is provided. The last section provides the overall conclusion of the dissertation.

2. DO ATTITUDES AFFECT BEHAVIORAL CHOICE OR VICE-VERSA: QUANTIFYING AND UNCOVERING LATENT SEGMENTS WITHIN A HETEROGENOUS POPULATION

2.1. Introduction

This chapter aims to understand the relationship between attitudes, perceptions, and values on the one hand and behavioral choices on the other. There is a vast body of literature in a number of disciplines that has clearly demonstrated a strong inter-dependent relationship between attitudes and behaviors (De Vos, 2019; Ahn and Back, 2018; Fishbein and Ajzen, 2010; Dobson et al, 1978; Norman, 1975; Wicker, 1969). In the transportation context, attitudes about various transportation options as well as personality traits that describe the innate proclivities and preferences of the individual are likely to be strongly associated with residential and work place location choices (Kim et al, 2020; Ettema and Nieuwenhuis, 2017; Bhat, 2015a; Cao et al, 2010), mode choice (De Vos and Alemi, 2020; He and Thøgersen, 2017), parking choice (Ibrahim et al, 2020; Soto et al, 2018), vehicle ownership and type choice (Acker et al, 2014; Choo and Mokhtarian, 2004), activity engagement and time use patterns (Frei et al, 2015; Archer et al, 2013), and willingness to participate in the sharing economy and adopt new technologies (Manca et al, 2020; Alemi et al, 2018; Lavieri et al, 2018; Astroza et al, 2017; Egbue and Long, 2012)

In general, attitudinal constructs and factors have been used as explanatory variables in models of choices and behaviors (Ting et al, 2020; Chou et al, 2020; Jones et al, 2015). In the transportation literature, attitudes are often combined with the usual socio-economic and demographic characteristics, built environment factors, and variables that describe the options in the choice set to predict travel behaviors and energy use (Hwang and Lyu, 2020; Garcia et al, 2019; Ross et al, 2019; Soto et al, 2018; Kim et al, 2017; Ribeiro et al, 2017; Chen et al, 2017; Bhat et al, 2016; Heinen et al, 2013; Ory and Mokhtarian, 2005). In most, if not all instances, these studies have reported that attitudinal variables contribute significantly to explaining the choice behaviors of interest.

More recently, however, a growing body of literature reports that the directionality of the relationship between attitudes and behaviors is actually one in which behaviors shape attitudes (Ajzen, 2015). Sozer et al (2018) and Zajonc (2002) indicate, for example, that customer experiences derived from a service (behaviors) shape attitudinal dimensions associated with the service. In the marketing domain, management of customer experiences has long been considered an important tool in shaping customers perceptions of and attitudes towards the brand (Grewal et al, 2009). In the transportation context, Thøgersen (2006) utilized panel data to study the effect of behaviors on attitudes and found several significant effects. As the recognition of the importance of the relationships between attitudes and behaviors has grown, so has the desire to collect attitudinal data in travel surveys and model the underlying relationships. With the renewed interest in the topic, several studies have explored the causal relationship between attitudes and behaviors by relaxing the assumption of unidirectionality embedded in most socio-psychological theories (Moody and Zhao, 2020; Kroesen and Chorus, 2020; Kroesen and Chorus, 2018; Kroesen et al, 2017). According to these studies, attitudes and behaviors mutually influence each other over time; however, when there is dissonance (inconsistency) between attitudes and behaviors, people are more prone to adjust their attitudes to align with behaviors as opposed to adjusting their behaviors to align with attitudes. In other words, it is the attitudes that are changing in response to behaviors rather than behaviors changing in response to attitudes.

Although it is clear that attitudes and behaviors mutually influence each other over time, and attitudes themselves may change as more information becomes available (Sheela and Mannering, 2019), the question as to whether *attitudes affect behaviors* or *behaviors affect attitudes* at any cross-sectional point in time remains an intriguing one with very important implications for transportation demand forecasting, household energy use, and the design and implementation of policy interventions aimed at shaping behaviors. If it is true that behaviors affect attitudes (rather than the reverse), then information campaigns and strategies aimed at reshaping attitudes may not have the desired and intended behavioral effects. Policy interventions would need to directly target behaviors by providing individuals varied opportunities to obtain and accumulate alternative experiences first-hand by actually trying new and different mobility options; alternative behavioral experiences would then bring about changes in attitudes that would and could further reinforce desirable behaviors as individuals adjust their attitudes to reduce dissonance (Kroesen et al, 2017).

This chapter aims to develop a joint simultaneous equations model of attitudes and behaviors that explicitly recognizes the package nature of the relationship among them. Both attitudinal variables and behavioral choice variables are considered endogenous in nature, thus recognizing endogeneity associated with estimating relationships between these dimensions of interest. Treating both attitudes and behaviors as endogenous variables requires the specification and estimation of joint simultaneous equations model systems that accommodate error correlations, rendering it possible to account for the presence of correlated unobserved attributes that simultaneously affect both attitudes and behaviors.

However, unlike previous studies, this research effort explicitly recognizes that there may be population heterogeneity with respect to the nature of the relationship between attitudes and behaviors. While undoubtedly mutually reinforcing, attitudes may influence behaviors for some people and behavioral choices may affect attitudes for others *at a specific cross-section in time*. A multitude of directional relationships between attitudes and behaviors may exist in the population and it would be of interest to determine the extent or degree to which each of the directional relationships is prevalent in the population *at a specific cross-section in time*. By determining the degree to which each relationship exists in the population, and the characteristics of each market segment (in terms of socio-economic and demographic characteristics, for example), it would be possible to design policy interventions, behavioral experiences, and information campaigns that are appropriately targeted and implemented to achieve desired outcomes.

Because the segments in the population are not known a priori, they are considered latent and determined endogenously within a joint modeling framework. Thus, the model estimated in this paper takes the form of a joint equations model system with latent segmentation, similar to that presented in Astroza et al (2019). The model system includes a model component that endogenously assigns individuals to different causal segments, and this component is coupled with a simultaneous equations model component that relates attitudes and behaviors to one another in a manner consistent with the latent segment to which the behavioral unit has been probabilistically assigned. This methodology enables the identification of characteristics of the subgroups that predominantly depict alternative causal structures.

The model system in this study is estimated on a data set derived from the 2014 Who's On Board Mobility Attitudes Survey conducted in the United States. In addition to an extensive battery of attitudinal variables, the survey includes information about people's behavioral choices including use of various modes of transportation, residential location type choice, and car ownership. This particular chapter examines the nature of the relationships between *attitudes toward transit* and two behavioral choice variables, namely, *residential location choice* and *frequency of use of transit*. By considering multiple behavioral dimensions, this chapter sheds light on the extent to which attitudes affect behavior (or vice versa) in the context of different behavioral choices and identifies the relative presence of different latent segments (following different decision structures) in the population.

The remainder of this chapter is organized as follows. The next section offers a description of the data. The methodology is presented in the third section, model estimation results are presented in the fourth section, and the description of the latent segments is presented in the fifth section. Concluding thoughts are offered in the sixth and final section.

2.2. Dataset Description

The data set used in this chapter is derived from the 2014 Who's On Board Mobility Attitudes Survey (Transit Center, 2014), an online survey administered to a sample residing in 46 diverse metropolitan areas in the United States. The data set includes information for

11,842 respondents who responded to the survey. After filtering records for missing data, 9,600 observations were retained for analysis and model estimation. Table 1 presents a socio-economic and demographic profile of the sample.

Overall, the sample provides the richness of variation and diversity of information necessary to undertake a study of this nature. Among person-level characteristics, the sample has a slightly higher proportion of women. About one-fifth of the respondents in this sample are 65 years and above and more than one-half of the sample has an educational attainment of college graduate or higher. About 40 percent of the sample is employed full-time, while another 12.5 percent are employed part-time. The sample spends a fair amount of time online, with 34 percent indicating that they spend 4-8 hours online per day while five percent of the sample indicated an hour or few hours per week.

Among household attributes (the right column of Table 1), just about 20 percent of the sample has household income less than $35,000, while 23.7 percent of the sample has household income greater than or equal to $100,000. Just about 38 percent of the sample reports household sizes of three or more, and nearly 70 percent of the sample resides in detached housing units – which is consistent with the statistic that 61 percent of the sample resides in housing units owned by the household. With respect to transit richness, 61 percent of the sample reports residing in cities that may be characterized as transit progressive (Transit Center, 2014), i.e., cities where there is a substantial presence of transit modes. Only four percent of the sample resides in households with zero vehicles, and 25 percent of the sample reported residing in households with no workers (consistent with the age distribution noted earlier). About 40 percent of the sample indicated that the distance to the nearest transit station is less than 0.5 mile, while 38.6 percent reported that the nearest transit station is more than one mile from the residence. The sample is well distributed across the country, with the largest proportion (23.9 percent) drawn from the West Coast.

Among endogenous variables (left column bottom of Table 1), urban dwellers account for 27.8 percent of the sample. Another 32.4 percent of the sample resides in suburban and small-town locations that have mixed land use; the remaining 39.8 percent reside in suburban and small town/rural locations that would not be characterized as having mixed land use. Just about one-half of the sample reports that they never use transit at all even though it is available. Seventeen percent report using transit at least once per week.

The third endogenous variable of interest in this study is the *attitudes towards transit (transit proclivity)*. This endogenous variable constitutes a factor derived by conducting a factor analysis on 10 attitudinal statements in the survey data set. These attitudinal statements pertain to feelings about transit and are therefore used to derive a transit proclivity or propensity factor. Table 2 presents the attitudinal statements, the percent of the sample agreeing, being neutral, or disagreeing with each statement, and the factor loadings. After a number of trials, it was found that three of the statements had insignificant factor loadings, and hence the final factor was based on seven of the ten attitudinal statements. The loadings are intuitive and suggest that the factor represents a propensity or proclivity towards using transit as a mode of transportation.

Table 1. Socio-economic and Demographic Characteristics of the Sample (N=9600)

Individual Characteristics		**Household Characteristics**	
Exogenous Variables	Value (%)	***Exogenous Variables***	Value (%)
Gender		*Household income*	
Female	53.5	< $25,000	11.1
Male	46.5	$25,000 to $34,999	9.8
Age category		$35,000 to $49,999	14.2
16-17 years	0.2	$50,000 to $74,999	22.9
18-24 years	17.2	$75,000 to $99,999	18.3
25-34 years	22.8	≥ $100,000	23.7
35-54 years	19.2	*Household size*	
55-64 years	19.2	One	17.9
65 years and above	21.4	Two	44.2
Education attainment		Three and more	37.9
High school or less	17.0	*Housing unit type*	
Technical/training beyond high school	5.1	Detached Housing	69.4
Some college	26.2	Apartment housing	28.2
College graduate or higher	51.7	Others	2.4
Employment status		*Home ownership*	
Employed full-time	40.4	Rent	28.1
Employed Part-Time	12.5	Own	61.0
Not Employed	6.1	Living family rent-free or other	10.9
Other (student, retired, homemaker)	41.0	*Presence of kids*	
Time spent online		Presence of kids 0-4 years	8.0
More than 8 hours per day	18.0	Presence of kids 5-15 years	10.0
4 to 8 hours per day	34.0	Presence of kids 16-18 years	4.0
1 to 4 hours per day	42.0	*Transit Richness*	
A few hours per week or an hour per week	5.0	Deficient	38.6
Endogenous Variables		Progressive	61.4
Residential location choice (RLC)		*Vehicle ownership*	
Urban	27.8	Zero	4.0
Suburban and small town-mixed land use	32.4	One	30.7
Other suburban and small town + rural	39.8	Two	42.6
Frequency of transit use (FTU)		Three or more	22.8
Frequent: once per week or more	17.0	*Number of employed persons*	
Infrequent: less than once per week	32.6	Zero	25.0
Never (but has available)	50.4	One	35.3
Attitudes Toward Transit (ATT) – Factor Score		Two or more	39.7
Scale-less underlying continuous variable		*Distance from home to nearest transit station*	
		Less than 0.5 mile	40.0
		0.5-1 mile	21.4
		More than 1 mile	38.6
		Geographic Region	
		Northeast	16.3
		South	18.5
		West/Southwest	19.0
		West Coast	23.9
		Midwest	22.3

Table 2. Transit Attitudes and Factor Loadings (Ordinal Measurement Model)

Attitudinal Statements	Agree (%)	Neutral (%)	Disagree (%)	Factor Loading (Std Error)
I like the idea of doing something good for the environment when I ride transit	50.9	39.8	9.3	1.00 (base)
I am not sure I know how to do all the things to make the bus or train trip work	39.3	26.2	34.5	—
I worry about crime or other disturbing behavior on public forms of transportation	51.8	28.0	20.2	—
I feel safe when riding public transportation	39.4	41.2	19.4	0.972 (0.037)
Public transit does not go where I need to go	52.2	27.1	20.7	-0.298 (0.023)
Riding transit is less stressful than driving on congested highways	50.8	29.2	20.0	1.275 (0.049)
It would be easier for me to use transit more if I were not so concerned about traveling with people, I do not know	24.3	25.4	50.3	0.378 (0.025)
My family and friends typically use public transportation	17.2	20.3	62.5	1.483 (0.062)
I like to make productive use of my time when I travel	62.8	29.5	7.7	—
I sometimes take public transit to avoid traffic congestion	31.0	20.0	49.0	2.553 (0.135)

The results from the ordinal measurement model were used to compute factor scores for each individual in the sample. This continuous factor score was used in the model estimation effort to retain the variation in transit proclivity represented by the factor. This continuous factor score does not have a specific underlying scale, but simply represents the range of lower and higher positive attitudes towards transit. Thus, we do not show any specific descriptive statistics for this variable in Table 1.

The three endogenous variables considered in this study are as follows:

- Residential Location Choice (RLC): Three categories
    - Urban
    - Suburban + Small Town with Mixed Land Use
    - Suburban + Small Town/Rural without Mixed Land Use
- Frequency of Transit Use (FTU): Three categories

- Frequent (once or more per week)
- Infrequent (less than once per week)
- Never

- Attitude Towards Transit (ATT): Continuous factor score

This chapter explores the causal relationship between attitudes and behavioral choices by relaxing the unidirectional assumption that is typically embedded in many travel behavior models. The three endogenous variables may be related in six possible different causal structures. It is entirely possible that all six causal structures are prevalent in the population, i.e., there is at least some fraction of the population following each of the causal structures at a specific cross-section in time. However, the estimation of a joint simultaneous equations model system that involves three mixed (RLC [nominal in nature], FTU [ordinal in nature], and ATT [continuous in nature]) endogenous variables and six different latent segments is computationally challenging, and the interpretation of results obtained from such a large-scale model estimation effort may prove difficult. Further, the appropriate number of segments is determined by assessing the improvement in model fit (measured by Bayesian Information Criterion) with the addition of a segment (Bhat, 1997). In this study, preliminary trials showed that the model system with four latent segments offered the best fit. Therefore, four plausible causal structures (and hence, four possible latent segments) are considered and included within the scope of this paper. The four causal structures may be depicted as follows:

Structure 1	RLC (R)	**Structure 3**	ATT (A)
	RLC → FTU		ATT → RLC
	FTU + RLC →ATT		RLC + ATT → FTU
Structure 2	FTU (F)	**Structure 4**	ATT (A)
	FTU → RLC		ATT → FTU
	RLC + FTU →ATT		FTU + ATT → RLC

Note: RLC = Residential Location Choice

FTU = Frequency of Transit Use

ATT = Attitude towards transit (Transit propensity)

Individuals are making a bundle of choices jointly (involving attitudes, residential location choice, and frequency of transit use), and the causal relationships depict the nature and direction of influence among the endogenous variables and capture the reasoning or logical flow of thought that an individual may exercise. For example, an individual may reason *at any cross-section in time* that he or she likes the idea of riding transit (positive attitude) and therefore resides in a residential location that facilitates a high level of transit use. The logical flow of relationships among the dimensions represents a *contemporaneous causation*, the notion that "*behavior is caused at the moment of its occurrence by all the influences that are present in the individual at that moment*" (Lewin, 1936). Within the context of a contemporaneous causation, the first two structures are those where behaviors affect attitudes towards transit (ATT), while the latter two structures are those where attitudes towards transit (ATT) influence behaviors. The relationship between residential location choice (RLC) and frequency of transit use (FTU) may go either way. On the one hand, residential location may engender transit use; on the other hand, the frequency of transit use may motivate an individual to seek a residential location that supports the level of transit use undertaken and desired by an individual.

2.3. Modeling Methodology

In the case where both attitudinal and behavioral choice variables are represented as continuous variables, it is econometrically feasible to identify and estimate bidirectional causal models – thus enabling an explicit portrayal of the mutually reinforcing relationship that exists between attitudes and behaviors. However, when the behavioral choice variables of interest are not continuous (and are often discrete in the context of travel behavior), then a bidirectional causal model is not econometrically identified, and identification restrictions must be imposed for logical consistency purposes (Pendyala and Bhat, 2004). This necessitates the estimation of recursive joint equations model systems when considering multiple endogenous variables of different nature. In other words, when dealing with discrete choice variables (or, more generally, limited dependent variables), the joint equations model system can reflect the influence of attitudes on behaviors *or* the influence of behaviors on attitudes, *but not both* (after accommodating for unobserved covariance effects). It should be noted, however, that the recursive joint equations model system that depicts uni-directional relationships does not necessarily imply a sequential ordering in the decision mechanism. By estimating both attitudes and behaviors in a joint equations framework, while recognizing the presence of unobserved correlated attributes that affect multiple dimensions, the system of equations portrays *jointness* in the determination of attitudes and behaviors while recognizing that one dimension influences the other. A more detailed discussion about the important distinction between sequentiality and simultaneity in the choice processes at play may be found in Astroza et al (2019).

Another important note here is that inference about causality is inextricably tied to observations of individuals and their choices over time. In other words, longitudinal data is very desirable for any effort aimed at unraveling and identifying causal relationships and structures. Generally, cause-and-effect patterns play out over time, involve leads and lags, and are inherently dynamic in nature. Although the profession has seen the collection of longitudinal panel survey data on occasion, the prevailing norm continues to be the collection of (repeated) cross-sectional data from a sample of the population. In the absence of true longitudinal panel data, it is extremely challenging to unravel cause-and-effect relationships that transpire over time. Even when panel survey data is available and changes in behaviors are observed over time in conjunction with changes in exogenous attributes, there is no guarantee that the change in behavior was *caused* by the change in the exogenous attributes. Given these considerations, the analysis in this paper should be construed as depicting contemporaneous causation, i.e., *the causal relationships that exist at a single snapshot in time*.

2.3.1. The Joint Model of Behavioral Choices and Attitudinal Factors

The remainder of this section describes in detail the model formulation adopted in this paper. Consider an individual q (q=1, 2, 3,…, Q) facing a multi-dimensional choice system comprised by one continuous variable (attitudes towards transit), one ordinal variable (frequency of transit use), and one nominal variable (residential location). The discussion starts with the formulation for each type of variable, and then presents the structure and estimation procedure for the multi-dimensional system. For this section, assume that the individual belongs to a specific segment *h*.

Let y_{qh} be the continuous variable (corresponding to the *attitudes towards transit* score) for individual *q* given that he/she belongs to segment *h*. Let $y_{qh} = \boldsymbol{\gamma}_h' \boldsymbol{s}_{qh} + \eta_{qh}$ in the usual linear regression fashion, where $\boldsymbol{s}_{qh}$ is a column vector of exogenous attributes as well as possibly the observed values of other endogenous variables, $\boldsymbol{\gamma}_h$ is a column vector of corresponding coefficients, and η_{qh} is a normal standard scalar error term (the variance of η_{qh} is normalized to one for all segments *h*, because, though y_{qh} is a continuous variable, it represents a scale-less latent factor score in our empirical analysis that is constructed from other observed indicators). Note that some elements of $\boldsymbol{\gamma}_h$ can be zero for some of the exogenous variables, indicating that the corresponding exogenous variables do not impact choice-making in segment *h*. Further, because latent segmentation is used as a way to introduce, across the segments, heterogeneity in the recursive effects among the endogenous variables, $\boldsymbol{\gamma}_h$ will necessarily be zero on some of the endogenous variables within each segment (see Astroza et al, 2019 for a detailed explanation).

Let there be one ordinal variable for the individuals. In the empirical context of the current paper, the ordinal variable corresponds to the *frequency of transit use* and has three different levels: never, infrequent (less than once per week), and frequent (once per week or more). Let the ordinal index for the individual given that he/she belongs to segment *h* be j_{qh} $(j_l = 1, 2, 3)$ and let n_q be the actual observed value. Then, assume an ordered-response probit (ORP) formulation as: $y^*_{qh} = \boldsymbol{\varphi}'_h \boldsymbol{z}_{qh} + \xi_{qh}$, $j_{qh} = n_q$ if $\psi_{h,n_q-1} < y^*_{qh} < \psi_{h,n_q}$, $j_{qh} \in \{1, 2, 3\}$, where $\boldsymbol{z}_{qh}$ is a column vector of exogenous attributes as well as possibly the observed values of other endogenous variables, $\boldsymbol{\varphi}_h$ is a column vector of corresponding coefficients, and ξ_{qh} is a standard normal scalar error term. Similar to the case of the continuous variable, $\boldsymbol{\varphi}_h$ can be zero on some of the endogenous variables within each segment (structural heterogeneity). For identification conditions, set $\psi_{h,0} = -\infty$, $\psi_{h,3} = +\infty$, and $\psi_{h,1} = 0$. Only one threshold, $\psi_{h,2}$, is then estimated.

Let there be one nominal (unordered-response) variable for the individuals. In the empirical context of the current paper, the nominal variable is *residential location*, which has I=3 alternatives (shown in Table 1). Using the typical utility maximizing framework, it is possible to write the utility for alternative i for individual q given that he/she belongs to segment h as: $U_{qih} = \boldsymbol{\beta}'_h \boldsymbol{x}_{qih} + \varepsilon_{qih}$, where $\boldsymbol{x}_{qih}$ is a column vector of exogenous attributes as well as possibly the observed values of other endogenous variables, $\boldsymbol{\beta}_h$ is a column vector of corresponding coefficients, and ε_{qih} is a normal scalar error term. Let the variance-covariance matrix of the vertically stacked vector of errors $\boldsymbol{\varepsilon_{qh}} = [(\varepsilon_{q1h},\ \varepsilon_{q2h},\ .\varepsilon_{q3h})']$ be $\boldsymbol{\Lambda}_h$. Again, $\boldsymbol{\beta}_h$ can be zero on some of the endogenous variables within each segment. Define $\boldsymbol{U_{qh}} = (U_{qh1}, U_{qh2}, U_{qh3})'$. Several important identification issues need to be addressed for the nominal variable. First, one of the alternatives has to be used as the base when introducing alternative-specific constants and variables that do not vary across the alternatives. This is because only utility differences matter in terms of the nominal variable choice. For future reference, let $\boldsymbol{u}_{qh}$ be the vector of utility differences with respect to the chosen alternative for the nominal variable and let $\overleftrightarrow{\boldsymbol{\Lambda}}_{qh}$ be the corresponding covariance matrix. Also, because only utility differences matter, only the covariance matrix of the error differences is estimable. Taking the difference with respect to the first alternative, only the elements of the covariance matrix $\breve{\boldsymbol{\Lambda}}_h$ of $\breve{\boldsymbol{u}}_{qh} = (U_{qh2} - U_{qh1}, U_{qh3} - U_{qh1})$ is estimable.

The jointness across the different types of dependent variables may be specified by writing the covariance matrix of the $[4 \times 1]$ vector $\breve{\boldsymbol{y}}_{qh} = \left(\boldsymbol{u}_{qh}, y^*_{qh}, y_{qh}\right)$ as:

$$\mathrm{Var}(\breve{\boldsymbol{y}}_{qh}) = \breve{\boldsymbol{\Omega}}_{qh} = \begin{bmatrix} \overleftrightarrow{\boldsymbol{\Lambda}}_{qh} & \boldsymbol{\Sigma}_{uy^*h} & \boldsymbol{\Sigma}_{uyh} \\ \boldsymbol{\Sigma}'_{uy^*h} & 1 & \sigma_{y^*yh} \\ \boldsymbol{\Sigma}'_{uyh} & \sigma_{y^*yh} & 1 \end{bmatrix}, \qquad (1)$$

where $\boldsymbol{\Sigma}_{uy^*h}$ is a 2×1 vector capturing covariance effects between the $\boldsymbol{u}_{qh}$ vector and the scalar y^*_{qh}, $\boldsymbol{\Sigma}_{uyh}$ is a 2×1 vector capturing covariance effects between the $\boldsymbol{u}_{qh}$ vector and the scalar y_{qh}, and $\boldsymbol{\Sigma}_{y^*yh}$ is the covariance between y^*_{qh} and y_{qh}. The covariance matrix in Equation (1) needs to be mapped appropriately in terms of a corresponding covariance matrix (say $\boldsymbol{\Omega}_h$) for the vector $\left(\boldsymbol{U}_{qh}, y^*_{qh}, y_{qh}\right)$, with appropriate identification conditions imposed on $\boldsymbol{\Omega}_h$ to recognize that only utility differences matter for the nominal variable. The approach to do so is discussed in detail in Bhat (2015b). This needs some additional notations and discussion, which are omitted in the interest of brevity.

Next, let $\boldsymbol{\theta}_h$ be the collection of parameters to be estimated:

$\boldsymbol{\theta}_h = [\boldsymbol{\gamma}'_h, \boldsymbol{\varphi}'_{\boldsymbol{h}}, \psi_{h,2}, \boldsymbol{\beta}'_h;\ \text{Vech}(\boldsymbol{\Omega}_h)]$, where Vech($\boldsymbol{\Omega}_h$) represents the vector of estimable parameters of $\boldsymbol{\Omega}_h$. Then the likelihood function for the individual *q* given that he/she belongs to segment *h* may be written as:

$$L_q(\boldsymbol{\theta}_{\boldsymbol{h}}) = \phi_1(y_{qh} - \boldsymbol{\gamma}'_h \boldsymbol{s}_{qh}) \times \Pr\left[\tilde{\boldsymbol{\psi}}_{low,qh} \le \tilde{\boldsymbol{u}}_{qh} \le \tilde{\boldsymbol{\psi}}_{up,qh}\right], \qquad (2)$$

$$= \phi_1(y_{qh} - \boldsymbol{\gamma}'_h \boldsymbol{s}_{qh}) \times \int_{D_{\tilde{u}_{qh}}} \phi_3(\tilde{\boldsymbol{u}}_{qh} \mid \breve{\boldsymbol{\Omega}}_{qh}) d\tilde{\boldsymbol{u}}_{\boldsymbol{qh}},$$

where $\tilde{\boldsymbol{u}}_{qh} = (\boldsymbol{u}_{qh}, y^*_{qh})'$, the integration domain for the probability $D_{\tilde{u}_{qh}} = \{\tilde{\boldsymbol{u}}_{qh} : \tilde{\boldsymbol{\psi}}_{low,qh} \le \tilde{\boldsymbol{u}}_{qh} \le \tilde{\boldsymbol{\psi}}_{up,qh}\}$ is simply the multivariate region of the elements of the $\tilde{\boldsymbol{u}}_{qh}$ vector determined by the range $(-\infty, 0)$ for the nominal variable and by the observed outcome of the ordinal variable. That is, $\tilde{\boldsymbol{\psi}}_{low,qh} = (-\infty, -\infty, \psi_{h,n_q-1})$ and $\tilde{\boldsymbol{\psi}}_{up,qh} = (0, 0, \psi_{h,n_q})$, and $\phi_R(.)$ is the multi-variate normal density function of dimension *R*.

2.3.2. Segmentation Model

The derivation thus far is based on the notion that individual *q* belongs to a single segment *h*. However, the actual assignment of individual *q* to a specific segment is not observed; but it is possible to attribute a probability $\pi_{qh}\ (h = 1, 2, \ldots, H)$ to individual *q* belonging to segment *h*. The conditions that $0 \le \pi_{qh} \le 1$ and $\sum_{h=1}^{H} \pi_{qh} = 1$ must be met. To enforce these restrictions, following Bhat (1997), the following logit link function is used:

$$\pi_{qh} = \frac{\exp(\boldsymbol{\mu}_h' \boldsymbol{w}_q)}{\sum_{j=1}^{H} \exp(\boldsymbol{\mu}_j' \boldsymbol{w}_j)}, \tag{3}$$

where $\boldsymbol{w}_q$ is a vector of individual exogenous variables, and $\boldsymbol{\mu}_1 = \mathbf{0}$ serves as a vector identification condition. Defining $\boldsymbol{\theta} = [\boldsymbol{\theta}_1', ..., \boldsymbol{\theta}_h'; \boldsymbol{\mu}_1', ..., \boldsymbol{\mu}_h']'$, then the likelihood function for individual q is:

$$L_q(\boldsymbol{\theta}) = \sum_{h=1}^{H} \pi_{qh} \left[L_q(\boldsymbol{\theta}_h) \mid q \in \text{segment } h) \right], \tag{4}$$

and the overall likelihood function is then given as:

$$L(\boldsymbol{\theta}) = \prod_q L_q(\boldsymbol{\theta}). \tag{5}$$

Typical simulation-based methods to approximate the multivariate normal cumulative distribution function in Equation 1 can prove inaccurate and time-consuming. As an alternative, the Maximum Approximate Composite Marginal Likelihood (MACML) approach (Bhat, 2011), which is a fast-analytic approximation method, is used. The MACML estimator is based solely on univariate and bivariate cumulative normal distribution evaluations, regardless of the dimensionality of integration, which considerably reduces computation time compared to other simulation techniques used to evaluate multidimensional integrals. For a detailed description of the MACML approach in the specific case of a joint system of continuous, ordinal, and nominal variables, the reader is referred to Bhat (2015b).

2.4. Model Estimation Results

Model specifications that incorporate latent segments can prove to be computationally challenging to estimate (Astroza et al, 2019). To help facilitate the identification of good starting values for model parameters, the study employed a strategy of first estimating four different causal structures separately and independently, assuming that the entire sample constituted a single segment. The parameter estimates from these independent models were used as starting values for the full-fledged model with latent segmentation. Also, to help inform the specification of the joint model, the best specifications were obtained for the individual models corresponding to Residential Location Choice (RLC), Frequency of Transit Use (FTU), and Attitude Towards Transit (ATT). These specifications were used as a starting point to inform the specification of the joint model system with multiple segments.

Models with different numbers of latent segments were estimated and compared. It was found that the model with four latent segments (i.e., all four causal structures considered in this study) offered the best fit compared to models with one, two, or three latent segments. For the four-segment model, the log-likelihood value at convergence is –164,377.29 and, with 242 parameters, the Bayesian Information Criterion (BIC) is 165,486.8; the corresponding BIC values for the one, two, and three segment models are larger at 166,257.3, 165,932.5, and 165,599.2 respectively. Just to explore further, a five-segment model was also estimated and evaluated (by adding one of the causal structures in which attitudes act as a mediator between residential location choice and frequency of transit use), and the fit was found to be inferior to the four-segment model (BIC for the five-segment model was 165,525.1). As such, the remainder of this section is dedicated to discussing results for the four-segment model.

In the interest of brevity, the joint equations model estimation results for each of the four causal structures are not presented here (but attached in the ***Appendix A, Table 13-15*****)**. Rather, complete estimation results are presented for one causal structure for illustrative purposes (Table 3). In general, the effects of exogenous variables on endogenous variables do not vary by causal structure, and there is no reason that they should. The exogenous variable influences are largely based on patterns of relationships within the data set and there is no reason for these relationships to vary across the causal structures considered. Indeed, an examination of the detailed model estimation results for the four causal structures shows that the exogenous variables depict similar coefficient values and signs. A brief description of the influence of various exogenous variables on the endogenous variables of interest is provided here. These relationships can be seen in Table 3.

An examination of exogenous variable influences shows that women respondents show a lower inclination to reside in urban areas relative to non-urban areas. Admittedly, this result needs to be interpreted with care, because residential locations are likely to be based on all individuals in a household. However, since the survey used here was an individual-based survey (only one individual responded per household), and this result came out to be statistically significant, the variable is retained to potentially reflect the notion that, at least within the group of single adult households, women tend to reside in non-urban settings. Women respondents are also more likely than men to use transit and have a more positive attitude towards transit. Younger individuals (particularly below 35 years of age) are more likely to be urban dwellers when compared with older individuals. Older individuals (35 years or above) use transit less frequently than their younger counterparts; consistent with this finding, younger individuals below the age of 35 years are found to have a more positive attitude towards transit. College graduates are found to favor urban residential location type, as do those employed full time. Time spent online is significantly related to the endogenous variables; those who spend more than eight hours per day online are more likely to reside in urban and suburban mix areas, show a propensity towards higher frequency of transit use, and demonstrate a more positive attitude towards transit. It is likely that those who are technology oriented prefer transit-oriented urban lifestyles (Hong and Thakuriah, 2018).

Among household attributes, home ownership is negatively associated with urban and suburban mix residential choice and negatively associated with transit use, but positively associated with attitudes towards transit. It appears that homeowners are positively disposed towards transit, and their infrequent (or non-existent) use of the service does not provide a sufficient basis to change that perspective. Lower incomes are associated with urban living (consistent with existing evidence, e.g., Booi and Boterman, 2019) and higher propensity to use transit. Individuals in larger households are less likely to favor urban residential locations and are less inclined to use transit, presumably because of the lifecycle stage and need to fulfill household obligations. This is further reinforced by the finding that the presence of children negatively impacts urban residential location choice and propensity to use transit.

As expected, households with high levels of vehicle ownership (three or more vehicles) are less likely to reside in urban and suburban mix areas, depict a lower propensity to use transit, and have more negative attitudes towards transit. The causal relationships involving vehicle ownership are unknown and merit further investigation. Vehicle ownership is an endogenous mobility choice variable too, but has been treated in this study as an exogenous variable for simplicity and computational tractability. It is entirely possible that vehicle ownership is affected by residential location choice, propensity to use transit, and transit attitudes; exploring the causal influences that shape vehicle ownership remains a task for future research efforts. Those who reside in transit progressive cities are more prone to using transit and have a more positive attitude towards transit, while those in the South region of the United States (which is generally more sprawled and auto oriented) have a lower propensity to use transit and have a more negative attitude towards transit.

In general, all of the exogenous variable impacts are consistent with expectations and demonstrate that socio-economic and demographic variables play a significant and important role in shaping attitudes and mobility/location choices. For each of the segments, it was not possible to reject the hypothesis that the diagonal terms in the 2×2 covariance sub-matrix of the differenced error terms corresponding to the residential location choice alternative utilities were 1.0 and that all the off-diagonal elements in the sub-matrix were 0.5. This implies that the error terms of the residential location choice alternatives are independently and identically distributed. Assuming that the error term in the base alternative in each dimension is independent of the error terms in other dimensions, and scaling the variance of the utilities of each alternative error term in the residential location choice model to one, the implied covariance (correlation) matrix among (1) the urban residential location utility (UL), (2) the suburban/small town mix residential location utility (SUBT), (3) the propensity underlying frequency of transit use (FTU), and (4) the ATT factor score, is presented toward the bottom of Table 3 for causal structure 1 (only the lower diagonal elements are presented because of the symmetric nature of this matrix). There are statistically significant error correlations, and this was found to be the case for every causal structure considered in this paper. In general, the error correlations in the other causal structures had the same signs as those for the first causal structure in Table 3, clearly indicating that, in each segment, there is a residual association between the dependent variables that is not captured by the explanatory variables included in the model specification. This result justifies the use of a joint package (simultaneous equations) approach to model relationships among the endogenous variables considered in this study. Not surprisingly, the positive correlation in the second column and last row of the covariance (correlation) matrix suggests that unobserved factors that increase the utility of residing in an urban area also increase positive views of transit, even if these factors do not necessarily increase the actual use of transit. A possible explanation is that a variety seeking individual (who likes to try different experiences) may like to reside in an urban location (where there is a variety of amenities in close proximity) and may also have a positive attitude towards alternative (a variety of) modes of transportation. The correlations in the third column suggest that unobserved factors that lead to residing in suburban and small towns also reduce transit use propensity as well as positive attitudes toward transit. These results are clear evidence of unobserved residential self-selection effects (see Bhat and Guo, 2007 for a detailed discussion). Those who intrinsically (due to unobserved individual factors) do not have positive views about transit and are not very likely to use transit self-select to live in suburbia.

Table 4 presents a summary of the endogenous variable effects, which are of interest in the context of understanding relationships among dependent variables under different causal structures (estimates for all four causal structures are shown in Table 4). Note that these may be considered to be representative of “true” causal effects after “cleansing” any relationships among the endogenous variables caused by “spurious” unobserved correlation effects. In general, it can be seen that the relationships are significant and consistent with expectations, indicating that these three endogenous variables affect one another in behaviorally intuitive ways after accommodating unobserved covariances. In causal structure 1 (RLC → FTU; RLC + FTU → ATT), it is found that those in suburban and small-town locations show a lower propensity to use transit. Compared to those in suburban and small town/rural areas with no mixed land use, the residents of urban and suburban mix areas have a more positive attitude towards transit (again, this is after accommodating unobserved factors that may influence these endogenous variables). Likewise, frequent and infrequent transit users have a more positive attitude towards transit than those who never use transit; between these two groups, frequent users have a more positive attitude than infrequent users. In causal structure 2 (FTU → RLC; FTU + RLC → ATT), it is found that frequent users of transit are more likely to reside in urban areas and suburban and small-town areas with mixed land use areas rather than suburban and small-town areas without mixed land use. Transit users also have a more positive attitude towards transit. Similarly, urban dwellers are likely to have a more positive attitude towards transit. In causal structure 3 (ATT → RLC; ATT + RLC → FTU), those with a positive attitude towards transit are more likely to favor urban and suburban mix residential locations and exhibit a greater propensity to use transit. Those residing in suburban mix locations depict a lower propensity to use transit than their counterparts in other urban and suburban/rural areas. In causal structure 4 (ATT → FTU; ATT + FTU → RLC), positive attitudes towards transit lead to a more urban and suburban mix residential location choice (relative to those residing in suburban/rural locations) and a higher propensity to use transit. Similar to indications in other causal structures, those who use transit more frequently are more likely to choose urban and suburban mix locations for residence (relative to suburban/rural locations), with this tendency being particularly high for urban locations.

Table 3. Illustrative Model Estimation Results: Causal Structure 1 (RLC → FTU; RLC + FTU → ATT)

Explanatory Variables	Residential Location Choice RLC (*base*: other suburban & small town + rural)				Frequency of Transit Use FTU (never, infrequent, and frequent)		Attitude Towards Transit ATT (continuous factor scores)	
	Urban dwellers		Suburban and small-town mix					
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	-0.779	-6.12	-0.561	-7.21	0.206	18.86	-0.653	-17.42
Individual Characteristics								
Gender								
Female	-0.193	-3.71	—	—	0.112	3.23	0.099	4.12
Age category								
18-24 years	0.510	4.19	—	—	—	—	0.157	5.88
25-34 years	0.294	3.94	—	—	—	—	0.111	3.21
18-34 years	—	—	0.163	2.11	—	—	—	—
35-54 years	—	—	—	—	-0.300	-5.95	—	—
55-64 years	—	—	—	—	-0.412	-6.32	—	—
65 years and above	—	—	—	—	-0.587	-7.35	—	—
Education attainment								
College graduate or higher	0.189	2.63	—	—	—	—	—	—
Employment Status								
Employed full-time	0.265	4.71	-0.105	-4.19	—	—	—	—
Time spent online								
More than 8 hours per day	0.322	3.28	0.224	2.96	0.702	3.29	0.061	2.11
Household Characteristics								
Home ownership								
Own	-0.642	-5.39	-0.206	-3.12	-0.131	-4.12	0.075	2.42
Household income								
Less than $35,000	0.203	3.14	-0.241	-4.51	0.073	2.12	—	—
More than $75,000	—	—	—	—	—	—	—	—
Household size								
Two or more	-0.245	-3.21	—	—	-0.131	-3.78	—	—
Presence of children								
Presence of children 0-4 years	-0.110	-2.11	-0.125	-2.02	-0.102	-4.12	—	—
Presence of children 0-15 years	—	—	—	—	—	—	0.124	5.63

Table 3. Illustrative Model Estimation Results: Causal Structure 1 (RLC → FTU; RLC + FTU → ATT) (Continued)

Explanatory Variables	Residential Location Choice RLC (*base*: other suburban & small town + rural)				Frequency of Transit Use FTU (never, infrequent, and frequent)		Attitude Towards Transit ATT (continuous factor scores)	
	Urban dwellers		Suburban and small-town mix					
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Household Characteristics								
Vehicle ownership								
Three or more	-0.710	-8.22	-0.321	-6.10	-0.239	-3.29	-0.104	-4.62
Location Characteristics								
Lives in Transit Rich City								
Progressive	—	—	—	—	0.412	9.55	0.086	3.06
Region								
South	—	—	—	—	-0.183	-4.90	-0.098	-3.10
Threshold Parameter	—	—	—	—	1.217	19.96	—	—

Correlation Between Error Terms

$$\begin{array}{c} \\ \text{URB} \\ \text{SUB} \\ \text{FTU} \\ \text{ATT} \end{array} \begin{array}{c} \begin{array}{cccc} \text{URB} & \text{SUB} & \text{FTU} & \text{ATT} \end{array} \\ \begin{bmatrix} 1.000 & & & \\ 0.000 & 1.000 & & \\ 0.000 & -0.167 & 1.000 & \\ 0.121 & -0.098 & 0.221 & 1.000 \end{bmatrix} \end{array}$$

URB: Urban residence utility
SUB: Suburban and small-town mix utility

Goodness of Fit Statistics (Four-Segment Model System)
Log likelihood at convergence, L(β) = -164,377.29 (242 parameters); Log likelihood with constants, L(c) = -217,269.31
Log likelihood with no constants, L(0) = -278,366.45; Adjusted ρ^2(c) = 0.2424; Adjusted ρ^2(0) = 0.4086

Table 4. Relationships Among Endogenous Variables for the Four Causal Structures/Segments

Variables	Residential location choice (*base:* suburban and small town+rural)				Frequency of Transit Use (never, infrequent, and frequent)		Attitude Towards Transit (continuous factor score)	
	Urban Dwellers		Suburban & Small-Town Mix					
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Segment 1 (RLC→FTU; RLC+FTU→ATT)								
Residential Location Choice								
Urban dwellers	—	—	—	—	—	—	0.146	4.98
Suburban and small-town mix	—	—	—	—	-0.089	-3.34	0.078	2.87
Frequency of Transit Use								
Frequent (≥ once per week)	—	—	—	—	—	—	1.298	21.43
Infrequent (< once per week)	—	—	—	—	—	—	0.653	25.31
Segment 2 (FTU→RLC; FTU+RLC→ATT)								
Frequency of Transit Use								
Frequent (≥ once per week)	1.122	4.10	0.308	3.55	—	—	1.311	18.32
Infrequent (< once per week)	0.462	3.92	0.237	4.21	—	—	0.703	22.01
Residential Location Choice								
Urban dwellers	—	—	—	—	—	—	0.127	3.22
Suburban and small-town mix	—	—	—	—	—	—	0.083	2.04
Segment 3 (ATT→RLC; ATT+RLC→FTU)								
Attitude Towards Transit	0.312	4.62	0.119	5.32	0.624	19.05	—	—
Residential Location Choice								
Urban dwellers	—	—	—	—	—	—	—	—
Suburban and small-town mix	—	—	—	—	-0.110	-3.46	—	—
Segment 4 (ATT→FTU; ATT+FTU→RLC)								
Attitude Towards Transit	0.156	4.63	0.0799	2.63	0.631	24.12	—	—
Frequency of Transit Use	—	—	—	—	—	—	—	—
Frequent (≥ once per week)	0.901	8.31	0.198	2.10	—	—	—	—
Infrequent (< once per week)	0.347	4.32	0.180	2.98	—	—	—	—

2.5. Size and Characteristics of Latent Segments

This section presents information about the latent segments in the population. As posited earlier in this paper, it is hypothesized that different segments in the population follow different causal structures in their contemporaneous decision-making processes. This section offers information about the size and characteristics of the latent segments to determine the extent to which behaviors affect attitudes or attitudes affect behaviors in the survey sample of this study. Table 5 presents the results of the latent segmentation membership model.

Table 5. Latent Segmentation Model

Segmentation Variables	Segment 1 (base)	Segment 2 Coef (t-stat)	Segment 3 Coef (t-stat)	Segment 4 Coef (t-stat)
Constant	—	-0.289 (-6.23)	-0.302 (-8.11)	-0.561 (-9.32)
Age 18-34 years	—	-0.134 (-2.88)	-0.309 (-3.01)	-0.481 (-3.76)
Age 35-64 years	—	-0.163 (-2.11)	-0.235 (-2.34)	-0.432 (-3.08)
Gender: Female	—	-0.193 (-3.53)	0.187 (5.03)	0.059 (3.32)
Lives in transit rich city	—	—	-0.205 (-3.31)	-0.223 (-4.10)
College graduate or higher	—	—	-0.211 (-2.22)	-0.231 (-2.57)
Distance to nearest transit station < 0.5 mile	—	0.103 (4.12)	-0.254 (-3.21)	-0.102 (-2.18)
Hhld Income > $75,000	—	-0.131 (-3.25)	0.138 (5.19)	0.064 (2.74)
Segment Size	41% 3,936	25% 2,400	21% 2,016	13% 1,248

Segment 1 Causal Structure: RLC (R) → FTU (F); RLC (R) + FTU (F) →ATT (A)

Segment 2 Causal Structure: FTU (F) → RLC (R); FTU (F) + RLC (R) →ATT (A)

Segment 3 Casual Structure: ATT (A) → RLC (R); ATT (A) + RLC (R) → FTU (F)

Segment 4 Causal Structure: ATT (A) → FTU (F); ATT (A) + FTU (F) → RLC (R)

The model offers a first glimpse into the profile of the segments. In general, it appears that individuals are more likely to belong to the first segment in which residential location choice affects frequency of transit use, and these two behavioral choices together impact attitudes (see the last row of Table 5 for the segment size information). It is found that 41 percent of the sample is assigned to this first segment, with all other segments substantially smaller in size (the size of each segment may be determined based on the procedure discussed in Bhat (1997). The second largest segment is the second segment in which frequency of transit use affects residential location choice, and these two choice behaviors together shape attitudes. In other words, the two causal structures (the first and second) in which *behaviors shape attitudes* account for two-thirds of the sample. The other one-third of the sample is collectively assigned to the other causal segments (the third and fourth segments) in which *attitudes affect behaviors*. It appears that, in the context of this sample (which is a rather large sample drawn from diverse areas in the United States), behaviors influence attitudes for a majority of the respondents, consistent with recent evidence in the literature (Moody and Zhao, 2020; Kroesen et al, 2017) which suggests that people adjust their attitudes in accordance with their behavioral choices and experiences, presumably in an effort to reduce cognitive dissonance.

The results of the effects of exogenous variables in Table 5 indicate that individuals younger than 65 years of age are increasingly less likely to belong to the second, third, or fourth segments (see the progression of coefficients from left to right for the two age groups). Women, however, are more likely to belong to the third and fourth causal segments than the first two causal segments. Compared to men, women appear to be more set with respect to their attitudes and likely to exhibit behavioral choices according to their attitudes. On the other hand, those who live in transit-rich cities and those who are college graduates are more likely to belong to the first two segments in which behaviors shape attitudes (notice the negative signs on these variables associated with the third and fourth segments). Those who live close to a transit station are also more likely to belong to the first two segments; perhaps their attitudes are shaped by the proximity to transit that engenders greater level of transit use. On the other hand, higher income individuals are more likely to belong to the third and fourth segments where attitudes shape behaviors. It is possible that individuals who have reached this level of income have opinions and attitudes that have matured, and also have the wealth to actually live a lifestyle consistent with their attitudes/opinions/preferences. That is, there is perhaps less presence of cognitive dissonance for such individuals than their lower income counterparts (lower income individuals may be less able to get out of a less-than-desirable situation, and may change their attitudes as a coping mechanism).

It is interesting to note that, within the two distinct sets of causal structures (one where behavior shapes attitudes, and the other set where attitudes influence behavior), the causal structure that is more dominant is the one where residential location choice affects frequency of transit use. In other words, the longer-term choice (residential location) influences the shorter-term mode use decision (frequency of transit use). This type of relationship is quite consistent with that often invoked in integrated models of transport and land use where land use choices are often considered higher in the hierarchy and assumed to influence shorter term activity-travel choices. However, it is also found that the sizes of the segments in the causal structures where frequency of transit use influences residential location choice are not trivial. These segments (Segments 2 and 4) are quite sizable in their own right. Individuals in these latent segments appear to be choosing a residential location choice that is conducive to and consistent with their level of transit use. Overall, it can be concluded that there is considerable *structural heterogeneity* in the sample, and any travel forecast that assumes the same causal structure for the entire sample is likely to yield erroneous estimates of impacts of alternative transport policies and investments.

Table 6 presents a detailed overview of the profile of the various latent segments in the sample. The left half of the table shows the percent of individuals in each latent segment that belong to a socio-economic group; the right half of the table shows the percent of individuals in each socio-economic group that is assigned to each of the latent segments. The percent of individuals in each socio-economic group that belongs to a specific segment does not vary greatly. This is a reflection of the strong effect of the constants in Table 5 in determining segment membership, relative to other observed exogenous variables. This suggests that there is still room for improvement in determining the factors that influence segment membership, which may be explored in future studies with a more exhaustive set of demographic variables as well as built environment contextual variables. However, while the latent segments may appear rather similar in profile, distinct patterns can be gleaned as one transitions across segments. For example, consider the age profile of the segments. In the first segment, 58.4 percent of individuals belong to the 35+ age group (R→F→A); this percentage gradually increases from left to right, ending with 63 percent of those in the last segment (A→F→R) belonging to the 35+ year age group. In other words, the segments in which attitudes affect behaviors have a slightly older age profile than the first two segments where behaviors affect attitudes. It is entirely plausible that there are more people in the older age groups whose attitudes have matured and hardened, and their choice behaviors are influenced by their attitudes.

Table 6. Profile of the Four Latent Segments

Person Characteristics		Percent (%) within segment				Percent (%) within attribute				Overall Sample
Attribute	Categories	R→F→A	F→R→A	A→R→F	A→F→R	R→F→A	F→R→A	A→R→F	A→F→R	
Age Categories (years)	16-24	17.8	17.8	16.6	16.4	42.3	25.3	20.0	12.4	17.4
	25-34	23.8	23.6	21.1	20.6	43.2	25.6	19.4	11.8	22.8
	35 or more	58.4	58.6	62.3	63.0	40.3	24.1	21.8	13.8	59.9
Gender	Female	53.9	49.0	57.6	54.1	41.6	22.6	22.6	13.2	53.5
	Male	46.1	51.0	42.4	45.9	40.9	27.1	19.1	12.9	46.5
Marital status	Single	30.8	31.3	27.9	27.9	42.5	25.8	19.5	12.2	29.9
	Married	57.9	57.1	60.0	59.6	40.9	24.1	21.6	13.4	58.4
	Divorced	11.3	11.5	12.1	12.5	40.0	24.3	21.7	14.0	11.7
Frequency of transit use	≥ Once per week	17.8	17.8	16.6	16.4	42.3	25.3	20.0	12.4	17.0
	< Once per week	23.8	23.6	21.1	20.6	43.2	25.6	19.4	11.8	32.6
	Never	58.4	58.6	62.3	63.0	40.3	24.1	21.8	13.8	50.4
Distance from Home to Transit Station	< 0.5 mile	41.3	44.1	34.3	37.8	42.6	27.1	17.9	12.4	40.1
	≥ 0.5, <1 mile	20.9	20.2	23.2	22.2	40.4	23.2	22.8	13.6	21.4
	≥ 1 mile	37.7	35.7	42.4	40.0	40.4	22.9	23.1	13.6	38.5
Vehicle ownership	Zero	4.0	4.2	3.5	3.7	42.2	26.6	18.8	12.4	3.9
	1 vehicle	30.8	31.7	29.6	30.4	41.4	25.5	20.2	13.0	30.8
	2+ vehicle	65.2	64.1	66.9	65.9	41.2	24.2	21.4	13.2	65.4
Household size	1 person	18.0	18.8	17.1	17.8	39.6	25.1	21.2	14.1	18.0
	2 person	43.3	43.8	44.9	45.7	39.5	23.9	22.3	14.3	44.1
	3+ person	38.7	37.4	37.9	36.5	42.1	24.3	21.0	12.6	37.9
Annual household income	< $35K	21.0	21.9	19.9	20.6	41.4	25.8	19.9	12.9	21.0
	≥ $35K, < $50K	14.2	14.8	13.8	14.2	41.1	25.6	20.3	13.1	14.2
	≥ $50K, < $75K	22.8	24.2	21.7	22.4	41.2	26.1	19.9	12.8	22.9
	≥ $75K	42.0	39.1	44.6	42.8	41.3	23.0	22.3	13.4	41.9
Residential location choice	Urban dweller	28.4	29.3	25.7	26.5	42.2	25.9	19.4	12.5	27.8
	Suburban	32.3	32.4	32.3	32.5	41.2	24.7	20.9	13.2	32.4
	Suburban & rural	39.3	38.3	41.9	40.9	40.7	23.7	22.1	13.5	39.8
Segment Size						41%	25%	21%	13%	100%
						3,936	2,400	2,016	1,248	9,600

Similar differential patterns across segments can be seen throughout the table. When compared with males, females are more likely to belong to causal structures in which attitudes shape behaviors. Single individuals who have never been married are more likely to belong to segments in which behaviors shape attitudes when compared with individuals who have been married or divorced. It generally appears that those in younger stages of life (from an age and lifecycle perspective) are less likely to have attitudes that have matured and hardened in comparison to those in later stages of life. Attitudes for these demographic groups may still be evolving to a slightly greater extent than others in the population.

Those who use transit more frequently are more likely to fall into the first two segments than those who never use transit. Individuals in households with no vehicles are similarly likely to fall into segments where behaviors shape attitudes, in comparison to those in households with more vehicles. Urban dwellers are more likely to be in the categories where behaviors shape attitudes in comparison to those in suburban and small town or rural settings. Again, all of these comparisons should be viewed carefully in *relative* terms because the differences are quite small. Although this analysis is not based on longitudinal data, the patterns in the table may be indicative of a transition process that may be at play. Broadly speaking, a majority of individuals fall into the segments where behaviors affect attitudes, but it appears that (some) individuals transition into other segments (where attitudes influence behaviors) as they age through lifecycle stages.

2.6. Discussion and Conclusions

Energy-behavioral analysts are increasingly concerned with the relationships between human attitudes and perceptions on the one hand and behavioral choices on the other. There is interest in exploring the possibility of using attitudinal variables and constructs to better explain and more accurately predict household energy use under a variety of scenarios, particularly in the context of emerging transport and building technologies. Across a number of disciplines, the relationships between attitudes and behaviors have been well documented. Various studies, however, assume different causal relationships between attitudes and behaviors. Most studies appear to treat attitudes as affecting behavioral choices, but there are a number of studies (as noted in the introductory section) where behavioral choices are assumed to affect attitudes. A few studies have attempted to treat the attitude – behavior relationship as a bi-directional one, but econometric identification issues render the estimation of such models challenging when the endogenous variables are not continuous in nature. There is considerable uncertainty as to the direction of causality between attitudes and behaviors at any point in time, and this study constitutes an attempt at shedding deep insights into the nature of the relationship. More specifically, this chapter recognizes that different causal structures may be prevalent in a population, leading to the presence of multiple population segments. In other words, population heterogeneity may arise not only in terms of sensitivity to different attributes of alternatives, but also in terms of differing causal structures driving consumer decision-making processes.

In an effort to unravel *the extent* to which different causal structures relating attitudes and behaviors are prevalent in the population, this chapter adopts a latent segmentation approach to reflect the notion that the analyst does not observe and is not aware of the causal structure adopted by each individual in the population. The latent segmentation approach endogenously assigns individuals to different causal structures, thus enabling the identification of segments in the population and the degree of heterogeneity that may be prevalent. In this study, a joint equations model that relates residential location choice, frequency of transit use, and attitudes towards transit is estimated. The former two variables constitute behaviors, while the third variable is an attitudinal factor score. The model system is estimated on a large sample data set that includes both attitudinal and behavioral choice variables. Four different latent segments are considered; two latent segments in which attitudes affect choice behaviors and two segments in which choice behaviors affect latent segments. The two causal structures in which attitudes appear as a mediating factor between the two behavioral choice variables are ignored in this study.

The overall finding is that the majority of the sample in the data set used in this study are assigned to the latent segments in which behavioral choices affect attitudes. Nearly two-thirds of the sample falls into these two segments, while only about one-third falls into the two segments where attitudes affect behaviors. In other words, the findings of this chapter appear to corroborate some recent evidence that people appear to modify their attitudes in response to their behaviors and based on their experiences to reduce the cognitive dissonance that may exist. It appears that attitudes at any cross-section in time are shaped by the behavioral choices and experiences of the individual at that point in time. As time progresses, it is entirely possible that attitudes and behaviors will evolve; but within the context of a snapshot, the study results here clearly indicate that attitudes are shaped by behaviors more so than the other way around. Thus, the travel demand forecasting models that assume the same causal structure across the entire population are likely to return erroneous predictions of travel demand in response to policy and investment scenarios. It would be beneficial to probabilistically assign individuals in a population to different causal segments, and then forecast travel demand for different segments according to the causal structure that drives their decision-making process.

From a transportation policy perspective, it would appear that information campaigns and advertisements may not be all that effective in a world where the majority of the population has their attitudes shaped by behaviors. In other words, attempts to influence and change attitudes (towards certain products or mobility options) using information campaigns may not necessarily yield expected results because attitudes are shaped by behaviors for two-thirds of the population (at least in the sample of this study). This implies that it is necessary to run pilots and campaigns where individuals actually get to experience modal options and different products first-hand; people need to be able to exercise alternative behavioral choices, learn through experience, and re-shape their attitudes in response to the behaviors and choices that they get to experience. Programs in which individuals are able to actually try out new and different alternatives (modes and services, for example) may yield greater benefit than messaging aimed at trying to influence attitudes. It should, however, be recognized that a sizable portion of the sample was also allocated to segments where attitudes affect behaviors; hence programs that aim to change attitudes should not be discontinued, particularly for more mature segments of the population who may be rather set in their ways and formed rather rigid opinions and attitudes. To make different campaigns work most effectively, they need to be targeted to the appropriate segments depending on the causal structures that they follow.

3. ACCOUNTING FOR THE INFLUENCE OF ATTITUDES IN MODELING THE ADOPTION AND USAGE OF ON-DEMAND TRANSPORTATION AND ELECTRIC VEHICLES

3.1. Introduction

Developing countries around the world have experienced phenomenal growth in vehicle ownership and use over the past few decades. India is a rapidly developing economy with a population of about 1.4 billion people and is scheduled to take over as the most populous country in the world within the next few years (United Nations, 2019). Rapid and consistent economic development over the past few decades has fueled the rise of the middle class that is increasingly urban, educated, and globalized and numbers anywhere between 100 and 600 million people depending on the criteria and thresholds used to define this segment of the population (Roy, 2018; Kharas, 2017). Although the middle class was adversely impacted during the pandemic, it is likely that any setback is only temporary, and the purchasing power of the Indian middle class will continue to rise as the country emerges from the pandemic (Kochhar, 2021).

The growth of the middle class in India has been accompanied by a surge in vehicle ownership and use. According to data published by the Ministry of Road Transport and Highways (MoRTH) of the Government of India, the number of cars, jeeps, and taxis increased from 695,400 in 1971 to 33,649,000 in 2017 (Road Transport Year Book, 2019). The number of two-wheelers experienced a surge from just about 587,100 in 1971 to approximately 187 million in 2017. Both cars/jeeps/taxis and two-wheelers essentially experienced a compounded annual growth rate of more than 10 percent between 2007 and 2017 (Road Transport Year Book, 2019). Transportation contributes substantially to air pollution in India, accounting for 11 percent of all greenhouse gas (GHG) emissions, one-third of particulate matter (PM) pollution, and an even higher proportion of nitrogen oxides - all of which are harmful to human health (Kumar, 2021; Guttikunda, 2015).

The air pollution, energy intensity, and infrastructure congestion challenges presented by transportation in India has motivated the search for sustainable transportation solutions that will reverse the growth in automobile use, carbon emissions, and fossil fuel consumption (Kumar, 2021). According to recent articles by the International Council on Clean Transportation (ICCT), it is imperative that the nation embrace emerging vehicular technologies to reverse the growth in India's road transport emissions. The ICCT notes that battery electric vehicles, for example, have the lowest lifecycle GHG emissions, both today and into the foreseeable future (Muncrief**,** 2021). Thus, transportation electrification is seen as a mechanism by which the negative externalities due to growth in road transportation can be mitigated to a substantial degree. Indeed, there is growing adoption of electric vehicles (EV) in the Indian market, achieving a growth rate of 44 percent with about one million units sold in FY20 (Chaudhary, 2020).

Besides electrification, another potential mobility solution that may help soften the negative impacts of road transportation is the rise of ridesharing or ridehailing services. In India, two of the most popular ridehailing services are Uber and Ola. Both of these companies offer on-demand door-to-door mobility service via a smartphone app that can be used to summon a ride in real-time, track vehicle location and trajectory, and make payment for a completed ride. Ridehailing services have experienced impressive growth in India. Unconfirmed numbers suggest that Uber served 14 million rides per week in 2019, while Ola recorded more than 28 million bookings per week during 2018-2019 (including all types of mobility on demand services) (The Economic Times, 2020). While these services often provide private rides to individuals, they offer the potential to advanced shared mobility services where multiple individuals share a ride (similar to a carpool). Ridesharing is being identified as one among the strategies that a country such as India should embrace to help mitigate the adverse effects of private automobile use (Singh, 2019). If the fleets transition to electric vehicles in the future, the cause of sustainable transportation may be advanced further.

This chapter aims to identify the factors contributing to the adoption of these two promising transportation innovations in the Indian context. Using survey data collected from more than 43,000 respondents from across the nation, the study simultaneously models the use of ridehailing services and the ownership of an electric vehicle. Although these two endogenous variables do not directly affect one another, the modeling framework accommodates an error correlation across these two endogenous variables to account for the possible presence of correlated unobserved attributes that simultaneously influence adoption of ridehailing services and ownership of an electric vehicle. What is particularly unique about this study is that it incorporates the influence of latent attitudinal constructs in a holistic model structure, thus enabling the identification of the role of attitudes, perceptions, and preferences in determining the adoption of on-demand mobility services and electric vehicle ownership. The latent attitudinal constructs are themselves treated as endogenous variables with socio-economic and demographic variables serving as exogenous variables. The entire model system is estimated in one step using an enhanced integrated choice and latent variable (ICLV) modeling approach that provides the ability to unravel complex relationships among multiple behavioral phenomena of interest.

There are a number of past studies that have focused on modeling the adoption and use of ridehailing services (e.g., Malik, 2021; Wadud, 2020; Lavieri and Bhat, 2019; Alemi, 2018) and the adoption and ownership of electric vehicles (e.g., Dua et al, 2021; Shalender and Sharma, 2020; Langbroek, 2016). Ridehailing services are generally used to a greater degree by individuals who are younger, more highly educated, employed, and residing in urban contexts (Malik, 2021; Alemi, 2018). Electric vehicles are generally found to be adopted and owned by individuals who are older, have higher income, and reside in urban areas where charging infrastructure may be better and distances between trip origins and destinations are likely to be smaller than in more suburban and rural settings (Shalender and Sharma, 2020; Tal and Nicholas, 2013). While electric vehicles constitute a transportation innovation with clear positive benefits from a GHG emission reduction perspective, the potential for on-demand mobility services to bring about GHG emission reductions remains uncertain. On the one hand, on-demand mobility services may elevate automobile use at the expense of alternative mode use, thus resulting in a detrimental impact on air quality. On the other hand, if used in a shared modality, on-demand mobility services may contribute to a substantial reduction in private car use, thus leading to positive impacts on congestion and pollution (Guo et al, 2019). Despite the rich body of literature dedicated to ridehailing usage and electric vehicle adoption, there is very little research that explicitly explores the interaction between these transportation innovations - particularly in developing countries such as India. This study therefore fills an important gap in the literature and sheds new light on the adoption of promising new transportation technologies in the Indian context, while explicitly accounting for attitudinal variables within a holistic integrated modeling framework.

The remainder of this chapter is organized as follows. The next section provides a detailed description of the survey and data set used in this study, together with descriptive statistics about the endogenous variables of interest. The third section presents the model structure and the modeling methodology. Model estimation results are presented in the fourth section. A discussion of the implications of the findings and conclusions is furnished in the fifth and final section.

3.2. Description Of Survey and Data Set

The data for this chapter is derived from a comprehensive survey effort undertaken in India by the Ola Mobility Institute as part of its Ease of Moving Index framework. In 2018, a detailed survey capturing socio-economic, demographic, mobility, and attitudes/perception variables was conducted across 20 cities in India (with a collective population of 90 million). The cities were of various sizes and were categorized as promising cities, booming cities, and metro cities. The cities spanned the entire country, and a total of more than 43,000 survey responses were obtained. Each survey respondent answered nearly 50 questions, thus providing a wealth of data for understanding people's preferences, mobility choices, and perceptions of mobility services, public transport, and state of roadways. The survey included questions that addressed issues of sustainability and public transport usage. Barriers related to advancing more sustainable modes of transport or public transport usage were identified through the survey. Complete details about the survey may be found elsewhere (Ola Mobility Institute, 2018). The survey was administered in person by survey personnel who visited households randomly to administer the survey.

This section presents the characteristics of the survey sample extracted for use in this chapter. Sample characteristics are presented in the first subsection and a more in-depth examination of endogenous variables and attitudinal indicators of interest are presented in the second subsection.

3.2.1. Sample Characteristics

In general, the estimation of a joint econometric model that incorporates multiple latent constructs on a sample size of 43,000 is rather computationally prohibitive. For purposes of computational tractability, a random sample of 7,500 respondents was extracted from the large sample. The characteristics of the 7,500 individuals were compared in detail against the original 43,000+ sample to ensure that the extracted subsample was not systematically different in any way. Once the representativeness of the extracted subsample was established, further filtering was done. First, only those individuals who reside in households with at least one vehicle were included in the analysis subsample. Second, any records with missing data on critical socio-economic, attitudinal, or endogenous behavioral variables of interest were excluded. The final analysis subsample consists of 2,972 persons, all of whom reside in a household with at least one vehicle. The analysis had to be limited to such households because one of the key endogenous variables of interest is electric vehicle (EV) ownership. As households with zero vehicles would have no opportunity to own any vehicle (let alone an EV), it was considered prudent to limit the analysis to households that own at least one vehicle.

Table 7 presents the socio-economic and demographic characteristics for this subsample of 2,972 respondents. The sample is predominantly female, comprising 65.3 percent of the sample. About 59 percent of the sample is 20-40 years and 22 percent is 40-60 years of age. About 63 percent report being employed, about 12.6 percent report being a homemaker, and 15.1 percent indicate that they are students. The monthly income is reported for employed individuals. It is found that 27.8 percent of all individuals (not just employed individuals) report a monthly income between ₹30,000-₹50,000 (Indian Rupees) and another 12.1 percent report income between ₹50,000-₹100,000. The educational attainment variable shows that nearly 40 percent have a college degree, and another 31 percent have attained a postgraduate degree. About 11 percent have a doctoral degree, suggesting that this subsample is more highly educated relative to the general population in India.

In terms of vehicle ownership, a distinction is made between two-wheelers and four-wheelers (cars). About 22 percent of individuals report owning zero two-wheelers, 54 percent report owning one two-wheeler, and 20.7 percent report owning two two-wheelers. With respect to cars, there are no zero-car individuals due to the nature of the subsample. About 73 percent own one car and 25 percent own two cars. The travel time to work distribution shows that 27.5 percent have a one-way commute time of 15-30 minutes. If one were to consider the number of kilometers traversed for daily commuting, it is seen that 38.3 percent commute 20-40 km and 27.7 percent commute 40-60 km. Monthly expenditures for transport show that 24.2 percent spend more than ₹5,000 for transport; only 5.1 percent spend less than ₹1,000. Public transport is a preferred mode of transportation for only 17.8 percent of the subsample of respondents; this percentage is lower than for the sample overall, largely due to the car-owning nature of the subsample. It is seen that 29.3 percent prefer taxis/cabs, 27.7 percent prefer personal vehicles, and 20.6 percent prefer three-wheeled auto rickshaws. Overall, the sample offers the richness of variation in various characteristics that would render it suitable for use in econometric choice modeling efforts.

Table 7. Socio-Demographic and Travel Characteristics (N=2,972 persons)

Socio-Demographic and Travel Characteristics			
Exogenous Variable: Socio-demographic Characteristics	Value (%)	**Exogenous Variable: Travel Characteristics**	Value (%)
Gender		*Travel time from home to work*	
Female	65.3	<15 min	10.4
Male	34.7	15-30 min	27.5
Age category		30-60 min	19.8
<20 years	11.4	≥60 min	5.6
20-40 years	59.3	Unemployed	36.7
40-60 years	22.1	*Kilometers commuted in city daily on average*	
≥60 years	7.2	<10 Km	5.4
Employment Status		10-20 km	21.6
Employed	63.3	20-40 Km	38.3
Homemaker/Housewife	12.6	40-60 Km	27.7
Student/Studying	15.1	≥60 Km	7.0
Unemployed	9.0		
Monthly Income for Employed Individuals (per month in Indian Rupees)		*Percentage of Monthly Salary spent on transport (in Indian Rupees)*	
<₹15,000	2.0	<₹1,000	5.1
₹15,000-₹30,000	18.8	₹1,000-₹3,000	31.3
₹30,000-₹50,000	27.8	₹3,000-₹5,000	39.4
₹50,000-₹100,000	12.1	≥₹5,000	24.2
≥₹100,000	2.6	*Preferred Mode of Transport*	
Unemployed	36.7	Auto	20.6
Educational Attainment		Non-Motorized	4.6
High school	18.2	Personal Vehicles	27.7
Graduate Degree	39.7	Public Transport	17.8
Post-Graduate Degree	30.9	Taxi/Cabs	29.3
Doctoral and above	11.2	**Endogenous Variables**	
Number of Two-Wheelers Owned		***On-Demand Transportation (Ola/Uber)***	
Zero Vehicle	21.9	Never	90.9
One Vehicle	53.9	Used Rarely (Monthly/Yearly)	1.0
Two Vehicle	20.7	Used Frequently (Daily/Weekly)	8.1
Three or more vehicle	3.5	***Personal Vehicle, Fuel Type Use***	
Number of Cars Owned		Compressed Natural Gas (CNG)	11.4
One Car	73.0	Diesel	35.3
Two Cars	24.8	Electric	7.0
Three or more cars	2.2	Petrol	46.3

3.2.2. Endogenous Variables and Attitudinal Indicators

This study is concerned with the adoption of new and emerging transportation technologies in India. As such, two endogenous variables are of interest. The first is the adoption and use of *on-demand transportation or ridehailing services* (e.g., Uber, Ola). The second endogenous variable corresponds to *electric vehicle ownership* (vehicle fuel type choice). The distributions for these two endogenous variables are shown at the end of Table 7. With respect to on-demand transportation services, 91 percent of the respondents indicate that they never use such services. About eight percent use the services frequently (daily/weekly) and a modest one percent use the services rarely. In terms of fuel type, each individual was asked to report on the vehicle that he or she drives and uses. Seven percent of respondents indicated that they own and use an electric vehicle (EV). Around 35 percent have a diesel vehicle and 46 percent have a petrol vehicle. Given the income and education profile of the respondent subsample, it is not too surprising to see the higher rate of EV penetration in the subsample relative to the general population. In the modeling exercise of this paper, no explicit relationship is assumed between EV ownership and on-demand transportation mode use. However, an error correlation is incorporated to reflect the possible presence of correlated unobserved attributes affecting both outcomes.

In addition to the two behavioral outcomes of interest, the model system incorporates two latent attitudinal constructs. The first construct represents *car owning proclivity*. Figure 1 shows the distribution of respondents with respect to the attitudinal indicators that define this latent attitudinal construct. About 91 percent of this subsample consider owning a car important or very important. Car ownership is the second indicator defining this latent construct. The second latent construct captures the *environment-friendly lifestyle.* Two indicators capture this latent construct as shown in Figure 1. It is interesting to note that, even though 91 percent of respondents consider it important or very important to own a car, it is also seen that 95 percent consider it important or very important for their means of transportation to be environmentally friendly. About 52 percent of respondents indicate that they believe that EVs will replace conventional vehicles by 2030 and only 29 percent indicated that they did not agree with the statement. These two indicators define the environment-friendly lifestyle. The model framework adopted in this paper is described in the next section.

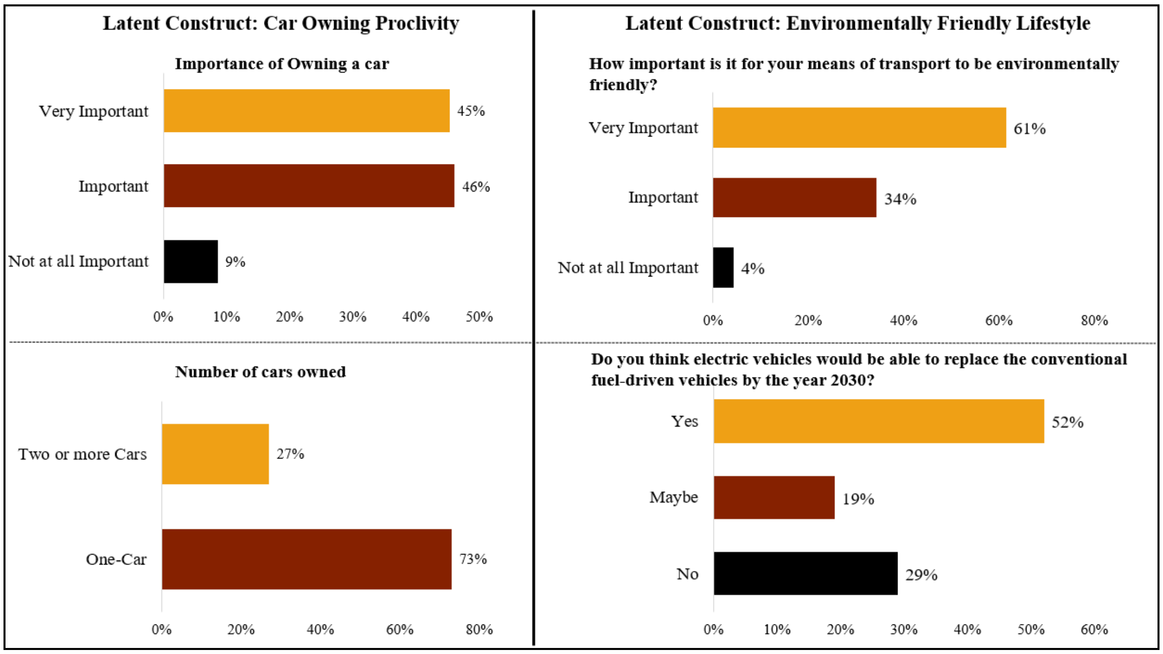

Figure 1. Indicator Variables Defining Two Latent Attitudinal Constructs

3.3. Modeling Framework

This section presents the model structure and the model estimation methodology employed in this chapter. The methodology accommodates multiple endogenous variables (that do not affect one another directly), multiple latent attitudinal factors that affect the endogenous variables and are themselves affected by socio-economic variables, and flexible error correlation structures accounting for the presence of correlated unobserved attributes that simultaneously affect multiple endogenous variables.

3.3.1. Model Structure

The model structure adopted in this study is shown in Figure 2. A host of socio-economic, demographic, and travel related attributes serve as exogenous variables. There are two latent stochastic constructs, namely, environment-friendly lifestyle and car-owning proclivity, with a possible error correlation between them. The environment-friendly lifestyle construct is defined by the importance of using environmentally friendly means of transportation and the belief that EVs will replace conventional vehicles by the year 2030. Car owning proclivity is characterized by two indicators, namely, the number of cars owned and the importance of owning a car. Both of these latent attitudinal constructs are influenced by exogenous variables, and in turn, influence the endogenous variables. The two endogenous variables include electric vehicle ownership (binary dependent variable: yes or no) and on-demand transportation user (binary dependent variable: never used or used rarely/frequently). Some consolidation of categories had to be done to define the endogenous variables in the model structure because of very small sample sizes in certain end categories. Thus, this model structure is a bivariate model with two binary dependent variables that do not affect one another directly. However, an error correlation between the endogenous variables accounts for the presence of correlated unobserved attributes that simultaneously impact the two endogenous variables of interest. The latent attitudinal constructs affect the endogenous variables. Through the modeling framework presented in Figure 2, it is possible to capture the influence of both socio-economic and attitudinal variables on the adoption of emerging transportation services and technologies. The entire model structure is estimated in a single step using a novel methodology capable of reflecting endogeneity and multiple error correlations. The methodology is presented in the next subsection.

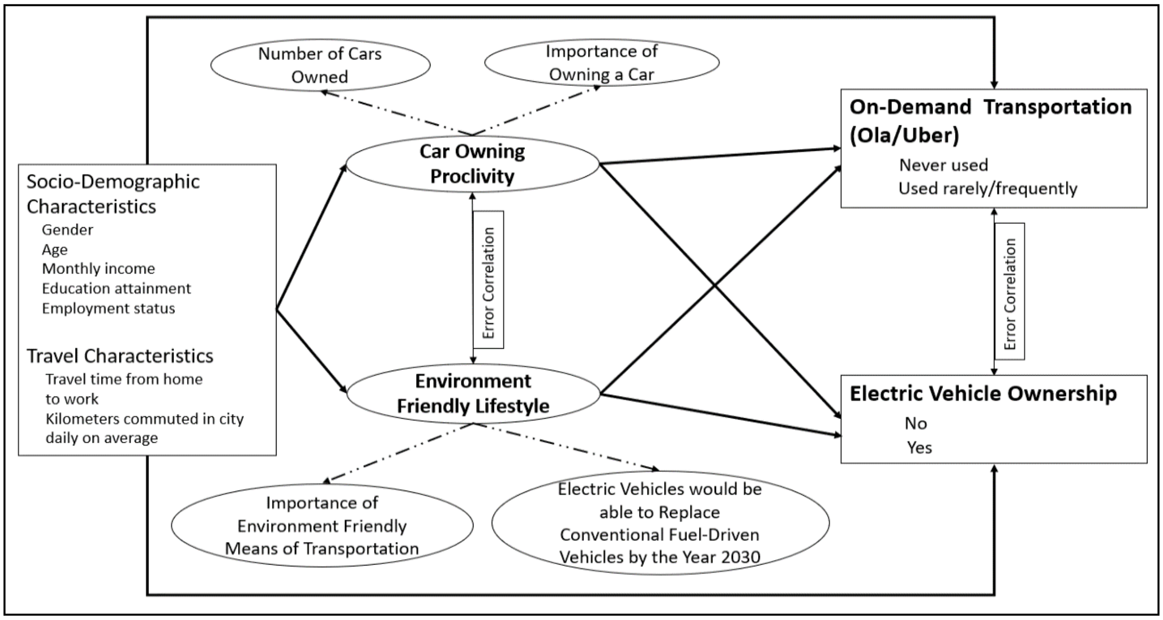

Figure 2. Structure of Integrated Choice and Latent Variable Model System

3.3.2. Model Estimation Methodology

In this section, the integrated choice and latent variable (ICLV) model, which has been proposed and applied for an unordered choice variable in the literature (e.g., Bhat and Dubey, 2014), is modified to accommodate multiple correlated binary choices as needed for this study.

The model formulation begins by assuming that there are "I" correlated ordered choice variables "c_i" (i = 1, 2, …, I) and their latent utility functions $u_i{}^*$ are formulated as:

$$u_i{}^* = x_i\beta_i + z^*\gamma_i + \varepsilon_i. \quad (6)$$

In the above equation, x_i is a row vector of observed explanatory variables and z^* is a row vector of latent psychological factors while β_i and γ_i are two column vectors of coefficients in the respective utility function. ε_i is a random component in each utility function and assumed to follow a standard multivariate normal distribution associated with a symmetric correlation matrix as:

$$cr = \begin{bmatrix} 1 & cr_{12} & \dots & cr_{1I} \\ cr_{12} & 1 & \dots & \dots \\ \dots & \dots & 1 & cr_{I-1,I} \\ cr_{1I} & \dots & cr_{I-1,I} & 1 \end{bmatrix}. \tag{7}$$

The utility function value of u_i^* will determine an ordered choice variable, denoted as c_i, based on comparisons against a number of ordinal thresholds, denoted as $\psi_{i,0}, \psi_{i,1}, \dots \psi_{i,M_i}$ ($\psi_{i,0} < \psi_{i,1} \dots < \psi_{i,M_i}$). Among those $(M_i + 1)$ thresholds, $\psi_{i,0} = -\infty$ and $\psi_{i,M_i} = +\infty$. When $\psi_{i,m-1} < u_i^* < \psi_{i,m}$, the ordered choice variable c_i takes the value "m" from the choice set $\{1,2,\dots, M_i\}$. Note that a binary choice can be considered as a special case of ordered choices, where M_i takes the value of "2" and the choice set is $\{1, 2\}$.

In Equation (6), the row vector of latent psychological factors z^* contains "J" elements, each of which can be denoted as z_j^* (j = 1, 2, …, J) and formulated as:

$$z_j^* = w_j \alpha_j + \eta_j. \tag{8}$$

In the above formula, w_j is a row vector of observed variables to explain z_j^* and α_j is a column vector of coefficients. η_j is a random component in the model and assumed to follow a standard multivariate normal distribution associated with a symmetric correlation matrix as:

$$zr = \begin{bmatrix} 1 & zr_{12} & \dots & zr_{1J} \\ zr_{12} & 1 & \dots & \dots \\ \dots & \dots & 1 & zr_{J-1,J} \\ zr_{1J} & \dots & zr_{J-1,J} & 1 \end{bmatrix}. \tag{9}$$

Each latent psychological factor $z_j{}^*$ can influence one or more latent propensity function values, which in turn determine the same number of observed ordinal indicators (e.g., the extent to which one agrees on a certain statement). In total, there are "K" such latent propensity function values, which are denoted as $y_1{}^*$, $y_2{}^*$,…, $y_K{}^*$ and laterally combined to form a row vector y^*. The relation between z^* and y^* can be expressed as:

$$y^* = z^* \cdot \mathrm{z2y} \cdot d + \xi. \tag{10}$$

In the above formula, "$z2y$" is a dummy matrix of J rows and K columns, indicating whether a factor in z^* influences a latent propensity value in y^*. When an element in j[th] row and k[th] column of the matrix takes the value of "1", the j[th] factor in z^* does influence the k[th] propensity value in y^*. When it takes the value of "0", there is no influence. For example, $z2y = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, indicating that there are two psychological factors and three ordinal indicators, where the first factor influences the first and second propensity values and the second factor influences the third value. Then, d is a column vector of K loading factors while ξ is a row vector of random components following independent standard normal distribution.

The propensity function values of $y_k{}^*$ will determine an observed ordinal indicator, denoted as y_k, based on comparisons against a number of ordinal thresholds, denoted as $\theta_{k,0}, \theta_{k,1}, \dots \theta_{k,N_k}$ ($\theta_{k,0} < \theta_{k,1} \dots < \theta_{k,N_k}$). Among those $(N_k + 1)$ thresholds, $\theta_{k,0} = -\infty$ and $\theta_{k,N_k} = +\infty$. When $\theta_{k,n-1} < y_i{}^* < \theta_{k,n}$, the ordinal indicator takes the value "n" from the set $\{1,2,\dots, N_k\}$.

To *estimate the model*, the latent variables in Equation (8) can be substituted into Equations (6) and (10) to obtain new equations as below:

$$u_i{}^* = x_i\beta_i + \sum_{j=1}^{J}(w_j\boldsymbol{\alpha_j} + \eta_j)\gamma_{ij} + \varepsilon_i = x_i\beta_i + \sum_{j=1}^{J}(w_j\boldsymbol{\alpha_j}\gamma_{ij}) + \sum_{j=1}^{J}(\eta_j\gamma_{ij}) + \varepsilon_i$$

$$= V_i + \textstyle\sum_{j=1}^{J}(\eta_j\gamma_{ij}) + \varepsilon_i\ , \tag{11}$$

$$y_k{}^* = \sum_{j=1}^{J}(w_j\boldsymbol{\alpha_j} + \eta_j) \cdot \mathrm{z2y}_{jk} \cdot d_k + \xi_k$$

$$= \sum_{j=1}^{J}(w_j \cdot \boldsymbol{\alpha_j} \cdot \mathrm{z2y}_{jk} \cdot d_k) + \sum_{j=1}^{J}(\eta_j \cdot \mathrm{z2y}_{jk} \cdot d_k) + \xi_k$$

$$= T_k + \textstyle\sum_{j=1}^{J}(\eta_j \cdot \mathrm{z2y}_{jk} \cdot d_k) + \xi_k\ . \tag{12}$$

Thus, the variance-covariance matrix $COV(u_i{}^*) = \Lambda' \cdot zr \cdot \Lambda + cr = COV1$, where $\Lambda = [\gamma_1, \gamma_2, \dots, \gamma_I]$, a matrix formed by laterally combining the column vectors γ_i. The variance-covariance matrix $COV(u_i{}^*, y_k{}^*) = \Lambda' \cdot zr \cdot z2y * d' = COV2$, where "$\cdot$" represents matrix multiplication and "$*$" represents element-wise multiplication. The variance-covariance matrix $COV(y_k{}^*) = (\mathrm{d} * \mathrm{z2y}') \cdot zr \cdot (\mathrm{z2y} * \mathrm{d}') = COV3$. By comparing latent variables (i.e., $u_i{}^*$ or $y_k{}^*$) against corresponding thresholds, ordered choices or ordinal indicator values can be determined while random components in latent variables follow a multivariate normal distribution associated with covariance matrices $COV1$, $COV2$ and $COV3$. Thus, a multivariate ordered probit model can be formulated, and a composite maximum likelihood estimation method (CML) can be employed for model estimation. The composite likelihood function consists of three parts that incorporate all of the coefficients to be estimated.

The first part is formulated to incorporate coefficients in $COV1$ as:

$$\mathrm{LL}_1(\cdot) = \textstyle\sum_{i=1}^{I-1}\sum_{j=i+1}^{I}\sum_{m=1}^{M_i}\sum_{n=1}^{M_j}\{I(c_i = m) \cdot I(c_j = n) \cdot \ln\left[P(c_i = m, c_j = n)\right]\}.$$

(13)

In the above formula, $P\left(c_i = m, c_j = n\right)$ represents the joint choice probability from a bivariate ordered probit model and can be expressed as:

$$\Phi_2\left[\delta_i\left(\psi_{i,m} - V_i\right), \delta_j\left(\psi_{j,n} - V_j\right), \delta_i\delta_j\rho_{ij}\right] - \Phi_2\left[\delta_i\left(\psi_{i,m-1} - V_i\right), \delta_j\left(\psi_{j,n} - V_j\right), \delta_i\delta_j\rho_{ij}\right]$$

$$-\Phi_2\left[\delta_i\left(\psi_{i,m} - V_i\right), \delta_j\left(\psi_{j,n-1} - V_j\right), \delta_i\delta_j\rho_{ij}\right] + \Phi_2\left[\delta_i\left(\psi_{i,m-1} - V_i\right), \delta_j\left(\psi_{j,n-1} - V_j\right), \delta_i\delta_j\rho_{ij}\right],$$

(14)

where $\delta_i = \frac{1}{\sqrt{COV1_{ii}}}$, $\delta_j = \frac{1}{\sqrt{COV1_{jj}}}$, $\rho_{ij} = COV1_{ij}$ and $\Phi_2[x, y, \rho]$ is the cumulative distribution function of the standard bivariate normal distribution.

The second part is formulated to incorporate coefficients in $COV2$ as:

$$\mathrm{LL}_2(\cdot) = \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{m=1}^{M_i}\sum_{n=1}^{N_k}\{I(c_i = m) \cdot I(y_k = n) \cdot \ln\left[P(c_i = m, y_k = n)\right]\}.$$

(15)

In the above formula, $P(c_i = m, y_k = n)$ can be expressed as:

$$\Phi_2\left[\delta_i\left(\psi_{i,m} - V_i\right), \delta_k\left(\theta_{k,n} - T_k\right), \delta_i\delta_k\rho_{ik}\right] - \Phi_2\left[\delta_i\left(\psi_{i,m-1} - V_i\right), \delta_k\left(\theta_{k,n} - T_k\right), \delta_i\delta_k\rho_{ik}\right]$$

$$-\Phi_2\left[\delta_i\left(\psi_{i,m} - V_i\right), \delta_k\left(\theta_{k,n-1} - T_k\right), \delta_i\delta_k\rho_{ik}\right] + \Phi_2\left[\delta_i\left(\psi_{i,m-1} - V_i\right), \delta_k\left(\theta_{k,n-1} - T_k\right), \delta_i\delta_k\rho_{ik}\right],$$

(16)

where $\delta_i = \frac{1}{\sqrt{COV2_{ii}}}$, $\delta_k = \frac{1}{\sqrt{COV2_{kk}}}$, $\rho_{ik} = COV2_{ik}$.

The third part is formulated to incorporate coefficients in $COV3$ as:

$$\mathrm{LL}_3(\cdot) = \sum_{k=1}^{K-1}\sum_{j=k+1}^{K}\sum_{m=1}^{N_k}\sum_{n=1}^{N_j}\left\{I(y_k = m) \cdot I\left(y_j = n\right) \cdot \ln\left[P\left(y_k = m, y_j = n\right)\right]\right\}.$$

(17)

In the above formula, $P\left(y_k = m, y_j = n\right)$ can be expressed as:

$$\Phi_2\left[\delta_k\left(\theta_{k,m} - T_k\right), \delta_j\left(\theta_{j,n} - T_j\right), \delta_k\delta_j\rho_{kj}\right] - \Phi_2\left[\delta_k\left(\theta_{i,m-1} - T_k\right), \delta_j\left(\theta_{j,n} - T_j\right), \delta_k\delta_j\rho_{kj}\right]$$

$$-\Phi_2\left[\delta_k\left(\theta_{i,m}-T_k\right),\delta_j\left(\theta_{j,n-1}-T_j\right),\delta_k\delta_j\rho_{kj}\right]+\Phi_2\left[\delta_k\left(\theta_{i,m-1}-T_k\right),\delta_j\left(\theta_{j,n-1}-T_j\right),\delta_k\delta_j\rho_{kj}\right], \tag{18}$$

where $\delta_k=\frac{1}{\sqrt{COV3_{kk}}}$, $\delta_j=\frac{1}{\sqrt{COV3_{jj}}}$, $\rho_{kj}=COV3_{kj}$. When there are a large number of ordinal indicators and "K" takes a large integer value, it is unnecessary to incorporate all "K" ordinal indicators into Equation (12). Instead, a subset of representative indicators can be selected for each latent factor in z^* to form a new subset of ordinal indicators to compute $\mathrm{LL}_3(\cdot)$ and thereby achieve better computational efficiency. Finally, all three parts can be added to form a composite log-likelihood function with respect to all of the model coefficients as:

$$\mathrm{LL}(\alpha,\beta,\gamma,\mathrm{d},\psi,\theta,\mathrm{zr},\mathrm{cr})=\mathrm{LL}_1(\cdot)+\mathrm{LL}_2(\cdot)+\ \mathrm{LL}_3(\cdot). \tag{19}$$

The composite log-likelihood function above and its analytical gradient are coded in Gauss matrix programming platform (Aptech Systems, 2015), where the composite log-likelihood function can be maximized to consistently estimate all coefficients and a sandwich robust covariance matrix can be computed for statistical inferences on parameter estimates.

3.4. Model Estimation Results

Detailed model estimation results are presented in this section. The entire model system is estimated as a joint model through a methodological framework that enables parameter estimation in a single step while fully accounting for the endogeneity of latent attitudinal constructs. Estimation results are discussed separately for the latent construct model components and the dependent variable model components for ease of exposition.

3.4.1. Latent Construct Model Components

The latent construct model component estimation results are presented in Table 8. There are two latent attitudinal constructs, *car owning proclivity* and *environment-friendly lifestyle*, considered in this study. Factor loadings presented in Table 8 show that the indicators are appropriate and statistically significant in representing the latent attitudinal constructs. The number of cars owned, and the level of importance attached to owning a car are both exhibiting positive factor loadings for the latent factor representing car owning proclivity. Similarly, the importance of an environmentally friendly lifestyle and the belief that electric vehicles will replace conventional vehicles by 2030 load positively onto the latent factor representing an environment-friendly lifestyle. As expected, the latent factors are negatively correlated with one another as they represent and capture opposite dimensions.

A range of socio-economic and demographic characteristics affect these latent factors. Younger individuals are found to be less environmentally oriented, a finding that is somewhat counter to expectations as some literature has shown that younger individuals tend to be more environmentally conscious (Davis et al, 2012). But some recent studies (see Lavieri and Bhat, 2019; Gifford and Nilsson, 2014) also identify a decrease in the younger generation's environmental consciousness, suggesting that this may be the result of an increase in the importance of material pleasures among the young, as well as an increased level of optimism that technology will solve environmental problems. Also, there is recent evidence that suggests environmental consciousness is less about age, and more about level of awareness, information, and knowledge (Otto and Kaiser, 2014). Older individuals are more auto oriented and show a greater level of car owning proclivity; this is consistent with expectations and previous findings in the literature (Bansal and Kockelman, 2017). Those who are unemployed exhibit lower levels of car owning proclivity as well as environmentally friendly lifestyles; once again, this finding is consistent with prior research and reflects that unemployed individual do not have the income and information to lean positively towards either of these latent factors. Indeed, it is found that those with a lower income exhibit a lower level of environmental friendliness.

Table 8. Determinants of Latent Variables and Loadings on Indicators

	Car Owning Proclivity		Environment-Friendly Lifestyle	
	Estimate	t-stat	Estimate	t-stat
Exogenous Variables				
Age				
<20 years	—	—	-0.846	-3.624
≥60 years	0.189	1.441	—	—
Employment Status				
Unemployed	-0.355	-2.650	-0.544	-2.823
Monthly Income (Indian Rupees)				
<₹15,000	—	—	-0.611	-2.205
Travel time from home to work				
<15 min	-0.831	-6.395	0.438	2.725
≥60 min	0.490	3.320	-0.249	-2.072
Indicator Variables: Factor Loadings				
Number of cars owned	0.685	4.841	NA	NA
Importance of owning a car	0.214	1.861	NA	NA
Importance of environment friendly means of transportation	NA	NA	0.483	2.643
Electric vehicles would be able to replace the conventional fuel-driven vehicles by the year 2030	NA	NA	0.643	2.817
Thresholds for Indicator Variables (in order as listed above)				
Threshold 1-1	0.701	13.08	NA	NA
Threshold 2-1	-1.406	-32.35	NA	NA
Threshold 2-2	0.139	5.314	NA	NA
Threshold 3-1	NA	NA	-1.986	-12.92
Threshold 3-2	NA	NA	-0.384	-8.732
Threshold 4-1	NA	NA	-0.749	-8.755
Threshold 4-2	NA	NA	-0.137	-3.956
Error Correlation				
Car Owning Proclivity	NA	NA	-0.391	-2.530

Commute time has a significant influence on the latent factors. Those with short commutes to work may not feel a compelling need for an automobile and hence exhibit a lower level of car owning proclivity. They also exhibit a higher level of environmental friendliness. On the other hand, those with long commutes exhibit a greater proclivity for car ownership and lower levels of environmental friendliness. These findings are consistent with results reported in the literature (Ashalatha et al, 2013), where a close association between commute length and latent attitudinal factors towards car ownership and the environment have been reported (although the direction of causality remains open to debate).

3.4.2. Bivariate Model of Behavioral Outcomes

The bivariate model of on-demand transportation mode use and electric vehicle ownership is presented in Table 9. It should be noted that there is no direct effect between these two endogenous variables. In this particular model structure, there is no compelling reason or basis to assume that one endogenous variable directly affects the other. Therefore, rather than introduce a direct effect between the endogenous variables, the joint model specification and estimation procedure enables the computation of an error correlation between the endogenous variables to account for correlated unobserved attributes that may affect both behavioral dimensions of interest. In this instance, the error correlation is quite small, negative, and very weakly significant from a statistical standpoint. A variety of explanations are possible. For example, those who eschew mode sharing in favor of a lifestyle that emphasizes ownership are less likely to embrace on-demand transportation services. Note that neither of the latent constructs captures the proclivity towards *sharing* modes or vehicles; hence the effect of this proclivity is likely being captured in the error correlation. This unobserved attribute has an opposite effect on the two endogenous variables, thus engendering a negative correlation.

The latent constructs are found to affect both endogenous variables and are statistically significant. Car-owning proclivity decreases the probability of using on-demand transportation, as expected. On the other hand, an environment-friendly lifestyle increases the probability of embracing and using on-demand transportation services and owning an electric vehicle. Thus, bringing about greater environmental awareness and providing incentives for individuals to embrace an environmentally friendly lifestyle will help elevate the uptake of both on-demand (possibly shared) transportation services and electric vehicles.

The exogenous variables influence the endogenous variables along expected lines. Females are slightly more likely to use on-demand transportation services (consistent with recent research, e.g., International Finance Corporation, 2018; Alemi et al, 2018), although the coefficient is not statistically significant. In many developing countries, on-demand transportation services have provided mobility independence for females (who generally exhibit a much lower driver's license holding rate than males) (International Finance Corporation, 2018). Females are less likely to own EVs; this finding is consistent with the literature (e.g., Priessner et al, 2018) and is attributed to greater levels of range anxiety. Older individuals (more than 40 years of age), who are likely to have owned and used conventional vehicles for some time, are less likely to own EVs. Employed individuals, who are likely to have the monetary resources and need for personal cars (to facilitate commuting), exhibit a lower propensity to use on-demand transportation services and a lower propensity to own EVs (due to range and cost barriers). However, those in the highest income bracket exhibit a modestly higher inclination towards owning EVs (effect is statistically insignificant, but intuitive). Given the higher cost of EVs, this finding is consistent with expectations and the evidence to date regarding EV ownership trends (e.g., Tal and Nicholas, 2013). Lowest income individuals embrace on-demand transportation services, while those with higher incomes are less likely to use on-demand transportation services - largely because they own personal vehicles and do not have a need to rely on shared mobility services. Once again, these findings are consistent with those reported in the literature (Brown, 2018; Gehrke et al, 2019). However, there is some previous research that reports results contrary to our finding. A few studies have reported that high income individuals are more frequent users of ridehailing services relative to low-income individuals (e.g., Tirachini and Rio, 2019; Dias et al, 2017). A higher education attainment is associated with a lower proclivity towards on-demand transportation usage. Long commuting distances are associated with lower levels of on-demand transportation service usage (due to high cost to travel long distances using such services) and lower levels of EV ownership (due to concerns about driving range). These findings are consistent with prior research (Najya, 2019; Sun et al, 2017).

Table 9. Joint Model of On-Demand Transportation Use and EV Ownership

	On-Demand Transportation (Never used/Used)		Electric Vehicle Ownership (No/Yes)	
	Estimate	t-stat	Estimate	t-stat
Latent Constructs				
Car Owning Proclivity	-0.335	-3.063	—	—
Environment Friendly Lifestyle	1.835	2.065	0.994	1.842
Exogenous Variables				
Gender				
Female	0.100	1.536	-0.901	2.387
Age				
≥40 years	—	—	-1.022	-2.288
Employment Status				
Employed	-0.261	-3.106	-1.025	-2.340
Monthly Income (Indian Rupees)				
< ₹15,000	0.352	1.544	—	—
≥ ₹50,000	-0.499	-3.089	—	—
≥ ₹100,000	—	—	0.247	1.505
Education Attainment				
Post-graduate and above	-0.252	-3.151	—	—
Average Daily Commute Kilometers				
≥ 40 kms	-0.268	-3.163	-0.297	-1.431
Thresholds				
Threshold 1-1	1.153	13.29	NA	NA
Threshold 2-1	NA	NA	1.556	2.917
Error Correlations				
On-Demand Transportation Use	NA	NA	-0.042	-1.477
Model Statistics: Number of observations = 2,972 individuals Number of parameters = 39 Null Log-likelihood (only thresholds) =-55,449 Full Log-likelihood (joint model) = -46,630 Pseudo Rho-Squared = 0.159				

NA: Not applicable

"—" indicates that the variable is insignificant in the model

The joint model is found to offer a goodness-of-fit that is consistent with expectations for a model of this nature. In comparing the full log-likelihood of the joint model versus the null log-likelihood corresponding to a model with only thresholds, it is found that the specification significantly enhances fit with a resulting pseudo ρ^2 value of 0.16. The joint model exhibits an even greater improvement in log-likelihood value relative to a naive specification that neglects the endogeneity of the latent attitudinal constructs (essentially treating them as exogenous variables similar to socio-economic and demographic variables).

3.5. Study Implications and Conclusions

Many rapidly developing countries around the world are at a crossroads when it comes to transportation, air quality, and sustainability. On the one hand, rapid economic development is leading to rising incomes, and higher levels of car ownership and use. On the other hand, this increase in car ownership and use is leading to negative externalities in the form of congestion, air pollution, and rapid growth in energy consumption. Rapid innovation in the transportation sector offers hope to break this vicious cycle of growth in car ownership and use. In the past several years in particular, there have been rapid developments in two key areas - namely, the emergence of on-demand mobility services (such as Uber and Ola) and the rapid development and evolution of battery electric vehicles that no longer depend on fossil fuels for energy. India is a rapidly growing economy that is experiencing all of the ill-effects of rapid growth in car ownership and use and could therefore benefit from increased adoption of transportation innovations that are sustainable.

This chapter is concerned with identifying factors that contribute to the adoption of on-demand transportation services and electric vehicle (EV) ownership in the Indian context. While there is an extensive and growing body of research related to these transportation innovations in the developed world, evidence-based research on these topics remains sparse in the Indian context. Using a unique survey data set collected in 2018 from a sample of 43,000 respondents spread across 20 cities in India, this chapter develops a holistic integrated modeling framework to shed light on the factors that affect adoption of on-demand transportation services and electric vehicles in India. In particular, not only does this paper consider the socio-economic and demographic variables that affect these behavioral choices, but the study places a special emphasis on understanding the important role played by attitudes, values, and perceptions in determining adoption of on-demand transportation services and EVs.

The model constitutes a simultaneous equations model with latent attitudinal constructs that are themselves endogenous and dependent on socio-economic and demographic variables. Thus, the model includes two endogenous variables of interest (adoption of on-demand transportation services and EV ownership), both of which are binary in nature. In addition, the model system incorporates two attitudinal constructs that are represented by attitudinal indicators. One latent construct captures the car owning proclivity of the individual while the other latent construct captures the environmentally friendly lifestyle orientation of the individual. Each latent attitudinal construct is mapped to a pair of attitudinal indicator variables in the survey data set.

The analysis focuses on a random subsample of 2972 respondents, all of whom report owning at least one car. It is found that only seven percent of this subsample owns an EV, and only nine percent use on-demand transportation services such as Uber and Ola. Thus, the uptake of these emerging mobility technologies remains quite low, and policies and interventions are needed to rapidly increase the adoption of these technologies. Within this subsample of car-owning individuals, 91 percent indicate that owning a car is important or very important. At the same time, however, 95 percent indicate that it is important or very important for their means of transport to be environmentally friendly. Just over one-half of this subsample believes that EVs will replace conventional vehicles by 2030. In other words, there is a strong interest and optimism in environmentally friendly versions of private transportation. It is also found that EVs are largely owned by individuals in the highest income category (due to cost), and that certain groups such as females, employed individuals, and long-distance commuters are less likely to own an EV. This is very likely to stem from range anxiety and concerns related to the ability to recharge the EV battery when away from home in the middle of a trip.

Results of the joint model system suggest that subsidies and rebates for purchase of EVs may help enhance market adoption. Individuals outside of the highest income bracket report lower levels of EV ownership; hence affordability is a key determinant of EV adoption and subsidies can help advance EV ownership among a larger segment of the Indian middle class. Second, cities across the country need to invest in charging infrastructure to alleviate range anxiety. As many residents in India may not be able to charge EVs at home (due to the nature of the housing unit, e.g., apartments), the ability to charge at the office, businesses, stores, restaurants, and other EV charging depots may go a long way in enhancing EV adoption. Finally, it is found that attitudes and values significantly affect the use of on-demand transportation services and EV ownership. Influencing attitudes and values through information and awareness campaigns, free trial experiences, and real-world demonstrations may prove helpful in advancing more sustainable vehicular ownership and use. On-demand transportation services are gaining in usage but are not necessarily sustainable unless the vehicles are battery powered and rides are shared. The simultaneous equations model estimated in this study shows that those who are more environmentally friendly in their lifestyle preferences are more likely to embrace both of these innovations than others. As such, information campaigns that bring about greater environmental friendliness and awareness among people would help motivate higher levels of adoption of on-demand transportation services (thus reducing reliance on privately owned vehicles) as well as ownership of EVs (if vehicle ownership is desired by the individual/household). Through the implementation of these mechanisms, coupled with investments in alternative modes of transportation that afford a high level of service (e.g., Metro systems, bus rapid transit, dedicated bus lanes), India can advance the cause of sustainable transportation.

4. DEVELOPMENT OF AN INTEGRATED TRANSPORT AND RESIDENTIAL ENERGY CONSUMPTION MODEL SYSTEM

4.1. Introduction

The US Environmental Protection Agency (EPA) estimates that the nation's transportation, commercial, and residential sectors contributed 29, 19, and 21 percent respectively, of the total greenhouse gas (GHG) emissions in 2016 (EIA, 2017), indicating that human activity plays a significant role in shaping the carbon footprint in communities and cities. It is therefore of considerable importance to quantify the consumption of energy that is attributable to each of these sectors, as the energy consumption patterns directly translate into GHG emissions that contribute to global climate extremes. In an effort to address this need, this chapter presents an integrated model system that can be used to compute the household energy footprint.

Within the scope of this paper, household energy footprint is assumed to comprise of two main components. The first component is the *transport energy consumption,* and the second component is the *residential energy consumption* that stems from electricity, natural gas, and other utility expenditures. The transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which each of the different vehicles in a household is driven. The residential energy footprint primarily stems from the consumption of electricity and natural gas, although other fuel sources may also contribute to a household's utility expenditure pattern. The scope of analysis of residential energy footprint can be very broad depending on the extent of the supply chain that is considered and the extent to which embedded energy is included in the accounting system. For purposes of quantifying and characterizing the residential energy footprint in this paper, only the actual operational energy consumption (utility expenditures) is considered. The total household (operational) energy footprint may then be viewed as a sum of the transport energy consumption and residential energy consumption, with both components accounting only for the operational energy consumption within the respective domains.

There is a relationship, however, between residential and transport energy consumption. The residential energy consumption may be posited as being influenced by activity-travel characteristics of household members. If household members travel extensively outside the home, then the residential energy consumption may decrease if the households take necessary energy saving precautions when they are not at home. Such households may have large transportation energy footprints and smaller residential energy footprints. Conversely, households that spend a lot of time at home may have smaller transport energy footprints, but larger residential energy footprints. The estimation of the household energy footprint should take into account the potential relationship that may exist between transport and residential energy footprint.

Despite considerable work in this area, an integrated model of household energy footprint that accounts for the relationship between transport and residential energy consumption remains elusive. This chapter aims to fill this critical gap by presenting a comprehensive integrated model system and energy analysis tool that can be used to quantify the total household energy footprint, including the separate transport and residential energy consumption components.

The model system is developed through a multi-step process that involves fusing information contained in the 2017 National Household Travel Survey (NHTS) data set (which includes detailed vehicle and travel information) and the 2015 Residential Energy

Consumption Survey (RECS) data set (which includes detailed residential energy-related information). The model system involves computing the transport energy footprint based on household vehicle mix and miles of travel, and then computing both electricity and natural gas consumption while explicitly accounting for the influence that activity-travel behavior may have on the residential energy consumption patterns.

The remainder of this chapter is organized as follows. The next section offers an overview of the work in this topic area. The third section presents a brief overview of the two data sets used and fused in this study. The fourth section offers a detailed description of the integrated modeling framework and methodology. The fifth section presents an illustrative application of the model system to a synthetic population for the Greater Phoenix area in Arizona. The sixth and final section offers concluding remarks.

4.2. Understanding And Quantifying the Household Energy Footprint

There is a vast body of literature devoted to analyzing and quantifying energy consumption patterns of various entities. However, modeling tools developed thus far do not explicitly account for inter-dependencies among constituent energy consumption components that are vital to forecasting the energy footprint in response to changes in population characteristics and built environment conditions, technology, transportation network attributes, and public policies.

Many studies have focused on developing activity-based residential energy consumption models to improve energy efficiency or reduce demand during peak periods (e.g., Widen et al, 2009). Widen et al (2009) developed a daily electricity and hot-water demand profiles from time-use data and visualized the energy use connected to everyday activities. Another study assessed the implication of time-saving appliances on household activity time use and energy use and found no evidence suggesting that ownership of time-saving appliances increases residential energy use (Brencuc and Young, 2009). Cheshmehzangi (2020) explored the impact of COVID-19 on household energy use in China and concluded that due to additional time spent at home, cooling/heating and entertainment use is likely to increase in longer term which, in turn, impact the household energy use. Reyna and Chester (2017) developed an archetype-based bottom-up engineering model to forecast electricity and natural gas consumption. Their findings indicated a substantial increase in residential energy demand between 2020 and 2060. Other studies in the domain have focused on understanding the factors that influence residential energy consumption patterns. It has been reported that spatial configuration and land use patterns are important determinants of residential energy consumption (e.g., Wang et al, 2016). Yang et al (2019) studied the impact of urbanization on China's residential energy consumption and found that increased urbanization leads to an increase in both urban and rural residential electricity consumption. Other studies (e.g., Goldstein et al, 2020; Belaid, 2019) have explored the influence of dwelling unit characteristics and size, household characteristics, and household behaviors on residential energy consumption. Variation in temperatures, especially due to global climate change, significantly influences residential energy consumption. More recently, Zhang et al (2018) applied a microsimulation-based approach to estimate residential energy consumption. The study involved the fusion and synthesis of data across energy and census data sets to estimate a model of residential energy consumption of the individual household. The work in this chapter is intended to extend that model in very significant ways by integrating transportation energy consumption and activity-travel behaviors to advance towards obtaining a holistic household energy footprint estimation model system.

Likewise, there is a vast body of work dedicated to measuring and quantifying transport energy consumption patterns without explicitly considering the implications for building related energy consumption. Auld et al (2019) integrated activity-based modeling with traffic simulation software POLARIS to study the impacts of connected autonomous vehicles (level 4-automation) deployment and found an increase in fuel use by 21 and 43 percent over a 30 to 50 percent reduction in value of travel time. Behavior, Energy, Autonomy, and Mobility (BEAM) modeling framework has been used to simulate plug-in electric vehicle (PEV) mobility, energy consumption, and spatiotemporal charging demand (Sheppard et al, 2017). Hensher (2008) utilized an integrated transport, land use, and environmental strategy simulation software to assess the influence of different policy measures such as carbon tax, variable user charges, fuel efficiency gains, and improvement in public transit on CO_2. The Automotive Deployment Options Projection Tool (ADOPT) has been developed to estimate the impact of vehicle technology improvement on petroleum use and greenhouse gas emissions (Brooker et al, 2015). Garikapati et al (2017) developed a framework to estimate household energy footprint at the traffic analysis zone (TAZ) level through an interface with a standard metropolitan travel demand model. They noted that any travel energy footprint calculation that does not account for variation in vehicle fleet mix distribution across space is likely to not only be erroneous, but also fail to provide the policy sensitivity that may be desired for analyzing alternative fuel vehicle scenarios (owing to evolution of technology, changes in the marketplace, or incentives and disincentives instituted through public policy interventions). Other efforts aimed at quantifying transport energy consumption include those by Tirumalachetty et al (2013) and Das and Parikh (2004). Within the same domain, the other line of research is focused on understanding the factors influencing the transportation energy consumption patterns. Brand et al (2019) assessed the impacts of lifestyle changes and transition to electric vehicles (EV) on transportation energy consumption. Disruptive transportation technologies offer a promising mobility future, but an uncertain energy consumption future. Wadud et al (2016) assessed the impact of autonomous vehicles on energy consumption and found that automation could double energy use or cut it to one-half of current levels under different scenarios. Similarly, Chen et al (2017) concluded that fuel consumption in an autonomous vehicle future would reduce by 45 percent under optimistic scenarios and increase by 30 percent under pessimistic scenarios. Another study assessed the energy implications of ride-hailing services in Austin and found that the energy use may increase by 41-90 percent compared to baseline, pre-ride hailing, personal travel conditions (Wenzel et al, 2019). Ding et al (2017) explored the impacts of the built environment on vehicle miles of travel (VMT) and energy consumption and found that vehicle energy consumption is inversely related to employment density and street connectivity.

To be sure, a few studies have attempted a more holistic and integrated approach to energy analysis; for example, Sekar et al (2018) utilized decomposition analysis to study the impact of changes in activity time use on energy consumption patterns. The authors find that lifestyle changes caused by technology contribute to shifts in energy use across sectors. Another study assessed the impact and benefits of vehicle-grid integration (VGI) on California's planned 2025 power system. The findings indicated that residential smart charging complemented by time-of-use tariffs are the policies to advance California dual plug-in-electric vehicle adoption and renewable energy goals (Szinai et al, 2020). Another study utilized regression-based analysis to simulate electricity and natural gas demand in response to a shift in commuting patterns brought in by policy interventions (Keirstead and Sivakumar, 2012). Kitou and Horvath (2003) developed a systems model to telework and concluded that telework has the potential to reduce emissions, but these reductions will be counterbalanced due to employees spending additional time at home. Despite these and many other advances (e.g., Sheppard et al, 2017) in the development of energy modeling tools, an integrated model system that considers the inter-relationship between transport and residential energy consumption in computing a household energy footprint remains elusive; this effort is intended to fill this gap.

4.3. The Transport and Residential Energy Survey Data Sets

An integrated transport and residential energy analysis tool require information from two major survey data sets as explained previously. Transportation, activity participation, and vehicle fleet related information need to come from a travel survey data set while residential energy consumption information needs to come from an energy survey data set. For the development of the integrated model, the two data sets used in this study are the 2017 National Household Travel Survey (NHTS) data set and the 2015 Residential Energy Consumption Survey (RECS) data set. To control for geographic variations, the model development and application efforts utilized samples exclusively from the western region of the country in this study. The model system can be estimated, calibrated, and applied in any context using appropriate geographically local data.

The National Household Travel Survey (NHTS) data set is derived from a large-scale travel survey conducted about every 8-10 years by the US Department of Transportation to understand and quantify travel undertaken by people on a daily basis. Respondent households are asked to furnish detailed information about household and person level socio-demographic characteristics, vehicles owned or leased by the household, and trips undertaken by each member of the household on a specific travel day. Thus, the NHTS is a rich source of information about vehicle ownership and fleet composition for households, which is precisely the information needed to compute the transport energy consumption of households.

The integrated model system includes a household vehicle fleet composition and utilization (VFCU) model so that energy estimates are sensitive to vehicle fleet mix. In this study, four vehicle types were considered: car, van, SUV, and truck. These four vehicle types were further subdivided according to age based on whether the vehicle is less than or equal to eight years old. Thus, there are a total of eight vehicle type categories; in addition, the motorcycle is added as a ninth vehicle category. A multiple discrete continuous extreme value (MDCEV) model of VFCU is developed in this effort to determine the mix of vehicle types that a household may own, together with the amount of mileage that each vehicle will be driven by the household on an annual basis (Bhat, 2008). Information about vehicle type and mileage is available in the NHTS, thus making it possible to estimate such a model. In addition, the NHTS provides detailed activity-travel information for each member of the household for a specific travel survey day. The activity-travel information is used to derive the total time that an individual spends outside home at various activity locations, time spent traveling, and time spent in home (although in-home activities are not explicitly recorded). By aggregating information about travel and activities across individuals within a household, it is possible to derive the total time spent outside home, inside home, and traveling for a household.

The Residential Energy Consumption Survey (RECS) data set is derived from a large-scale energy consumption survey that is conducted about every six years. The most recent edition of the RECS data set is of 2015 vintage and used in this study. Although the sample size is reasonably large (by survey design standards), the sample is rather small when compared with the sample size for the NHTS. The sample size utilized in this study comprises 1,555 households (with complete information) distributed across the western region of the country. Similar to the NHTS, the RECS data set includes information about the respondent household, together with detailed information about residential energy consumption – that can be used to estimate residential electricity and natural gas consumption models.

To account for potential inter-relationships between transport and residential energy consumption, the proposed integrated modeling framework involves imputing vehicle fleet composition and utilization (VFCU) information and activity-travel behavior information derived from the NHTS to the household records in RECS. The enhanced RECS data set can then be used to estimate residential energy consumption models that are sensitive to activity-time allocation patterns, VFCU, and transport energy consumption, as well as household characteristics, location attributes, climatic conditions, and housing unit characteristics.

Table 10 presents a summary of the two household samples. A slightly larger percent of households in the RECS data rent their home compared to the sample in the

NHTS data. The household income categories do not line up exactly between the two surveys; in the NHTS, nearly 30 percent of households make less than $35,000, while in the RECS, nearly 40 percent of households make less than $40,000. Over 85 percent of households in both data sets reside in urban areas. The distribution of the sample from a geographic perspective suggests there is significant differences in the spatial distribution of the samples across the western region, but the differences do not adversely affect the model development efforts described in this paper. Similarly, the two samples exhibit noticeable differences in distributions of household size, number of adults and children, and dwelling unit type. While these differences are noteworthy and merit some additional investigation, they do not adversely affect data fusion/imputation processes here because models are specified to account for such differences. In terms of other characteristics, nearly 50 percent of the households reside in hot-dry/mixed-dry conditions and about 36 percent of the households have three bedrooms. The table also furnishes descriptive statistics for square feet of residences.

4.4. Model Development and Estimation Results

This section of the chapter provides a summary of the model development and estimation process. The effort undertaken in this study can be broken down into two distinct phases. First, there is the model development phase in which information is fused between two data sets and models are estimated so that they can be applied to any region's population to quantify the household energy footprint. Thus, there is the data fusion and model estimation phase (Figure 3, Steps 1-4). Second, there is the model application phase (Figure 3, Step 5). In this phase, the efficacy of the model is demonstrated by applying the model system developed in the first phase to a real-world case study.

Table 10. Description of Household Characteristics (Western Region)

2017 National Household Travel Survey (NHTS) (N = 26,743 households)		2015 Residential Energy Consumption Survey (RECS) (N = 1,555 households)	
Variable	Value (%)	Variable	Value (%)
Home ownership		*Home ownership`*	
Own	72.4	Own	66.2
Rent	27.6	Rent	33.8
Annual Household income		*Annual Household income*	
Low (less than $35,000)	26.4	Low (less than $40,000)	35.9
Medium ($35,000 to $99,999)	41.9	Medium ($40,000 to $99,999)	37.0
High ($100,000 or more)	31.7	High ($100,000 or more)	27.1
Household in urban/rural area		*Household in urban/rural area*	
Urban	86.6	Urban	86.9
Rural	13.4	Rural	13.1
Region		*Region*	
Mountain West States	15.7	Mountain West States	30.2
Pacific States	84.3	Pacific West States	69.8
Household Size		*Household Size*	
One	31.8	One	20.1
Two	42.6	Two	37.2
Three or more	25.6	Three or more	42.7
No. of Adults in household (Age ≥ 18 y.o.)		*No. of Adults in household (Age ≥ 18 y.o.)*	
One	34.4	One	24.1
Two	54.6	Two	55.7
Three or more	11.0	Three or more	20.2
No. of children in household (Age ≤ 17 y.o.)		*No. of children in household (Age ≤ 17 y.o.)*	
Zero	84.4	Zero	65.6
One	8.2	One	14.2
Two or more	7.4	Two or more	20.2
*Housing unit type**		*Housing unit type*	
Detached	70.5	Detached	68.7
Attached	26.2	Attached	9.1
Apartment	3.3	Apartment	22.2
		Climatic Condition	
		Very Cold/Cold	22.8
		Hot-Dry/Mixed-Dry	48.2
		Hot-Humid/Mixed-humid	29.0
		Number of Bedrooms	
`		≤ One	12.0
		Two	25.9
		Three or more	36.1
		Four or more	26.0

Total Square Feet of Home (in square meters)	Min	Max	Mean
	228 (21.18)	7986 (741.92)	1862.6 (173.04)

**Housing unit type information is not available in 2017 NHTS and was imputed based on 2009 NHTS data.*

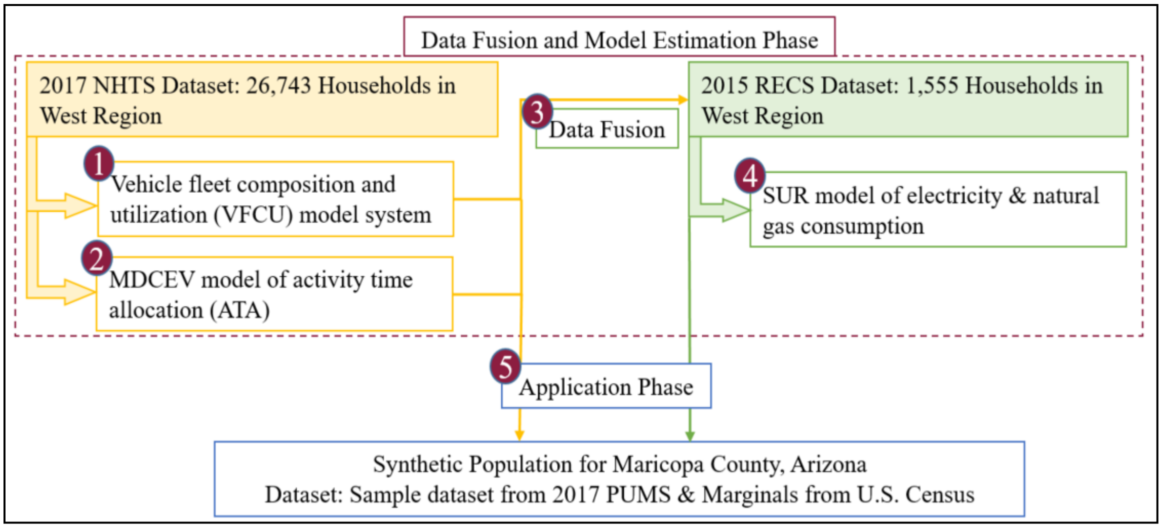

Figure 3. Model Development and Application Framework

An integrated model of transport and residential energy consumption should include components capable of estimating and quantifying:

- Transport energy consumption due to vehicle fleet mix and vehicle miles of travel
- Electricity consumption due to household operations
- Natural gas consumption due to household operations

The *first* step of the system development process involved estimating a vehicle fleet composition and utilization (VFCU) model system on the NHTS data set. The VFCU model system estimated and implemented here is similar to that developed previously (You et al, 2014). The model system includes a number of components:

a) A household mileage budget prediction model: The MDCEV model allocates a continuous household mileage to different vehicle alternatives, thus creating a vehicle fleet composition and mileage profile for each household. To accomplish this, a budget prediction model is needed. The mileage reported in the NHTS data is used to estimate a log-linear regression model of total household mileage.

b) A MDCEV model of vehicle fleet composition: The MDCEV model explicitly recognizes that households may choose to own and consume multiple vehicles of different types. A total of nine vehicle-type alternatives are considered in this study and the MDCEV model is estimated for this choice set. The model is capable of accounting for diminishing marginal utility (satiation effects) and zero consumption (corner solutions) wherein some vehicle alternatives may not be chosen by a household at all.

c) Ordered Probit models of vehicle counts by type: The MDCEV model is able to predict the types of vehicles that a household owns (consumes), but it does not explicitly provide the number of vehicles within each type that a household may own. For example, a household may own two cars that are less than eight years old. While the MDCEV model is able to predict that the household owns cars less than eight years old, it does not explicitly provide a count of the number of cars within that vehicle class. The ordered probit models of vehicle counts by type help establish the number of vehicles that are owned within each class of vehicles that the MDCEV predicts that a household owns.

This entire VFCU model stream was estimated on the NHTS sample for this study and the model was subjected to extensive testing and validation on a 20 percent holdout sample. A few additional steps explained in You et al (2014) were implemented to ensure that the model predictions matched real world vehicle fleet composition and utilization distributions. The model validation result on a 20 percent holdout sample is shown in Figure 4.

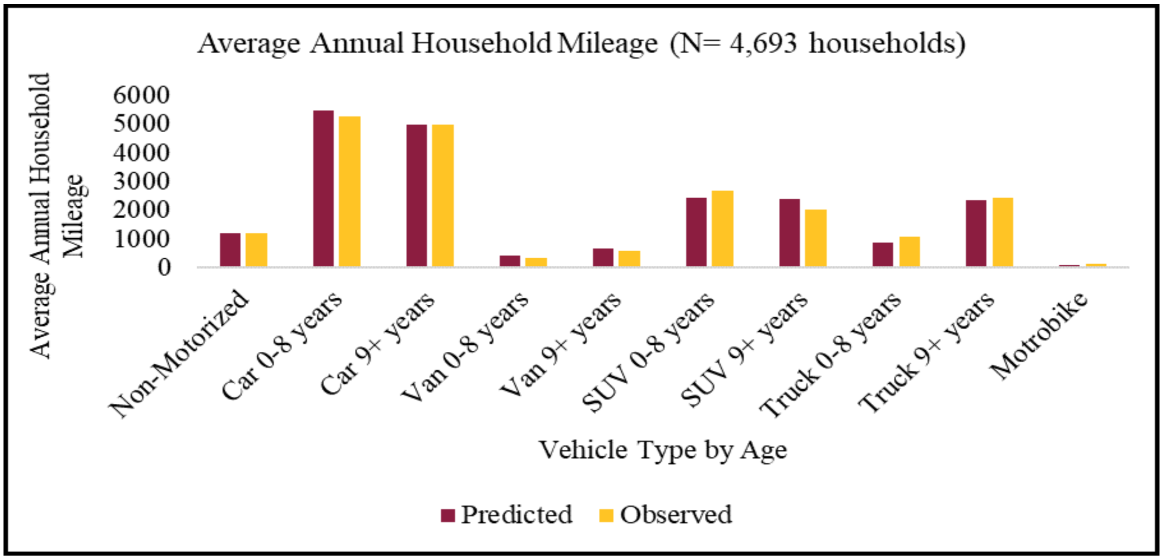

Figure 4. Average Annual Household Mileage Distribution

The *second* step of the process involved *estimating* a MDCEV model of activity time allocation (ATA). The activity time allocation model allocates a budget of 1440 minutes to various activity categories including out-of-home mandatory activity time (e.g., work, school), out-of-home non-mandatory activity time (e.g., social, shopping), in-home time, and travel time. Further, separate MDCEV time allocation models were estimated for weekdays and weekend days to account for the fact that individuals perform different activities by day of week with consequent implications on residential energy consumption patterns. The activity-travel diary information in the NHTS is used to compute these time durations for each household in the sample. The household time budget is assumed to equal *1440* × *number of adults in the household* × *number of weekdays/weekend-days in a year*. This budget is then allocated through a multiple discrete continuous choice process to the four broad activity categories. Because the budget is predetermined in the activity time allocation (ATA) context, there is no need for a model component dedicated to estimating the budget. The MDCEV-*predicted* time allocation patterns are compared against the *actual* patterns in a 20 percent holdout sample to calibrate and validate the model. The model validation results on a 20 percent holdout sample are shown in Figure 5 and Figure 6. The model was found to perform very well in replicating observed distributions of activity time allocation and was hence deemed appropriate for imputing activity time allocation patterns to households in the RECS data.

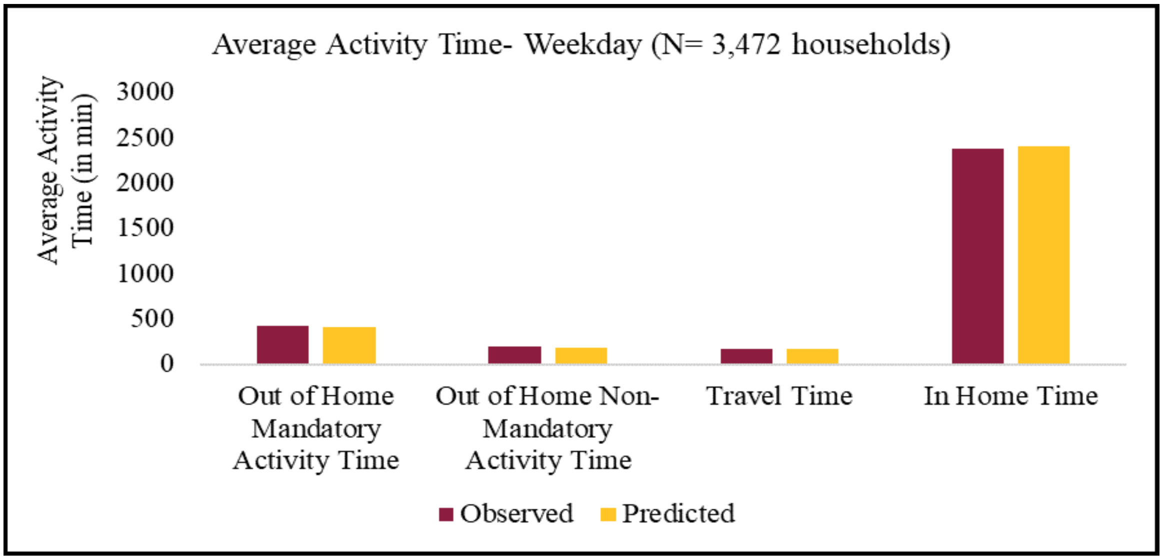

Figure 5. Average Activity Time- Weekday

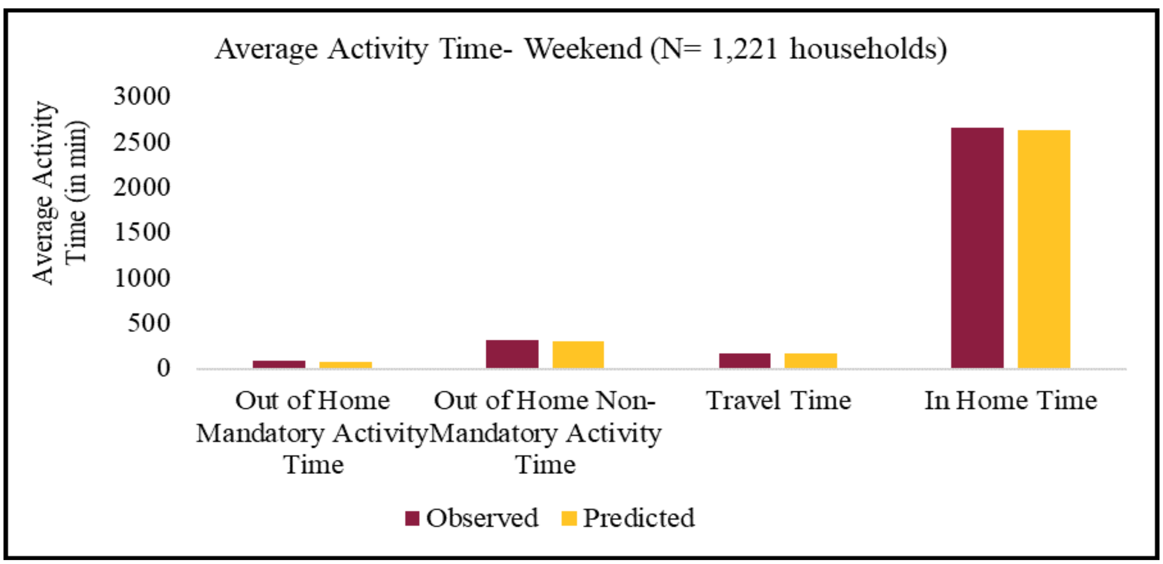

Figure 6. Average Activity Time – Weekend

The *third* step involved the *application* of the MDCEV model of vehicle fleet composition and utilization (estimated in Step 1) to the RECS data set to predict, impute, and append vehicle ownership and mileage information to the household records in the RECS data set. Similarly, the MDCEV model of activity time allocation was applied to the household records in the RECS data set to estimate and append the amount of time that each household devoted to various activity categories. It should be noted that all records in the RECS data set are household level records; hence the time allocation pattern predicted and appended corresponds to activity durations at the household level (for example, the time spent traveling corresponds to the total time spent traveling accumulated over all adult household members).

At the end of the *third* step, each RECS household record has vehicle fleet composition information and corresponding annual mileage values. These vehicle mileage values were converted into transportation energy consumption estimates using the fuel economy data published by the US Environmental Protection Agency (2018). Using *energy conversion factors,* the total BTU of transport energy consumption was computed for each household and appended to the records in the RECS data set. It should be noted that vehicle body type and age are explicitly considered in the computation of the transportation energy footprint.

The fully enhanced RECS data set now contains information about household characteristics, climatic conditions, and the housing unit (original variables contained in RECS), together with vehicle fleet composition and utilization information, transport energy consumption information, and household activity time allocation information. In the *fourth and final step*, this enhanced data set was used to estimate a seemingly unrelated regression (SUR) equations model of residential electricity and natural gas consumption (these variables are native to the RECS data set). The SUR model recognizes the presence of error correlation between the electricity and natural gas consumption utility expenditure which is embedded in the model system and incorporates activity time allocation variables as explanatory factors, thus capturing the potential inter-dependency between residential energy consumption and household time allocation to activities and travel (please refer to Zellner, 1962 for more details on the SUR model). Estimation results for the SUR model are presented in Table 11.

Table 11. Seemingly Unrelated Regression (SUR) Equations Model Estimation Results

Annual Electricity Consumption (in BTU) Regression Equation		*Annual Natural Gas Consumption (in BTU) Regression Equation*	
Explanatory Variable	**Coef (t-stat)**	**Explanatory Variable**	**Coef (t-stat)**
Constant	36829 (20.14)	Constant	-459.1 (-0.17)
Home Ownership = Owned	2645.6 (2.20)	Low Income Hhld (< $40,000)	-2772.7 (-1.83)
High Income Hhld (≥ $100,000)	1843.8 (1.70)	High Income Hhld (≥ $100,000)	2923.1 (1.73)
Number of Adults ≥ 3 (age ≥ 18)	3049.8 (2.53)	Number of Adults ≥ 3 (age ≥ 18)	2526.9 (1.47)
Housing unit type = Apartment	-10938.8 (-7.78)	Housing unit type = Apartment	-11446.2 (-6.36)
Location = Urban	-10933.2 (-7.78)	Location = Urban	17141.4 (8.67)
Region = Mountain	5971.6 (5.31)	Region = Mountain	12571.1 (7.92)
Climate = Mix-Humid	4404.9 (3.80)	Climate = Mix-Humid	-5056.4 (-3.12)
Number of Bedrooms = 1	-3500.1 (-2.01)	Number of Bedrooms ≥ 4	9028.9 (5.06)
Annual Out-of-Home Non-Mandatory Activity Duration (in min) × HHSize = 1	-0.055 (-2.85)	Annual Out-of-Home Non-Mandatory Activity Duration (in min) × HHSize ≥ 3	0.010 (2.40)
Annual Out-of-Home Non-Mandatory Activity Duration (in min) × HHSize ≥ 3	0.0094 (3.06)	Travel Time Duration (in min) × HHSize ≥ 3	0.013 (2.40)
Travel Time Duration (in min) × HH Size =1	-0.066 (-2.96)	Total square feet	5.949 (8.24)
Number of Observations: 1,555 households R-squared: 0.206		Number of Observations: 1,555 households R-squared: 0.293	

Model estimation results are behaviorally intuitive and consistent with expectations, potentially suggesting that the data imputed to RECS is consistent with patterns of energy consumption and household activity time allocation that are seen in the real world. In the electricity consumption regression equation, it is found that out-of-home non-mandatory activity time (e.g., time spent outside home shopping or socializing) negatively affects electricity consumption for one-person households, but positively for three or more person households. When the individual in a single-person household spends time outside home, there is presumably nobody at home – thus reducing energy consumption. Similar, finding emerge for out-of-home travel time for single person household. In a large household with three or more persons, it is possible that some individuals are at home (consuming energy) even when others in the household are pursuing activities outside home; indicating that multi-person households' activities might not be coordinated and synchronized in time and space (Schwanen et al, 2007; Gliebe and Koppelman, 2002), contributing to a larger energy consumption footprint. High-income households consume more electricity than other households (Goldstein et al, 2020), presumably because they can afford greater levels of consumption of goods and services (Sovacool, 2011; Loveday et al, 2008). Households with more adults consume more electricity (McLouglin et al, 2012). Homes in urban areas consume less electricity as do households in apartments. These tend to be smaller homes in urban locations and hence consume less energy (Glaeser and Kahn, 2010). Similarly, houses with one bedroom consume less electricity, a finding similar to that reported by Belaid et al (2019). Houses in mix-humid conditions and mountain regions tend to consume more electricity, presumably due to the need to run the air conditioning.

The equation for natural gas consumption reveals that Out-of-home time allocation for non-mandatory activities has a positive impact on natural gas consumption for larger households, similar to the finding for electricity consumption. The same pattern is seen for travel time as well. As household income increases, so does natural gas consumption, presumably due to higher levels of consumption of goods and services in high-income households (Davis and Muehlegger, 2010). Natural gas consumption also increases with number of adults in the household. Interestingly, it is found that homes in urban areas consume more natural gas as do homes in mountain regions. This may be reflective of the energy mix in homes located in these spatial contexts. As the number of bedrooms increases, energy consumption increases. Households in mix-humid condition tend to consume less natural gas, presumably because natural gas is often used for heating; and in mix-humid conditions, households may need more cooling that uses electricity rather than natural gas.

At the end of the four steps in the model development and estimation phase, an integrated model of transport and residential energy consumption that can be applied to a population of agents (households) is obtained (Figure 3, Step 5). The suite of models that comprise the integrated transport and residential energy analysis tool constitute the following:

a) MDCEV model of household vehicle fleet composition and utilization (mileage)
b) MDCEV model of household daily activity time allocation
c) Transport energy computation model utilizing energy intensity tables that provide conversion factors (EPA, 2018) to translate miles of household travel by various vehicle types to equivalent energy consumption
d) Residential energy consumption model (SUR model) of electricity and natural gas consumption

It should be noted that both NHTS and RECS are national data sets, and hence caution should be exercised when applying models estimated on large regional samples to individual jurisdictions (e.g., cities or counties). Unfortunately, the RECS data set is not quite large enough to support very localized model estimation efforts. Hence, in this study, the entire sample from the western region was used for model development purposes.

Given this geographic scope of the model estimation data set, it may be reasonable to apply the model to jurisdictions that fall squarely within the region. For illustrative purposes, the model was applied to the Greater Phoenix area in Arizona; this case study is described next.

4.5. Illustrative Case Study

The case study involved applying the model system to a synthetic population generated for Maricopa County (Greater Phoenix area) in Arizona and computing and mapping the energy footprint per household across the census tracts in the region. Synthetic population generation and energy computations may be done at any geographic resolution; the census tract is used here for illustrative purposes and convenience.

The case study region of Maricopa County, AZ, includes 916 census tracts and encompasses a population of 4,155,501 persons residing in 1,489,533 households in 2017. A synthetic population was generated for the region using a software package called PopGen (Konduri et al, 2016). PopGen creates a synthetic population for a region by weighting and expanding a sample data set such that the weighted sample is representative of the true population with respect to marginal distributions on a number of control variables of interest such as household size, household income, number of workers, number of children, person age, person gender, and person employment status. The marginal control distributions representing true population characteristics are typically obtained from the census or regional agency databases. The American Community Survey (ACS) Public Use Microdata Sample (PUMS) data serves as the seed sample which will be weighted and expanded to a full synthetic population that matches the marginal control distributions. For each census tract, the sample is weighted to match marginal control distributions on variables of interest, and then households are drawn according to weightbased probabilities to create a synthetic population that matches true population numbers. PopGen embeds an iterative proportional fitting (IPF) algorithm to obtain population-level joint distributions of control variables of interest at the census tract level, and an iterative proportional updating (IPU) algorithm that computes weights for sample household such that the weighted sample is representative of the control totals estimated through the IPF steps. Once the weights are computed, households are drawn probabilistically to generate a synthetic population on a census tract by tract basis. More details about PopGen algorithms can be found in Konduri et al (2016). Synthetic populations for all census tracts are combined to form the county-wide synthetic population of households and persons. As the sample records drawn into the synthetic population are derived from PUMS, the records are rich with information necessary to apply a model of the nature described in this paper.

The entire suite of models (Figure 3, Step 1-4) described in the previous section is applied to the synthetic population. First, the MDCEV model of vehicle fleet composition and utilization is applied; this provides the vehicle fleet mix and mileage for each household. Second, the MDCEV model of activity time allocation is applied; this provides the time spent by each household (as a whole) in various activity categories including in-home, out-of-home mandatory activities, out-of-home non-mandatory activities, and travel time. Note that the application of the MDCEV models requires that they be exercised in forecasting mode; the procedures described in Pinjari and Bhat (2021) are used to accomplish this. By the end of this step, each synthetic population household is appended with vehicle fleet composition and utilization as well as activity-time allocation information. Then, the energy intensity conversion factors are used to compute the transport energy consumption for each household. Finally, the SUR model of residential energy consumption is applied to compute residential electricity and natural gas consumption as a function of various factors, while accounting for the relationship between residential energy consumption and activity time allocation.

After the residential and transport energy footprints are computed for each household in the synthetic population, summaries are derived, and aggregate measures of energy consumption are calculated at the census tract level. The spatial distribution of energy consumption per household for census tracts in the Maricopa County, AZ, region is depicted. The first picture, Figure 7, depicts transport energy consumption, the second graphic, Figure 8, depicts residential energy consumption (sum of electricity and natural gas consumption), and the third map, Figure 9, displays total energy footprint obtained by adding up the residential and transport energy consumptions. The thematic maps reveal that total energy consumption is higher in more affluent, lower density outlying cities and towns. In general, a clear pattern can be seen across all three figures. Census tracts in the middle (urban core areas) are greener, while census tracts in outlying suburban areas and towns are more red (signifying a higher level of energy consumption per household). This pattern may emerge because of a number of reasons; households in outlying suburban areas are likely to be more affluent and residing in larger homes, have larger households, have higher vehicle ownership, and need to drive to reach destinations. Census tracts can be categorized into one of four groups, depending on where they fall – on average – compared to the overall region wide average energy footprint per household:

- HH: Both residential and transportation energy consumption per household is above the regional averages

- HL: Higher residential energy consumption and Lower transport energy consumption
- LH: Lower residential energy consumption and Higher transport energy consumption
- LL: Lower residential energy consumption and Lower transport energy consumption

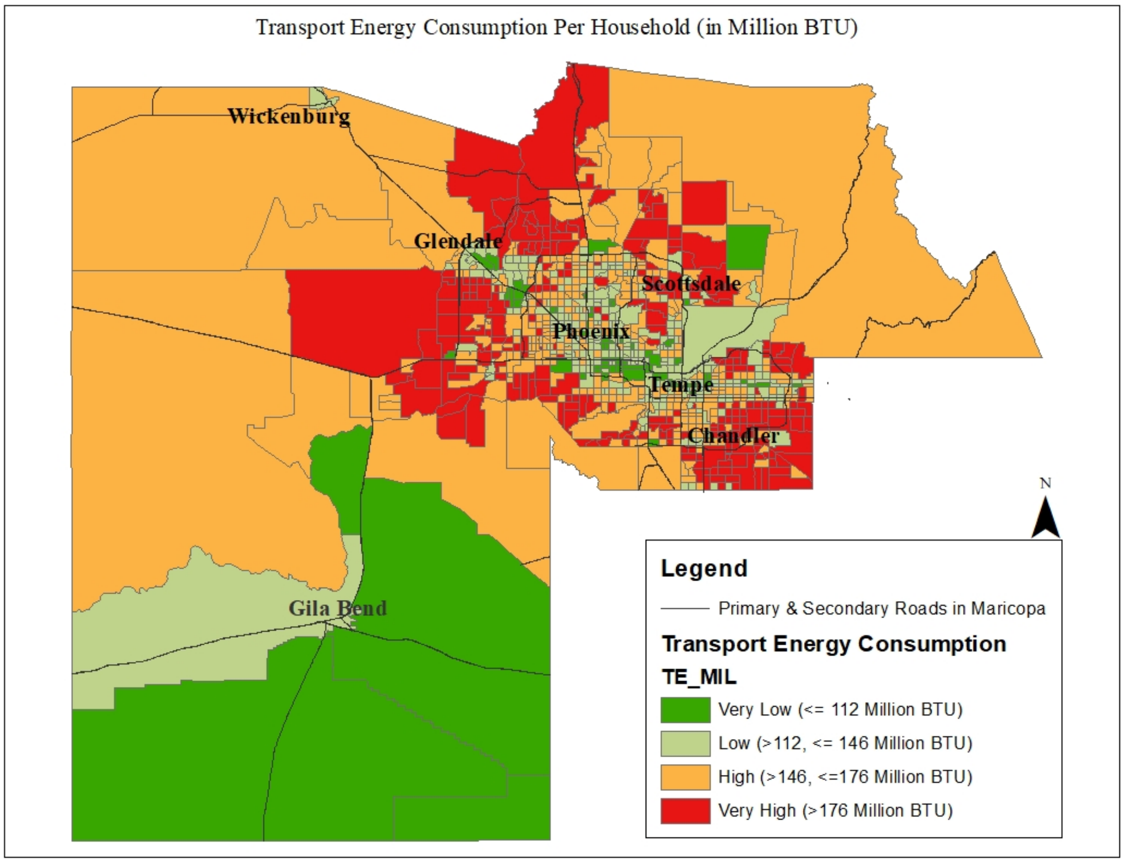

Figure 7. Visualization Map Depicting Transportation Energy Consumption in Greater Phoenix Metropolitan Area

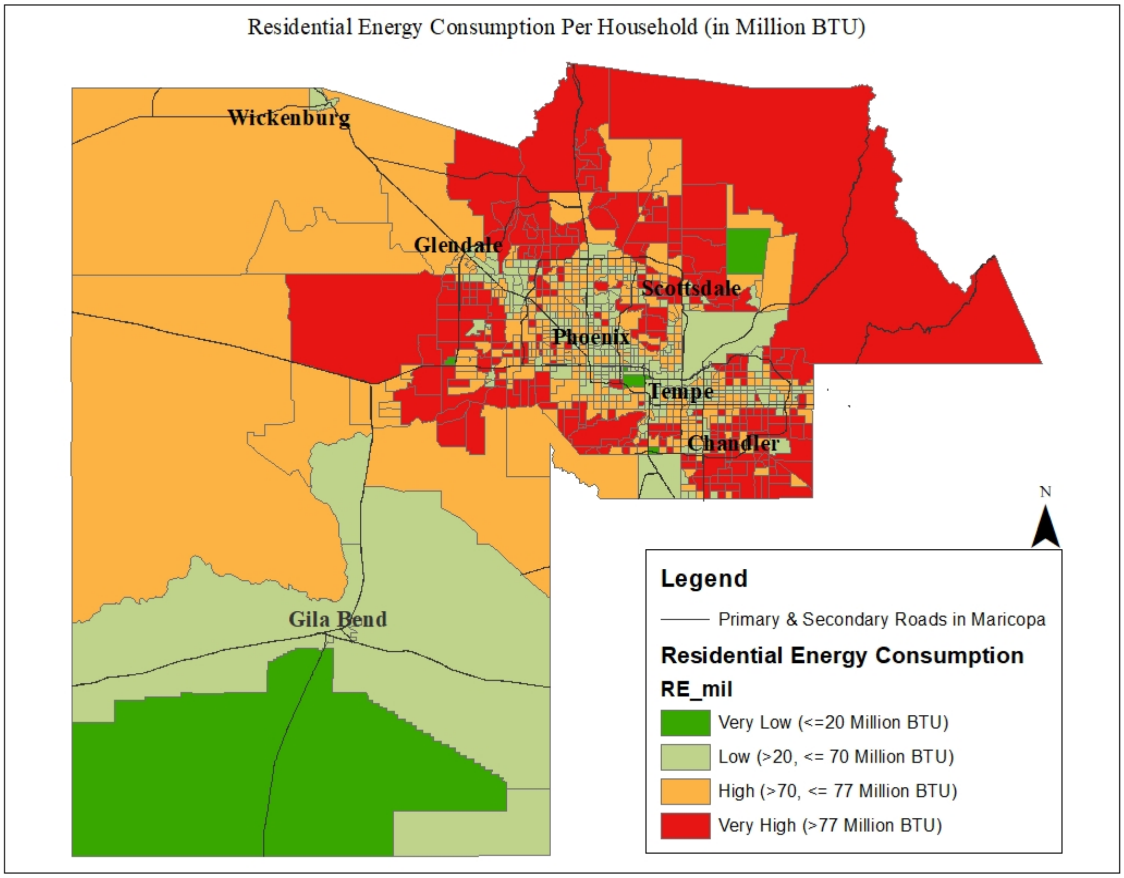

Figure 8. Visualization Map Depicting Residential Energy Consumption in Greater Phoenix Metropolitan Area

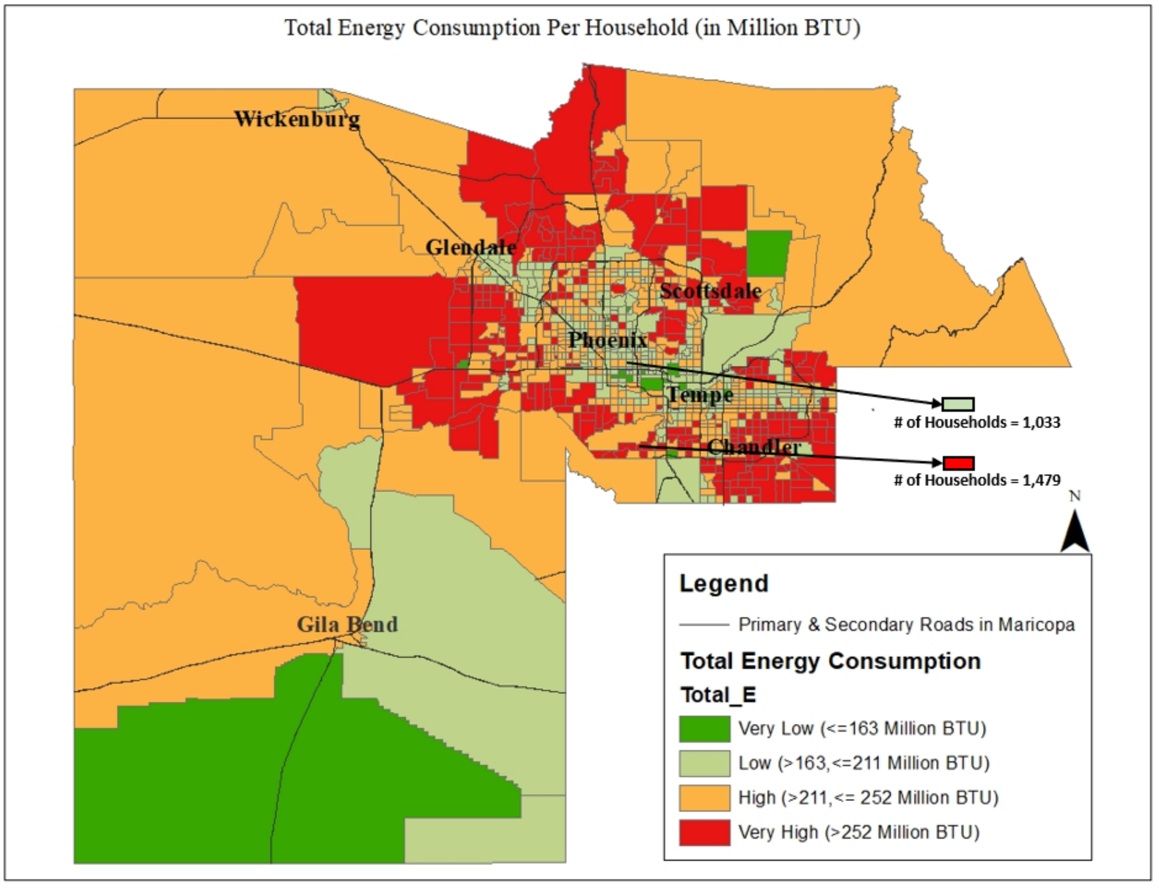

Figure 9. Visualization Map Depicting Total (Transportation and Residential) Household Energy Consumption in Greater Phoenix Metropolitan Area

The average annual energy footprints were computed to be 59,405,158 BTU of residential energy consumption and 119,604,797 BTU of transport energy consumption (per household). These numbers are generally consistent with expectations and match real-world energy consumption estimates (EIA, 2017).

Figure 10 shows a comparison between the HH and LL household segments. It can be seen that there are very clear differences between households that are high consumers of residential and transport energy and households that are low consumers of energy. Because the distributions of energy consumption are skewed, the size of each segment varies. While 17 percent of households fall into the HH segment, 40 percent of households fall into the LL segment. This is consistent with expectations as the average is likely to be impacted by outliers in the energy consumption spectrum. The comparison between the HH and LL segments shows a number of patterns, suggesting that the integrated model developed in this effort offers intuitively reasonable estimates of household energy footprint.

Households that are energy guzzlers have substantially higher incomes levels than households in the LL category. In fact, of the households in the HH category, nearly one-half belong to the high-income group. While 88 percent of households in the HH category own their homes, only 46 percent of households in the LL category do so. Among households in the HH category, 95 percent reside in detached housing units; the corresponding percent for households in the LL category is just 45 percent. Households in the LL category show substantially smaller household sizes, with about 40 percent of the households in this segment having only one person. Overall, it can be seen that household structure, composition, and income significantly impact household energy consumption patterns.

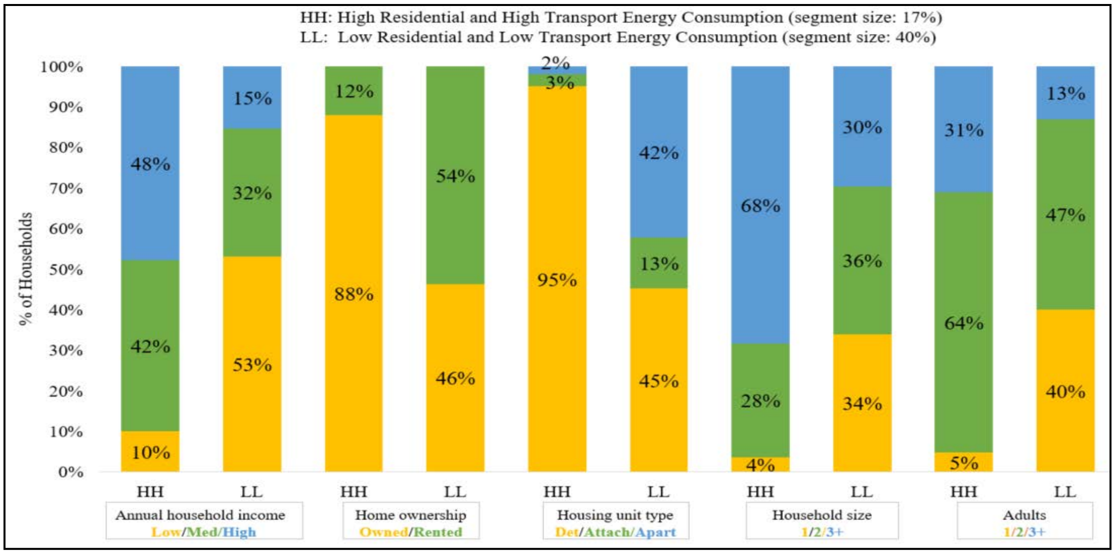

Figure 10. Comparison of Household Profiles Based on their Energy Consumption Bin

In the interest of brevity, the graph comparing HL and LH households is not shown in this chapter. However, some interesting differences are seen between these two groups of households. The HL segment (high residential and low transport energy consumption) comprises 26 percent of the population, while the LH segment comprises 17 percent of the households in the region. In general, households that have higher transport energy consumption tend to be larger and more affluent, which is to be expected given their higher activity levels.

To further illustrate the efficacy of the modeling tool presented in this paper, two census tracts that have different energy consumption profiles were compared. The two census tracts that were compared are highlighted in the third panel of Figure 9. One census tract has a low per-household energy consumption (L) while the other has a large per-household energy consumption (H). What makes households in one census tract to be higher energy consuming entities than households in another census tract? Households in the respective census tract were compared with respect to their attributes and the results are shown in Figure 11. Both census tracts have about an equal number of households. The census tract with high-energy consumption (H) has 1,476 households while the census tract with low total energy consumption (L) has 1,033 households. In other words, the number of households in the census tracts is not necessarily affecting the energy consumption per household. Rather, it is the attributes of the households that contribute to the differences.

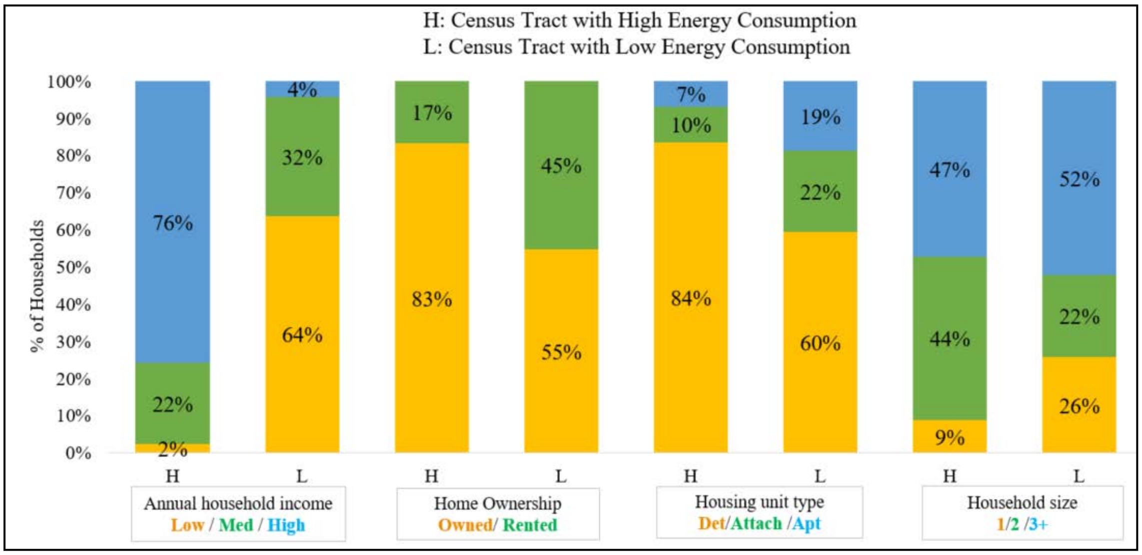

Figure 11. Comparison of Two Zones with Different Energy Consumption Profiles

As expected, a larger proportion of households in the high-energy consumption zone are owned (than in the lower energy consumption zone). The disparity in income distribution is extremely telling. While 64 percent of households in the low-energy consumption zone are low income, only 2 percent of households in the high-energy consumption zone fall into this income category. Similarly, high-energy consumption zone has a higher percent of detached single-family dwelling units than the low-energy consumption zone. The low-energy consumption zone has 26 percent single-person households while the high-energy consumption zone has only nine percent in this household size category.

It is clear that socio-economic and demographic characteristics as well as housing unit attributes significantly impact energy consumption patterns of households. In addition, built environment attributes, mix and density of land uses, and availability of multiple modes of transportation are likely to impact energy consumption footprints. The spatial patterns seen in Figure 9 suggest that density and access may be playing an important role in shaping energy consumption footprints as well. It would be valuable to determine the relative contributions of socio-economic/demographic factors on the one hand and built environment and multimodal access factors on the other hand, to the household energy footprint. By doing so, it would be possible to devise land use, housing, and transportation policy interventions that reduce the energy footprint and advance sustainable development patterns.

4.6. Discussion And Conclusions

The energy constituents are usually modeled separately and the factors influencing those consumption patterns are understood within the realm of respective domains. Human activities play a central piece in linking the consumption patterns across the energy sectors. A holistic integrated framework that accounts for the interrelationship among different energy consumption sectors is needed to devise effective policy measures in a rapidly evolving marketplace. This chapter presents an integrated transport and residential energy analysis tool that is capable of quantifying the transport energy consumption and residential energy consumption of an individual household. The motivation to build such a tool stem from the possible inter-relationships that may exist between these two energy consumption footprints. A household that travels more and spends more time outside the home is likely to have a high transport energy footprint but may have a lower residential energy footprint and vice versa. Only operational energy consumption is considered within the scope of the tool presented in this paper; energy consumed during travel is transport energy consumption and electricity and natural gas consumed at home constitute the residential energy consumption footprint.

In order to facilitate an integrated approach to residential and transport energy consumption analysis, detailed activity-travel and vehicle fleet composition and utilization information is modeled using the National Household Travel Survey (NHTS) data set and then applied to the Residential Energy Consumption Survey (RECS) data set to impute transportation related variables in the RECS data set. The enhanced RECS data set is then used to estimate regression equations of electricity and natural gas consumption that incorporate transport and activity time allocation related variables as explanatory factors. In general, it is found that household activity-time allocation patterns affect residential energy consumption, albeit differently for households of different sizes. While single-person households depict a clear trade-off between residential and transport energy consumption, larger households depict a more complementary (mutually reinforcing) relationship – suggesting that integrated models of household and transport energy consumption need to recognize heterogeneity in the nature of the relationships between them across the population of households in a region. In general, households that travel more are likely to have active lifestyles that also contribute to higher levels of residential energy consumption.

The integrated model system is applied to a synthetic population for the Greater Phoenix area in Arizona to demonstrate the efficacy of the model. The entire model stream is applied to the synthetic population to estimate transportation and residential energy consumption footprints for all households in the region. These computations facilitated the identification and comparison of different energy consumption market segments, and the findings are very intuitive with larger households, higher income households, households in detached single-family units, and households owning their home exhibiting higher levels of energy consumption. Households in outlying suburban areas depicted higher energy footprints, suggesting that the built environment may be playing some role in shaping energy consumption patterns. The tool presented in this chapter can be used to analyze the energy footprint implications of alternative urban designs and modal investments.

Admittedly, within the scope of this study, the outside home energy comprises of travel energy and not the energy that might be consumed while pursuing an activity at a location. This does limit the study to present a complete holistic picture, but the integrated modeling framework proposed in this paper can be extended to incorporate energy consumption beyond what is considered in this chapter. This will advance the field towards obtaining a holistic picture of household energy footprint which can then be used to analyze different policy scenarios. For example, is it beneficial to incentivize individuals to spend more time in locations where the energy supply is renewables? Or incentivizing individuals to spend more time in shared space? Further, independent residential and transportation energy consumption model might not be able to analyze such alternative policy scenarios highlighting the usefulness of integrated modeling frameworks.

5. MODELING IMPACTS OF ELECTRIC VEHICLES (EV) ADOPTION AND UTILIZATION ON HOUSEHOLD ENERGY CONSUMPTION

5.1. Introduction

Many countries around the world are at the crossroads when it comes to transportation, air quality, and sustainability. In the United States, transportation sector accounts for 40 percent of total emissions, with light-duty vehicles being the major contributor (US Environment Protection Agency, 2019). This has pushed for regulations and programs that encourages the transitions from internal combustion vehicle engine to battery electric vehicles and plug-in hybrid electric vehicles. The current estimates indicate that about 2 million battery electric vehicles have been sold in the U.S. since 2010 (Argonne, 2021) and the forecast suggest that EVs will account for about 60 percent of new car sales in US by 2040 (*Electric Vehicle Outlook*, *2017*). The International Council on Clean Transportation (ICCT) notes that battery electric vehicles, for example, have the lowest lifecycle GHG emissions, both today and into the foreseeable future (Muncrief**,** 2021), which will advance the goals to decarbonize transport sector.

The profession has heavily gravitated towards exploring the factors that impact households and vehicle-level vehicle miles travelled (VMT), mainly due to the contribution of VMT to traffic congestion, emission, and energy /fuel consumption (Roy et al, 2020). Transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which different vehicles in the households are driven. There are a number of studies that are aimed at understanding factors that influence adoption of electric vehicles (EVs) (e.g., Dua et al, 2021; Shalender and Sharma, 2020; Langbroek, 2016), but there is limited work focusing on ownership and use of EVs among households that actually own one or more EVs. Given the elasticity associated with fuel cost and motivation to own EVs, one would expect that consumers will maximize the utilization of electric vehicles. However, some studies have shown that EVs are utilized less than gasoline vehicles, while some indicated otherwise. For instance, Burlig et al (2021) utilized the Pacific Gas and Electric Company residential consumer data and electric vehicle registration data from California Department of Motor Vehicles to quantify EV usage patterns. The findings indicated that electric vehicles travel 5,300 miles per year, under half of the US fleet average. Similarly, Davis (2019) concluded that electric vehicles are driven less than gasoline vehicles. On the contrary, recently, Chakraborty et al (2021) utilized the unique repeat survey of Plug-in electric vehicles owners in California and found that PEVs are driven the same amount as conventional vehicles are, not less as some studies have shown. Most household travel surveys have few, if any, records of households that own EVs, thus rendering it difficult to analyze the usage of EVs relative to gasoline vehicles. Using data from the 2017 National Household Travel Survey, this study attempts to fill this critical gap by presenting a comprehensive comparison of the utilization patterns of electric vehicles relative to gasoline vehicles.

If electric vehicles were to be utilized more than gasoline vehicles, that may negate some of the benefits associated with transition to an EV future. It is expected that EVs will yield lower energy consumption per mile which will, in turn, decrease carbon emissions from the transport sector. However, wide scale adoption and utilization of electric vehicles could significantly increase total electricity demand (Moon et al, 2018) as about 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021). In other words, increased EV ownership and utilization might offset or tradeoff the benefits associated with transitioning to an EV future. To account for these inter-relationships and tradeoffs, a data fusion across two datasets, namely, 2017 National Household Travel Survey and 2015 Residential Energy Consumption Survey, is performed to understand the implications of electric vehicle ownership and utilization on household energy consumption. This study utilizes the integrated transport and residential energy consumption modeling framework, developed in *Chapter four*, to understand the implications of electric vehicles on household energy consumption. The resulting integrated transport and residential energy consumption model system will shed light on the overall household energy footprint implications of shifting vehicle/fuel type choices.

The remainder of this chapter is organized as follows. The next section provides a detailed description of the survey and data set used in this study. The third section presents descriptive results exploring the differences between electric and gasoline vehicles and its implication on residential energy consumption. A discussion of the findings and conclusions is furnished in the fourth and final section.

5.2. Dataset Description

The data for this study is derived from the 2017 National Household Survey which is a large-scale travel survey conducted about every 8-10 years by the US Department of Transportation to understand and quantify travel undertaken by people on a daily basis. Respondent households are asked to furnish detailed information about household and person level socio-demographic characteristics, vehicles owned or leased by the household by fuel type, annual household mileages, and trips undertaken by each member of the household on a specific travel day. Thus, the NHTS is a rich source of information about vehicle ownership and fleet composition for households, which is precisely the information needed to present a comprehensive comparison of the utilization patterns of electric vehicles relative to gasoline vehicles. More information about the 2017 NHTS dataset can be found in Chapter four. To carry out the study of this nature, the following steps are used to create the dataset:

Step 1: A subset of the 2017 NHTS dataset is created by extracting households with one or more electric vehicles. After extensive cleaning, 556 households with at-least one electric vehicle are identified and are found to be located across 26 states as shown in Figure 12.

Step 2: In step two, households with only gasoline vehicles were randomly drawn from 26 states. During the random draws, it was ensured that the same percentage of households are drawn within each state that matches the percentage of households with at-least one electric vehicles. This resulted in randomly drawing a total of 41,719 households with ONLY gasoline vehicles. Figure 12 presents the distribution between households with at-least one electric vehicles and households with only gasoline vehicles after controlling for geography at the state level.

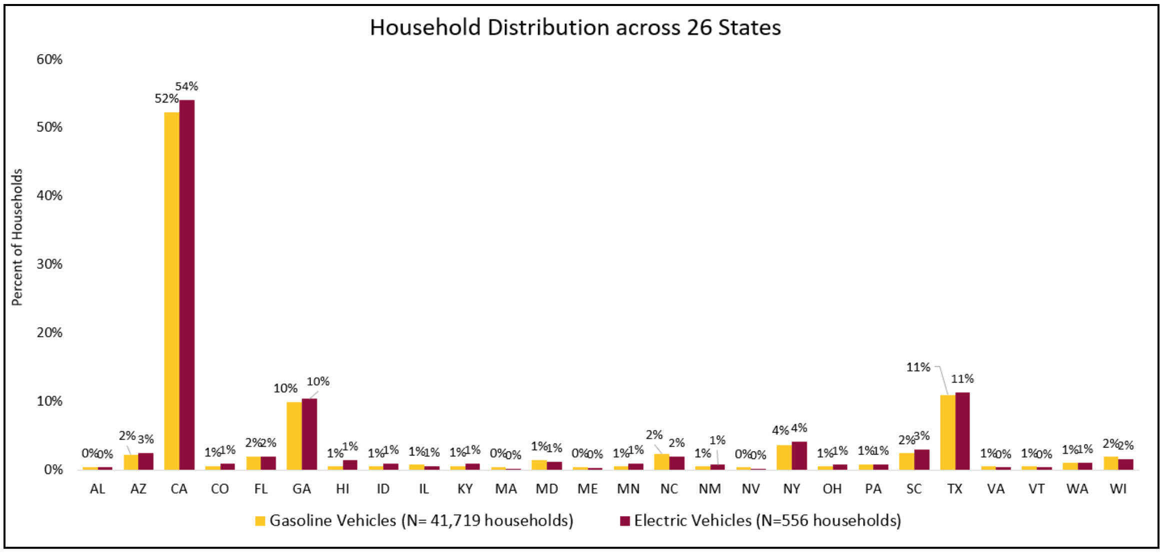

Figure 12. Distribution of Households with at-least one EV and Households with ONLY Gasoline Vehicles by State

Step 3: The household characteristics, vehicle characteristics, trip characteristics, and tour characteristics are compared to understand the differences in adoption and utilization patterns of electric vehicles relative to gasoline vehicles. At the household level, household income and household vehicle ownership are compared. Disaggregate level comparisons include vehicle age, vehicle type, length of vehicle ownership, and annual household mileages, which are all compared at the vehicle level. Trip and tour characteristics comprise of comparison for trip length and number of trips in a tour.

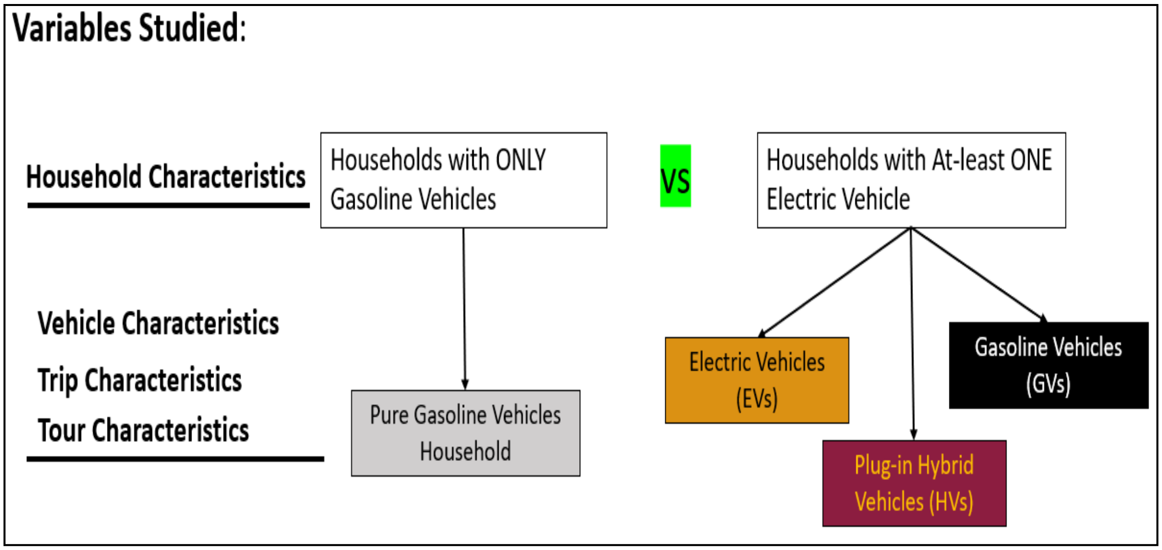

Figure 13. Subset of 2017 National Household Travel Survey (NHTS)

A comprehensive comparison among different characteristics will clearly highlight the extent to which electric vehicle are utilized differently than gasoline vehicles are. The findings will have implications on travel pattern, charging infrastructure investments, policy decisions and household energy footprint.

If electric vehicles are driven as much as gasoline vehicles are, that may counterbalance the some of the benefits associate with transit to an EV future. About 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021), indicating that increase utilization of electric vehicles might results in increase electricity consumption. To account for the potential inter-relationships and tradeoffs between transport and residential energy consumption, the developed integrated transport and residential energy modeling framework is utilized from chapter four. The integrated modeling framework involves imputing vehicle fleet composition and utilization (VFCU) information derived from the 2017 National Household Travel Survey (NHTS) to the household records in 2015 Residential Consumption Survey (RECS). The enhanced

RECS data set can then be used to understand the implications of shifting vehicle/fuel type choices on household energy consumption. The readers are referred to Chapter four for more details on model development and estimation framework which is used to impute vehicle fleet composition and utilization (VFCU) information in RECS. Once we have the vehicle fleet composition and utilization information in RECS, following steps are used to create the dataset:

Step a: From Chapter four, household vehicle fleet composition and utilization (VFCU) model sensitive to vehicle fleet mix is utilized to impute annual household mileages and household vehicle ownership patterns in 2015 Residential Energy Consumption Survey Dataset.

Step b: Knowing vehicle ownership patterns for households in RECS, a vehicle file is developed. The total imputed vehicles are 2,972 vehicles for 1,555 households in RECS. The household mileage information is attached corresponding to each vehicle.

Step c: Percentages of vehicles in the total fleet are randomly assigned to be electric or gasoline based on the following criteria:

Base Scenario: 0 percent EV fleet (all gasoline vehicle households)

Scenario 1: 20 percent of the vehicle fleet is EV

Scenario 2: 40 percent of the vehicle fleet is EV

Scenario 3: 60 percent of the vehicle fleet is EV

Scenario 4: 80 percent of the vehicle fleet is EV

Scenario 5: 100 percent of the vehicle fleet is EV (all EV households)

Step d: In this step, households' mileages are allocated between the vehicles. For single vehicle fuel-type households, the mileage allocation is straightforward as the vehicle can either be electric or gasoline. However, a household can own multiple vehicles with mixed vehicle fuel-type and the mileage allocation needs to account for heterogeneity in household vehicle fuel-type ownership. The following criteria is used to distribute the mileages:

(i) If all the vehicles in the households are gasoline, miles per gallon (MPG), corresponding to vehicle type by vehicle age, is used to convert mileages to gallon and the energy consumption is computed in British Thermal Unit (BTU).

(ii) If all the vehicles in the household are electric, miles per gallon equivalent (MPGe) is used to convert mileages to gallon equivalent. The average MPGe is computed based on the following electric car models (Energy Sage, 2021):

Electric Car Model	Efficiency (MPGe)
Nissan Leaf	111 MPGe
Chevrolet Bolt	118 MPGe
Tesla Model S	109 MPGe

The gallon equivalent is used to compute the energy consumption in British Thermal Units.

(iii) A household can own multiple vehicles of mixed vehicle fuel-type. In those scenarios, the mileages would have to be distributed between a mix of vehicle fuel type. To do that, we utilized the 2017 NHTS dataset which had information about households that own mixed vehicle fuel type. The households with mix vehicle fuel type were extracted and the average electric vehicle mileage ratio based on household income and household vehicle ownership was computed using equation 20.

$$\text{Electric vehicle mileage ratio} = \frac{\text{Average Electric vehicle Mileage in a Category}}{\text{Average Total household Mileage in a Category}} \quad (20)$$

Table 12 represents the electric vehicle mileage ratio for each category and the corresponding sample size. In general, a low-income household with two vehicles have 55 percent of mileage on electric vehicles, while a high-income household with two vehicles have 63 percent of mileage on EVs. The ratios obtained from Table 12 was utilized to allocate the household mileages in mixed vehicle fuel-type households. After allocating the mileages, the energy consumption was imputed for households in British Thermal Unit.

Table 12. Electric Vehicle Mileage Ratio

HH Vehicle Ownership/ Household Income	Low Income Households	Medium Income Households	High Income Households
1 Vehicle	1	1	1
2 Vehicles	0.555 (N=14 Vehicles)	0.376 (N=113 Vehicles)	0.634 (N=257 Vehicles)
3+ Vehicles	0.283 (N=44 Vehicles)	0.218 (N=174 Vehicles)	0.299 (N=580 Vehicles)

The above steps (c-d) are followed for each scenario to understand the change in household energy footprint with increasing electric vehicle penetration. In other words, for each scenario, households' gasoline footprint and electric vehicle footprint (sensitive to efficiency (MPG or MPGe, respectively)) is computed. The percent increase and decrease in residential energy footprint and household energy print, respectively, is calculated to understand the household energy footprint implications of shifting vehicle/fuel type choices.

5.3. Results

This section presents a comprehensive comparison of the utilization patterns of electric vehicles relative to gasoline vehicles and how they affect residential and total household energy use. The first subsection provides the results on adoption, utilization and replacement of household's vehicles. The next subsection provides insights on household energy footprint implications of shifting vehicle/fuel type choices.

5.3.1. Adoption, Utilization, and Replacement of Households Vehicles

Results on three dimensions, namely, adoption, utilization, and replacement are presented by comparing the household characteristics, vehicle characteristics, trip characteristics, and tour characteristics. These comparisons highlight the differences in the ownership and utilization patterns of electric vehicles relative to gasoline vehicles.

5.3.1.1. Household Characteristics

The household characteristics includes comparisons for household income and household vehicle ownership. Figure 14 indicates that household owning EVs are higher income households, which is consistent with previous findings (Jia et al, 2021; Lee et al, 2019). In other words, about 70 percent of the EVs are owned by high-income households (annual income of $100k or more), indicating inequity in EV ownership patterns. This pattern may be reflective of the higher cost associated with EVs, which serves as a barrier to EV adoption across different income groups, in addition to range anxiety and charging infrastructure (Adepetu and Keshav, 2017). As policymakers seek to integrate equity and environmental policy goals, equitable electrification can serve as a key component to a just transition.

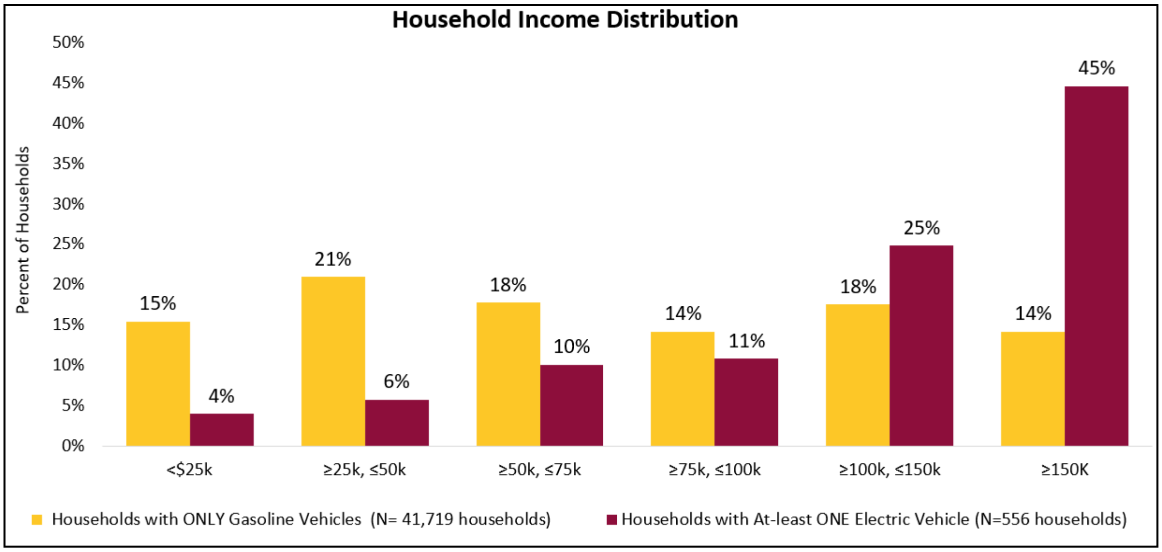

Figure 14. Household Income Distribution

About 51 percent of the households with at-least one electric vehicle own 3 or more vehicles in a household, while only 27 percent of the gasoline vehicle households own 3 or more vehicles. This pattern indicates that higher vehicle ownership households are shifting towards owning more mixed vehicle fuel type. Additionally, there might be income effect for higher vehicle ownership pattern within households that own one or more EVs. This emerging pattern indicates that household vehicle fleet composition and ownership model system need to be updated to account for mixed vehicle fleet fuel type choices to accurately quantify transport energy consumption and assess the implications of shifting vehicle/fuel type choices.

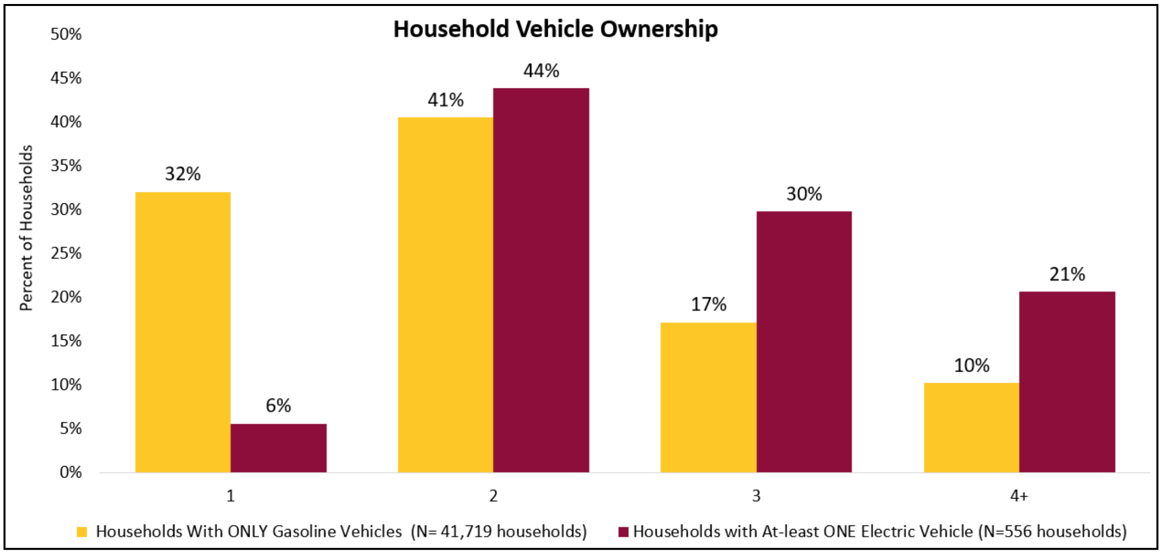

Figure 15. Household Vehicle Ownership

5.3.1.2. Vehicle Characteristics

Vehicle characteristics include comparisons on vehicle age, length of vehicle ownership, type of vehicles owned, and annual household mileages. This disaggregated level comparison highlights the differences between electric and gasoline vehicles at the vehicle level. Figure 16 shows the comparison of vehicle age distribution between the households with at-least one electric vehicles and households with only gasoline vehicles. About 77 percent of the electric vehicles are newer vehicles with vehicle age less than 5 years age, while 30 percent of the vehicles are less than 5 years in households with only gasoline vehicles. This is expected as electric vehicle technology is newer in the market and therefore, vehicle tend to be newer compared to other vehicle-fuel type. While electric vehicles are the newer vehicle in a household but given the barrier associated with EV technology, it is interesting to explore the length of vehicle ownership.

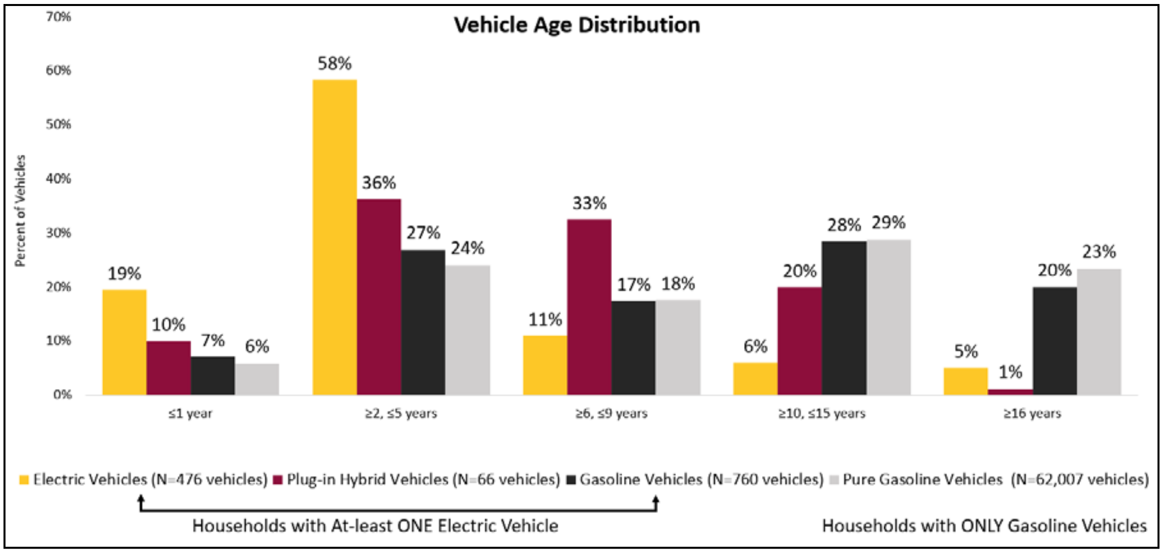

Figure 16. Vehicle Age Distribution

Figure 17 shows that nearly 72 percent of the respondents indicated that they own their electric vehicles longer than a year, while 87 percent indicated that gasoline vehicles are owned longer than a year. To understand length of vehicle ownership further, the California Vehicle Survey (CVS) Data was utilized. The 2017 CVS data was collected by California Energy Commission and includes revealed preferences and stated preferences for the residential and commercial light-duty fleet owners in California to assess consumer preferences for vehicle.

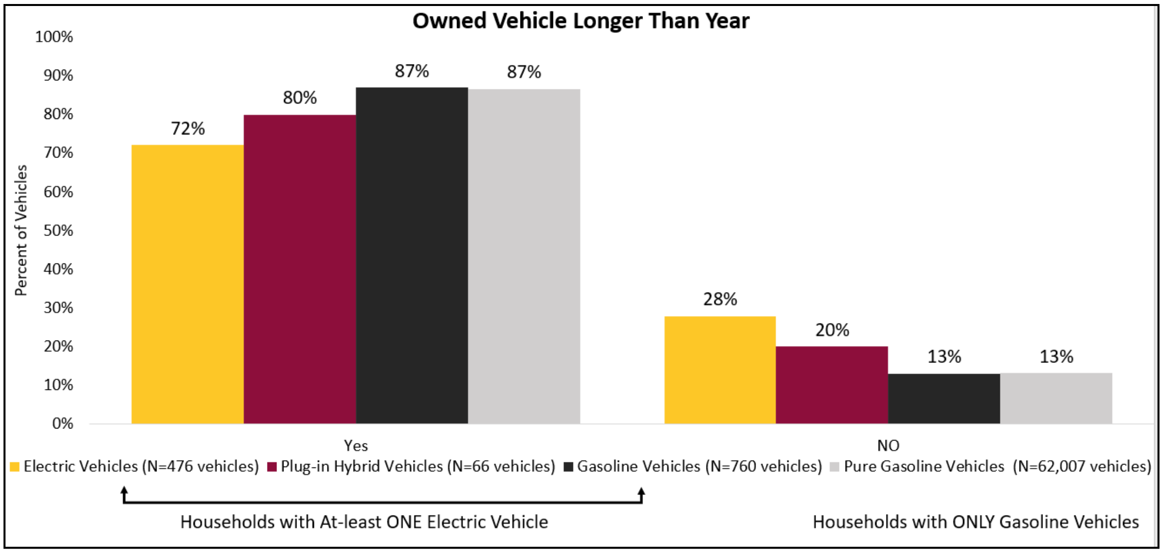

Figure 17. Owned Vehicle Longer Than Year

The 2017 CVS data (Figure 18) indicate that nearly 70 percent of the respondents would replace electric vehicles within 3 years and 4 percent indicated that they are never going to replace them. The shorter length of vehicle ownership is possibly due to the barriers (e.g., battery technology, range anxiety, charging infrastructure units) associated with owning electric vehicle technology. However, with the advancement in the technology, it might be possible that we might see electric vehicles are owned for longer-term, but initial findings suggest otherwise and raise questions whether electric vehicle technology is sustainable or not.

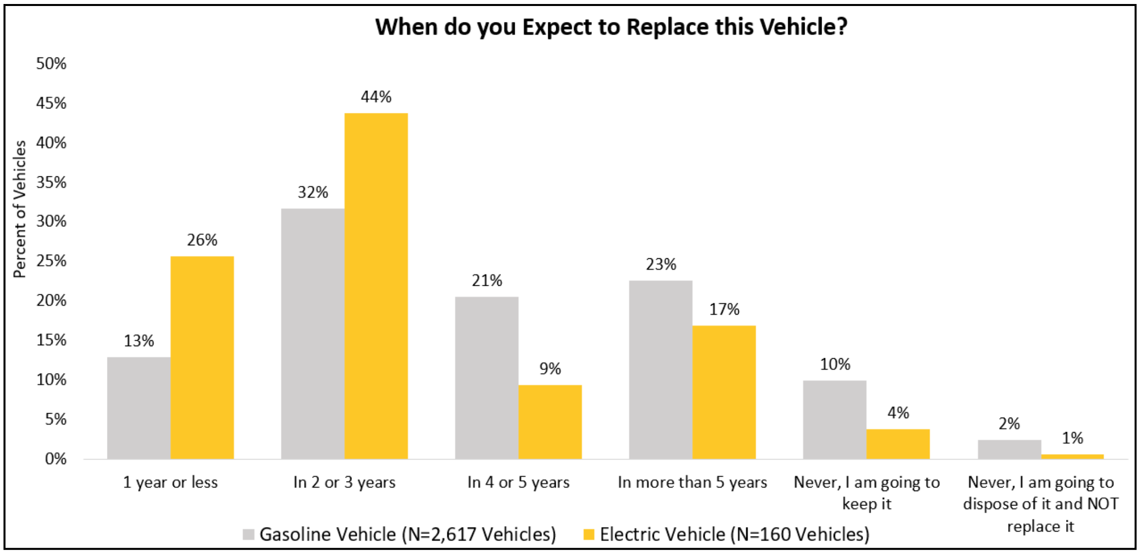

Figure 18. When do you expect to Replace this Vehicle?

Figure 19 indicates that about 77 percent of the electric vehicles are cars and 2 percent are in the Sports Utility Vehicle category. Krupa et al (2015) found that drivers currently driving larger size vehicles are less likely to adapt electric vehicles which are available in small class sizes. The findings point that with increased availability of vehicle type segments in the market might result in increased adoption of EVs.

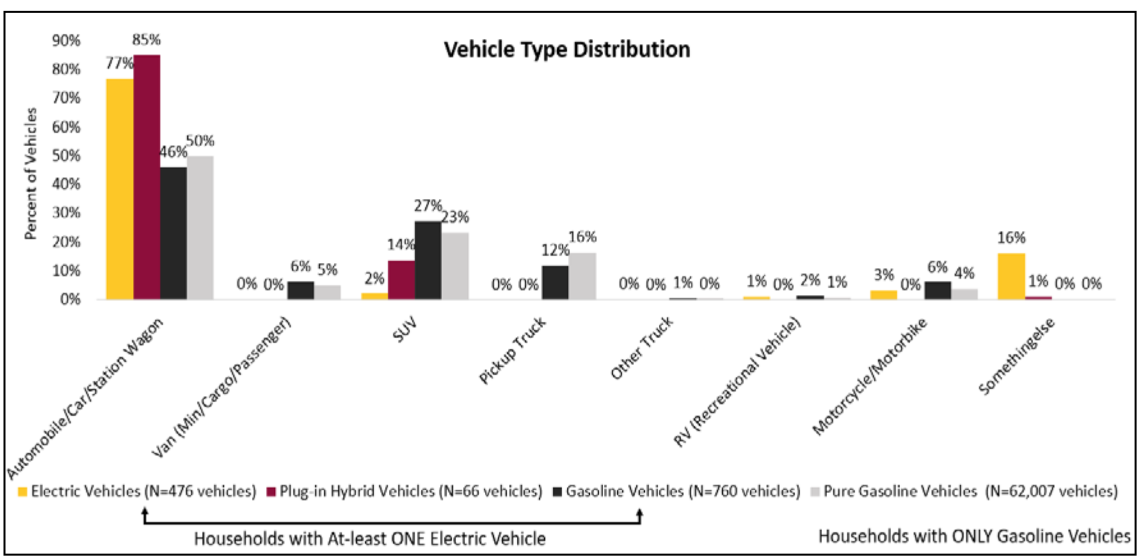

Figure 19. Vehicle Type Distribution

Contrary to two recent studies on vehicle miles traveled (Burlig et al, 2021; Davis, 2019), which indicated electric vehicles are driven less than gasoline vehicles, the annual household mileage distribution, shown in Figure 20, indicates that electric vehicles are driven as much as gasoline vehicles are, a finding similar to Chakraborty et al (2021). This would mean that as electric vehicle replaces gasoline vehicles, policies are needed to reduce amount of travel and the associated negative externalities like congestion. In other words, a shift to electric vehicles may not yield a decrease in amount of travel.

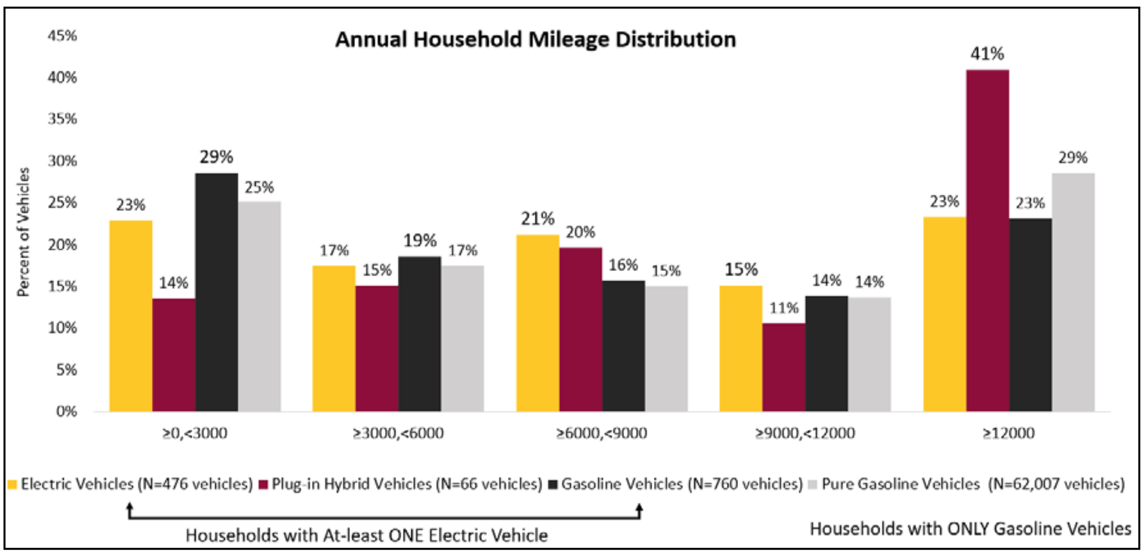

Figure 20. Annual Household Mileage Distribution

5.3.1.3. Trip and Tour Characteristics

The trip length distribution, shown in Figure 21, suggests that electric vehicles are utilized for short distance travel: about 43 percent of the trips made by electric vehicles are shorter than 3 miles, which is nearly same for households with pure gasoline vehicles. In general, a modest shift in trip length is possible, but it will be likely dependent on the range considerations. It is also interesting to note, Plug-in- hybrid vehicles are utilized more often for long-distance travel within households that owns mixed vehicle fuel type. This might be indicative of the fact that households are embracing sustainable transport technologies.

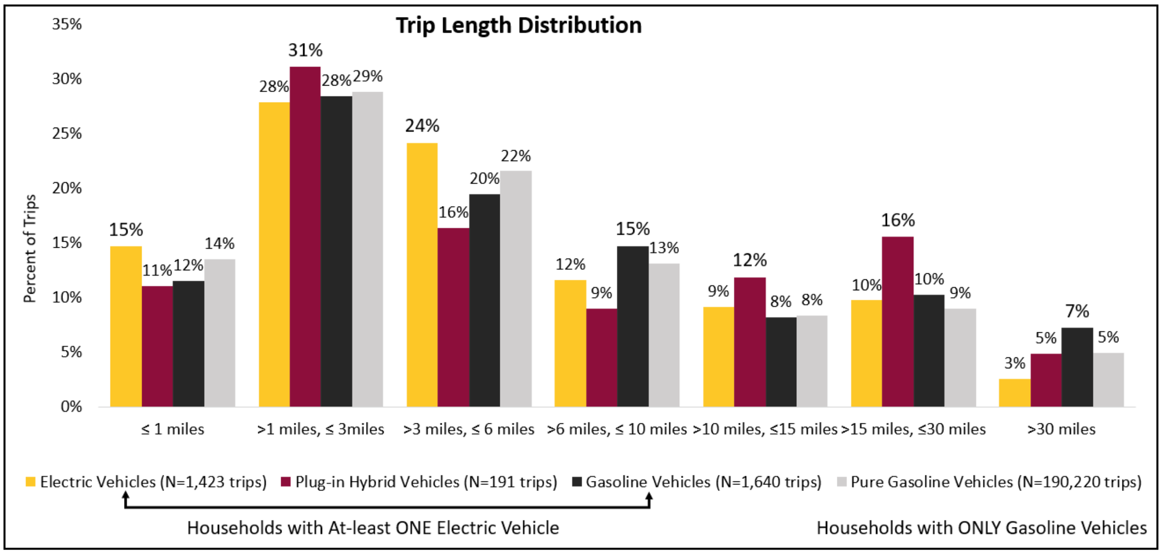

Figure 21. Trip Length Distribution

Similarly, trip chaining characteristic (number of trips in a tour) shown in Figure 22 indicates that with the increase in trip chaining patterns, households might shift to plug-in-hybrid or gasoline vehicles, but the usage is slightly different between electric vehicles and gasoline vehicles. This speaks of the potential of the technology to replace conventional vehicles.

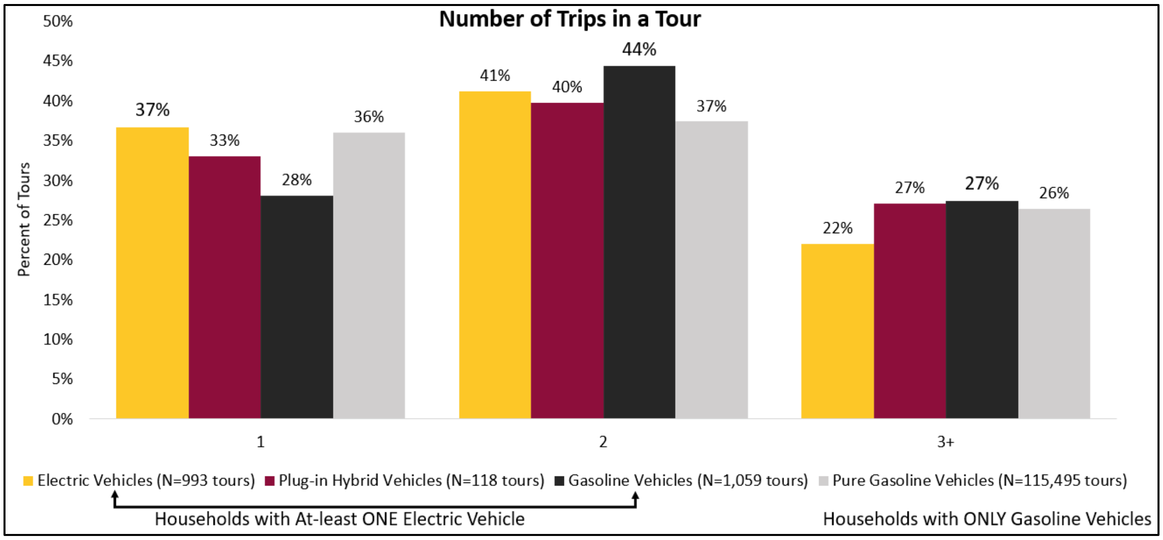

Figure 22. Number of Trips in a Tour

5.3.2. Implications of Electric Vehicles Adoption and Utilization on Household Energy Consumption

With rapid advancement in the electric vehicle technology, it is expected that EV will yield lower energy consumption per mile which will, in turn, decrease carbon emissions from the transport sector. However, wide scale adoption of electric vehicles could dramatically increase total electricity demand (Moon et al, 2018; Van Vliet et al, 2011), as about 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021). In other words, utility companies have had flat demand for years, which might change with wide scale adoption of electric vehicles. Mai et al (2018) presented plausible electrification scenarios encompassing end-use technology adoptions across all sectors and concluded that electricity share of total energy consumption will grow to 32 percent in medium scenario (widespread electrification opportunities in electric vehicles, heat pumps, and select industrial application) and 41 percent in high scenario (a combination of policy support, consumer enthusiasm, and technology advancement) by

2050. Gryparis et al (2020) evaluated the impact of EVs on electricity grid and found that high penetration of EVs results in an increase in electricity demand. Historically, it is observed that residential electricity demand has dramatically shifted with rapid adoption of refrigerators, air conditioning, and home electronics which might turn out to be true with electric vehicle adoption. However, there is limited literature that accounts for the interrelationships between transport and residential energy consumption while understanding the household energy footprint implications of shifting vehicle/fuel type choices. To account for these inter-relationships and tradeoffs, a data fusion across two datasets, namely, 2017 National Household Travel Survey and 2015 Residential Energy Consumption Survey, is performed to understand the implications of electric vehicle ownership and utilization on household energy consumption. The resulting integrated transport and residential energy consumption model system developed in Chapter four was utilized to understand the implications of electric vehicle ownership and utilization on household energy consumption. Specifically, scenario analysis is performed to understand the implications on household energy footprint with increased electric vehicle penetration rate.

This study is one of the first in-depth investigation into electric vehicle utilization relative to gasoline vehicles and its implication on household energy consumption. The results indicated that electric vehicles are utilized as much as gasoline vehicles are, clearly indicating the potential of the technology to replace trips made by gasoline vehicles. However, this may negate some of the benefits associated with transition to an electric vehicle future. In other words, with an increased EV penetration (from 0 percent to 100 percent), a continuous increase in residential energy consumption is observed (in Figure

23). With the greatest increase in EV penetration rate (Scenario 5), the residential energy consumption increases 38 percent from the base scenario (which is 0 percent EVs), suggesting a substantial shift in residential energy consumption. The findings from this research study suggest that electricity systems may need additional infrastructure to support the growing demand for electricity as EVs becomes prevalent in the population. Further, this increase might offset the reduction gained in transport energy consumption, as EV charging electricity demand is satisfied primarily by increased electricity generation from conventional fossil fuel-fired power plants and imports. However, interestingly, the total household energy use decreases by 55 percent when 100 percent of the vehicle feet is EV. This reduction in total household energy use clearly indicates the benefits associated with transportation electrification.

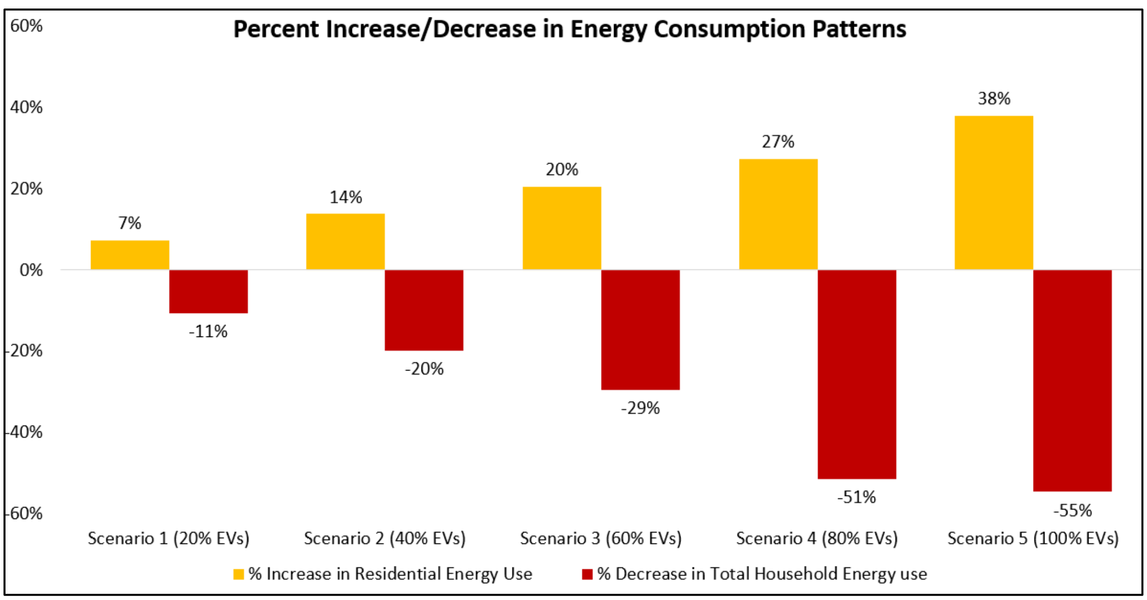

Figure 23. Percent Increase/Decrease in Household Energy Consumption

5.4. Conclusions And Discussions

A key element of the portfolio of strategies to advance sustainability of the transportation system is the adoption and use of electric vehicles, with the hope that an increase in adoption and use of electric vehicles will be accompanied by a reduction in gasoline vehicle ownership and use and overall household energy footprints. Many countries have formulated policies to encourage electric vehicle (EV) adoption so that EVs will account for an increased share of future vehicle fleets. Various incentives, rebates, and special privileges have stimulated the adoption of EVs, but the market share of EVs remains very small in most contexts. The current estimates indicate that about 2 million battery electric vehicles have been sold in the U.S. since 2010 (Argonne, 2021) and the forecasts suggest that EVs will account for about 60 percent of new car sales in US by 2040 (*Electric Vehicle Outlook*, *2021*). Transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which different vehicles in the households are driven. Most household travel surveys have few, if any, records of households that own EVs, thus rendering it difficult to analyze the usage of EVs relative to gasoline vehicles. Using data from the 2017 National Household Travel Survey, this study fills this critical gap by presenting a comprehensive comparison of the utilization patterns of electric vehicles relative to gasoline vehicles and how they affect residential and total household energy use.

The findings from this study indicate that households owning EVs differ substantially from household not owning EVs. In other words, EVs are owned by households that are high-income and have higher vehicles ownership patterns. Moreover, about 70 percent of the EVs are owned by high-income households, indicating inequity in

EV ownership patterns. With the rapid advancement in the technology, it is expected the barriers associated with battery technology, charging infrastructure, range anxiety, cost etc., might be overcome which might result in wide-scale adoption of EVs across segments of the society. Further, it is unlikely that EV penetration and usage will lead to substantial changes in travel patterns and amount of travel. However, modest shift in trip length is possible but likely dependent on range considerations.

There is a predicted sharp increase in residential energy consumption with a wide-scale adoption of electric vehicles. This may negate some of the benefits associated with transition to an EV future. Previous studies have also shown that wide scale adoption and utilization of electric vehicles could significantly increase total electricity demand (Moon et al, 2018), as about 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021). This requires advancement not only in vehicle technology but also on renewable energy sources to power electricity generation. The accessibility and availability of public charging infrastructure might cut some of the increase in residential energy consumption as consumers might be inclined to charge vehicles elsewhere other than at home. More interestingly, it is observed that the total household energy use may decrease by 55 percent, reinforcing the benefits associated with transportation electrification. The findings from this study will help utilities companies to design policy interventions that help curb the rising demand for electricity in the near future.

While this analysis offers insights on differences in utilization patterns of electric vehicles relative to gasoline vehicles and its implication on household energy consumption, there are some limitations that we need to keep in mind. First, the results from this study may not be generalized given the sample size. A more robust large survey sample across the nation will help us to accurately assess the impacts of electric vehicle (EV) adoption and utilization on household energy consumption. Second, with the availability of public charging units, it is important to account for variation in charging location choices to accurately quantify shift in energy consumption. Third, the travel patterns and activity time use has significantly shifted during COVID-19 pandemic which is not accounted in this research. In other words, some individuals might be spending more time in-home and less time traveling which might influence the household energy consumption pattern. Accounting for this shift in activity-time will help us to accurately reflect household energy use. Future research efforts will try to address these limitations.

6. CONCLUSIONS AND DISCUSSIONS

Traveler behaviors and attitudes are rapidly evolving and undergoing significant changes. The evolving nature of people's travel is beginning to reveal itself in long standing measures of transportation (mode shares, traffic volumes, congestion and delay, transit ridership). These changes have profound impacts in the ways we interact with our infrastructure, our vehicles, our environment, and with each other (Mobility Lab, 2018). More specifically, transport behaviors and attitudes impact a number of phenomena (energy consumption, air quality, well-being, health and safety, for example) and there is increasing interest to analyze, understand, and model the connections between transport and these other phenomena (Mobility Lab, 2018). Specifically, this dissertation develop multidimensional model systems to unravel the complex relationships among behavioral dimensions which can help us understand travel behavior implications for transport and household energy use.

To reduce the environmental burden of transport, previous studies have focused on solutions that accentuate towards techno-economical pathways. However, there is growing evidence that transport behaviors, lifestyle choices, and role of individuals attitudes and perceptions are considered influential factors in shaping society's engagement with technological opportunities in the face of environmental crisis. The objective of this dissertation is to develop multidimensional models to understand the travel behavior implications for transport and household energy use. To this end, the dissertation contains four distinct chapters that highlights the existence of structural heterogeneity in consumer decision-making processes, importance of attitudes, values, and perceptions in modeling the adoption and utilization of sustainable transport technologies, develops an integrated household energy analysis tool that accounts for the interrelationship between transport and residential energy consumption, and lastly, understand the household energy footprint implications of shifting vehicle/fuel type choices. Overall, the findings from this dissertation can be utilized to explore pathways that leads to decarbonize the transport sector.

Specifically, the ***second chapter*** of this dissertation explores the relationship between attitudes and behaviors by highlighting the existence of structural heterogeneity in the consumer decision-making processes. Energy-behavioral analysts are increasingly concerned with the relationships between human attitudes and perceptions on the one hand and behavioral choices on the other. There is interest in exploring the possibility of using attitudinal variables and constructs to better explain and more accurately predict household energy use under a variety of scenarios, particularly in the context of emerging transport and building technologies. The chapter adopts a latent segmentation approach to reflect the notion that the analyst is not aware of the causal structure adopted by each individual in the sample population. The finding of this research indicates that nearly two-thirds of the sample fall in the segment where behavioral experiences are shaping attitudes, while only about one-third falls in the segment where attitudes affect behaviors. This implies that it is necessary to run pilots and campaigns where individuals actually get to experience modal options and different products first-hand; people need to be able to exercise alternative behavioral choices, learn through experience, and re-shape their attitudes in response to the behaviors and choices that they get to experience. Programs in which individuals are able to actually try out new and different alternatives (modes and services, for example) may yield greater benefit than messaging aimed at trying to influence attitudes. Additionally, it is also clear from this research that attitudes/perceptions should not be treated as explanatory variables to a behavioral phenomenon rather they serve as an endogenous variable in the modeling exercise. Thus, clearly indicating that special emphasis should be placed on attitudes/perceptions while explaining a behavioral phenomenon of interest.

Building on the findings of the causal segmentation study, the ***third chapter*** explores the factors that influences the adoption of on-demand mobility services and electric vehicle ownership while placing *special emphasis* on *attitudes, perceptions, and preferences*. Many rapidly developing countries around the world are at a crossroads when it comes to transportation, air quality, and sustainability. Indeed, the challenges presented by vehicular growth in India has motivated the search for sustainable transportation solutions. One solution constitutes ridehailing services, which are expected to reduce car ownership and provide affordable means of transportation. Another key solution is the rise of electric vehicles (EVs), which are expected to reduce greenhouse gas emission and address the growing demand for sustainable urban mobility. Using a unique survey data set collected in 2018 from a sample of 43,000 respondents spread across 20 cities in India, this chapter attempts to shed light on the factors that affect adoption of on-demand transportation services and electric vehicles in India. In particular, not only does this paper consider the socio-economic and demographic variables that affect these behavioral choices, but the integrated modeling framework adopted in this study places a special emphasis on representing the important role played by attitudes, values, and perceptions in determining adoption of on-demand transportation services and EVs. Results from this indicated that attitudes and values significantly affect the use of on-demand transportation services and EV ownership, suggesting that information campaigns and free trials/demonstrations would help advance the adoption of sustainable transportation modes which, in turn, will impact transport and household energy use. The developed integrated modeling systems provides the capability to fully assess and understand the interrelationship between the behavioral phenomena of interest.

Taking the idea of integrated modeling framework, further, the ***fourth chapter*** develops an integrated household and residential energy consumption model system. Due to phenomenal growth in energy demand and corresponding human and environmental impacts, it is critical for communities and cities to explore pathways to simultaneously manage household's transportation and residential energy consumption patterns to advance economic vitality, wellbeing, and environmental sustainability of the region. Holistic integrated modeling frameworks present an opportunity to develop, analyze, and model these connections which may be desired for analyzing alternative energy future and policy scenarios. To explore this relationship, the information from the NHTS is fused with the RECS to develop a comprehensive computational modeling framework within an agent-based microsimulation environment that can be used to characterize and quantify the spatiotemporal dynamics of the components of household energy footprint. The characterization and quantification of spatio-temporal dynamics will enable us to track how transport and residential energy change over time as different users carry out their daily activities in space and time. The findings from this study indicates the existence of small but significant net complementary relationships between transport and residential energy consumption. Additionally, the modeling framework enabled the identification and comparison of energy consumption patterns across market segments.

Moreover, the resulting integrated transport and residential energy consumption model system can be utilized to assess the overall household energy footprint implications with the adoption and use of electric vehicles. It is hoped that an increase in adoption and use of electric vehicles will be accompanied by a reduction in gasoline vehicle ownership and use and overall household energy footprints. Transport energy consumption is dependent on the mix of vehicles that a household owns and uses, and the extent to which different vehicles in the households are driven. There is very limited understanding on how electric vehicles are utilized in comparison to gasoline vehicles. If electric vehicles are utilized more than gasoline vehicles, that may negate some of the benefits associated with transition to an EV future. It is expected that EVs will yield lower energy consumption per mile which will, in turn, decrease carbon emissions from the transport sector. However, wide scale adoption and utilization of electric vehicles could significantly increase total electricity demand (Moon et al, 2018) as about 80 percent of the electric vehicles are currently charged at home (National Resources Defense Council, 2021). Using data from the 2017 National Household Travel Survey, this chapter presents a comprehensive comparison of the utilization pattern of electric vehicles relative to gasoline vehicles. The findings from this study indicate that electric vehicles are utilized as much as gasoline vehicles are and with the wide-scale adoption of EVs, we might see an increase in residential energy consumption, however, the total household energy use decrease, pointing towards the long-term benefits associated with transportation electrification.

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APPENDIX

A CAUSAL SEGMENTATION MODEL RESULTS

Table 13. Model Estimation Result- Causal Structure 2 (FTU→RLC; FTU+RLC→ATT)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores)	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
Constant	-0.978	-7.51	-0.650	-8.31	0.182	19.32	-0.532	-19.90
Individual Characteristics								
Gender								
Female	-0.232	-4.07	—	—	0.109	4.10	0.112	3.98
Age category								
18-24 years	0.492	3.21	—	—	—	—	0.143	6.12
25-34 years	0.302	4.12					0.120	3.64
18-34 years	—	—	0.112	2.71	–	–	—	—
35-54 years	—	—	—	—	-0.295	-6.12	—	—
55-64 years	—	—	—	—	-0.403	-6.41	—	—
65 years and above	—	—	—	—	-0.569	-6.19	—	—
Education attainment								
College graduate or higher	0.183	2.74	—	—	—	—	—	—
Employment Status								
Employed full-time	0.263	4.85	-0.127	-5.32	—	—	—	—
Time spent online								
More than 8 hours per day	0.320	3.46	0.203	2.12	0.674	3.11	0.072	2.01
Household Characteristics								
Home ownership								
Own	-0.703	-4.08	-0.321	-4.14	-0.128	-3.94	0.084	3.02

Table 13. Continued- Causal Structure 2 (FTU→RLC; FTU+RLC→ATT)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores)	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
Household Characteristics								
Household income								
Less than $35,000	0.205	2.95	-0.272	-5.92	0.075	2.24	—	—
More than $75,000	—	—	—	—	—	–	—	—
Household size								
Two or more	-0.257	-4.32	—	—	-0.130	-4.03	—	—
Presence of kids								
Presence of kids 0-4 years	-0.127	-2.03	-0.134	-2.86	-0.110	-4.37	—	—
Presence of kids 0-15 years	—	—	—	—	—	—	0.122	6.12
Vehicle ownership								
Three or more	-0.694	-7.35	-0.329	-5.77	-0.240	-3.12	-0.105	-4.72
Location Characteristics								
Lives in Transit Rich City								
Progressive	—	—	—	—	0.403	8.31	0.078	3.10
Region								
South	—	—	—	—	-0.185	-5.04	-0.100	-3.92
Threshold parameter	—	—	—	—	1.205	18.75	—	—
Urban dwellers	—	—	—	—	—	—	0.127	3.22
Suburban and small-town mix	—	—	—	—	—	—	0.083	2.04

Table 14. Model Estimation Result- Causal Structure 3 (ATT→ RLC; ATT+RLC→FTU)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores**)**	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
Constant	-0.703	-6.15	-0.538	-7.21	1.103	19.42	-0.676	-12.32
Individual Characteristics								
Gender								
Female	-0.207	-3.27	—	—	0.114	5.04	0.105	3.22
Age category								
18-24 years	0.463	4.51	—	—	—	—	0.137	5.44
25-34 years	0.300	5.36	—	—	—	—	0.102	3.94
18-34 years	—	—	0.172	3.12	—	—	—	—
35-54 years	—	—	—	—	-0.294	-7.35	—	—
55-64 years	—	—	—	—	-0.423	-9.12	—	—
65 years and above	—	—	—	—	-0.570	-8.43	—	—
Education attainment								
College graduate or higher	0.185	2.86	—	—	—	—	—	—
Employment Status								
Employed full-time	0.266	3.88	-0.118	-4.75	—	—	—	—
Frequency of Transit Use								
Frequent: once per week or more	—	—	—	—	—	—	—	—
Infrequent: less than once per week	—	—	—	—	—	—	—	—
Time spent online								
More than 8 hours per day	0.317	5.38	0.217	2.74	0.780	3.12	0.068	2.75
Household Characteristics								
Home ownership								
Own	-0.655	-3.86	-0.275	-4.08	-0.125	-2.98	0.082	3.07
Household income								
Less than $35,000	0.201	3.07	-0.258	-6.26	0.071	2.10	—	—
More than $75,000	—	—	—	—	—	—	0.120	2.21
Household size								
Two or more	-0.250	-3.00	—	—	-0.137	-4.72	—	—

Table 14. Continued- Causal Structure 3 (ATT→ RLC; ATT+RLC→FTU)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores)	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t -stat**	**Coef**	**t -stat**
Household Characteristics								
Presence of kids								
Presence of kids 0-4 years	-0.119	-2.71	-0.128	-3.11	-0.101	-4.05	—	—
Presence of kids 0-15 years	—	—	—	—	—	—	0.111	4.51
Vehicle ownership								
Three or more	-0.726	-9.01	-0.331	-4.07	-0.240	-4.31	-0.112	-4.86
Location Characteristics								
Lives in Transit Rich City								
Progressive	—	—	—	—	0.392	9.00	0.099	5.32
Region								
South	—	—	—	—	-0.206	-4.62	-0.109	-5.02
Threshold parameter	—	—	—	—	1.190	18.63	—	—

Table 15. Model Estimation Result- Causal Structure 4 (ATT→FTU; ATT+FTU→RLC)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores)	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef`**	**t-stat**
Constant	-0.907	-6.29	-0.614	-7.61	1.083	20.04	-0.681	-15.44
Individual Characteristics								
Gender								
Female	-0.205	-4.98	—	—	0.112	4.86	0.104	3.27
Age category								
18-24 years	0.460	3.21	—	—	—	—	0.133	6.10
25-34 years	0.305	4.12	—	—	—	—	0.096	5.11
18-34 years	—	—	0.168	4.11	—	—	–	–
35-54 years	—	—	—	—	-0.296	-6.23	–	–
55-64 years	—	—	—	—	-0.426	-8.32	–	–
65 years and above	—	—	—	—	-0.571	-9.03	–	–
Education attainment								
College graduate or higher	0.188	3.11	—	—	—	—	—	—
Employment Status								
Employed full-time	0.270	3.65	-0.120	-3.04	—	—	—	—
Time spent online								
More than 8 hours per day	0.318	5.64	0.215	2.08	0.781	3.28	0.070	3.19
Household Characteristics								
Home ownership								
Own	-0.671	-4.29	-0.277	-3.95	-0.125	-3.27	0.079	3.00
Household income								
Less than $35,000	0.200	3.06	-0.259	-5.07	0.067	2.03	0.119	2.10
More than $75,000	—	—	—	—	—	—	—	—
Household size								
Two or more	-0.250	-2.85	—	—	-0.131	-3.94	—	—

Table 15. Continued- Causal Structure 4 (ATT→FTU; ATT+FTU→RLC)

Explanatory Variables	Residential Location Choice (*base*: Other suburban and small town + rural)				Frequency of Transit Use (never, infrequent, and frequent users)		Attitudes Towards Transit (continuous factor scores)	
	Urban dwellers		Suburban and small town mix					
	Coef	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**	**Coef**	**t-stat**
Household Characteristics								
Presence of kids								
Presence of kids 0-4 years	-0.120	-2.96	-0.134	-4.00	-0.099	-4.07	—	—
Presence of kids 0-15 years	—	—	—	—	—	—	0.107	4.42
Vehicle ownership								
Three or more	-0.731	-8.42	-0.339	-3.93	-0.241	-5.42	-0.110	-4.73
Location Characteristics								
Lives in Transit Rich City								
Progressive	—	—	—	—	0.397	10.25	0.093	4.12
Region								
South	—	—	—	—	-0.203	-5.14	-0.106	-4.75
Threshold parameter	—	—	—	—	1.188	25.67	—	—