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Emerging Mobility Services for the Transportation Disadvantaged

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16. Abstract - This STRIDE project focuses on the travel characteristics of and use of emerging mobility systems by transportation disadvantaged populations. In thrust 1, the research team investigated how vehicle ownership and income interact with geographical location to affect trip characteristics, in addition to how travel behavior varied over time. In thrust 2, travel behavior and mobility preferences of older adults (age 65 and older) were examined. In thrust 3, we used mobile device data to explore temporal patterns in visits to health care points of interest during 2020 and examined how these patterns were associated with block group-level sociodemographic and spatial characteristics in North Carolina. In thrust 4, we developed and applied a tool to the Gainesville Regional Transit System (RTS) to understand the changes in transit accessibility for neighborhoods with concentrations of vulnerable populations (older adults, individuals with disabilities, and low-income households) throughout the COVID-19 pandemic (during, recovery and projected in five years) for five types of trips (work, medical, education, grocery and social). In thrust 5, the research team examined how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to support existing travel patterns through comparisons to urban MaaS use. This work estimated logistic regression models to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity (i.e., mode choices and trip distances) in rural areas.

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ABSTRACT

This STRIDE project focuses on the travel characteristics of and use of emerging mobility systems by transportation disadvantaged populations. In thrust 1, the research team investigated how vehicle ownership and income interact with geographical location to affect trip characteristics, in addition to how travel behavior varied over time. Moreover, this thrust also explored the perception and use of active travel among households of different economic status in various spatial environments. In thrust 2, travel behavior and mobility preferences of older adults (age 65 and older) were examined. To evaluate the potentials of using shared mobility services to meet mobility needs of older adults, the research team further investigated the magnitude of cost-saving per month that would encourage travelers to switch from their current mode to ridesourcing services. In thrust 3, we used mobile device data to explore temporal patterns in visits to health care points of interest during 2020 and examined how these patterns were associated with block group-level sociodemographic and spatial characteristics in North Carolina. We reveal distinct inequities in visit patterns, which show block groups with higher population density and those with higher percentages of older adults, low-income individuals, racial and ethnic minorities, and people without household vehicles had lower rates of medical visits during the pandemic and experienced a slower recovery in visits after the state's most restrictive lockdown period. In thrust 4, we developed and applied a tool to the Gainesville Regional Transit System (RTS) to understand the changes in transit accessibility for neighborhoods with concentrations of vulnerable populations (older adults, individuals with disabilities, and low-income households) throughout the COVID-19 pandemic (during, recovery and projected in five years) for five types of trips (work, medical, education, grocery and social). The analysis shows uneven changed during COVID-19 and a recovery for most types of trips. In thrust 5, the research team examined how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to support existing travel patterns through comparisons to urban MaaS use. This work estimated logistic regression models to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity (i.e., mode choices and trip distances) in rural areas.

Keywords (up to 5): transportation disadvantage, travel behavior, mobility needs, equity, shared mobility

EXECUTIVE SUMMARY

This STRIDE project focuses on the travel characteristics of and use of emerging mobility systems by transportation disadvantaged populations. In thrust 1, the research team investigated how income and vehicle ownership status of different households jointly interact with the spatial environment to affect trip characteristics. The team also studied the perception and use of active travel among households which differ in terms of income and vehicle ownership in urban, suburban, and rural areas. Results suggest that low-income households with personal vehicles living in suburban areas make more trips compared to their counterparts in urban areas, while the opposite holds for higher-income households. Low-income, carless households living in suburban environments travel more frequently by walk and bike compared to low-income households with personal vehicles and higher-income households, potentially due to lack of other transportation options, such as public transportation. Public microtransit could be an effective transportation solution for disadvantaged households in suburban and rural areas. In trust 2, travel behavior and mobility preferences of the aging population (age 65 and older) in the U.S. were examined. Findings from analysis with 2017 National Household Travel Survey data confirmed common conjectures that average number of daily person trips and daily person miles generally decreased with increasing age as well as decreasing urbanization of the environment. Privately owned vehicles were the dominant transportation mode in the U.S with a significant lack of alternatives in the suburban and rural areas. These findings suggest that there is a great market potential and needs for ride-share services to fill the mobility needs of older adults in a way that cannot be filled by typical fixed route or on-demand paratransit. Findings from analyses with a stated preference survey suggest that ridesourcing services for older adults may have to focus on service quality, especially privacy, reliability, convenience, and flexibility to appeal to the market of older adults. Additional measures ensuring security, privacy and driver selection process may also be beneficial. In thrust 3, we used mobile device data to explore temporal patterns in visits to health care points of interest during 2020 and examined how these patterns were associated with block group-level sociodemographic and spatial characteristics in North Carolina. We reveal distinct inequities in visit patterns, which show block groups with higher population density and those with higher percentages of older adults, low-income individuals, racial and ethnic minorities, and people without household vehicles had lower rates of medical visits during the pandemic and experienced a slower recovery in visits after the state's most restrictive lockdown period. We recommend designing more equitable interventions to facilitate health care access during and beyond the COVID-19 pandemic. In thrust 4, concentrations of vulnerable populations (older adults, individuals with disabilities, and low-income households) were identified and neighborhoods with large populations identified. Three six time periods and three scenarios (impact of COVID-19 pandemic, recovery from COVID-19 pandemic and development in the

next five years) were developed to map changes in transit accessibility for five types of trips (work, medical, education, grocery and social) for four neighborhoods with concentrations of transportation disadvantaged populations. In thrust 5, the research team examined how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to support additional existing travel patterns through comparisons to urban MaaS use. Additionally, this research sought to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity in rural areas through estimating multinomial logistic mode choice and logarithmic distance models using travel data from the 2017 National Household Travel Survey. Results highlight the importance of trip distances on MaaS adoption in rural areas, and opportunities for partnerships with transit systems to further develop MaaS modes.

1.0 INTRODUCTION

The ability to access private or public transportation is fundamental for everyone to connect with the life-sustaining and social activities. Transportation disadvantaged (TD) populations, which include elderly people, people with disabilities, and people who do not own a vehicle, face mobility challenges because alternative transportation services are limited. As transportation network companies (TNCs) have begun to provide services in communities, they present an opportunity and a challenge for TD populations. On the one hand, transit ridership has declined (Clewlow & Mishra, 2017; Rayle et al., 2016). The decline in transit ridership could result in cuts to transit service that could eventually lead to cuts in transportation services for TD populations. At the same time, TNCs offer the possibility of providing services for TD populations through partnerships with transit agencies and other transportation service providers. Public transportation has been playing a critical role in providing fixed route and paratransit services for TD populations, yet the transportation needs of those populations are far from being adequately met. Nor is it clear how the new mix of transport providers can most effectively meet the needs of TD populations.

According to the U.S. Census Bureau's 2017 National Population Projections, one in every five residents in the U.S. will be 65 years old and over by 2030 (US Census Bureau, 2018). By 2035 the elderly population will outnumber those under the age of 18 for the first time in the country's history (US Census Bureau, 2018). As a popular retirement state, the issue of aging is even more prominent in Florida. Projections estimate Florida's population to reach 23.9 million by 2030, with more than one in four Floridians over the age of 65 (LeadingAge Florida, 2019). One of the challenges that comes with an aging population is greater need for transportation services. As the population age, it poses a unique set of demands for transportation services to fulfill their daily activities, for social, medical, and personal maintenance purposes. Adding to the complexity is the disproportional distribution of elderly in rural areas (Rural Health Information Hub, 2019), which generally has less transit services and mobility options. This increase in the number and diversity of older adults has monumental implications for transportation planning and service operation and management. The ability to access transportation is vital to the quality of life and community resilience. In this regard, emerging mobility technologies and services may hold the promise to provide efficient and innovative solutions to serve the mobility needs of Florida's aging population as it continues to grow.

In addition, between 2000 and 2011, the population below the poverty limit living in the suburbs increased by 64 percent (Kneebone & Berube, 2014). Employment decentralization, affordable housing scarcity, and gentrification have contributed to the increasing trends of poverty suburbanization in the U.S. (Raphael & Stoll, 2010). Regardless the cause of these migration trends, a large number of transit-dependent low-income households now live in suburban areas (Kneebone & Berube, 2014). In areas with no access to public transportation, the poor are often forced to commute by personal vehicle, which highly increases their transportation cost and adds

to existing traffic congestion problems. At the same time, the low-income users of transit systems operating in suburban areas experience longer commutes and overall lower access compared to urban areas, with significant quality of life implications (Barkley & Gomes-Pereira, 2015; Zimmerman et al., 2015). Traditional public transportation systems are not as efficient in suburban settings as they are in urban areas. However, transit agencies do not currently have a clear path on how to serve suburban populations adequately and efficiently.

Moreover, roughly one in five Americans live in rural communities, characterized by a complex range of dense small towns and sparsely populated lands (Ratcliffe et al., 2016). Despite their geographic differences, rural residents face similar transportation accessibility issues (AASHTO, 2010), as highlighted by a recent national survey where rural residents overwhelmingly identified access to public transportation, access to good doctors and hospitals, access to grocery stores, and availability of jobs as major problems at higher rates than peers in urban and suburban areas (Parket et al., 2018a). Connectivity to urban areas is critical for job access, healthcare, shopping, and other activities that affect disadvantaged rural populations' quality of life. Further complicating rural transportation access issues are the fact that rural populations are largely disadvantaged with higher proportions of older individuals (aged 65 years old or older), higher levels of concentrated poverty, and increased health issues compared to those living in urban areas (Parket et al., 2018b; Shirey and Summer, 2002). As a result, local and federal decision-makers are looking to MaaS as a potential solution to support rural to urban accessibility (NASEM, 2018; LockWood, 2004).

1.1 RESEARCH PRESENTED IN THIS REPORT

This project has a special focus on transportation disadvantaged groups, which currently constitute a large proportion of the US population. The project involves a collaboration between five universities within the STRIDE consortium, the University of North Carolina Chapel-Hill, North Carolina State University, the University of Florida, Auburn University, and Florida International University. The research conducted as part of this project is organized in five research thrusts. Although the focus of each thrust is different, they all provide insights and recommendations for equitable and efficient emerging mobility services, which will lead to environmentally, socially, and financially sustainable public transportation systems.

For thrust 1, found in Chapter 2 and Chapter 3, the research team explored the spatial and temporal heterogeneity in the travel behavior of different socioeconomic groups. In Chapter 2, our study compares the travel characteristics of low-income households having personal vehicles with that of low-income carless households and the higher-income households in three different spatial environments. In Chapter 3, the study explores the perception of the aforementioned categories of households on use of active travel as a means to reduce financial burden of travel vary across spatial environment. The findings of this research can be useful to

policy makers in many ways. For example, Chapter 3 provides insights on the differences in the perception on infrastructure and safety barriers that individuals in different locations face with respect to the use of active travel. Overall, the findings of this thrust may help public agencies plan contextual mobility solutions for the transportation disadvantaged groups in different spatial contexts.

For thrust 2, found in Chapter 4, travel behavior and mobility preferences of the aging population (age 65 and older) in the U.S. were examined. This research identified an urgent need for future research and practice to find out financially feasible and operationally effective strategies and programs of ride-share services that serve the mobility needs and challenges of older adults in the U.S. The findings of this research provide valuable insights into factors affecting older adults' decisions toward ridesourcing services and highlight the unique attitudes that influence their decisions. This knowledge can lead to better estimation of their mobility choices and better design of policies and services that meet the mobility needs of older adults. Findings of this study were limited geographically to the survey data collected in the state of Florida and ten other metropolitan areas.

For thrust 3, found in Chapter 5, we used mobile device data to explore temporal patterns in visits to health care points of interest during 2020 and examined how these patterns were associated with block group-level sociodemographic and spatial characteristics in North Carolina. We reveal distinct inequities in visit patterns, which show block groups with higher population density and those with higher percentages of older adults, low-income individuals, racial and ethnic minorities, and people without household vehicles had lower rates of medical visits during the pandemic and experienced a slower recovery in visits after the state's most restrictive lockdown period.

For thrust 4, found in Chapter 6, analyzes the efficiency and accessibility of Gainesville Regional Transit System (RTS). We first used a data envelopment analysis to assess the operational efficiency and spatial effectiveness of the transit system. We then used Census data to identify the location of transportation disadvantaged populations (older adults, persons with disabilities, and low-income populations). We then use a transit accessibility model to evaluate transit accessibility changes for three scenarios: the impact of COVID-19, recovery from the COVID-19 pandemic, and the development in the next five years based upon the RTS Transit Development Plan. These models could be applied to other transit agencies to understand how the efficiency of the transit system and the transit accessibility for various trips for residents of neighborhoods with a concentration of transportation-disadvantaged populations.

For thrust 5, found in Chapter 7, the research team examined how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to support additional existing travel patterns through comparisons to urban MaaS use. Additionally, this research sought to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity in rural areas through estimating multinomial logistic mode choice and logarithmic distance models using travel data from the 2017 National Household Travel Survey.

Results highlight the importance of trip distances on MaaS adoption in rural areas, and opportunities for partnerships with transit systems to further develop MaaS modes.

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TEMPORAL AND SPATIAL DIFFERENCES IN TRIP CHARACTERISTICS OF LOW-INCOME AND CARLESS HOUSEHOLDS

Research conducted by Dr. Eleni Bardaka and Subid Ghimire, North Carolina State University.

2.1 INTRODUCTION

It has been a commonplace knowledge that access to an automobile is a significant criterion in determining an individual's ability to access opportunities (Wachs & Kumagai, 1973). Individuals with automobiles find it easier to move around and participate in opportunities as compared to individuals or households that are unable to afford a car. A plethora of studies have shed light on car ownership, the factors associated with car ownership (Khan & Habib, 2021; Oakil, 2016) and the benefits it brings forth to myriad aspects of day to day life such as accessing food (Burns et al., 2021), health services (Bostock, 2001) as well as securing jobs (Klein et al., 2020) . Grengs (2010) explicated the importance of automobile ownership in the cities in U.S. by illustrating that even if carless individuals resided in areas with excellent transit services, their ability to access jobs would be much lower than the individuals living farther from transit stations or downtown areas but with continuous access to automobile. In accordance with this information on the importance of personal vehicles in a car-oriented society, much of the research on transportation disadvantage has focused on households or individuals without regular access to cars (Clifton & Lucas, 2018; Klein, 2020; Rogalsky, 2010). However, only a few studies have looked into the phenomenon of latent disadvantage of financial stress associated with car ownership among households of lower economic stratum (Currie & Delbosc, 2011; Mattioli & Colleoni, 2016) . Though research on the disadvantage associated with car ownership is slowly drawing academic attention in Europe (Carroll et al., 2021; Church et al., 2000) and in Australia (Currie, 2004), the U.S., which is one of the most car dependent societies in the world (Pucher & Lefèvre, 1996) is lagging behind on this area of research (Pyrialakou et al., 2016). We attempt to fill this gap by studying the trip patterns associated with latent disadvantage related to financial stress that low-income households go through while investing a large share of their income on vehicle ownership.

Blumenberg & Pierce (2012) illustrated the importance of automobiles to poor households by showing that they turn their additional income into mobility benefits through automobile ownership. Klein et al. (2020) argued about the importance of automobile for the poor and low-income individuals to get employment opportunities. Adding to these studies which show the importance of automobile for the poor, we hypothesize that even though the households in the lower-income stratum own a car to meet the mobility needs in a car-oriented society, their

mobility pattern would differ from their higher income counterparts because of their financial situation and the cost saving strategies they would introduce in their trip behavior.

Using trip characteristics like average trip length, average trip length in personal vehicles and trip rate, we attempt to investigate how vehicle ownership coupled with household income would associate with the level of mobility that individuals and households would be able to enjoy in a society. This study is further unique in its combined use of the past three National Household Travel Surveys to observe how trip rate has been changing over time and also in its consideration of the spatial context for exploring the phenomenon of transportation disadvantage. Spatio-temporal investigation of the phenomenon of transportation disadvantage is important because a specific socioeconomic profile might face transportation disadvantage (implied by mobility pattern) in one location and at a particular time and not necessarily in another location and time. There are only a few studies that look into the spatial heterogeneity in trip pattern for individuals and households of equivalent as well as different socioeconomic profile (Pucher & Renne, 2005; Roorda et al., 2010; Venter et al., 2007). Only one study to the authors knowledge illustrates the phenomenon of transportation disadvantage associated with carelessness over time by showing that children growing up without continuous access to cars would associate with lower levels of education and earning as compared to children who grew up with continuous access to cars in their household (Ralph, 2018). Roorda et al. (2008) use trips per day in two Canadian cities (Toronto and Montreal) to observe the evolution of travel behavior over time and across the two regions. However, they develop two separate multivariate regression models for the two cities and for two different years they consider in their study. The problem with this approach is that the models provide a cross-sectional snapshot of travel behavior of a specific location at a particular time but do not explain how the phenomenon has evolved over time and varies across space. Our study attempts to address this gap in the pertinent literature by studying how vehicle availability in the household and family income has been jointly interacting with geography and time to influence travel behavior.

The objective of this study is to quantitatively investigate the differences in the trip patterns of households who own and operate cars despite barely being able to afford other essential needs of the households, with the trip patterns of lower income/poor households without a car and the households which belong to higher income levels. In addition, this study also aims at studying how the difference in trip patterns for the three categories of households has varied over the years from 2001 to 2017 and across three geographical environments (rural, suburban, and urban). We assume that having a car in the household would enhance the levels of mobility of the poor but due to the bleak financial condition, we expect their mobility pattern to differ from that of higher income households. To investigate the case, we use the National Household Travel Survey data from 2001 to 2017 and study the trip pattern of the household categories of our interest and the way they have been changing over time and space. Specifically, we estimate a hurdle model to examine the trip rate to study the difference in travel demand between the households that differ in terms of their financial standing and auto availability.

While Walks (2018) illustrated the financial stress of car ownership among the poor by associating car ownership with debt and Rachele et al. (2018) associated car ownership with poorer health conditions for the lower-income group in a society, we attempt to advance the idea that having access to cars does not necessarily uplift individuals and households from transportation disadvantage they face by exploring the heterogeneity in their trip characteristics across space. This research has policy implications as it would apprise transportation planners about the clear transport disadvantage that carless individuals face as well as the latent disadvantage that would be prevalent among lower-income households despite car ownership which we exhibit through the difference in trip making behavior and the degree of vehicle use. Accounting for the spatio-temporal dimensions to the study would further provide them insights into how the phenomenon of transportation disadvantage associated with being carless and low-income would vary with space.

2.2 LITERATURE REVIEW

Transportation disadvantage is a multi-dimensional phenomenon brought about not only by a single determinant but the interaction between various factors like socioeconomic status of an individual or a community, the existing transportation system, and built environment properties (Cass et al., 2005; Currie & Delbosc, 2011). Transportation disadvantage could thus be defined in different ways and various studies do so. Lucas (2012) advocated the use of transportation disadvantage through the lens of social exclusion and argued that this approach would be able to address the multidisciplinary nature of transportation disadvantage. The highly cited definition on social exclusion given by Kenyon et al. (2002) reads as:

"*The unique interplay of a number of factors, whose consequence is the denial of access, to an individual or group, to the opportunity to participate in the social and political life of the community, resulting not only in diminished material and non-material quality of life, but also in tempered life chances, choices and reduced citizenship.*" The above definition on social exclusion portrays lack of mobility as a factor and the lack of access as a consequence. Hence, individuals and communities with inadequate mobility would be forced to face inequality of opportunity to participate in civic life. Trip characteristics like trip rate and trip lengths would provide ideas about the degree of participation of different socioeconomic groups in a civil society, which is entailed for well-being and the sense of inclusion.

The assumption of car ownership in envisioning transportation and land-use systems forces lower-income households to own and operate personal vehicles despite barely being able to manage other basic necessities of life so that they avoid the disadvantages associated with social exclusion (Jones, 2011). Clifton & Lucas (2018) mentioned that not having regular access to an automobile is directly associated with facing transportation disadvantage in the U.S. and

the UK. Moreover, Pucher & Renne (2005) used the 2001 National Household Travel survey to study the difference in rural and urban mobility and argued that car ownership was a necessity for travel in the U.S., more so in the rural areas. In order to participate in the normal activities of the society which is ultimately associated with an individual's well-being (Delbosc & Currie, 2011), car ownership has been implied as a requirement in an automobile dependent society. Moreover, car ownership in many instances has been found to be pivotal in getting employed and being able to work for longer hours (Gurley & Bruce, 2005) . The low-density form of urban development and suburban growth following the second world war, that expected people to drive cars makes automobile an essential requirement of daily life in the U.S (Jones, 2011) .

Some studies have illustrated the importance of public transportation to provide equity across various levels of socioeconomic standing (Kawabata & Shen, 2007) and some have viewed transportation disadvantage in terms of areas with scarce public transportation (Hurni, 2005). However, pertaining to the lack of flexibility, reliability and lower perceptions about safety associated with public transportation, automobiles are an attractive mode of travel. Moreover, Sanchez et al. (2004) illustrated that access to transit services had no impact on the employment outcomes of poor families. Grengs (2010) argued that the spatial mismatch hypothesis put forth by Kain (1968) to explain household and employment segregation among African Americans, entailed revision to account for the effect of modes and asserted that policies aimed at increasing access to vehicles among low-wage workers is the most prominent way to ensure equity.

Though an extensive body of literature have emphasized on the importance of cars for lower income families in the U.S., an area of research that has not been adequately delved into is the financial hardship associated with car ownership. Though car ownership would alleviate the mobility barrier that causes disadvantage, it comes at the expense of financial hardship pertaining to higher costs of car ownership. We hypothesize that financial hardship associated with car ownership, which is in itself a form of disadvantage (Mattioli & Colleoni, 2016), would force the lower-income households to be cautious with regards to the use of their vehicles pertaining to the higher costs of operating cars and also the extent to which they participate in societal activities. Our research is an attempt to illustrate this case by quantitatively observing the differences in trip pattern of lower-income households (both zero-car households and households having at least one car) and that of higher income households.

Transportation disadvantage associated with financial difficulty pertaining to car ownership have been named differently in the literature. Currie & Senbergs (2007) used the term 'Forced Car Ownership' and explored the growth of forced car ownership in Australia while Mattioli & Colleoni (2016) used the term 'Car-related economic stress' to describe the phenomenon of individuals or communities experiencing financial stress while owning an automobile. We use the term Car-related economic stress suggested by Mattioli & Colleoni (2016) as it is more neutral and also covers the dynamic nature of transportation disadvantage. For instance, higher

income households at a certain point might start experiencing car-related economic stress when there is a rise in oil prices.

Like Shay et al. (2016) argued, it is not just the socioeconomic attributes that make an individual or a community experience transportation disadvantage but also the built environment that they live in. It is therefore imperative to look into the phenomenon of transportation disadvantage and car-related economic stress in association with the spatial environment and the way they have been changing over time. Miller (2004) argues that spatio-temporal dimensions should be considered in the discussion of social exclusion. The spatial distribution of opportunities like employment and housing would interact differently with different sociodemographic characteristics like age, gender, lifecycle stage and income to influence an individual's mobility and participation in civic life. Furthermore, transportation disadvantage would also depend on an individual's life trajectories within a socio-spatial environment. Built environment properties as well as technological advancements and attitudinal factors are continuously changing over the decades and hence it is imperative to consider the dimension of time in the study of transportation disadvantage. Roorda et al. (2008) attempted to explain the evolution of travel demand over time using multivariate regression models but their models provide a cross-sectional snapshot of the travel demand of different years but do not adequately explain how trip rate changed over time. Further, they also do not explain how sociodemographics interact with the built environment properties and time to influence trip rate.

Our study focuses on trip rate to explain the phenomenon of transportation disadvantage that individuals are forced to experience when they do not have cars and to explore the idea that owning and operating cars could still be a form of disadvantage for poor/low-income households. Further, we investigate how the trip patterns and travel behavior is affected by the interaction of income and vehicle ownership with the built environment and how it has been changing over time since 2001 to 2017.

2.3 DATA AND METHODS

As discussed in detail in the literature review section, transportation disadvantage has been reviewed through different vantage points in the extant literature. On a broader sense, transportation disadvantage can be summed up as the situation whereby individuals experience difficulty in accessing opportunities because of the built environment and transportation system in place or because of the personal difficulties like physical/mental disability, age and income status (Rajé, 2003). Gaustad (2018) pointed out to socio-demographic characteristics such as age, immigration status, income levels and physical barriers to transportation as the significant factors defining transportation disadvantage. On the other hand, Hurni, (2005); Roberto, (2008); Shay et al., (2016) present transportation disadvantage in terms of specific areas that have scarce public transportation which makes it difficult for an individual without access to automobiles to participate in society. Some studies have portrayed transportation disadvantage as essentially a problem related to

accessibility (Grengs, 2010) , while some argue that both accessibility and mobility based measures need to be studied in conjunction to accurately capture the nature of transportation disadvantage (Pyrialakou et al., 2016). Even individuals with cars might face transportation disadvantage pertaining to the built environment an individual resides in and thus geographic context has been expressed to have a strong influence on the experience of transportation disadvantage (Delbosc & Currie, 2011).

Though different authors define transportation disadvantage differently, the unavailability of personally owned vehicle in an automobile dependent society is a commonplace idea in most studies pertaining to transportation disadvantage (Blumenberg & Pierce, 2012; Clifton & Lucas, 2018; Pucher & Renne, 2005). We pair the dimension of income with vehicle ownership and taking the definition put forth by Mattioli & Colleoni (2016) in our context, we define low-income households with at least one car as households experiencing *Car-Related Economic Stress* (CRES). Spending a large proportion of their income on car ownership might not be much of a burden to those with higher income but the families barely sustaining their lives could be forced to compromise on other areas of well-being because of the need to own a car. We note though that car ownership may not be the only or even the primary reason for causing difference in trip characteristics for CRES households but may be an important contributing factor. We study trip rate for individuals in the three categories of households that we define to examine how vehicle availability and income status are jointly inherent in determining an individual's mobility pattern.

We use the past three National Household Travel Surveys (NHTS) (2001, 2009 and 2017) to study the differences in travel patterns of households that are car-less, experiencing car-related economic stress, and higher-income. The NHTS is a rich source to study the travel behavior of American households and individuals as it provides data on trip patterns that can be associated with the residential location and socioeconomic attributes of the respondents (Highway Administration, 2019). NHTS records data on trips made by the households and individuals over a period of 24 hours. We employ the NHTS data in conjunction with federal definitions of poverty from the census to separate the categories of households of our interest. The U.S. Census Bureau provides country-level thresholds to determine if a household is above or below poverty based on household size and household income (Census Bureau). Using the thresholds from the census and the household income and corresponding family size in the NHTS, we classify whether a household is above or below the poverty line. Further, the national center for children in poverty mentions that families, on average, entail an income equal to twice the federal poverty level to sustain their basic needs (Koball & Jiang, 2018). We use 200 percent above the poverty line as a marker to define the low-income threshold. We define a household under poverty or low-income thresholds having at least one car as a household experiencing ***Car-Related Economic Stress (CRES).***

2.3.1. Categories of Households

Carless households: Households under poverty or low income and without a car are defined as carless in this study. These families irrespective of their location can be at a disadvantage pertaining to their bleak financial condition in addition to not having a personally owned vehicle (POV).

CRES households: These are households which are under poverty or fall under the low-income umbrella but have at least one car in their household. The cost entailed to own and operate a car in the U.S. may keep them under economic stress despite enjoying the mobility benefits provided by cars. Even if these households own and operate cars, we hypothesize that they may not be able to enjoy the levels of mobility that higher income households do because of the financial difficulty that would make them limit their activities.

Higher-Income households: These are households which belong to middle-income and high-income levels. Pertaining to the already existing common awareness about high vehicle ownership in the U.S., we presume that most of these households most possibly own a personal vehicle. Even if they do not own a car, we do not consider this group to be disadvantaged because not having a car does not necessarily make an individual or a household experience transportation disadvantage. For instance, an individual without a driving license would not struggle to access opportunities and thereby would not feel excluded, if the income is high enough to afford ride hailing services or if the individual resides in an area with a robust and reliable public transportation system.

Since the trip pattern of the households of our interest is not just affected by individual socioeconomic attributes but also by their location of residence, we consider spatial dimensions to our study for which we study their trip rate across three spatial environments: urban, suburban, and rural. The urbanicity indicators in all three NHTS used in our study are used to classify the household location of the respondent in urban, suburban, and rural areas. Relative population density at the household location was used to classify whether it belongs to an urban, suburban, or rural location. The entire country is first covered by a set of grids, and the population density at each grid would be computed and ranked into one of hundred possible groups. Grids in Group 0 would have little to no population while grids with group 99 contained the densest neighborhoods in the U.S, many of them in the neighborhoods in Manhattan. The density ranks of each cell is compared with the density ranks of the cells surrounding it to determine the population center. A cell is a population center if the eight surrounding cells have equal or lower population density. Population centers can be visualized as peaks in density surrounded by decline in density. An algorithm was developed to provide a better context for the block groups in the grids. Based on the density centile scores and the density profile of the household location block group, a block group was classified into four urbanicity classes:

(1) Urban: These are areas with population density centile score between 75 and 99 and are characterized by peaks in population density. Urban areas mostly reflect the downtown of major cities and some neighborhood surrounding.

(2) Second City: Second cities are areas with relatively lower population density compared to the urban areas. They have a density centile score between 40 and 90. Though having lower

density compared to urban areas, second cities are population/employment centers of their surroundings. These are characterized by thousands of satellite cities surrounding the major city areas in the metropolitan regions of the country.

(3) Suburban: These are areas closely tied to the urban areas or second cities and have a density score between 40 and 90. They have a similar density range as the second cities, but they are very distinct in terms of their density profile. While second cities are the population centers characterized by peaks in population density, suburban areas are a continuation of the decline in density from the urban areas or second cities.

(4) Rural: These are areas with population density scores ranging from 0 to 40. These areas extend beyond the suburban rings of the major metropolitan regions in the U.S.

For brevity, and because the lifestyle and the commuting pattern of residents in second city and urban areas would be relatively similar, we place second cities as urban locations in our study. These definitions are consistent across Chapter 3 as well.

We present the travel characteristics like trip lengths, self-reported annual vehicles miles, modal distribution, and trip rate to explore the phenomenon of transportation disadvantage. National Household Travel Survey assigns weights to each household, person, and trip so that the survey results represent the national population. The trip rate, average trip lengths and modal distribution illustrated by the figures in the results section are weighted.

2.3.2. Model Theory and Estimation

To understand the phenomenon of transportation disadvantage associated with financial status and auto availability, we study trip rate, explicitly, the number of trips an individual makes on a day as the dependent variable and associate it with **i. personal characteristics** like age, gender, medical conditions, and employment type; **ii. household characteristics** like the category of households in this study that has been deduced from income and auto availability and number of vehicles in the household per adult, and **iii**. **spatial characteristics** like the location of residence being in a rural, suburban, or urban setting and the availability of rail in the metropolitan statistical area (MSA). To observe how the trip rate has been changing over time, the datasets from 2001, 2009 and 2017 were appended together and the common variables were considered for the purpose of estimating the model. Any incomplete records were removed from the final dataset. Outlier analysis was conducted to study if there were any unusual data in our dataset following the steps suggested by Aguinis et al. (2013). Upon inspection of the dependent variables in the final dataset we were convinced that there were no unjustifiably high number of trips made by an individual on a travel day. Moreover, the variables in our model were also free from multi-collinearity.

Finally, the variable selection process was completed, compliant with what would make the model more predictive and efficient.

The data on the number of trips that an individual makes on a certain travel day is essentially count data and thereby a suitable count data model was searched for. The most commonly used count data model is the Poisson regression model (Greene, 2018), which assumes that mean and variance are equal for the dependent variable. However, this essential condition for application of Poisson model (mean being equal to variance) is often not realistic (Cameron & Trivedi, 1998). Because of over dispersion in our data, the Poisson model was clearly not suitable in this case. Thus, we considered the possibility of fitting a negative binomial model to our dataset. Negative binomial (NB) regression relaxes the equal dispersion assumption of Poisson regression by introducing an over dispersion parameter (a gamma distributed random variable to the Poisson mean) to the model. However, a negative binomial model fitted to our dataset predicted significantly smaller number of zeros compared to what was observed in the data. This is why we opt for the hurdle model which is a two-step model that applies separate processes for the zero counts in the data and the rest of the positive counts (Cameron & Trivedi, 1998). The intuition is that positive counts occur once a threshold or a hurdle is crossed. If the hurdle does not get crossed, then a zero count occurs. Hence, the hurdle model in our case has two parts. The first part is a binary logit model which models whether the observation takes a positive count or not and the next is a truncated negative binomial model whereby only positive counts are used to fit the model. The hurdle model is estimated using the method of maximum likelihood in two steps; first, using all observations for the binary response model and thereafter using the set of positive observations to estimate a zero-truncated count data model. We also considered the zero-inflated model. A zero-Inflated model can be applied when the zeros in the dataset are of two types: sampling zeros and structural zeros (Rose et al., 2006). However, in our case, the zero-trip reports in the dataset are essentially sampling zeros because not making a trip on a certain day cannot be intuitively considered as structural zero as there would be no individuals who would never make a trip. With respect to model fit, the results on Vuong's statistics showed that the hurdle model would be the most suitable among the count data models for our data. The process for estimating the model was completed in the statistical software R.

2.4. RESULTS

2.4.1. Descriptive analysis

Socioeconomic Characteristics

Exploring the NHTS 2017 data, it is observed in Table 2-1 that our classification of households based on income levels and car ownership also reveals variation in socio-demographic

characteristics. For instance, 37.56% of carless households is made up of Black or African Americans while they make only 10.04% of higher-income households. On the other hand, White Americans make up half of the carless population while they represent 77.25% of the higher-income population.

Table 2-1 Socioeconomic Characteristics of the Three Categories of Households in 2017

	Carless	CRES	Higher-Income
Gender (%)			
Male	43.89	49.04	51.44
Female	56.11	50.96	48.56
Life Cycle of Household (%)			
Single adult	15.41	5.21	6.86
2+ adults-0 children	35.79	54.77	49.44
2+ adults with children	22.73	20.8	29.46
Single parent	18.98	8.35	3.63
Retired	7.07	10.87	10.61
Education (%)			
Less than undergraduate	83.34	75.7	53.07
Undergraduate	12.29	17.23	26.59
Graduate	4.36	7.03	20.34
Race (%)			
American Indian	3.35	0.79	0.39
Asian	5.36	7	8.15
Black or African American	37.56	25.12	10.04
Multiracial	3.28	4.12	3.93
Native Hawaiian	0.26	0.18	0.25
White	50.19	62.79	77.25
Residential Location in: (%)			
Rural	13.15	37.35	39.72
Suburban	10.69	18.25	25.21
Urban	76.15	44.4	35.07
Medical Condition (%)			
Pre-existing medical condition	8.88	3.7	2.31
No Medical condition	92.23	96.3	97.69

This observation shows that White Americans and Asians are more likely to own cars as compared to households of another race. Moreover, as it is evident in Table 2-1, individuals in higher-income households are also found to be more educated as compared to individuals in Carless and CRES households. Another interesting observation from Table 2-1 is that more than two-thirds of carless low-income households reside in urban areas while only 10.69% and 13.15% of carless households reside in suburban and rural areas respectively. On the other hand, almost 40% of higher-income households live in rural areas. This finding is in alignment

with the past studies which suggest the concentration of poor in the core city centers in the U.S (Glaeser et al., 2008).

Vehicle Age

Comparing the age of the vehicles for the three categories of households, it can be observed that on average, the age of vehicles owned by a CRES household is three years older than that owned by higher-income households. This consistent pattern of difference in vehicle age from 2001 to 2017 in all geographical setting elucidates that households under economic stress may not be able to afford newer cars. Further, having older vehicles could also make the CRES household prone to financial shocks as they would need to keep expending on maintenance of older vehicles frequently. Klein et al. (2020) illustrate how individuals who were once equipped with cars are desperate to get another if their car breaks down and the hardships poor individuals are subjected to go through in the absence of a car. However, this is an area of research beyond the scope of this study.

Distribution of Number of Vehicles in the Household

Studying Table 2-2, it can be observed that a larger proportion of higher-income households from urban areas do not have cars in their households as compared to higher-income households in suburban areas. Moreover, a larger proportion of higher-income households in suburban areas do not have cars relative to households in rural areas. Similarly, most CRES households have only one car while most higher income households have two cars in their households. This would corroborate the existing knowledge on households converting a part of their income to own a car to meet their mobility needs and most households undergoing Car-related economic stress would add vehicles to their households if they could afford it (Blumenberg & Pierce, 2012).

Table 2-2 Distribution of Vehicle Count

		Urban			Suburban			Rural		
Household Category	**Vehicle Count**	2001	2009	2017	2001	2009	2017	2001	2009	2017
CRES	1	62.57	59.68	61.56	54.0	52.12	56.79	48.58	45.55	49.66
	2	27.22	29.54	25.66	31.68	33.34	27.08	32.09	34.19	30.83

	3	8.16	7.93	8.0	9.93	8.61	10.62	12.1	12.41	12.33
	>=4	2.04	2.84	4.76	4.39	5.92	5.51	7.22	7.86	7.17
Higher Income	0	4.46	7.47	7.70	1.02	1.4	0.88	0.95	0.86	0.55
	1	39.15	35.74	38.12	29.55	27.69	28.28	18.82	18.98	18.35
	2	38.27	37.63	35.64	44.89	46.26	42.26	43.51	41.77	38.45
	3	12.39	12.38	11.74	17.54	16.93	18.72	21.83	22.94	24.0
	>=4	5.72	6.76	6.78	6.99	7.71	9.85	14.88	15.53	18.64

Number of Cars in Household Compared to Household Size

Observing Table 2-3, it is evident that a larger proportion of higher income households have household vehicles either in equal or greater number to the household size. Contrary to the case of higher income households, higher proportion of CRES household own cars in numbers lesser than the number of family members in urban and suburban areas. However, in the rural areas it is not the case consistently from 2001 to 2017. This suggests the need to own cars for accessing opportunities in rural and suburban areas of the US.

Table 2-3 Comparison of Household Size and Number of Vehicles in the Household

		Urban			**Suburban**			**Rural**		
Household Category	**Vehicle Count**	2001	2009	2017	2001	2009	2017	2001	2009	2017
CRES	<HH size	53.75	63.53	59.32	50.81	60.32	53	45.63	47.01	46.61
	>= HH size	46.24	36.46	40.67	49.18	39.68	47	54.36	52.97	53.39
Higher Income	<HH size	37.81	39.46	44.56	39.69	38.48	38.51	32.76	29.01	31.26
	>= HH size	62.19	60.54	55.44	60.31	61.52	61.49	67.23	70.99	68.74

We now present trip characteristics, such as modal distribution, trip rate and trip length for the individuals belonging to the three categories of households across space and over time from 2001 to 2017. We also estimate a hurdle model as a count data model to explain trip rate of the three categories of households defined in this study.

Modal Distribution

As Figure 2-1 depicts, the modal distribution in all of three years, suggests that for households with a car in their household, at least around 80% of their trips are made using cars. Car use is much more prevalent in the rural and suburban areas in the U.S. which is indicated by large modal share of car. Even people from households without a car make almost half of their total trips using cars in suburban areas. Individuals in households without cars may resort to strategies such as asking for rides and scheduling their trips with their friends (Lovejoy & Handy, 2011). Moreover, for CRES households in the suburban areas more than 80% of their trips are

made using cars. Though the proportion of trips using cars, made by car-less households in rural areas decreased to half of the total trips in 2017 from 60% of the trips using cars in 2009, it still indicates that cars are a necessity for daily life in the rural and suburban U.S (Pucher & Renne, 2005). Except in the urban areas in the year 2017, the difference in modal share of cars between Higher-Income households and CRES households is at least 2%, across all geographical settings and throughout the years. Similarly, the CRES households also do walk more compared to higher income households. This could be because the CRES households do not own as many cars in their households as the number of family members as they view cars as a household necessity rather than a commodity for luxury. Moreover, resorting to other modes like bike and walk could be a way for the CRES households to alleviate the transportation costs associated with driving.

Figure 2-1 Modal Distribution

Trip Rate

Figure 2-2 articulates the weighted average trip rate for individuals in the three categories of households. It can be deduced that the overall trip rate for all three categories except for carless households in urban areas has been decreasing over the years which may be attributed to the advent of ubiquitous use of internet, teleworking, online shopping and food deliveries (Pendyala et al., 1991). Furthermore, Figure 2-2 also articulates that individuals in higher

income households generate more trips compared to Carless or CRES households which associates higher income with higher trip generating behavior. Moreover, though CRES and Carless households defined in this study have the same financial standing, the higher trip rate for individuals in households facing car-related economic stress provides basis for associating the availability of vehicle in a household with higher trip generating activity.

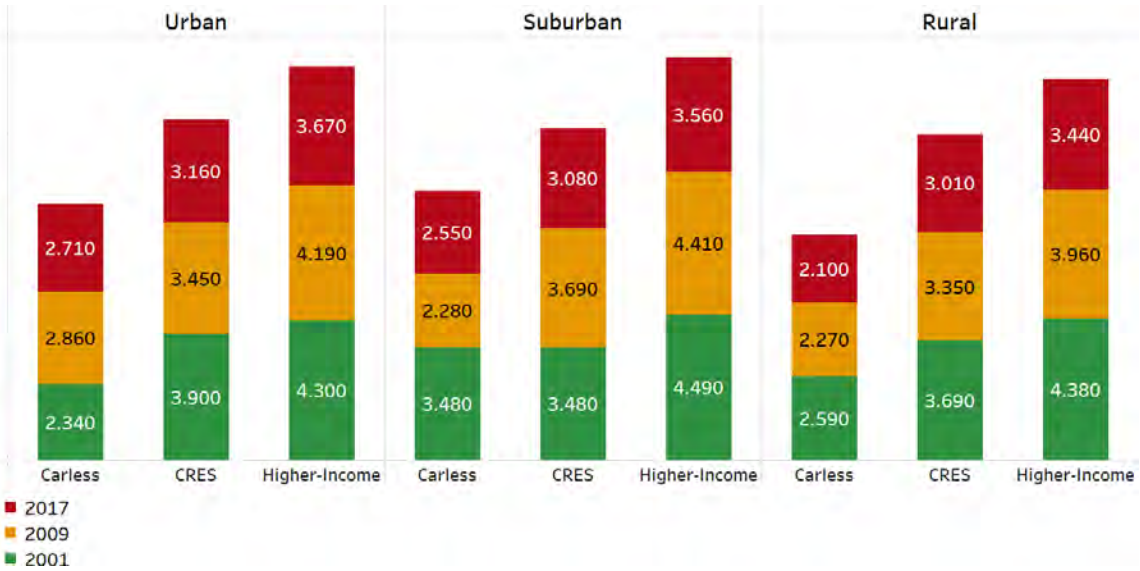

Figure 2-2 Trip Rate

Trip Lengths

The weighted average trip length for all three categories of households in three different spatial environments regardless of mode and purpose, and the average trip length in personally owned vehicles for CRES and Higher-Income households are presented in Figure 2-3 and Figure 2-4 respectively. Furthermore, Figure 2-4 shows the average self-reported annual miles of vehicle driven for the CRES and Higher-Income households. As can be observed from Figure 2-3, the average trip length for Higher-Income households is higher than that of CRES households and much higher than that of Carless households in year 2017 and 2009. Surprisingly, the average trip length for Carless households in rural and suburban areas is higher than that for CRES and Higher-Income households in year 2001. Running the analysis without the weights, we find the pattern of average trip lengths in 2001 to be comparable to what is observed in 2009 and 2017. So, digging deeper into the trip weights for year 2001, we observe that on average, each trip made by a carless individual was assigned a weight of 2.56 million while the trips made by CRES and Higher-Income individuals was assigned a weight of 1.5 and 1.37 million respectively in the rural areas. Moreover, similar levels of differences between weights can be observed in suburban areas among the three categories of households in 2001. Higher trip weights are assigned because of the lower number of people surveyed in that socioeconomic group. This problem is not existent in 2009 and 2017 because more people were surveyed, and hence the

difference in trip weights were not found to be as large as that in the year 2001. Nevertheless, based on average trip lengths in 2009 and 2017, it can be reasonably argued that vehicle availability increases the sphere of an individual's mobility. Furthermore, it is also quite evident that Higher-Income households on average travel further per trip compared to CRES households.

The average trip length made by someone in a CRES and Higher-Income household using a personally owned vehicle is depicted in

Figure 2-4 Average Trip Length in Personally Owned Vehicles and it is self-evident that on average, Higher-Income households make longer trips than CRES households in their cars.

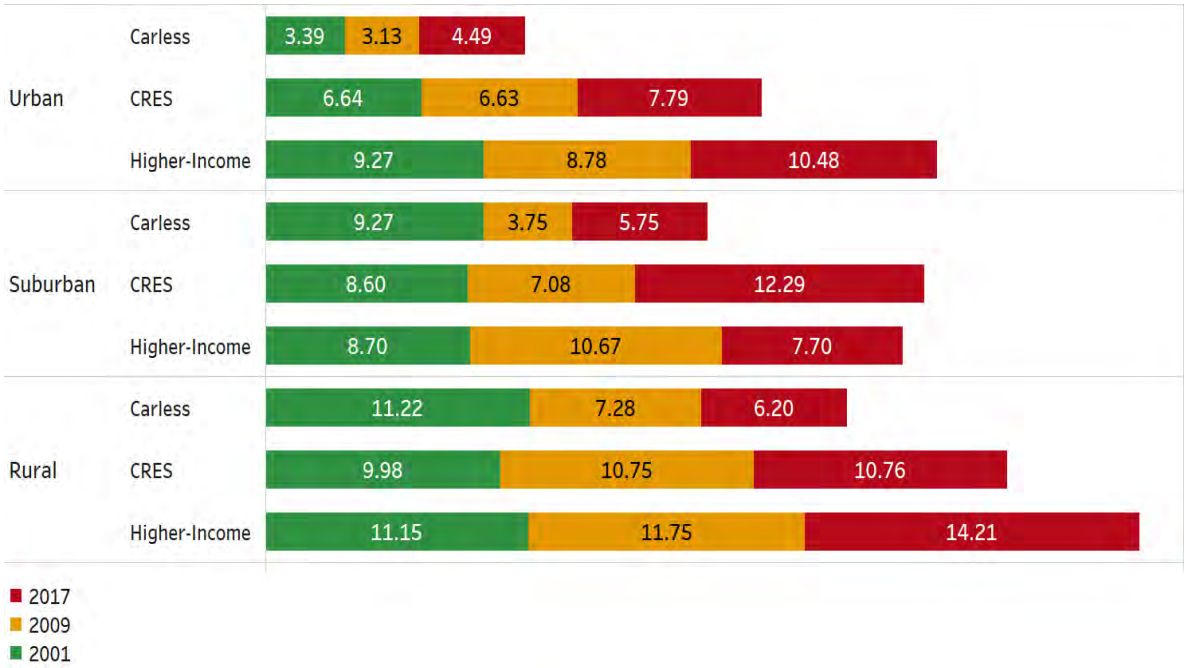

Figure 2-3 Average Trip Length

Figure 2-4 Average Trip Length in Personally Owned Vehicles

As **Error! Reference source not found.** depicts, the weighted self-reported annual miles driven for their cars on average are also higher for Higher-Income households compared to CRES households. However, in 2009 and 2017, it is observed from Figure 2-4 that individuals in suburban areas experiencing Car-Related Economic Stress drive their vehicles more than Higher-Income households do. This could be associated with poor and low-income households living in suburban areas but being employed in core urban areas that makes them drive more for work daily.This could counter intuitively also be analyzed as poor/low-income households in suburbs being compelled to own and operate cars to keep their employment which would be accessible only if they have a car.

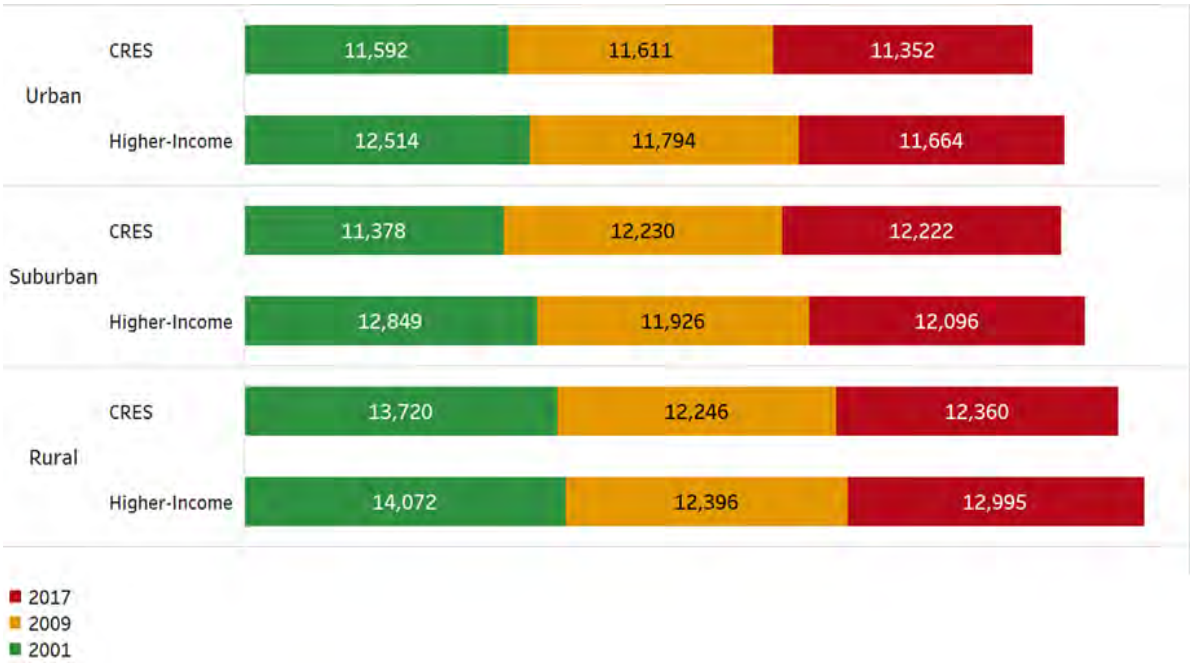

Figure 2-5 Self-Reported Annual Miles of Vehicle Driven

2.4.2. Econometric Analysis

Finally, we statistically explore trip rate between the three categories of households by estimating a hurdle model. Table 2-4 Description of Variables Used in the Hurdle Model shows the explanation of the independent variables used in the model while .

Table 2-6 Hurdle Model to Explain Trip Rateshows the model results. The descriptive analysis provides insights on the average travel characteristics of the different socioeconomic groups, but it is essential to explore the interrelationship between the variables which affect the outcome variable for which we resort to hurdle model as the econometric model to explain trip rate. Furthermore, it is always interesting to observe how two independent variables jointly affect the magnitude of the outcome variable. Interaction effects in econometric models help us explore such phenomenon. For instance, car-ownership might significantly affect an individual's trip rate in a rural area but not necessarily in an urban area. Exploring such phenomenon using an econometric model alongside the average effects provides ample insights on the spatio-temporal heterogeneity in the effect of socioeconomic characteristics on travel behavior.

Table 2-4 Description of Variables Used in the Hurdle Model

Variable Name	Description
Personal Characteristics	
Education: Undergraduate	1 if the individual has an undergraduate degree: 0 otherwise
Education: Graduate	1 if the individual has a graduate degree: 0 otherwise
Gender: Female	1 if the individual is a female: 0 otherwise
Age	age of the respondent
Has Medical Condition	1 if the individual has a medical condition, 0 if the person does not have a medical condition
Part-time job	1 if the individual works part-time; 0 otherwise
Multiple jobs	1 if the individual has multiple jobs; 0 otherwise
Household Characteristics:	
CRES	1 if the households have at least 1 car and the equivalent income is less than low-income limits (households experiencing car-related economic stress), 0 otherwise
Higher-Income	1 if the households are higher income households (either middle income or high income); 0 otherwise
Vehicles per adult	numeric variable that explains the number of vehicles available in the household divided by household size
2+ adults 0 children	1 if 2 or more adults are there in the household without children, 0 otherwise
2+ adults with children	1 if the individual lives in a household with 2+ adults with children, 0 otherwise
Single parent	1 if the individual is a single parent, 0 otherwise
Retired	1 if the individual is retired or if the household has 2+ retired adults, 0 otherwise
Spatial Characteristics:	
Suburban	1 if the household resides in suburban area; 0 otherwise
Urban	1 if the household resides in urban area; 0 otherwise
MSA has rail	dummy variable that takes the value 1 if the household is in MSA with rail and 0 if the MSA does not have rail or the household is not in MSA
Temporal Characteristics:	
Year 2009	1 if the observation refers to year 2009; 0 otherwise
Year 2017	1 if the observation refers to year 2017; 0 otherwise

Table 2-5 illustrates the descriptive statistics for data sets that are used to fit the necessary model to explain the trip generation behavior. Moreover, most of the variables in our model are categorical variables, the proportion of each variable and their variation within each category of households that we define is elucidated in Figure 2-6.

Table 2-5 Descriptive Statistics

Descriptive Statistics for Trips per Day						
Statistic	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Age	43.51	14.553	16	32	55	92
Vehicles per adult	1.103	0.513	0	1	1.3	8

.

Table 2-6 shows the results of the hurdle model. The dependent variable is trips per day. Model-I shows the results of the average relationship for trips per day while Model-II includes interaction terms that explain how the trip rate varies by geography for individuals in different categories of households. Model-III introduces additional interaction terms between categories of households, geography and time which explain how trip rate has been varying over space and time for the three categories of households defined in this study.

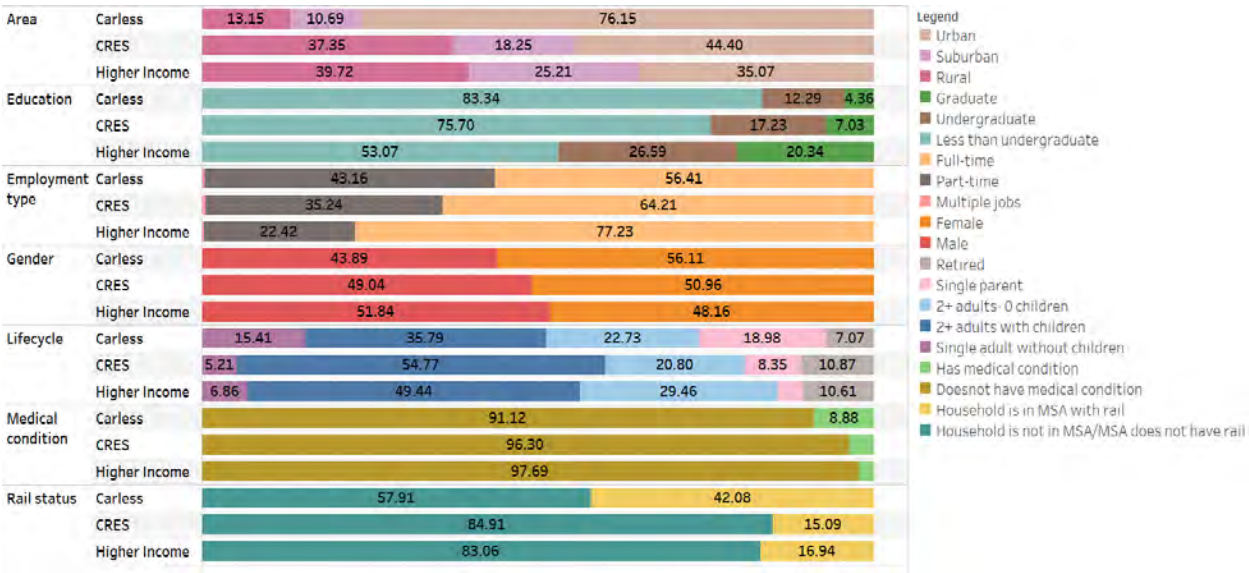

Figure 2-6 Proportion of Categorical Variables in Each Category of Household

The hurdle model is a two-part model. The first portion of the .

Table 2-6 represents the zero-truncated negative binomial model, and the second portion presents the binary logit model that explains the odds of making a trip. The coefficients of these

models can be interpreted in the same way as the coefficients of a count data model and the binary logit model. It can be observed from all the three models in .

Table 2-6 that the variables of our interest in this study, explicitly, the category of household that we define are statistically significant, which implies that trip rate is associated with a household's financial standing as well as the status of auto availability.

Table 2-6 Hurdle Model to Explain Trip Rate

	Model-I	Model -II	Model- III
Count Data Part: Zero Truncated Negative Binomial Model			
Intercept	1.369 (0.006) ***	1.436 (0.016) ***	1.377 (0.017) ***
Suburban	0.016 (0.002) ***	−0.047 (0.023) *	−0.084 (0.024) ***
Urban	0.041 (0.001) ***	−0.038 (0.017) *	−0.052 (0.017) **
CRES	0.145 (0.006) ***	0.084 (0.016) ***	0.139 (0.017) ***
Higher-Income	0.178 (0.006) ***	0.109 (0.016) ***	0.170 (0.017) ***
Education: Undergraduate	0.105 (0.001) ***	0.105 (0.001) ***	0.106 (0.001) ***
Education: Graduate	0.114 (0.002) ***	0.114 (0.002) ***	0.114 (0.002) ***
2+ adults- 0 Children	−0.128 (0.002) ***	−0.128 (0.002) ***	−0.127 (0.002) ***
2+ adults with Children	−0.077 (0.002) ***	−0.076 (0.002) ***	−0.076 (0.002) ***
Single Parent	0.088 (0.003) ***	0.088 (0.003) ***	0.089 (0.003) ***
Retired	−0.148 (0.003) ***	−0.147 (0.003) ***	−0.147 (0.003) ***
Gender: Female	0.048 (0.001) ***	0.048 (0.001) ***	0.048 (0.001) ***
MSA has Rail	−0.061 (0.002) ***	−0.061 (0.002) ***	−0.060 (0.002) ***
Age	0.003 (0.000) ***	0.003 (0.000) ***	0.003 (0.000) ***
Year 2009	−0.052 (0.002) ***	−0.052 (0.002) ***	0.038 (0.014) **
Year 2017	−0.088 (0.001) ***	−0.088 (0.001) ***	0.062 (0.014) ***
Vehicles per Adult	0.030 (0.001) ***	0.030 (0.001) ***	0.030 (0.001) ***
Part-time Employment	0.085 (0.001) ***	0.085 (0.001) ***	0.085 (0.001) ***
Multiple Jobs	0.067 (0.009) ***	0.067 (0.009) ***	0.067 (0.009) ***
Has Medical Condition	−0.040 (0.004) ***	−0.040 (0.004) ***	−0.040 (0.004) ***
Suburban: CRES		0.078 (0.024) **	0.109 (0.024) ***
Urban: CRES		0.057 (0.017) ***	0.067 (0.018) ***
Suburban: Higher-Income		0.062 (0.023) **	0.099 (0.024) ***
Urban: Higher-Income		0.084 (0.017) ***	0.099 (0.017) ***
CRES: Year 2009			−0.074 (0.015) ***
Higher-Income: Year 2009			−0.095 (0.014) ***
CRES: Year 2017			−0.143 (0.014) ***

Higher-Income: Year 2017			−0.154 (0.014) ***
Binary Logit Part			
Intercept	4.300 (0.072) ***	3.914 (0.122) ***	3.836 (0.132) ***
Suburban	0.101 (0.016) ***	0.597 (0.204) **	0.355 (0.210) .
Urban	0.126 (0.015) ***	0.597 (0.130) ***	0.436 (0.133) **
CRES	−0.092 (0.055) .	0.311 (0.116) **	0.490 (0.128) ***
Higher-Income	0.021 (0.055)	0.410 (0.115) ***	0.475 (0.126) ***

Hurdle Model to Explain Trip Rate (Continued)

	Model-I	Model-II	Model-III
Education: Graduate	0.435 (0.018) ***	0.434 (0.018) ***	0.426 (0.018) ***
2+ adults – 0 Children	−1.251 (0.045) ***	−1.252 (0.045) ***	−1.257 (0.045) ***
2+ adults with Children	−1.316 (0.044) ***	−1.318 (0.044) ***	−1.322 (0.044) ***
Single parent	−0.618 (0.057) ***	−0.620 (0.057) ***	−0.619 (0.057) ***
Retired	−1.326 (0.047) ***	−1.326 (0.047) ***	−1.330 (0.047) ***
Gender: Female	0.128 (0.012) ***	0.128 (0.012) ***	0.129 (0.012) ***
MSA has Rail	−0.114 (0.016) ***	−0.114 (0.016) ***	−0.116 (0.016) ***
Age	0.007 (0.000) ***	0.007 (0.000) ***	0.007 (0.000) ***
Year 2009	−0.058 (0.020) **	−0.058 (0.020) **	0.601 (0.147) ***
Year 2017	−0.311 (0.014) ***	−0.310 (0.014) ***	−0.129 (0.118)
Vehicles per Adult	0.155 (0.014) ***	0.153 (0.014) ***	0.151 (0.014) ***
Part-time Employment	−0.195 (0.013) ***	−0.196 (0.013) ***	−0.196 (0.013) ***
Multiple Jobs	−0.138 (0.098)	−0.139 (0.098)	−0.144 (0.098)
Has Medical Condition	−0.866 (0.026) ***	−0.866 (0.026) ***	−0.864 (0.026) ***
Suburban: CRES		−0.611 (0.207) **	−0.356 (0.213) .
Urban: CRES		−0.452 (0.133) ***	−0.291 (0.137) *
Suburban: Higher-Income		−0.476 (0.205) *	−0.233 (0.210)
Urban: Higher-Income		−0.484 (0.130) ***	−0.321 (0.134) *
CRES: Year 2009			−0.748 (0.153) ***
Higher-Income: Year 2009			−0.655 (0.148) ***
CRES: Year 2017			−0.325 (0.123) **
Higher-Income: Year 2017			−0.149 (0.120)
McFadden's Pseudo R^2	0.008	0.0081	0.0082
N	216426	216426	216426

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.1$

From Model-I, it can be deduced that on average, the trip rate for someone in a CRES household is exp (0.145) = 15.60% higher than the trip rate for an individual in a Carless

household while the trip rate for Higher-Income households is 19.5% higher than the trip rate for Carless households. Thus, the trip rate for the CRES households is also relatively lower than that of Higher-Income households. Furthermore, it can be observed in Model-I that average trip rate in urban areas is higher than that in suburban areas. However, though average trip rate is higher for households with personal vehicles and on average, in urban areas as compared to the suburban areas, it might vary differently across space for different households. In order to observe this phenomenon, we add interaction between the households categories and geographical location in the hurdle model.

Model-II in .

Table 2-6 includes the interaction between categories of household and their household location. The reference category in this model is Carless household in rural areas. The coefficient of the variables suburban and urban indicate that Carless households in suburban and urban areas on average have lower trip rate but higher odds of making a trip compared to Carless households in rural areas. Interestingly, we observe that CRES households in suburban areas travel more frequently than CRES households in urban areas. On the contrary, higher-income households in the suburban areas have lower trip rate compared to their counterparts in the urban areas. In the urban and suburban areas, as expected, both CRES and higher-income households travel more frequently compared to the carless households. Furthermore, we also observe that the trip rate among the higher-income households is greater than that among CRES households in both the suburban and urban areas.

Over the years, as Model-I explains, the trip rate on average has been decreasing by 5% and 8% respectively in years 2009 and 2017. Model-III on the other hand illustrates that the trip rate for Carless households has been increasing over the years, albeit by a small amount, antithetical to what has been observed for CRES and Higher-Income households. On the other hand, the odds of making a trip for someone in a Carless household is 82.39% higher in year 2009 than that for someone in carless households in year 2001, while the odds of making a trip have alleviated over the years for both CRES and Higher- Income households.

Several insights can be deduced from the results of the models. As expected, the travel behavior of an individual depends both on financial status and vehicle availability. Vehicle availability is a significant determinant of trip rate, as can be observed from the higher trip rate for someone in a CRES household which have equivalent income as that of carless households. This observation provides sufficient basis to assert that vehicle ownership is strongly associated with an individual's ability to access opportunities. Furthermore, an interesting observation that can be drawn from the models is that the effect of spatial environment varies by household type. Moreover, the change in trip rate over the years is also found to vary with the household type. Specifically, the average trip rate for someone in a Carless household has been increasing

over the years from 2001 to 2017 but it has decreased for both CRES and Higher-Income households.

We attempt to advance the definition of transportation disadvantage from commonplace knowledge of being carless and pair car ownership with income of a household. Having access to a car eases the mobility requirements but also adds financial burden to the household, which contributes to lower trip rates compared to higher income households.

2.5. CONCLUSION

This research focuses on studying transportation disadvantage on an aggregate level by exploring how trip characteristics like trip rate and vehicle use would be affected by vehicle availability and financial status of a family. We find that trip rate is directly associated with vehicle availability in a household. Continuous access to vehicles would render the trip rate of an individual in a low-income family comparable to that with someone in a higher-income household. This corroborates the existing widely available literature which associate being carless with transportation disadvantage. However, the households experiencing financial stress while still owning a car do not use vehicles to the same extent that individuals from higher income households do as operating a personally owned vehicle is an expensive household commodity. We attempt to expand the idea that though car ownership is an important requirement for participation in a car-oriented society to overcome the disadvantage pertaining to lack access to opportunities, households could still be disadvantaged even if they own personal vehicles. The financial status of a family also plays a significant role in determining their well-being associated with their mobility as well as in accessing opportunities.

Moreover, it is observed that trip rate on average is higher in the urban areas of United States as compared to suburban areas. However, trip characteristics for the different households vary with spatial environment. For instance, carless households in rural areas are found to travel more frequently compared to their counterparts in suburban and urban areas. This could be because of dispersed land-use and lack of enough opportunities concentrated in an easily accessible area, which would make them travel more frequently to access the opportunities that their counterparts in suburban and urban areas can access without having the need to travel as much. On the contrary, low-income households with cars generate more trips in the suburban and urban areas. Furthermore, we see that low-income households with cars travel more frequently in the suburban areas compared to their counterparts in the urban areas. On the other hand, higher-income households generate more trips in urban areas compared to the suburban areas. The higher trip rate for higher-income households in urban areas could be

because of more activities to participate in the urban areas, relative to the suburban areas. However, it could be because of the relatively bleak financial condition, low-income households with personal vehicles do not travel as much in the urban areas and may be travelling mostly for employment and utilitarian purposes. The higher trip rate for car owning low-income households in suburban areas as compared to their counterparts in urban areas may be because of the limited opportunities and lower degree of land-use mix which makes them travel more frequently to meet their needs. We also observe that larger proportion of lower-income households in the suburban areas have lower number of vehicles in their households as compared to household size. This could also partly explain why low-income households with cars make lesser trips per day compared to higher-income households on average, as there could be household members who might not have continuous access to cars. Furthermore, the higher-income households in suburban areas could afford ridehailing services which may be an expensive mode of travel for the low-income households.

Another interesting observation can be observed longitudinally from 2001 to 2017. We see that while the average trip rate for the carless households increases from 2001 to 2017, it has been decreasing over this period of time for the households with cars regardless of their financial condition. We expect that our study is going to add insights to the understanding of transportation disadvantage. However, further exploration is entailed on providing equitable travel opportunities. Though the importance of car availability is an established notion, our study suggests that it does not necessarily provide equitable travel opportunities across different spatial environment.

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PERCEPTION AND FREQUENCY OF USE OF ACTIVE TRAVEL AMONG HOUSEHOLDS VARYING IN INCOME, VEHICLE OWNERSHIP AND HOUSEHOLD LOCATION

Research conducted by Dr. Eleni Bardaka and Subid Ghimire, North Carolina State University.

3.1 INTRODUCTION

Active travel, such as walking and cycling, has been gaining attention in the academic literature pertaining to its health (Dill, 2009; Oja et al., 2011; Titze et al., 2014) and environmental benefits (Fallah Zavareh et al., 2020; Xia et al., 2015). Recent studies on active travel focus on broad issues like the determinants for their adoption and policies for modal shift towards active travel rather than primarily engineering questions such as how wide the bicycle lane and sidewalks should be (Handy et al., 2014). For example, Porter et al. (2020) explored the 2017 National Household travel survey data to study the barriers that users report as the reason for not using cycling and walking more as a means of travel. However, it is also important to account for the socioeconomic attributes and the built environment characteristics that can play a major role in determining the prevalence of active travel (Cervero & Duncan, 2003; Mertens et al., 2017; Stinson & Bhat, 2004). There are only a few studies which advocate about considering the rural context for improving the prevalence of active travel in rural areas (Tribby & Tharp, 2019). This study adds to the study of Porter et al. (2020) to investigate the infrastructure and safety barriers that households of different economic status and living in various geographical settings perceive.

This study is unique in its use of National Household Travel Survey (NHTS) 2017 in descriptively analyzing the idea of active travel to overcome financial burden among households of different socioeconomic status. Since the built environment also impacts the perception of individuals with regards to the mode they use and their perception on active travel (Van Acker et al., 2014), this study explores the variations in perception of individuals belonging to different socio-spatial environments. We classify people who use active travel among two groups: Exclusively Exercise Users and Multi-Purpose Users (Porter et al., 2020). People who use active travel only for the purpose of exercise are termed as Exclusively Exercise Users and the people who use it for utilitarian reasons in addition to exercise are referred to as Multi-Purpose Users. Tribby & Tharp (2019) showed that income is a significant determinant of the use of active travel. We couple family income with vehicle ownership to classify the households into three categories namely, Carless households: households belonging to low-income category without a car, households facing Car-Related Economic Stress (Mattioli & Colleoni, 2016): low-income households having at least one vehicle in the household and finally Higher-Income households (middle and high income households). We study the frequency of bicycle and walk trips of

these households in three different spatial settings (urban, suburban, rural) in addition to their perception about active travel to overcome the financial stress associated with travel. The idea of resorting to active travel to overcome financial burden is studied only for Multi-Purpose Users. Similarly, perceived barriers of Exclusively Exercise Users and Multi-Purpose Users belonging to three different household categories that we define, on making bicycle and walk trips has also been explored. In essence, this study attempts to understand how individuals experiencing automobile related transportation disadvantage use and perceive active travel and if their perceptions would be different from that of higher-income individuals. This could provide insights into whether making active travel more appealing could be a means to overcome the disadvantage that lower-income individuals face with respect to their travel needs.

Furthermore, this research also attempts to explore the frequency of use of active travel among households that differ in terms of income, vehicle availability and residential location. Using the past three NHTS surveys, we attempt to observe how the frequency of active travel has been varying over the years for people with different socioeconomic background. We do so by estimating two Zero-Inflated Negative Binomial (ZINB) models; one to explain the frequency of bike trips and the other to elucidate the frequency of walk trips in a week. The models are estimated with the count of walk and bike trips in a week as the response variable and several sociodemographic properties, like the categories of households that we define, age, gender, education, and built environment properties like geography and availability of rail in the Metropolitan statistical area, as explanatory variables.

This research provides three fundamental insights on active travel: **i.** perception on active travel to overcome the financial burden of travel among individuals in different financial conditions **ii.** perceived infrastructure and safety barriers to the use of active travel in different geographies and among users who travel actively for different purpose and **iii.** statistical investigation on the factors determining the frequency of use of active travel and the way it has been varying over time and across space for people in different socioeconomic categories.

3.2. LITERATURE REVIEW

Though active travel has many health benefits (Krizec, 2007) and has seen increased use (specifically the walk mode) (Buehler & Pucher, 2011), it still accounts only for a small proportion of total trips in the U.S. Only 11.4% of all trips in 2009 were made either by a bicycle or by walking (Milne & Melin, 2014) while the figure was almost 12% in the year 2017 (FHWA NHTS Brief: Non-Motorized Travel, 2017). Nevertheless, rising fuel and auto prices along with awareness about environmental and health benefits of active travel has drawn attention towards promoting active travel both at the policy level as well as in academic research (TR News, 2012). This is virtually evident in the recent household travel surveys, that have started

including new subjective measures about the number of trips and perception on active travel (Ma & Dill, 2015). More states and cities have been prioritizing active travel and increasing funding accordingly to make active travel more conducive for a decade now (Milne & Melin, 2014). However, the small progress with respect to the prevalence of active modes of travel entails inquiry into the barriers that active travel users perceive with respect to safety and infrastructure conditions. Handy et al. (2014) enlist distance, infrastructure, access, equipment and social environment as key factors associated with the success of policies aimed to increase bicycling. Porter et al. (2020) used the 2017 National Household Travel survey to study the barriers that exercise and multi-purpose bicyclists face, but did not consider how the built environment and socioeconomic status may jointly affect the perception and the extent of use of active travel (Acker et al., 2013).

Handy et al. (2002); Porter et al. (2020) argued that high traffic volume is a significant factor discouraging bicycle use and dedicated bicycle lanes and increased density would help promote cycling (Chataway et al., 2014; Ma & Dill, 2015). Similarly, with regards to trips by walking, numerous studies attribute safety from crime, infrastructure (unavailable/poor sidewalks), and car-ownership as the reason that would influence people's choice to make walk trips (Fallah Zavareh et al., 2020; Ferrer & Ruiz, 2018; Tilahun & Li, 2019). (Lee et al., 2017) illustrated that built environment properties that promote walking would be different from those that promote cycling or transit. Hence, it is important to study the perceived barriers to walking and cycling separately and in relation with the built environment.

Though studies explore the perception on travel time for the individuals who travel actively (Ralph et al., 2020), only one study to the authors' knowledge shows that individuals resort to walk trips because of the costs it would save (Olojede et al., 2017). Studies on perception on active travel to overcome financial burden associated with travel are scant in the extant literature. In the U.S., which is one of the most car-dependent societies in the world (Pucher & Lefèvre, 1996) and where in most part, the built environment is sprawled, car availability provides ample mobility benefits (Blumenberg & Pierce, 2012), but it also leads to financial hardship among lower income populations and makes them prone to financial shocks. Such phenomenon is referred to in the literature as "Forced Car Ownership" by Currie & Senbergs (2007) and by the term "Car-Related Economic Stress" by Mattioli & Colleoni (2016). We use the term Car-related economic stress to define the households under low-income thresholds having at least one car to account for the issue of financial stress related to automobile ownership that low-income households face (Walks, 2018). To overcome the financial burden associated with mobility requirements, active travel could be an appealing alternative if appropriate policies and socio-spatial environment are present. Individuals reporting active travel as an effective means of reducing the financial burden of travel would provide a strong case to explore methods to promote active travel from the view-point of equity (Palm et al., 2021). This study contributes to the literature by investigating this idea using data from the 2017 National Household Travel Survey.

3.3. METHODOLOGY

The data for our analysis was obtained from the National Household Travel survey (NHTS) conducted by the Federal Highway Administration. NHTS is a rich source to study the travel behavior and trip pattern of American individuals and households (NHTS Data User Guide, 2017). Since, the surveys have been conducted at regular intervals from 2001, it is possible to observe the trend in the phenomenon that is being explored. Furthermore, the NHTS also provides information as to where the household is located which helps in comparing the phenomenon across space.

The 2017 National Household Travel Survey includes questions about the frequency of bike trips in a week and the number of bike trips made for exercise. If the number of total bike trips is found to be equal to the number of bike trips made for exercise then such respondents are classified as Exclusively Exercise Users (Porter et al., 2020) : people who use bike only for the purpose of exercise, in this study. The same process is applied to walk trips to classify people into users who use walk trips only for the purpose of exercise. If the total number of bike or walk trips in a week was found to be greater than the number of walk or bike trips made for the purpose of exercise, then such users are referred to as Multi-Purpose Users. Only the perception of Multi-Purpose users on active travel to reduce the financial burden of travel has been explored.

Furthermore, the 2017 NHTS also asks respondents who reported the use of one of the means of active travel (walk or bike) as to why they did not resort to its use more frequently. The responses are classified in terms of infrastructure or safety barriers in the NHTS. We explore the responses and attempt to understand if individuals varying in terms of their financial condition, residential location and vehicle availability perceive the barriers to active travel differently. Furthermore, walk and bike trips have been investigated separately in this study and to account for the effect of space, we study these perceptions in three different spatial settings: urban, suburban, and rural.

To statistically explore the frequency of use of bike and walk trips by households of different economic status, we use zero-inflated negative binomial (ZINB) model. Since the frequency of use of bike and walk trips is a count variable, we looked for the most suitable count data model and concluded that ZINB model would be the most suitable count data model in this case. The most commonly known type of count data model is the Poisson model which is unsuitable in cases when over-dispersion is existent in the count data (Greene, 2018). Since we observed over-dispersion in our data, we explored if the Negative Binomial model would be suitable. However, a shortcoming of the Negative Binomial model is that it cannot explain the over-dispersion that arises out of excess zeros available in the count results. Figure 3-1 shows the distribution of the number of bike and walk trips in a week from the 2017 NHTS data and it clearly shows that there are excess zeros in the response variable. In such cases, either hurdle

or zero-inflated models are suitable based on the type of zeros available in the data (Greene, 2018). If only sampling zeros were available then the model used would have been a hurdle model (Rose et al., 2006) but since the data on making a trip using bike or by walking contains both sampling as well as structural/certain-zeros, a ZINB model has been considered to be the most suitable count data model. More specifically, the zeros in the number of bike/walk trips could come from both the people who never use bike or walk for their trips (certain-zero) and from people who travel actively but did not do so in the week while the survey was conducted (sampling zero).

The zero-inflated model assumes that excess zeros in the distribution are generated from a separate process as compared to the count values and thus they can be modeled independently. A zero-inflated model consists of a logit model which investigates the odds of the outcome always being zero and a count data model which explains the frequency of the outcome. The count data part in the ZINB model also considers the zeros in the response variable unlike the hurdle model which only considers the positive outcomes for the count model part.

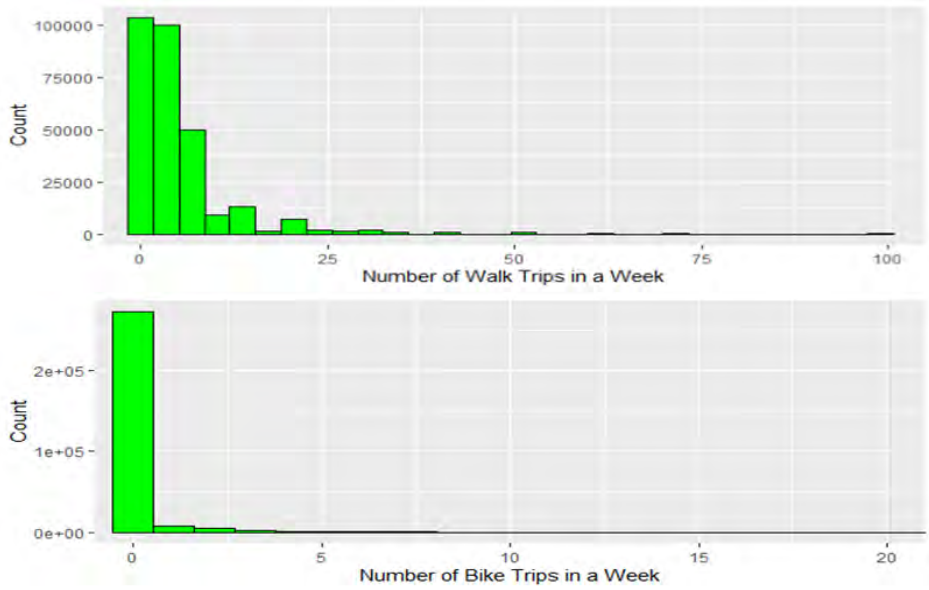

Figure 3-1 Distribution of Walk and Bike Trips

3.3.1 Definition of Household Categories

To classify households based on family income and vehicle ownership, we first use the poverty thresholds that census provides based on family size for the years 2001, 2009 and 2017, the years for which the NHTS data is available. Using the thresholds from the census and applying it

on the values of family income and corresponding household size in the NHTS data, we classify people into poor/low-income categories and higher income categories. We then define households under poverty/low-income without any personally owned vehicle as Carless households and referring to the term used by (Mattioli & Colleoni, 2016) to explain the issue of financial stress related to car ownership, we categorize households under/low-income thresholds with at least one car in their household as households facing Car-Related Economic Stress. Finally, the households above poverty thresholds were classified as Higher-Income households. (Fairnie et al., 2016) showed that individuals in carless households were up to three times as likely to use active travel on a day compared to someone in a car-owning household. We define households by pairing car ownership with family income to investigate the extent to which disadvantaged groups like Carless households and households facing economic stress while owning cars would travel actively. We do so by estimating two zero-inflated negative binomial models whereby the number of bike and walk trips a respondent report to have made is the response variable.

3.3.2 Variable Selection and Data Cleaning

Though the previous National Household Travel surveys conducted in 2009 and 2001 do not provide information about the perception on active travel, they however provide the frequency of trips the respondents report to have made using bikes and by walking. This provides us with the flexibility to append the data from these years together and explore how the frequency of use of active travel among households on average and households varying in income status and vehicle availability has varied over the years. The datasets provided by the 2001, 2009, and 2017 NHTS consist of household, person, vehicle, and trip files. Combining household, person, and trip files, we create a unique record on **i.** personal characteristics like age, gender, medical condition, working status, availability of driver's license, **ii.** household characteristics like family income and vehicle availability which we couple to define three household categories, **iii.** spatial characteristics like availability of rail in the Metropolitan Statistical Area (MSA) and finally the trip characteristics for each respondent would be available. The household file of Year 2017 was merged with the corresponding person and trip file and the same process was repeated for Year 2009 and 2001. Only those variables that were available in all three household surveys were considered for estimating the model and those variables which could be associated with the use of active travel were included. The data from the past three travel surveys were appended together and outlier analysis was conducted.

A few unusual records on the number of bike and walk trips (altogether eight records) were removed. Finally, the association between the variables was also observed using Cramer's V value to check for multicollinearity. No two variables in the model are found to be significantly

correlated with each other. The process for estimating the model was finally completed in the statistical software R.

3.4. RESULTS

3.4.1. Descriptive analysis

Perception on Bike Use as a means to Reduce Financial Burden of Travel

Figure 3-2 articulates how people in different household categories perceive of using bicycles to reduce financial burden of travel. It is self-evident in Figure 3-2 that it is mostly the poor/low-income households mainly residing in urban areas that perceive the use of bicycles as a means of overcoming the financial burden of travel. On the other hand, the higher income households mostly do not agree to the use of bicycles as a means of reducing the financial burden of travel. The effect of the built environment on perception is also vivid in Figure 3-2. A larger proportion of poor/low-income households (both Carless and CRES) in rural areas do not agree to the use of active travel as a means of overcoming financial burden but the poor households in urban areas do. This finding corroborates the role of urbanicity in shaping an individual's perception of active travel (Tribby & Tharp, 2019).

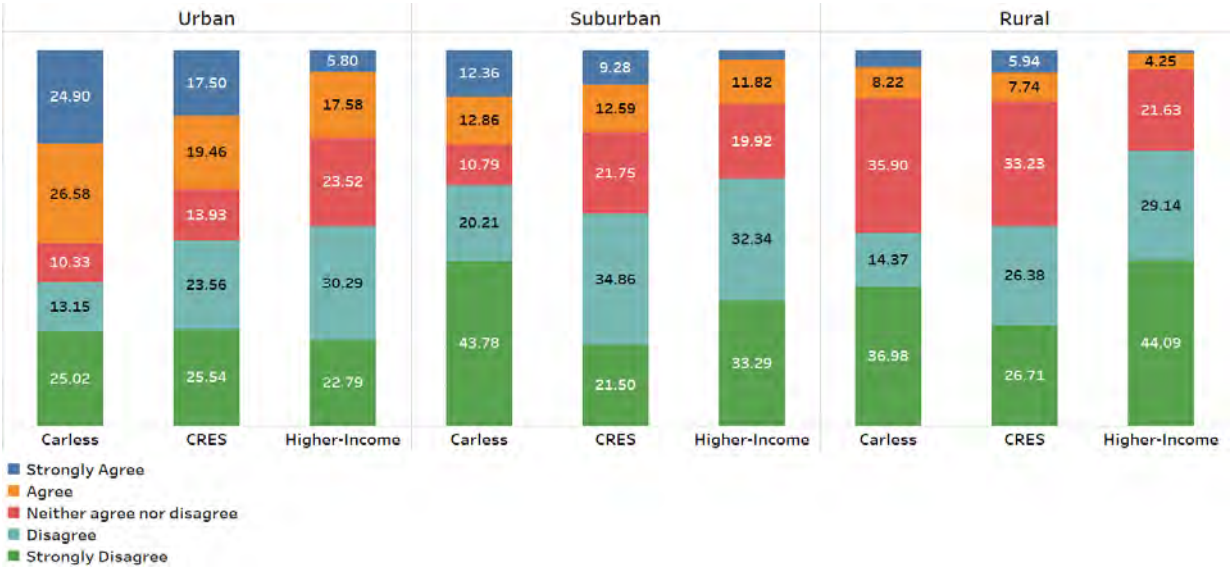

Figure 3-2 Bicycle as a Means to Reduce Financial Burden of Travel

Perception on Walking to Reduce Financial Burden of Travel

Figure 3-3 shows the perception of three categories of households on walking as a means of overcoming the financial burden associated with travel. Like what is observed in Figure 3-2, similar observations across space can be found in Figure 3-3. 71.12% of individuals in carless

households in urban areas agree with walking as a means of overcoming the financial burden of travel compared to only 19.84% of higher-income households.

Though carless and CRES households have equivalent income, the availability of vehicle in the households also appears to affect the perception on active travel to overcome financial burden. It is evident from Figure 3-3 that the proportion of CRES households who agree that walking could help them reduce the financial burden of travel is relatively lower than that of Carless households in all the three spatial environments.

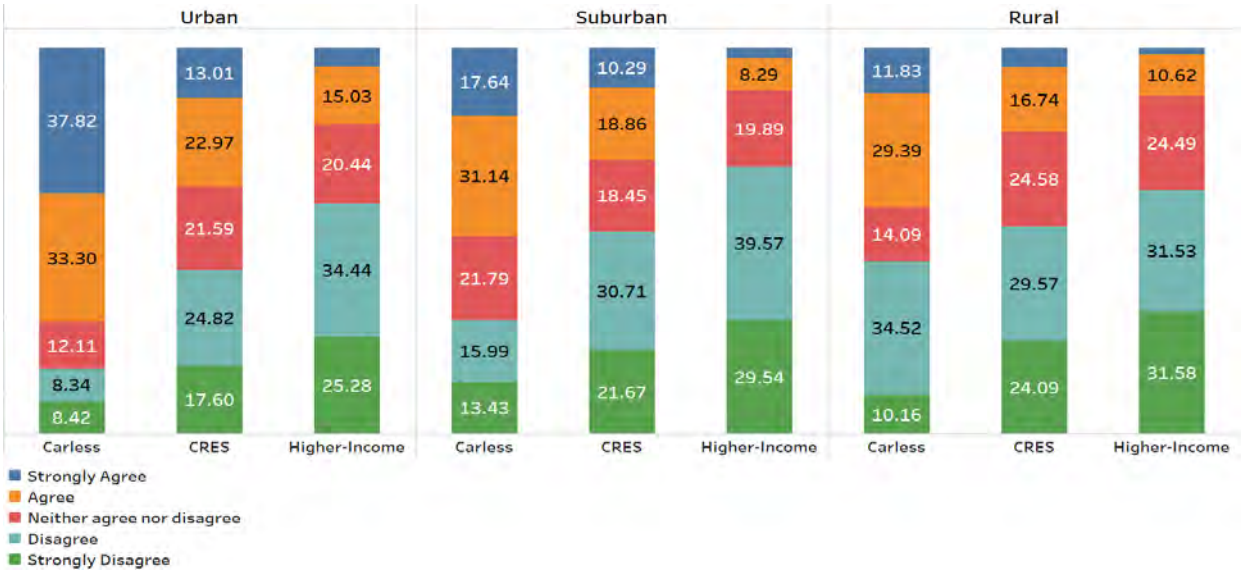

Figure 3-3 Walking as a Means to Reduce Financial Burden of Travel

Perceived Barrier to Using Bike and Walk Trips: Infrastructure Barriers

Figure 3-4 presents the infrastructure barriers that exclusively exercise users and multi-purpose users in different spatial environments perceive with regards to the use of bicycles. Figure 3-5 shows the corresponding infrastructure barriers related to walk trips. The results indicate that in addition to the socio-spatial differences among the users, the purpose for which they travel actively also affects their perception on active travel. For instance, 21.11% of exclusively exercise bicycle users in carless and poor households living in urban areas report that lack of availability of sidewalks is the reason they do not cycle more. On the other hand, only 13.75% of multi-purpose users belonging to same spatial environment and socio-demographic characteristics attribute to the lack of sidewalks as the reason they do not cycle more frequently. Similar observations can be made from Figure 3-5 with respect to perceptions on infrastructure barriers to walking. Interestingly, perceived infrastructure barriers to walk and bike trips are also found to vary significantly. For instance, 61.18 % of multi-purpose bicycle users in carless households in rural areas report that no sidewalks are the reason they do not

bike more but only 13.39 % of multi-purpose bicycle users from carless households in rural areas say that the unavailability of sidewalks is the reason they do not walk frequently. Moreover, Figure 3-4 shows that most people associate the lack of good sidewalks and nearby trails as significant reasons for not using bicycles frequently. On the other hand, as Figure 3-5 shows, no nearby parks are perceived by the largest proportion of people to be the primary barrier to walking more frequently.

Figure 3-4 presents the infrastructure barriers that exclusively exercise users and multi-purpose users in different spatial environments perceive with regards to the use of bicycles.

Figure 3-4 Infrastructure Barriers to Using Bicycles

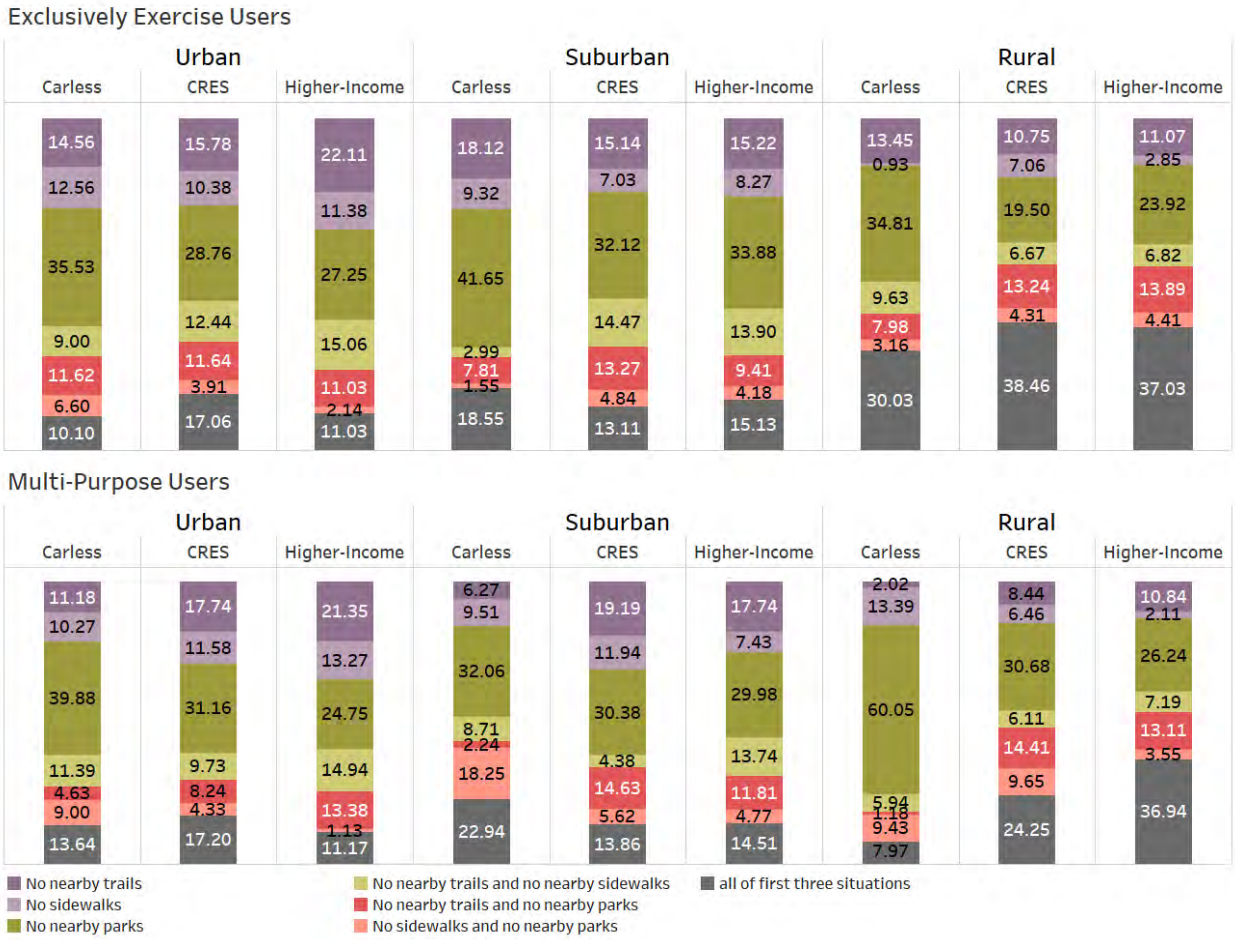

Figure 3-5 Infrastructure Barriers to Walking

Perceived Barrier to Using Bike and Walk Trips: Safety Barrier

Figure 3-6 and Figure 3-7 show the safety barriers that exercise, and multi-purpose users of active travel perceive. The figures show that the perception on barriers to active travel in terms of safety depends not only on socioeconomic and spatial variables but also on the purpose for which it is used. For instance, compared to 76.72% of exclusively exercise users in carless households in rural areas, only 19.02% of multi-purpose users in carless households in rural areas report that poor lighting condition is the primary reason they do not cycle more. Similarly, only 10.36% of exclusively exercise users in suburban areas from carless households mention that heavy traffic is why they do not walk more while 32.83% of multi-purpose users in carless households in the suburbs report that they did not walk more because of heavy traffic.

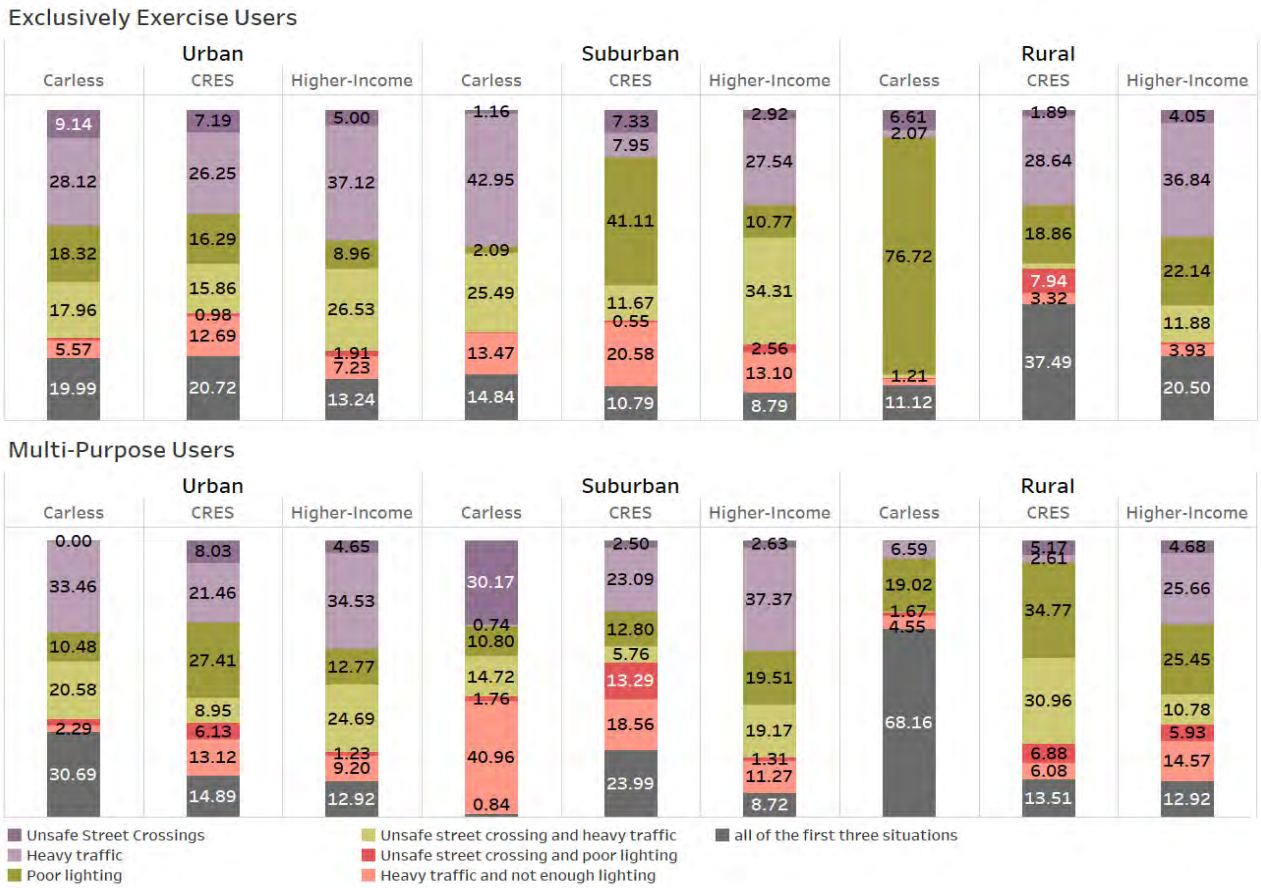

Figure 3-6 Safety Barriers to Using Bicycles

Additionally, it also appears that individuals with similar socioeconomic characteristics have varying perceptions on walk and bike trips. Explicitly, safety perceptions on walking is found to be different from safety perceptions on using bike trips. To exemplify, 33.46% of multi-purpose users from carless households living in urban areas report that heavy traffic is the primary safety barrier to bike use while only 18.67% of people with equivalent socio-demographic and residential characteristics perceive of heavy traffic as the primary barrier to walking. These findings indicate that the policies aimed at increasing bicycle use might not necessarily be useful in encouraging people to walk more and vice versa.

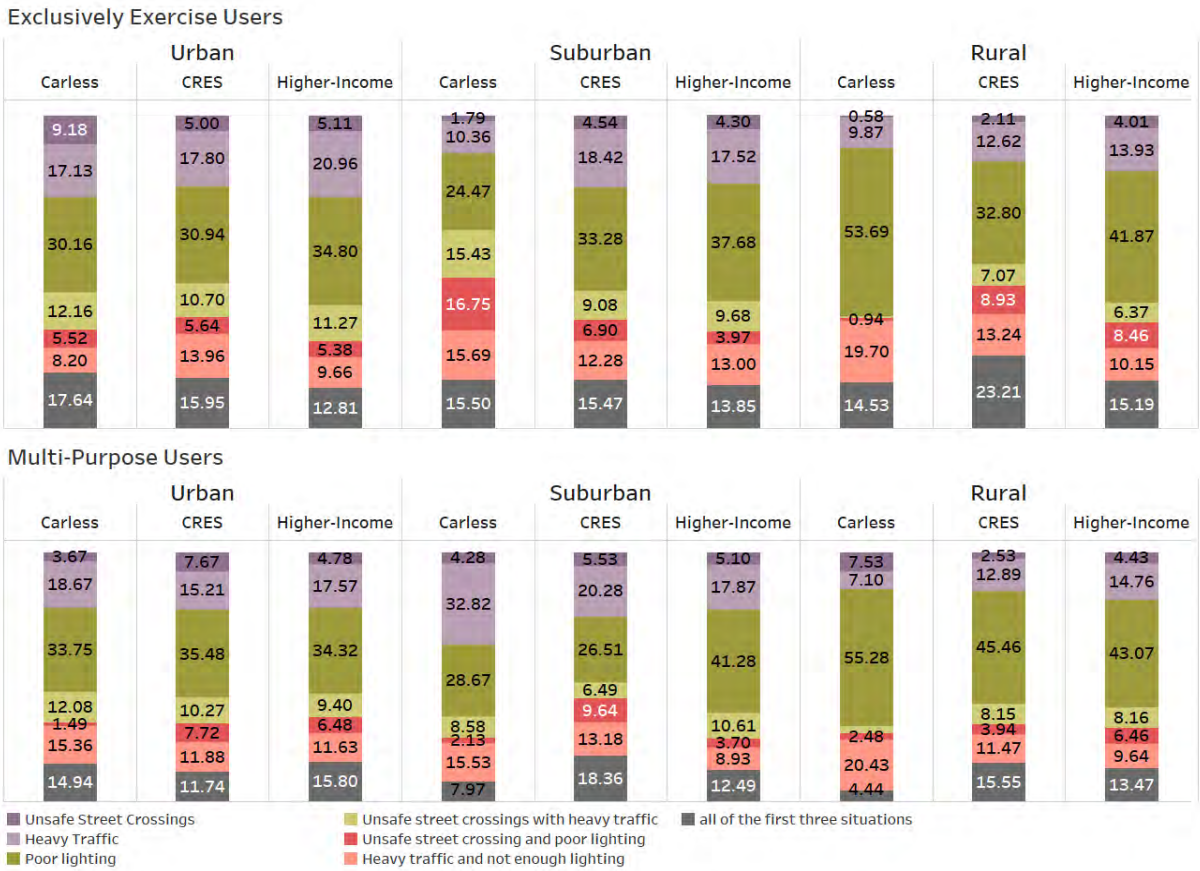

Figure 3-7 Safety Barriers to Walking

3.4.2. Econometric Analysis

The variables selected to explain the use of active travel along with their descriptions are illustrated in Table 3-1. Table 3-2 shows the results of the zero-inflated negative binomial (ZINB) model that explains the frequency and use of bike trips while Table 3-3 depicts the results of the ZINB model to explain the frequency and use of walk trips.

As both tables illustrate, the zero-inflated model has two parts to it, the first being a count data model (negative binomial model in this case) and the other being a logit model to explain the "certain- zeros" in the data. Both Table 3-2 and Table 3-3 depict 3 models. Model-I shows the average effect of the independent variables on the number of bike/walk trips an individual makes in a week while Model-II and Model-III progressively incorporate the interaction effects to examine if spatial environment would affect the three categories of households differently and to understand how the use of active travel has been varying differently for the three categories of households over time.

Table 3-1 Variables Used in the Zero-Inflated Models

Variable Name	Description
Suburban	1 if the household is in a suburban area; 0 otherwise
Urban	1 if the household is in an urban area; 0 otherwise
Year 2009	1 if observation refers to year 2009; 0 otherwise
Year 2017	1 if observation refers to year 2017; 0 otherwise
CRES	1 if the households have at least one car and the equivalent income is less than low-income limits (households experiencing Car-Related Economic Stress); 0 otherwise
Higher-Income	1 if the households are higher income households (either high income or middle-income households), 0 otherwise
Age	numeric value which gives the age of the respondent
Gender: Female	1 if the individual is female and 0 otherwise
Medical Condition	1 if the individual has a medical condition, 0 if the individual does not have a medical condition
Driver	1 if the individual has a driver's license and 0 otherwise
MSA has Rail	1 if the household is in MSA with heavy rail and 0 if the MSA does not have rail or the household is not in MSA
Worker	1 if the individual is employed; 0 otherwise
Education: Undergraduate	1 if the individual has an undergraduate degree; 0 otherwise
Education: Graduate	1 if the individual has a graduate degree; 0 otherwise

Both the count model and zero model of the ZINB model in Table 3-2 and Table 3-3 show that the categories of households which we define are statistically significant. Thus, the use of active travel by an individual is jointly predicated on family income as well as vehicle availability in the household.

Table 3-2 Zero-Inflated Model to Explain the Frequency of Bicycle Trips

	Model-I	Model-II	Model-III
Non-Zero State: Count Data Part			
Intercept	1.436 (0.078) ***	1.496 (0.125) ***	1.192 (0.200) ***
Suburban	0.009 (0.028)	0.372 (0.170) *	0.438 (0.177) *
Urban	0.292 (0.025) ***	0.099 (0.127)	0.140 (0.132)
Year 2009	0.164 (0.055) **	0.159 (0.055) **	0.208 (0.216)
Year 2017	0.082 (0.048) .	0.079 (0.048) .	0.439 (0.194) *
CRES	-0.359 (0.057) ***	- 0.391 (0.121) **	−0.172 (0.220)
Higher-Income	- 0.504 (0.054) ***	- 0.565 (0.116) ***	−0.210 (0.205)
Age	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Gender: Female	- 0.265 (0.021) ***	- 0.266 (0.021) ***	−0.267 (0.021) ***
Medical condition	0.034 (0.050)	0.031 (0.049)	0.033 (0.049)
Driver	- 0.590 (0.039) ***	- 0.597 (0.039) ***	− 0.590 (0.039) ***
MSA has rail	- 0.024 (0.027)	- 0.026 (0.027)	− 0.020 (0.027)
Worker	- 0.111 (0.023) ***	- 0.110 (0.023) ***	−0.107 (0.023) ***
Education: Undergraduate	- 0.021 (0.026)	- 0.021 (0.026)	−0.017 (0.026)
Education: Graduate	0.152 (0.027) ***	0.152 (0.027) ***	0.160 (0.027) ***
Suburban: CRES		- 0.391 (0.183) *	− 0.428 (0.191) *
Urban: CRES		0.160 (0.137)	0.139 (0.143)
Suburban: Higher-Income		- 0.369 (0.172) *	−0.447 (0.180) *
Urban: Higher-Income		0.214 (0.129) .	0.162 (0.135)
Year 2009: CRES			−0.074 (0.245)
Year 2017: CRES			−0.267 (0.217)
Year 2009: Higher-Income			−0.045 (0.226)
Year 2017: Higher-Income			−0.419 (0.202) *
Zero State: Odds of Always Zero			
Intercept	0.724 (0.073) ***	0.593 (0.114) ***	0.553 (0.186) **
Suburban	−0.158 (0.026) ***	0.039 (0.147)	0.060 (0.151)
Urban	−0.233 (0.023) ***	−0.080 (0.112)	−0.069 (0.117)
Year 2009	0.141 (0.049) **	0.139 (0.049) **	0.107 (0.187)
Year 2017	−0.217 (0.043) ***	−0.219 (0.043) ***	−0.166 (0.171)
CRES	0.609 (0.052) ***	0.803 (0.107) ***	0.660 (0.203) **
Higher-Income	0.473 (0.050) ***	0.601 (0.103) ***	0.710 (0.190) ***
Age	0.017 (0.001) ***	0.017 (0.001) ***	0.017 (0.001) ***
Gender: Female	0.642 (0.019) ***	0.642 (0.019) ***	0.641 (0.019) ***
Medical condition	0.936 (0.041) ***	0.935 (0.041) ***	0.935 (0.041) ***
Driver	−0.058 (0.036)	−0.061 (0.036) .	−0.059 (0.036) .
MSA has rail	0.127 (0.025) ***	0.124 (0.025) ***	0.128 (0.025) ***
Worker	−0.119 (0.021) ***	−0.119 (0.021) ***	−0.116 (0.021) ***
Education: Undergraduate	−0.464 (0.024) ***	−0.463 (0.024) ***	−0.459 (0.024) ***
Education:Graduate	−0.659 (0.025) ***	−0.658 (0.024) ***	−0.651 (0.025) ***
Suburban: CRES		−0.253 (0.159)	−0.252 (0.164)

Zero-Inflated Model to Explain the Frequency of Bicycle Trips (Continued)

		Model-II	Model-III
Urban: CRES		−0.251 (0.121) *	−0.241 (0.126) ˙
Suburban: Higher-Income		−0.192 (0.150)	−0.221 (0.154)
Urban: Higher-Income		−0.130 (0.115)	−0.150 (0.119)
Year 2009: CRES			0.117 (0.213)
Year 2017: CRES			0.150 (0.193)
Year 2009: Higher-Income			0.005 (0.196)
Year 2017: Higher-Income			−0.126 (0.179)
AIC	228010.64	227999.001	227991.22
Log Likelihood	-113974.32	-113960.5	-113948.61
Num. obs.	293566	293566	293566

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; ˙ $p < 0.1$

Table 3-3 Zero-Inflated Model to Explain the Frequency of Walk Trips

	Model-I	Model-II	Model-III
Non-Zero State: Count Data Part			
Intercept	1.952 (0.018) ***	1.840 (0.030) ***	1.843 (0.050) ***
Suburban	−0.199 (0.006) ***	−0.036 (0.042)	0.033 (0.044)
Urban	−0.109 (0.006) ***	0.031 (0.032)	0.090 (0.033) **
Year 2009	0.149 (0.012) ***	0.150 (0.012) ***	−0.038 (0.051)
Year 2017	0.307 (0.010) ***	0.306 (0.010) ***	0.304 (0.046) ***
CRES	−0.190 (0.014) ***	−0.019 (0.029)	−0.063 (0.054)
Higher-Income	−0.299 (0.014) ***	−0.194 (0.029) ***	−0.188 (0.051) ***
Age	0.000 (0.000) **	0.000 (0.000) *	0.000 (0.000) *
Gender: Female	−0.100 (0.005) ***	−0.100 (0.005) ***	−0.101 (0.005) ***
Medical condition	−0.077 (0.008) ***	−0.078 (0.008) ***	−0.079 (0.008) ***
Driver	−0.014 (0.009)	−0.016 (0.009) ˙	−0.012 (0.009)
MSA has rail	0.092 (0.006) ***	0.089 (0.006) ***	0.091 (0.006) ***
Worker	0.001 (0.005)	0.001 (0.005)	0.001 (0.005)
Education: Undergraduate	−0.015 (0.006) *	−0.015 (0.006) *	−0.012 (0.006) *
Education: Graduate	0.037 (0.006) ***	0.037 (0.006) ***	0.041 (0.006) ***
Suburban: CRES		−0.210 (0.045) ***	−0.270 (0.046) ***
Urban: CRES		−0.260 (0.033) ***	−0.308 (0.035) ***
Suburban: Higher-Income		−0.152 (0.043) ***	−0.229 (0.044) ***
Urban: Higher-Income		−0.109 (0.032) ***	−0.175 (0.034) ***
Year 2009: CRES			0.193 (0.056) ***
Year 2017: CRES			0.044 (0.051)
Year 2009: Higher-Income			0.202 (0.052) ***
Year 2017: Higher-Income			−0.012 (0.048)
Zero State: Odds of Always Zero			
Intercept	−2.672 (0.057) ***	−2.508 (0.094) ***	−2.133 (0.153) ***

Zero-Inflated Model to Explain the Frequency of Walk Trips (Continued)

		Model-II	Model-III
Suburban	0.032 (0.019)	0.253 (0.117) *	−0.005 (0.131)
Urban	−0.057 (0.018) **	−0.401 (0.102) ***	−0.682 (0.119) ***
Year 2009	0.299 (0.031) ***	0.300 (0.031) ***	0.398 (0.158) *
Year 2017	−0.183 (0.028) ***	−0.183 (0.028) ***	−0.616 (0.150) ***
CRES	1.172 (0.043) ***	1.018 (0.089) ***	0.552 (0.159) ***
Higher-Income	1.078 (0.043) ***	0.914 (0.088) ***	0.571 (0.154) ***
Age	0.010 (0.000) ***	0.010 (0.000) ***	0.010 (0.000) ***
Gender: Female	−0.049 (0.013) ***	−0.049 (0.013) ***	−0.050 (0.013) ***
Medical condition	0.942(0.018) ***	0.940 (0.018) ***	0.937 (0.018) ***
Driver	−0.292 (0.021) ***	−0.291 (0.021) ***	−0.292 (0.021) ***
MSA has rail	0.162 (0.019) ***	−0.163 (0.019) ***	−0.160 (0.019) ***
Worker	0.252(0.016) ***	0.251 (0.016) ***	0.252 (0.016) ***
Education: Undergraduate	−0.621 (0.020) ***	−0.620 (0.020) ***	−0.614 (0.020) ***
Education: Graduate	−1.089 (0.028) ***	−1.089 (0.028) ***	−1.077 (0.028) ***
Suburban: CRES		−0.163 (0.019) ***	0.165 (0.136)
Urban: CRES		0.293 (0.106) **	0.650 (0.123) ***
Suburban: Higher-Income		−0.246 (0.119) ***	−0.009 (0.133)
Urban: Higher-Income		0.377 (0.103) **	0.635 (0.121) ***
Year 2009: CRES			−0.191 (0.169)
Year 2017: CRES			0.539 (0.159) ***
Year 2009: Higher-Income			−0.072 (0.163)
Year 2017: Higher-Income			0.403 (0.154) **
AIC	1536406.75	1536210.635	1536079.863
Log Likelihood	−768172.375	−768066.317	−767992.932
Num. obs.	293566	293566	293566

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$

In Table 3-2, the count data model in Model-I suggests that the frequency of bicycle use for someone in a CRES household and higher-income household is lower than that for someone in a carless household by a factor of exp (-0.359) = 0.69 and 0.60 respectively. Similarly, the zero model shows that if an individual belongs to a CRES or higher-income household, the odds for the individual to belong to the certain-zero category (someone who never uses bicycle for travel) is 1.83 and 1.60 times the odds for someone in a carless household respectively. Thus, people are more likely to use bicycles if they do not have cars available in the household. This finding is in alignment with the findings of Fairnie et al. (2016). Moreover, the count model illustrates that the frequency of bicycle trips on average has been increasing over the years. Model-II explains how household category and residential location jointly influence the frequency of bicycle use. Furthermore, the frequency of bicycle trips for carless households in suburban areas is higher than that in rural areas but the coefficient explaining the bicycle trips

for carless households in urban areas is not statistically significant. The CRES households in suburban areas use bicycles less frequently than their counterparts in rural areas while the coefficient explaining the frequency of bike trips for CRES households in urban areas is not found to be statistically significant. In the suburban areas, higher-income households travel less frequently using bicycles as compared to CRES households and also the frequency of bicycle trips is much lower for both CRES and higher-income households as compared to carless households. Moreover, the frequency of bicycle trips for higher-income households in suburban areas is also lower than that of higher-income households in urban areas. Model-III shows that the frequency of bicycle trips for the carless households has increased by 1.55 times in 2017 compared to 2001 but the increase is not significant in year 2009. On the contrary, the frequency of the use of bicycles is found to have decreased by 34.23% for the higher-income households over the years from 2001 to 2017.

Table 3-3 shows the results for the ZINB model to explain the frequency of walk trips and how it has been changing over time and across space. Like what has been observed for bicycle trips, an individual in a CRES and higher-income household on average, would use walk trips less frequently and also has higher odds of never using a walk trip as compared to someone in a carless household. Specifically, the frequency of walk trips for CRES and higher-income households is lower than that for carless households by a factor of 0.83 and 0.74, respectively. In Model-I, we interestingly observe that, everything else being constant, the frequency of walk trips on average is higher in rural areas than in suburban and urban areas. This could be because people in rural areas may use walk trips as exercise or for recreation frequently, which in many circumstances might not be an appealing thing to do in suburban or urban areas. In Model-II, we observe that the frequency of walk trips for CRES households in suburban areas is relatively higher than in urban areas. On the other hand, the frequency of walk trips for higher-income households is lower in the suburban areas as compared to their counterparts in the urban areas. Moreover, we also observe that in both suburban and urban areas, CRES households walk more frequently as compared to the higher-income households. The zero-model part in Table 3-3 indicates that the odds for someone living in an urban area to belong to the certain-zero category with respect to walk trips is lower than that for an individual in a suburban area, implying that on average urban areas are more favorable for walking as compared to suburban areas.

These results show how geography and the built environment affect the choice and frequency of active travel. Moreover, the results also suggest that the effects of the spatial setting vary by household type. Another interesting finding is that the built environment characteristics which would promote walking would differ from that aimed at increasing bike use. This is corroborated by the variable which explains the availability of rail near the location of household. The zero-model part in Model-I of Table 3-2 shows that if an individual resides in a MSA with heavy rail, it increases the odds for the individual to belong to the certain-zero category with respect to bike trips. On the contrary, an individual who resides in an MSA with

heavy rail has lower odds of belonging to the certain-zero category with respect to making walk trips.

The model results also indicate that education is a significant explanatory variable which is associated with higher frequency of trips by walking or cycling. It could be because highly educated people are more aware of the health and environmental benefits associated with active travel. Moreover, it is also evident that women use bicycles less frequently than men and the zero-model indicates that the odds for women to never resort to using bicycles is 1.9 times higher than that for men. In addition, Table 3-3 also indicates that women on average make 9.51% lower number of walk trips compared to men but odds for women to belong to the certain-zero category is lower than that for men.

3.5. CONCLUSION

This study is unique in its use of national data to explore the trend in use of active travel in the U.S. for carless and low-income households. This research primarily examines the factors that affect the use of active travel. We find that individuals in a household with personal vehicles and the higher-income households are less likely to travel actively compared to carless households. However, geography and the built environment are also found to affect the use of active travel and impact the perceived barriers to active travel. Furthermore, the impact of spatial environment on the use of active travel is found to differ by socioeconomic status. For instance, the frequency of bicycle trips for higher-income households in urban areas is higher than that in suburban areas but for the carless households the frequency of bicycle trips is relatively higher in suburban areas. Additionally, we observe that the frequency of walk trips in suburban areas is higher than that in urban areas for people in low-income households with cars. However, higher-income households walk more in urban areas as compared to suburban areas. Overall, we observe that the households with personal vehicles resort to active travel less frequently. This is also demonstrated by the lower frequency of walk trips among the low-income households with cars and higher-income households compared to carless households in all three spatial environments. Apart from the purpose of exercise, active travel may not be an appealing means to access opportunities, particularly in suburban environments, which is why higher-income and low-income households with personal vehicles travel less actively in suburban areas but for the carless households traveling actively could be a compulsion because other transportation facilities like public transportation would be rare and ridehailing could be too expensive for them. Hence, carless households in suburban areas could be facing transportation disadvantage because of the existing interaction between available land uses and the transportation system and it would be imperative to prepare contextual solutions to help them overcome their disadvantage. Furthermore, the higher frequency of bike and walk trips among low-income households with cars as compared to higher-income households in suburban areas could be because in a larger share of low-income households, the number of household members may exceed the number of cars in the households. Hence, despite the

availability of vehicles in the household some household members may be traveling actively when the household vehicle is not available for use. Additionally, low-income households in suburban areas own cars as an essential element of household expenditure for longer commute but whenever opportunities are accessible to them by traveling actively, they could be doing so to alleviate the costs incurred in operating cars.

The average use of bike and walk trips is found to be increasing over the years from 2001 to 2017. However, the frequency of bike trips is increasing over time for the carless households but decreasing for the CRES and higher-income households. The results also imply that the policies targeted to increase bike trips has to be different from the policies required to promote walking and furthermore the policies also need to be contextualized to the built environment properties. This is exemplified by the opposite effects of the availability of rail on the frequency of bike and walk trips. Though this study is also unique in its attempt to capture the perception of individuals on use of active travel as a means to reduce financial burden, further research is entailed on the impact of specific policies aimed at promoting active travel among higher income and car-owning families. We expect that this research is going to be useful to transportation planners as it provides insights about how people belonging to different socioeconomic status and living in different spatial environments perceive active travel. This study can be further expanded in many ways. For instance, we use national data in our study. Since each suburban and urban area would differ from each other, this study can be replicated at regional and local levels.

3.6 EMERGING MOBILITY SOLUTIONS FOR SUBURBAN AREAS

The thrust 1 of the research, presented in Chapter 2 and Chapter 3 can be associated with the overarching phenomenon of poverty suburbanization in the U.S. The phenomenon of poverty suburbanization can be elucidated as the low-income population moving from the inner cities to outer suburbs (Watkins et al., n.d.) which could be attributed to factors like affordable housing or employment decentralization to the suburban areas (Kneebone, 2017). Many American cities were envisioned in the post-world war period whereby people were expected to own cars and drive to work (Jones, 2011). Pertaining to the scarce public transportation supply in the suburban areas (Foth et al., 2013), the lower-income population residing there could be forced to own cars to meet their mobility needs and to get employed despite barely being able to sustain other necessities of daily life. This phenomenon referred to as Car-Related Economic Stress in this study makes it imperative for planners and scholars to ruminate about the possible mobility solutions targeted to enhance the mobility requirements of the poor without having them to undergo the financial burden of car ownership. Clearly, the solutions should look beyond the traditional car-oriented approach. Realizing this, the research team investigated the prevalence of walking and cycling trips and the way it has varied over time for the poor/low-income households. An interesting finding the authors came across was that most low-income households despite the status of vehicle ownership perceived that alternative mobility solutions like traveling actively could be a useful means to overcome the financial burden of travel. Along this line, it was also observed that from 2001 to 2017, the average use of bike and walk trips increased for low-income households without cars while walk trips saw increased use for households under poverty with cars during that period. The decrease in the frequency of use of bike trips for the car-owning low-income households may be associated with the inadequate infrastructure and insecurities about their own safety while traveling actively (Porter et al., 2020). This provides a strong basis to explore further emerging mobility solutions which could be able to radically ameliorate the mobility of lower income population in the suburban areas. In addition to active travel, one such emerging mobility solutions could be microtransit.

While ride hailing services like Uber/Lyft have been posited as capable of solving the problems of providing first/last mile solutions that traditional fixed route public transportation do not, they are not explicitly advantageous pertaining to the lens of equity as most users of this service are found to be disproportionately young, highly educated and higher income individuals (Brown et al., 2021; Clewlow & Mishra, 2017; Frenken & Schor, 2017; Tirachini & del Río, 2019; Young & Farber, 2019). Furthermore, because these services operate to maximize their profits, they mostly serve the areas with high demand which happen to be core urban areas (Yu & Peng, 2019). Thus, suburban, and rural areas with scarce public transportation and a stark problem of first/last mile access are often neglected. Moreover, since ride hailing services are found to compete with public transportation (Graehler et al., 2019), increase

Vehicle Miles Traveled (VMT) (Schaller Consulting, 2018; Tirachini & Gomez-Lobo, 2020), as well as worsen congestion (Erhardt et al., 2019), an option somewhere between traditional public transportation and ride hailing could be microtransit whereby users on default are expected to share their rides while providing highly flexible routing and scheduling services. microtransit would be a flexible, economical, and user-friendly travel option for the individuals and households experiencing transportation disadvantage. However, as Palm et al. (2021) argues, equity should be at the core of new and emerging transportation services, microtransit would be appealing in an environment where ride hailing are already extant only if they help individuals overcome the disadvantage pertaining to their mobility. Exploring the potential markets for microtransit services and connecting them to transit hubs as a mechanism to provide equitable transportation to the transportation disadvantaged would be an interesting area of future research. Previous pilot studies show that the implementation of the microtransit services in any urban or suburban region must be contextualized to the built environment characteristics and the market segment it would attract (Westervelt et al., 2018). Hence, market segment for these services and their usefulness to the marginalized groups and people experiencing transportation disadvantage in different socio-spatial environment is an area which entails further research.

Referring to Lucas et al. (2016), microtransit services have the potential to provide sufficient levels of equity by reaching out to the under-served areas where public transit is rare, and also egalitarian form of equity by prioritizing the mobility of disadvantaged households or individuals and prioritizing the criticality of the trip purpose. Bardaka et al. (2020) propose a methodology wherein pro-social behavior and empathy in terms of flexibility of schedules from the user's end to prioritize critical trips lies at the heart of the planning and design of microtransit system. They hint towards public private partnerships to be inherent in the operation of such services as market pricing would not be applicable. As a matter of fact, the pilot studies that test the microtransit services hitherto do not fully incorporate the idea of equity into their operation and Weckström et al. (2018) argues that one reason why Kustusplus (microtransit service) failed in Helsinki was because of the price being unaffordable for lower-income households while the waiting time of the service were not appealing for those at higher-income levels. Depending upon the nature of the built environment and socioeconomic profile, microtransit services could serve the transportation disadvantaged groups very well in some cities and regions while they may fail to do in so in other areas (Westervelt et al., 2018). Though microtransit has considerable potential to alter the geography of public transportation systems (Mayaud et al., 2021), research on it is still in its nascent stage. Further research on multiple dimensions of microtransit is essential.

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TRAVEL BEHAVIOR AND MOBILITY PREFERENCES FOR THE AGING POPULATION

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4.1 INTRODUCTION

According to the U.S. Census Bureau's 2017 National Population Projections, one in every five residents in the U.S. will be 65 years old and over by 2030 (U.S. Census Bureau, 2018). By 2035 the elderly population will outnumber those under the age of 18 for the first time in the country's history. As a popular retirement state, the issue of aging is even more prominent in Florida. Projections estimate Florida's population to reach 23.9 million by 2030, with more than one in four Floridians over the age of 65 (LeadingAge Florida, 2019). One of the challenges that comes with an aging population is greater need for transportation services. As the population age, it poses a unique set of demands for transportation services to fulfill their daily activities, for social, medical, and personal maintenance purposes. Adding to the complexity is the disproportional distribution of elderly in rural areas (RHIhub, 2019), which generally has less transit services and mobility options.

This increase in the number and diversity of older adults has monumental implications for transportation planning and service operation and management. The ability to access transportation is vital to the quality of life and community resilience. In this regard, emerging mobility technologies and services may hold the promise to provide efficient and innovative solutions to serve the mobility needs of Florida's aging population as it continues to grow. In order to develop and implement effective alternative transportation for every community, understanding the latest travel patterns of older adults in neighborhoods with different levels of urbanization is urgently needed. In addition, examining how older adults' attitudes and preferences toward emerging mobility services may differ from younger individuals and how these attitudes may influence their mobility choice behavior could be helpful for planners and policymakers to better plan for older adults to meet their mobility needs.

This research aims at investigating the potential of integrating emerging mobility services to serve the needs of an aging population. The objectives of this study are: 1) advance the understanding in the travel patterns and mobility needs of elderly, considering age cohort diversity, geographic distribution and racial and ethnicity attributes; and 2) explore elderly's potential acceptance and adoption of emerging mobility services and vehicle technologies.

A comprehensive review of literature related to travel behavior, transportation needs, and mobility options of older adults in the U.S. was conducted for this research. Older adults are defined as those age 65 and older, which is consistent with the definition used in most existing studies (e.g., Yang et al., 2018; Shen et al., 2016). Besides, using data from the latest 2017 National Household Travel Survey (NHTS) (FHWA, 2019), we compared and contrasted the travel behaviors of older adults in the three different environments. Especially, we examined the aspects of travel behaviors relevant to implementation of public transit and shared mobility for individuals with special mobility needs including medical conditions and mobility assistance devices (e.g., walkers and wheelchairs). We note that national scale studies with such details are currently lacking. It is expected that results of this analysis can provide information for the development and implementation of effective mobility options in every ZIP code. Furthermore, we investigated the decisions of older adults to switch to ridesourcing services and which factors, including socioeconomic and demographic parameters and attitudinal factors, may influence their decisions. Specifically, the respondents were asked in a survey about their expected monthly cost savings that would motivate them to switch from typical travel modes to ridesourcing services. The hypothesis is that those who require less economic benefit or cost-savings to switch to ridesourcing are more likely to use ridesourcing services, while those with negative views or facing challenges may require higher economic motivation.

4.2. LITERATURE REVIEW

A literature review was conducted of previous studies related to older adult's travel behavior. This section summarizes the findings in terms of the elderly's travel patterns, mobility needs, and emerging mobility options for older adults. The review of literature began with those examining the travel patterns of older adults, followed by discussions of their transportation needs and emerging mobility options that can fulfill the needs.

4.2.1 Travel Patterns of Older Adults

4.2.1.1 National Household Travel Survey

Lynott and Figueiredo (2011) summarized travel patterns of older adults in the U.S., using the National Household Travel Survey (NHTS) conducted in 2001 and 2009. It was reported that the number of daily trips and daily miles by older adults (age 65 and older) both declined in 2009 when compared to those in 2001. This decline in travel was due in part to rising gas prices and the economic downturn during which interview for the 2009 NHTS took place (April 2008 through April 2009) (Circella, 2016). Lynott and Figueiredo (2011) showed that older men (65+)

consistently drove more than women of the same age, although the difference in miles driven between older men and women was smaller in 2009 than 2001. While per capita VMT of older men decreased from 2001 to 2009, older women's per capita VMT increased.

Samus (2013) also examined trip-making behaviors of older adults using the NHTS data, but in addition to the 2001 and 2009 NHTS data he also included the 1990 version of the data, known as the Nationwide Personal Travel Survey (NPTS). His analysis investigated more detailed trip characteristics than those in Lynott and Figueiredo (2011). Samus (2013) noted that privately owned vehicles (POVs) remained the dominant mode of transportation in the United States throughout the years. The decline of POV share in 2009 was likely caused by the economic downturn and gas price increase when the interview for NHTS took place. The average numbers of daily trips made for medical purposes by different age groups. It shows that daily trips for medical purposes had increased steadily for people aged 55 and above. The increase is mostly likely due to the fact that the practice of medicine had increased in specialization over the years. One particular medical condition may involve more than one specialist. It is interesting to note that people aged 85 and older actually took less average daily medical trips than the two younger groups (i.e., 65 to 84 years old). Note that life expectancy in the US in 2009 is approximately 78 years old (The World Bank, 2020). For the small number of individuals who managed to live independently (i.e., to participate in the telephone interviews of NHTS) past 80 years old, they were likely in a better general health condition than the average members of the two younger groups. Another likely explanation is that older adults aged 85 and older could not go for medical care as often as they needed due to lack of transportation.

Yang et al. (2017) examined daily engagement in active transportation (i.e., walking and biking) by older adults as reported in the 2009 NHTS. Total active travel, public transportation trips, travel purpose diversity (i.e., the number of different trip purposes), total and maximum distance traveled for older adults were compared with those made by middle-aged adults (45 to 64 years old). Yang et al. (2017) showed that all indicators of active transportation and public transportation use steadily declined as people aged. In addition to factors related to declining physical conditions associated with aging, the decline in active travel may also be attributed to the fact that older adults engaged in more shopping trips during the day than middle-aged adults. Shopping activities are typically less convenient to be made with active modes or public transportation.

The most recent implementation of NHTS was in 2017, administered via a web-based self-report platform (U.S. Census Bureau, 2020). McGuckin and Fucci (2018) summarized travel patterns by age groups across multiple waves of NHTS (2001 and 2009) and NPTS (1983, 1990, and 1995). Overall, in 2017, people in the U.S. spent just under an hour a day in a vehicle as a driver or passenger. With exception of those over 65 years old, the average minutes spent in a vehicle decreased marginally from 2009 to 2017 across all age groups. Older adults over 65 years old in 2017 spent approximately 2 more minutes in vehicles than in 2009, although there

is a small chance that the increase is not statistically significant as the margin of errors for 2009 and 2017 estimates overlapped by a small margin.

4.2.1.2 American Time Use Survey

Shen et al (2016) examined travel patterns of older adults in the U.S. by analyzing the 2015 American Time Use Survey (ATUS), a nationally representative survey by the U.S. Census Bureau (U.S. Census Bureau, 2020). They compared characteristics of daily trips made by older adults (i.e., age 65 and up) with those made by the younger generations (i.e., ages 25 to 64). Trip characteristics examined included proportions of daily trips made with different transportation modes, the average daily times of driving privately owned vehicles (POVs) and riding in POVs as passengers, the proportions of trips made in different time periods during a day, and the proportions of trips made on weekdays and weekends. The results showed that the percentage of ATUS respondents who made at least one trip during the surveyed day was 88% for adults in age group 25 to 64 years, 75% for 65 to 74 years, and 68% for 75+ years. The mode share of POV drivers decreased as age increased, but the mode share of POV passengers actually increased as adults aged. The most striking finding is that more than 90% trips across all age groups involved POVs, either as drivers or passengers. Mode share of public transportation (i.e., bus and train) for the age group 65 to 74 years is the largest among all three groups at 1.1% for bus and train. For adults aged 75 and above, POVs as passengers is an important transportation mode as it not only supports those that no longer drive SOV but also those who used to ride public transportation.

Regardless of age differences, females were less likely to drive POVs and more likely to ride in POV as passengers than their male counterparts. For female POV drivers, the average driving time was shorter than male drivers. All age groups made more trips on weekdays than on weekends. However, for adults older than 75 years old, the average number of weekday trips is 2.6, which is not much different from the number of weekend trips at 2.4. Older adults age 65 and above were more likely to travel in the mornings and early afternoons (from 8:00 am to 3:59 pm) than younger adults, but they were less likely to travel in the late afternoons and early evenings (from 4:00 pm to 7:59 pm). It was suggested that older drivers may avoid driving in the dark due to diminished night vision (Shen et al., 2016).

4.2.2. Mobility Needs of Older Adults

As demonstrated with travel patterns identified in NHTS and ATUS data, the older adult population in the U.S. is highly dependent on POVs for mobility needs. However, it is expected that some older adults will eventually cease driving for declining physical conditions associated with aging (Ragland, Satariano, & MacLeod, 2004). After the cessation of driving, maintaining a certain level or mobility for participation of activities outside of their residences is very important for the well-bring of older adults (Dickerson et al., 2019; Choi and DiNitto, 2016). Existing literatures show that mobility needs of older adults depend strongly on the residential locations. Older adults living in urban, suburban, and rural areas have different preferences and needs for mobility.

4.2.2.1 Suburban Communities

To investigate the mobility needs of older adults and to identify potential solutions for meeting the needs, Ragland et al. (2019) conducted a survey in 2018 in Contra Costa County, California, a municipality consisting mostly suburban communities housing commuters to employment hubs in the San Francisco Bay Area such as Oakland and San Francisco. In addition to adults age 65 and older (i.e., common definition of seniors), adults age between 55 and 64 were also sampled to cover the entire population of baby boomers (born between 1946 and 1964).

The survey was administrated via phone interviews with questions designed to identify older adults' travel patterns, mobility limitations, consequences of reduced mobility, and needs and preferences for mobility options and residential neighborhood features. A total of 510 respondents meeting the age criterion completed the survey.

4.2.2.1.1 TRAVEL PATTERNS

Ragland et al. (2019) shows that older adults age 80 and above had made fewer trips per week than those age 55 to 79 (see **Error! Reference source not found.**). Driver license possession was associated with more trips. Those who lived alone also made fewer trips than otherwise.

Ragland et al. (2019) showed that shopping (grocery and other shopping) was the most frequent trip purpose among the respondents, followed by social activities and self-care or recreational activities. Similar to the patterns exhibited in NHTS and ATUS data, POV is the dominant mode for all trip purposes, because "drive yourself" and "others drive you" were the modes for over 90% of all trips. Among trip purposes fulfilled with public transportation, work is the most frequent purpose, followed by cultural activities and doctor's appointments. As

expected, shopping activities had very low rate of public transportation usage due to inconvenience with carrying purchased items getting on and off buses.

Of the two active transportation modes (i.e., walk and bicycle), walking was a mode of transportation more often than bicycles. Respondents reported frequent walking for social and recreational activities. The lack of usage of bicycle as a mode of transportation is most likely due to perceived risk involvement and physical conditions of the older adults. This viewpoint is supported by the mode shares of walk and bicycle for self-care and recreational activities. Older adults clearly favored walking (8.6%) than bicycling (1.4%) for recreational physical activities.

Ragland et al. (2019) reported that 45% of the survey respondents indicated that they had used rideshare services (i.e., TNC services) previously. Proportions of members in an age group that had used rideshare services decrease with age. 57% of respondents in age group 55 to 65 had used TNC services before, compared to 48% for age 65 to 74, 32% for age 75 to 84, and 23% for age 85 and above. Across all age groups and genders, the most prevalent reason for not having used TNC services before was driving oneself with POV exclusively, rather than not having the means to do so.

Special transportation services refer to paratransit and/or non-emergency medical transport, which were utilized by approximately 10% of the survey respondents (Ragland et al., 2019). Most respondents who reported that they never used these services indicated that they did not need the services, or they could drive themselves. Inconvenience and lack of awareness of such services were reported by a small number (6%) of respondents as the reason of not having used it. However, 27 respondents (5%) suggested better paratransit or personalized transport options could improve their mobility.

4.2.2.1.2 MOBILITY LIMITATIONS

To investigate mobility limitations of the survey respondents, the survey contained questions asking respondent's ability to get around independently. These questions addressed disabilities, medical conditions, mobility assistance devices (i.e., canes, walkers, wheelchairs), and situations when driving would be avoided. Many female respondents reported avoidance of driving at night and raining days, suggesting that mobility services can be beneficial for older females at nights and during times of adverse driving conditions. Note that respondents could choose more than one situation for this question, thus the sum of situation percentages for each gender are more than 100% (i.e., total number of situations/total number of respondents > 100%). Ragland et al. (2019) also found that the number of respondents reported avoidance of driving increased with age and presence of medical conditions.

4.2.2.1.3 CONSEQUENCES OF REDUCED MOBILITY

To investigate consequences associated with reduced mobility, the survey asked respondents to recall missed appointments or events essential for daily living (e.g., medical care, grocery shopping) due to lack of transportation in the previous six months. Ragland et al. (2019) found that 7% of all respondents experienced missed appointments and these events were positively associated with the following characteristics in the respondents:

- Older age
- Lower household income
- Lower education status
- Live alone
- No driver licenses
- Poor health
- Disabilities

For the missed appointments, respondents were asked to state barriers to obtaining transportation for the events. Some respondents offered more than one reasons. For such cases, the one stated first is categorized as the primary reasons and any additional reasons secondary.

4.2.2.1.4 NEEDS AND PREFERENCES FOR MOBILITY OPTIONS AND NEIGHBORHOOD FEATURES

To find out the respondents' needs and preferences for alternative mobility options, the survey first asked respondents to state their opinions toward driving cessation and their preferences for mobility afterwards. Ragland et al. (2019) reported that most respondents (70%) strongly agreed that loss of mobility is very isolating and depressing. Approximately 55% of respondents indicated that they did not like to request a ride from others. Over 50% of respondents agreed that they expect to always be driving. However, the level of agreement decreased as age increased. It is interesting to note that nearly 36% of respondents age above 85 expected to always drive.

4.2.2.2 Urban Communities

Loukaitou-Sideris, Wachs, Levy-Storms, and Brozen (2018) noted that transportation infrastructures in many U.S. cities have not been designed to accommodate the mobility needs of older adults. Consequently, older adults living in the cities encounter mobility challenges more often than younger generations. Especially, many low-income, minority older adults living in the cities have no access to vehicles and rely on public transportation for their mobility needs. In a city where mobility options are limited, this subgroup of the older population can suffer many adverse consequences from reduced mobility and low quality of life (Marottoli, 2009).

Loukaitou-Sideris, Wachs, and Pinski (2019) conducted a study to identify travel patterns and mobility needs of low-income, minority older adults living in Westlake, an inner-city neighborhood in Los Angeles (LA), California. Low-income older adults were defined as those older than 65 years old, living in either one- or two-person households with household income less than $25,000, or living in households with three or more persons with household income less than $35,000. A mixed-methods approach that combined aggregate travel patterns identified from the California Household Travel Survey (CHTS) (Caltrans, 2020) with information obtained from direct interaction with 81 low-income older adults living in Westlake was used to unearth mobility challenges faced by these older adults.

4.2.2.2.1 QUANTITATIVE ANALYSIS OF CALIFORNIA HOUSEHOLD TRAVEL SURVEY

Loukaitou-Sideris, Wachs, and Pinski (2019) analyzed the CHTS data by trip purposes made by low-income, inner-city, older adults of LA, compared to residents in other areas of LA county. Inner-city was defined as a few Census tracts surrounding downtown LA, which historically have lower average income level and more minority residents than other areas in LA county. The study area, Westlake, is within these inner-city Census tracts.

The study found that the average daily distance traveled by an older adult who was not poor and resided outside the inner-city was 23.6 miles daily, while low income, minority older adults in LA's inner city traveled only 12.7 miles per day on average. Despite the shorter daily total distance traveled, low-income seniors took more trips per day (i.e., 6.8 compared with the LA County average of 6.2). The mode share for car trips for the inner-city, low-income older adults was 43%, while non-poor residents outside of the inner city of LA was twice as high (86%). Older inner-city residents were more likely to take a trip for medical cares by walking or transit than older adults living in other parts of LA county. High mode shares for walking and transit were likely due to the fact that downtown and inner-city neighborhoods have higher densities of retails and services than outlying suburbs. In addition, it was also found that low-income,

older, inner-city adults had significantly lower rates of car ownership (48%) than older adults outside the inner city (73%).

4.2.2.2.2 QUALITATIVE ASSESSMENT OF MOBILITY CHALLENGES WITH FOCUS GROUPS

To validate and enhance the findings of CHTS data analysis, Loukaitou-Sideris, Wachs, and Pinski (2019) organized focus groups and conducted neighborhood walkabouts to interact with 81 Westlake residents age 65 and above. The focus groups used travel diary and open-ended questions to elicit travel patterns, mobility needs, preferences, and challenges faced by the participants. The results showed that most study participants traveled by walking and taking public transit. 75% of the 81 participants did not own a car and some car owners did not drive very much. Walking is the most common travel mode for these low-income, older adults living in the inner city. This is consistent with findings from CHTS, which showed 42% of the daily distance traveled by this population was through walking. Study participants reported that they mostly walked to reach destinations essential for daily living such as grocery stores, banks, and drugstores. They also walked directly to bus stops for destinations further away. Most participants did not walk for recreation. The focus group participants also voiced challenges in the neighborhood that made walking difficult or unpleasant such as broken, uneven surfaces on the sidewalks and litters that were not picked up for a long time. Neighborhood crime was another impediment that could constrain their mobility.

Although generally satisfied with public transit, participants reported specific challenges riding buses that were indeed common for older bus riders. For example, if bus drivers did not pull over close to the curbs, getting on and off the buses would be particularly challenging for some older adults. Infrequent bus service was another common concern. Many participants said waiting time at bus stops was too long. Sometimes they had to wait for more than 30 min for the buses to come. It was also common for buses to pass stops without stopping during rush hours. It is noted that such complaints toward bus services were common in some urban communities (Diab, Badami, and El-Geneidy, 2015; Yoh, Iseki, Smart, and Taylor, 2011).

Additionally, the use of point-to-point transportation services (e.g., TNCs, taxi, and on-demand paratransit) was rare among participants, who reported that cost consideration, incompetency with technologies, and scheduling and regulatory restrictions (i.e., for using paratransit) limited the usefulness of the services. Most participants had never used Uber or Lyft. It is interesting to note that some focus group participants reported the reason for not having used TNC services as “having no use for it”, which is identical to the reason noted by respondents of the aforementioned Contra Costa County Survey. Participants who were aware of what Uber or Lyft is indicated that they would consider it as “the last resort.” Regarding paratransit, only four out of 30 eligible participants used city or county paratransit services regularly. Some participants found the application process for subsidized paratransit services burdensome.

Loukaitou-Sideris, Wachs, and Pinski (2019) pointed out that the upside of complementing quantitative analysis of travel data with focus groups was to gain insight on the real mobility challenges faced by the residents. The combined results enabled them to make specific recommendations tailored to mobility needs for the low-income older adults of Westlake, addressing a wide variety of issues including streetscape, public transit, point-to-point transportation services, and safety.

4.2.2.3 Rural Communities

According to a 2014 survey by AARP (Barrett, 2015) that asked U.S. adults age 45 and older about their preferences for residential locations, 78 percent of the respondents preferred to "age in place" rather than relocate to a different place for retirement. Frey (2007) also noted that older adults living in rural areas preferred to stay where they currently live for retirement. Thus, there is not likely to be significant changes to the number of rural older adult population in the near future. Providing transportation for rural older adults presents unique challenges due to the lower population densities and longer distances between destinations (National Rural Health Association, 2013). Identifying the travel patterns and specific challenges is necessary for designing effective transportation strategies that meet the mobility needs of older adults.

4.2.2.3.1 TRAVEL PATTERNS OF RURAL OLDER ADULTS

It has been established with multiple waves of NPTS and NHTS that the dominant mode of transportation for older adults in the U.S. is POVs (McGuckin and Fucci, 2018). For rural areas in the U.S., there is a higher level of dependence on POV as the mode of transportation than urban areas. With 2017 NHTS data, McGuckin and Fucci (2018) showed that the overall percent drivers in rural areas (91.9%) is higher than that in the urban areas (85.9%). In addition, the percent population with zero vehicles in the rural areas (2.3%) is lower than urban areas (7.6%). Older adults age 65 and above took slightly fewer daily trips (3.0) than those in the urban area of same age (3.2). The average Vehicle Miles Traveled (VMT) by rural adults age 45 and above has been consistently higher than that for their urban counterparts across the years.

Regarding public transportation use by rural older adults, Foster (1995) found that only 0.3% of trips by rural older adults age 75 and older living in Iowa were made by public transit. Of those trips, transit was most often used for medical purposes, followed by social/recreation and shopping trips. Yong et al. (2018) estimated with 2009 NHTS data that the likelihood for rural older adults age 65 and older to take public transit was only a quarter of the likelihood for urban adults of the same age. Glasgow and Blakely (2000) conducted a focus groups study in

rural New York and found that non-driving older adults (75 and over) relied heavily on rides from friends and family. For those without access to rides from acquaintances, they had to rely on other community mobility options (Hough, 2007). Mattson (2010) suggested that there was a certain level of unmet demand for travel by rural older adults due to lack of transportation.

4.2.2.3.2 MOBILITY NEEDS AND CHALLENGES OF RURAL OLDER ADULTS

Upon cessation of driving, older adults living in rural areas face significant transportation challenges from limited public and paratransit services available, and the long distances to reach destinations essential for daily living such as shopping, health care, and social/recreation activities. In addition, Molnar, Eby, St. Louis, and Neumeyer (2007) noted that rural older adults tend to be in worse heath conditions and have fewer financial resources than older adults in urban and suburban areas. For the majority of older adults who ceased driving as a result of physical conditions, the conditions also limited their abilities from using fixed-route public transit services due to difficulty walking to the bus stops or the inability to getting on and off the buses independently (Dickerson et al., 2007).

Focus groups participants (age 65 and older) in rural areas noted that many community mobility options were often inconvenient, limited in coverage or unable to accommodate certain disabilities (Glasgow & Blakely, 2000). St. Louis et al. (2011) noted that another barrier to rural public transportation use is that many older adults are unaware of the services that are available to them. Bond, Brown, and Wood (2017) noted that how older adults in rural areas used these transportation services was not well tracked. Despite a lack of ridership data to demonstrate the effectiveness of these services in serving older adults, rural transit agencies had reported increasing transit use by older adults for medical, shopping, and social trips as compared to past decades. There is a clear need for rural transit agencies to objectively measure older adult use of their services such that assessment of effectiveness and improvement strategies can be made.

4.2.3. Emerging Mobility Options for Older Adults

Although most older adults who have been driving expect to continue driving indefinitely (Ragland et al, 2018), many of them will eventually have to stop driving due to chronic illness or declining physical conditions associated with aging. Currently, the average life expectancy is about 7 years longer than the average age of driving cessation for men and 10 years for women (Foley, Heimovitz, Guralnik, and Brock, 2002). After driving ceases, traditional fixed-route transits can also become a challenge for these older adults because the same physical conditions that force them to stop driving can also make taking transit difficult (e.g., walking to

and from bus stops; getting on and off buses). Other than fixed-route transits, there have been other mobility services available for older adults who do not drive such as paratransit, senior center-based shuttles, volunteer drivers, and ride-share services offered by non-profit organizations (Rahman, Strawderman, Adams-Price, and Turner, 2016). Many transportation agencies have been implementing different strategies to make these services effective in meeting the mobility needs of older adults with varying degree of success (Bond, Brown, and Wood, 2017).

4.2.3.1 Dynamic Ride-Sharing Services

In the last decade, dynamic ride-sharing (also known as ride-hailing or ride-sourcing) services such as Uber and Lyft have significantly enhanced the mobility of those who do not own vehicles (Leistner and Steiner, 2017). Commonly referred to as Transportation Network Companies (TNCs), these for-profit services offer a real-time communication platform over the Internet that allow riders to find drivers using their smartphones. Many transportation agencies had recognized the potentials of incorporating TNC services into mobility programs for non-driving older adults.

The City of Gainesville, Florida in 2016 started a pilot program that used Uber to provide transportation for low-income citizens age 60 and older to reach various destinations in town (Leistner and Steiner, 2017). Participants of the program did not have disabilities to qualify for paratransit services. The city subsidized the program and hired a local provider to manage the program and to provide training for participants. The pilot program ran for 9 months. 40 older adults enrolled with women making up 83% of the total enrollment. 12% of participants were age between 61 and 64; 43% were between 65 and 74; and 45% were older than 75.

Leistner and Steiner (2017) found that those who used the service most often were indeed youngest of the total enrollment. 40% (i.e., Low and Inactive users) of the total enrollment completed less than one trip per month or discontinued use. Of these low and inactive users, 11 of them (67%) were age 80 or older. Encountering different Uber drivers from day to day did not appear to a factor deterring usage of the program by these older adults. On the other hand, unfamiliarity with smartphone could be a factor for low usage or discontinuation. Six users acquired smartphones for the first time at the beginning of the program. Although they received training on how to use the smartphones and the service, five of these six users (83%) discontinued use of the program. Of those 34 users who owned and used smartphones before program initiation, five (13%) discontinued use (Leistner and Steiner, 2017).

At the conclusion of the pilot, the program served 1,445 trips over 9 months. Overall, more than 35% of the pilot program users completed more than five trips per month. The majority of trips over the first 6 months were for social activities, shopping, and medical cares. The average

trip length was 5.6 miles. With a relatively small investment (i.e., compared to investment in additional fixed-routes or paratransit services) by the local government, the pilot showed that dynamic ridesharing can enhance mobility and accessibility of older adults (Leistner and Steiner, 2017). Dynamic ridesharing trips are generally faster and more convenient than transit trips, especially for shopping trips. Use of dynamic ridesharing services can provide a feasible alternative to fixed-route transit service for those who do not qualify for other subsidized mobility programs.

4.2.3.2 Non-Profit Ride-Share Services

Non-profit ride-share services for people with mobility challenges have existed since the early 1960s (Freund et al., 2020). Ride-share in this context is defined as a ride in a private vehicle arranged through a non-profit third party for a person with specific mobility limitations. Friends in Service Helping (FISH) and the National Volunteer Caregiver Network (NVCN) are two early national programs that provide transportation as a charitable service to address mobility needs for low incomes older adults with mobility challenges. The Independent Transportation Network (ITN), founded in 1995, is another significant non-profit ride-share service (Freund et al., 2020). Various non-profit ride-share services now exist throughout the United States. Traditionally, service requests are made, and rides arranged via telephone calls with dispatchers. In recent years, Internet and smartphone technologies enable some of these non-profit services to arrange dynamic, on-demand services (Freund et al., 2020).

Sponsored by the Center of Disease Control and Prevention, Freund et al. (2020) conducted an environmental scan that described ride-share services in the United States for older adults with mobility challenges. The environmental scan identified 917 non-profit older adult ride-share services. Many non-profit services only provide rides for trip purposes essential for daily living such as medical care, pharmacy, banking, and grocery shopping. Some services provide assistance for riders who are not able to get in and out of the vehicles by themselves. All services require requests be made in advance, but some offer on-demand services. Two thirds of the services are free for qualified riders. Among all existing non-profit ride-share services, currently telephone is the primary means for users to request and schedule rides. However, some non-profit ride-share services, such as ITN, had built internet communication platform that lets drivers know the specific mobility requirements of the riders before picking up (Freund et al., 2020).

Freund et al. (2020) analyzed the characteristics of riders, age between 65 and 81, who had used the services of ITN. The riders were mostly aged 75 and older, and majority were Caucasian (93 percent), female (74 percent), modest income (41 percent had an income less than $25,000) and lived alone (62 percent). Although many ITN riders had needs for mobility assistance (i.e., canes, walker, and wheelchairs), 70% of ITN riders reported good health.

Medical cares (43 percent) and shopping/personal services (25 percent), such as trips to the grocery store or hairdresser, were the most common.

With the rapid rate of technological advancement and prevalence of smartphones, non-profit ride-share services will soon be able to run services similar to Uber and Lyft for majority of older adults with mobility needs. Policy makers and stakeholders need to know the benefits and costs of these services in order to incorporate them for mobility programs for older adults with mobility limitations.

4.2.3.3 Automated Vehicles

Automated vehicles (also known as autonomous vehicles or self-driving vehicles) (NHTSA, 2018) are being recognized as a technology that can enhance mobility for non-driving members of the population, including older adults and those with medical conditions (Harper, Hendrickson, Mangones, and Samaras, 2016). Five levels of automation in vehicle technologies have been defined (NHTSA, 2018):

1. Driver assistance
2. Partial automation
3. Conditional automation
4. High automation
5. Full automation

The first three levels of vehicles provide assistance to typical driving tasks, but some level of human driver control is required. Level four and five vehicles can both operate without human control. Driver interaction may be required in level four vehicles for certain difficult or dangerous situations (e.g., snowing). Level five vehicles can operate without human drivers for all circumstances (SAE International, 2018). For older adults who cease driving due to physical conditions (e.g., reduced vision or movement disorder), only levels five automated vehicles can be used safely at all time. Currently, neither level four nor level five vehicles are available on the market and there is no solid prediction as to when they will be (IEEE, 2020).

Rahman et al. (2018) investigated older adults' (aged 60 and over) perception toward self-driving vehicles (i.e., level four and five automated vehicles), both as users of these vehicles and as pedestrians who will encounter these vehicles on the roads. An online survey was developed for the investigation assessing five factors concerning older adults' perception toward self-driving vehicles, including attitude, perceived usefulness, social norm, trust, and compatibility. Attitude measures respondents' positive or negative feelings toward automated vehicles. Perceived usefulness measures the degree to which the respondents believe that self-driving

vehicles are beneficial for themselves as users and as pedestrians. Social norm is defined as respondents' perception of how other people think about self-driving vehicles. Trust measures respondents' confidence in the performance of self-driving vehicles. Compatibility is defined as positive interactions between the drivers and the automated vehicles. In addition to these five factors of perception, older adults' acceptance (i.e., intention to adopt) of self-driving vehicles was also surveyed.

The results showed that older populations perceived self-driving vehicles with positive levels of attitude, perceived usefulness, trust, social norms, and intention to adopt as users of the vehicles. As pedestrians, older adults' perception of these factors was either neutral or negative, except for positive perceived usefulness. These results suggested high probability for the adoption of self-driving vehicles by the older population. On the other hand, the results raised concerns for older adults to deal with self-driving vehicles as pedestrians. The results also revealed that the chance for favorable perception of self-driving vehicles will be greater if the older adults are more familiar with them. Rahman et al. (2018) noted that future research should address older adults' income and financial status in order to assess the proportion of the older population that can afford automated vehicles as a mobility option.

4.3 ANALYSIS

4.3.1. Older Adults Mobility Analysis

Conducted by the Federal Highway Administration (FHWA), the NHTS is designed to collect a representative sample for daily travel activities of households in the entire U.S. (FHWA, 2019). The most recent implementation of NHTS was in 2017, administered via a web-based self-report platform. The sampled households did not include group housing such as military barracks, student dormitories, or assisted living facilities for the seniors. Thus, regardless of how old they were, older adults included in the completed survey resided in individual households and conducted their daily living independently to a certain degree. Individuals surveyed by the 2017 NHTS were asked to report all locations they had been from 4:00 am of an assigned survey day to 3:59 am the next day. A trip is defined as the "start and end movement from location to location by any mode of transportation" (FHWA, 2019). Thus, each segment of an individual's out-of-home tour across multiple stops was recorded as a trip.

For this analysis, we downloaded the 2017 NHTS data (FHWA, 2020) and selected all individuals age 65 and older. Data from 438 out of the total 73,426 individuals in this age group were excluded from the analysis because either they did not reveal their age, or their residential locations were not identified. To understand travel behavioral changes associated with aging, we divided this population into three groups: age 65 to 74, 75 to 85, and 85 and older.

The NHTS dataset was used without applying weights available from NHTS. The purpose of our analysis was to use cross-tabulation to explore the factors related to older adults' travel behavior rather than providing population-level estimates, for which applications of weights may be necessary. That is, we focused our analysis on revealing critical factors for older adults' travel behavior, not on finding the national averages of their behaviors. For this reason, we chose to analyze the complete data without applying weights.

Urbanization of respondents' locations were identified with an urban/rural indicator (HBHUR) in the 2017 NHTS data (FHWA, 2019). This indicator identifies a location with five levels of urbanization: urban, suburban, second city, small town, and rural. Second cities were defined as satellite cities surrounding major metropolitan areas and small towns were generally denser than rural areas (FHWA, 2009). Based on the HBHUR indicator, we grouped residential locations into three categories: urban, suburban (i.e., combining suburban and second cities), and rural (i.e., small towns and rural areas). The basic characteristics of the individuals are included in Table 4-1.

Table 4-1 Basic Statistics of Individuals and Trips Included in Analysis

Locations	**Urban**				**Suburban**				**Rural**			
Age groups	**65+**	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***
# Persons	4,258	1845	651	6,785	17,447	7,951	2,608	28,160	24,568	10,906	2,754	38,417
Average age	68.9	78.8	89.0	73.6	69.0	78.8	88.8	73.7	69.1	78.7	88.7	73.3
# Male	1,916	785	272	2,992	8,052	3,601	1,067	12,764	11,838	5,339	1,189	18,444
# Female	2,341	1,060	379	3,792	9,392	4,349	1,541	15,392	12,724	5,562	1,564	19,961
Average household size	1.9	1.9	1.8	1.9	1.9	1.8	1.7	1.9	1.9	1.8	1.8	1.9
Average household vehicles	1.6	1.5	1.2	1.6	1.9	1.7	1.3	1.8	2.3	1.9	1.6	2.1
% Zero vehicle households	9.53%	11.44%	21.66%	11.22%	3.43%	4.20%	10.85%	4.37%	1.33%	2.05%	7.77%	2.00%
% Surveyed individuals who did not travel on assigned survey days	19.3%	27.3%	38.1%	23.6%	18.4%	25.0%	33.9%	22.2%	21.7%	27.7%	36.2%	24.8%
Household Income levels												
<$25,000	866	441	194	1,517	2,591	1,627	717	4,982	3,937	2,576	916	7,483
$25000 to $49,999	905	477	167	1,555	3,867	2,210	767	6,888	6,235	3,382	815	10,493
$50,000 to $74,999	742	307	109	1,161	3,182	1,433	378	5,020	5,028	1,962	386	7,404
$75,000 to $99,999	481	166	49	699	2,564	825	206	3,601	3,450	996	185	4,645
$100,000 to $149,999	571	184	42	798	2,674	804	181	3,672	3,165	866	132	4,173
>$150,000	503	146	21	671	1,825	514	110	2,453	1,647	420	84	2,155

Locations	**Urban**				**Suburban**				**Rural**			
Age groups	**65+**	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***
Ambulation Assistive Devices (AAD)												
None	3,559	1,335	341	5,246	15,095	6,080	1,479	22,734	21,449	8,503	1,574	31,638
Canes, walkers, dog, crutches	327	265	191	789	980	967	670	2,667	1,232	1,142	703	3,111
Wheelchairs and scooters	93	98	88	289	460	336	258	1,067	622	539	286	1,477
Other devices**	278	147	31	460	907	566	201	1,685	1,261	718	191	2,183

* ST: Subtotal

** Devices used were not one of the answer options on the questionnaire.

Table 4-1 demonstrates that POVs were clearly the dominant mode of transportation in the U.S. as the percentages of households with zero vehicles were less than 10% for most location and age groups. It is important to note that some members of the households surveyed by NHTS did not travel on the assigned survey days. As shown in Table 4-1, Urban adults age 85 and older had the highest percentage of no traveling on the survey day. Regarding ambulation assistive devices (AAD) used, older adults in urban areas had the highest rate of requirement for assistive devices at 23%, followed by those in the suburbs (19%) and rural areas (18%). This higher rate of requirement for assistance for moving likely contributed to the higher percentage of no travel during the survey days.

Table 4-2 shows the numbers of average daily person trips and average daily person miles by age, gender, and residential locations. To arrive at trip rates and miles traveled that are representative of the population groups, the total number of individuals in all surveyed households, including those who did not travel were used in the calculation for each age and location combinations. The grand total of average daily trip rate (3.35 trips/person) and person miles (34.39 miles/person) for the entire group of adults 65 and older are comparable to numbers (i.e., 3.2 trips/person and 32.8 miles/person) reported by McGuckin and Fucci (2018), which were based on the same 2017 NHTS data. The small variation between the two sets of estimates were likely due to exclusion of missing data in our analysis.

Table 4-2 Average Daily Person Trips and Daily Person Miles by Age, Gender and Location

		Average Daily Person Trips (Trips/person)				**Average Daily Person Miles (Miles/person)**			
Age	Gender	Urban	Suburban	Rural	Grand Total	Urban	Suburban	Rural	Grand Total
65	Male	3.72	3.85	3.60	3.71	37.96	38.33	44.68	41.75
	Female	3.54	3.62	3.40	3.50	30.38	37.38	37.78	36.90
	Subtotal	3.62	3.73	3.50	3.60	33.79	37.82	41.10	39.19
75	Male	3.28	3.40	3.29	3.33	20.79	33.05	36.22	33.79
	Female	2.83	3.03	2.95	2.97	16.93	22.41	29.49	25.45
	Subtotal	3.02	3.20	3.12	3.14	18.57	27.23	32.82	29.39
85	Male	2.69	2.82	2.76	2.78	19.59	16.82	21.11	19.13
	Female	1.89	2.17	2.20	2.15	19.76	11.41	17.61	15.22
	Subtotal	2.23	2.44	2.44	2.41	19.69	13.62	19.12	16.86
Grand Total		3.31	3.44	3.30	3.35	28.14	32.38	36.97	34.39

In general, findings in

Table 4-2 are consistent with those in previous studies using the NHTS data. We found that older adults living in the suburbs made more trips per day than their urban and rural counterparts. Trip rates consistently decreased as age increased with no exception by gender or location. Average daily person miles generally decreased with age and increased with less urbanization with the exception of adults 85 or older living in urban areas. This group of respondents had longer person daily miles (19.69 miles/person) than those of the same age living in suburbs (13.62 miles/person) or rural areas (19.12 miles/person). Female respondents tend to make less trips and had shorter daily miles than males in all age and location groups, with the only exception being the group 85 and older in urban area. Females (19.76 miles/person) in this group traveled slightly more miles than males (19.59 miles/person). Further investigation indicates that this exception was likely due to a few outliers (i.e., see for the personal daily mile of income level $50,000 to $74,999 in Table 4-3) in the group who made long distance travel on the survey days.

Table 4-3 shows average trip rates and miles traveled by age, location, and household income. Trip rates for those age between 65 and 74 were highly predictive by income levels. Regardless of residential location, trip rates of this age group increased as income levels increased until flattening out beyond the $100,000 to $149,999 level.

Table 4-3 Average Daily Person Trips and Daily Person Miles by Age, Location, and Household Income Levels

	Urban				**Suburban**				**Rural**				**GT****
	65+	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***	**65+**	**75+**	**85+**	**ST***	
Income Level	*Average Daily Person Trips (Trips/person)*												
<$25,000	3.2	2.5	1.9	2.8	3.2	2.9	2.2	2.9	3.0	2.7	2.3	2.8	2.8
$25000 to $49,999	3.4	3.0	2.4	3.2	3.6	3.2	2.7	3.4	3.4	3.2	2.5	3.2	3.3
>$50,000	3.8	3.6	2.3	3.6	3.8	3.4	2.6	3.6	3.6	3.4	2.5	3.5	3.5
$75,000 to $99,999	4.0	3.4	2.7	3.7	4.0	3.4	2.3	3.8	3.8	3.4	2.5	3.6	3.7
$100,000 to $149,999	4.0	3.1	2.5	3.7	3.9	3.5	2.6	3.8	3.8	3.7	2.8	3.7	3.7
>$150,000	4.1	3.2	2.4	3.8	4.0	3.3	2.2	3.7	3.8	3.1	2.6	3.6	3.7
GT	3.6	3.0	2.2	3.3	3.7	3.2	2.4	3.4	3.5	3.1	2.4	3.3	3.4
Income Level	*Average Daily Person Miles (Miles/person)*												

	Urban				Suburban				Rural				GT**
	65+	75+	85+	ST*	65+	75+	85+	ST*	65+	75+	85+	ST*	
<$25,000	21.7	11.0	7.2	16.5	19.3	15.9	10.8	16.8	26.5	22.9	19.4	24.2	20.7
$25000 to $49,999	27.5	17.3	11.0	22.5	29.7	21.3	13.9	25.0	33.9	32.8	18.5	32.2	28.8
$50,000 to $74,999	35.6	32.0	63.5	37.2	34.8	27.4	20.8	31.5	41.9	33.2	20.9	38.3	35.7
$75,000 to $99,999	61.8	16.9	11.1	47.3	48.0	42.8	12.5	44.7	47.7	37.6	23.4	44.4	44.7
$100,000 to $149,999	42.6	17.9	14.1	35.4	40.7	33.4	13.8	37.7	52.1	48.2	19.1	50.1	43.5
>$150,000	34.2	26.2	12.7	31.7	71.7	52.2	9.0	64.7	67.0	51.3	19.8	62.0	59.4
GT	33.8	18.6	19.7	28.1	37.8	27.2	13.6	32.4	41.1	32.8	19.1	37.0	34.4

*ST: Subtotal; **GT: Grand Total

The same general pattern also applies to other age groups in different locations, although some fluctuation in trip rates were observed as income level increased. Similarly, daily person miles traveled also increased with income levels up to the level $75,000 to $99,999 and decreased as income level continue to increase. All age and location groups with income level below $25,000 had the lowest trip rates, especially those age 85 and older living in urban areas. In addition, this group also had a significantly lower daily personal miles than any other groups at 1.9 miles and the highest percentage (38.1%) that did not travel on the survey days (see Table 4-1), raising legitimate issues of immobility for low-income older adults living in urban environments.

Table 4-4 shows cross tabulation of average daily person trips and daily person miles by age, location, and AADs used. As expected, those requiring wheelchairs or scooters made fewer daily trips and traveled shorter distances than those using other devices. On average, respondents on wheelchairs or scooters made two less trips a day than those who ambulated without limitations. The general tendencies for trip rates to decrease with increasing age also exists among people with disabilities.

Table 4-4 Average Daily Person Trips and Daily Person Miles by Age, Location, and Requirements of Ambulation Assistive Devices

	Urban				Suburban				Rural				
	65+	75+	85+	ST	65+	75+	85+	ST	65+	75+	85+	ST	GT

Ambulation Assistive Devices	*Average Daily Person Trips (Trips/person)*												
None	3.8	3.4	2.8	3.6	3.9	3.5	3.0	3.7	3.7	3.4	3.0	3.5	3.6
Canes, walkers, crutches, dog	2.4	2.1	1.7	2.1	2.6	2.3	1.9	2.2	2.5	2.1	1.8	2.1	2.2
Wheelchairs, scooters	1.8	1.3	1.1	1.4	1.9	1.6	1.0	1.6	2.0	1.7	1.0	1.6	1.6
Other devices	2.9	2.8	3.1	2.9	2.8	2.4	2.3	2.6	2.7	2.4	2.3	2.5	2.6
GT	3.6	3.0	2.2	3.3	3.7	3.2	2.4	3.4	3.5	3.1	2.4	3.3	3.4
Ambulation Assistive Devices	*Average Daily Person Miles (Miles/person)*												
None	36.9	21.2	32.1	32.5	40.1	29.3	15.6	35.5	42.9	36.1	23.7	40.0	37.6
Canes, walkers, crutches, dog	17.4	13.4	5.7	13.1	24.7	22.5	11.2	20.1	27.3	18.2	12.9	20.4	19.4
Wheelchairs, scooters	11.3	6.9	6.0	7.8	30.5	20.4	6.0	21.0	23.3	19.2	11.3	19.0	18.6
Other devices	21.2	12.0	8.7	17.2	18.2	17.6	17.3	17.8	32.5	27.5	16.4	29.2	23.6
GT	33.8	18.6	19.7	28.1	37.8	27.2	13.6	32.4	41.1	32.8	19.1	37.0	34.4

Other than those on wheelchairs and scooters, older adults in suburban neighborhoods made more trips than those in the same age groups in urban and rural areas. However, the average trip rate for each age group of older adults on wheelchairs was relatively close across all three environments. This may be because these group of adults could only manage to travel out of homes for essential activities, for which locations are less of a factor in decisions of trip-making. The pattern of increasing daily mileage with decreasing urbanization is not clearly observed for respondents with disabilities. Some suburban age groups using canes and wheelchairs had longer daily person miles than their rural counterparts. This suggests that locations may not be as strong a factor in determining travel behavior for people with disabilities as they are for people without movement challenges.

Table 4-5 shows mode share percentages by age and location groups. The most striking finding is the level of dominance of POV share and the lack of transportation alternatives for rural and suburban older adults across all three age groups. For older adults in urban areas, shares of POVs increased with age, accompanied by decreasing shares of walk and bicycles and transit. This points to the reality that fixed-route transit services can not address the mobility need of most older adults due to their diminished physical abilities to use these services (i.e., need to

walk to and from the bus stops and get on and off buses, with occasional chances of standing for the entire ride).

Table 4-5 Percent Mode Shares by Age and Location

Trip Mode	Urban				Suburban				Rural				GT
	65+	75+	85+	ST	65+	75+	85+	ST	65+	75+	85+	ST	
Walk & Bicycles	18.5%	16.3%	12.8%	17.6%	9.4%	8.6%	8.8%	9.2%	7.2%	6.2%	7.9%	7.0%	8.8%
POVs	75.6%	78.3%	81.0%	76.6%	88.6%	89.7%	88.8%	88.9%	91.3%	92.2%	90.5%	91.5%	89.1%
Golf cars/ Segway*	0.1%	0.0%	0.1%	0.1%	0.1%	0.2%	0.3%	0.2%	0.3%	0.4%	0.3%	0.3%	0.2%
Transit	4.6%	4.1%	4.4%	4.5%	1.0%	0.8%	1.2%	1.0%	0.4%	0.6%	0.6%	0.5%	1.0%
Taxi, rental cars, Zip cars	0.7%	0.8%	0.2%	0.7%	0.4%	0.4%	0.4%	0.4%	0.2%	0.2%	0.3%	0.2%	0.3%
Other**	0.5%	0.5%	1.5%	0.6%	0.5%	0.3%	0.5%	0.4%	0.6%	0.5%	0.4%	0.5%	0.5%
GT	100.%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

*Golf cars/Segway was indicated by a small number of mostly rural respondents as a transportation mode.

**Modes not listed as options in the questionnaire, include getting rides from friends and relatives.

Table 4-6 shows the average trip rates and distance traveled by trip purposes. Social trips include NHTS trip purpose categories of social/recreation, visiting friends/relatives, and church. Trip rates for work, shopping, and social purposes all decreased consistently with age in all three locations. Older adults in suburbs had highest trip rates for these three purposes than those in urban or rural areas. Interestingly, trip rates for medical care were identical for age group 65+ and 75+ across all three locations. The rates were also identical for age group 85+ in suburban and rural areas at 0.19 trips/person, but slightly lower at 0.16 trips/person for the same age group adults in urban environment. The lower trip rate for medical care by urban older adults in this age group may be an indication of unmet mobility need in urban environment. Because medical care trips are especially critical for this age group, this particular finding suggests the need for addressing the mobility challenges faced by older adults in urban environment.

As for distances traveled by trip purposes, the average distances (miles/trip) traveled decreased consistently as age increased for all trip purposes, except for work trips. Urban respondents in age group 75+ had slightly lower average mileage per trip for work purpose than the 85+ group. The most important finding in

Table 4-6 is the significantly higher average distances traveled for medical care by all three age groups in rural areas than their counterparts in urban or suburban areas. Any potential strategies or programs to address rural mobility issues need to take medical care into account for both ambulatory medical services and urgent care.

Table 4-6 Average Daily Person Trips and Distances Traveled by Age, Location, and Trip Purposes

Trip Purposes	Urban				Suburban				Rural				GT
	65+	75+	85+	ST	65+	75+	85+	ST	65+	75+	85+	ST	
	Average Daily Person Trips by Trip purpose (Trips/person)												
Work	0.32	0.09	0.02	0.23	0.32	0.11	0.04	0.23	0.26	0.09	0.02	0.20	0.21
Shopping	0.93	0.82	0.63	0.87	0.95	0.86	0.66	0.89	0.95	0.86	0.67	0.90	0.89
Social	2.09	1.83	1.37	1.94	2.18	1.95	1.48	2.04	2.01	1.88	1.47	1.93	1.97
Medical care	0.16	0.19	0.16	0.17	0.16	0.19	0.19	0.17	0.16	0.19	0.19	0.17	0.17
GT	3.50	2.93	2.16	3.20	3.61	3.11	2.37	3.33	3.38	3.02	2.36	3.19	3.25
	Average Distances Traveled for the Purposes (Miles/trip)												
Work	9.86	6.38	7.67	9.46	10.74	7.90	7.53	10.31	14.00	10.84	5.22	13.50	11.8
Shopping	4.34	3.66	3.58	4.11	5.90	4.66	3.76	5.42	8.26	7.99	6.62	8.10	6.7
Social	6.43	6.10	5.34	6.27	7.59	7.08	5.70	7.33	10.01	9.18	7.31	9.63	8.4
Medical care	5.80	5.36	5.51	5.64	8.14	6.69	4.93	7.35	15.16	13.17	10.79	14.18	10.8
GT	6.15	5.38	4.86	5.88	7.45	6.41	5.13	7.02	10.07	9.14	7.36	9.68	8.3

To further address the mobility challenges faced by older adults with movement disabilities, we examined the mode shares for different trip purposes by older adults requiring AADs. For shopping and medical care trips, mode shares were dominated by POVs without much variation across age and location groups due to functional requirements of these activities (e.g., need to carry bags of groceries in cars after shopping; need to use cars to get to doctors' appointments on time). Mode shares for social trips (i.e., social/recreation, visiting, and church) showed more variations in mode shares by age groups and locations perhaps due to their flexibility in scheduling and no need to carry specific items afterwards.

Table 4-7 shows the comparisons of mode shares of social trips by age, locations, and requirement for AADs. Regardless of AAD requirement, shares of POVs increased with a small amount from age groups 65+ to 75+, accompanied by slight decreases in shares of walking and bicycling. The changes may be due to more cars being used for short distance social trips, because decline in physical abilities that occurred between age 75 and 84. However, POV shares then decreased from group 75+ to 85+. The decreases are most notable for those who used canes and wheelchairs, suggesting cessation of driving by these individuals that before the age of 85. Some of these individuals still capable had to walk for short distance trips and some of them took on transit. For those on wheelchairs age 85 or older, the share of 'Other' mode, likely referring to getting rides from others, had also increased to 5%. As for variation in social trip mode shares by locations, as expected, shares of POVs increased and shares of transit and non-motorized modes decreased as one moved from urban to rural environment, irrespective of AAD requirements.

Table 4-7 Mode Shares for Social Trips by Age, Location, and Ambulation Assistive Devices

Mode Shares by Age Groups							
	Walk & Bicycle	**POVs**	**Golf cars/ Segway**	**Transit**	**Taxi, Rental cars, Zip cars**	**Other**	**GT**
AAD	Age 65+						
None	12.45%	86.05%	0.30%	0.66%	0.31%	0.23%	100%
Canes, walkers, crutches, dog	11.68%	85.64%	0.12%	1.88%	0.38%	0.29%	100%
Wheelchairs, scooters	5.12%	89.83%	0.33%	1.90%	0.08%	2.73%	100%
Other	12.90%	85.36%	0.27%	1.14%	0.16%	0.16%	100%
Grand Total	12.34%	86.06%	0.29%	0.74%	0.31%	0.26%	100%
	Age 75+						
None	11.14%	87.30%	0.40%	0.70%	0.23%	0.23%	100%
Canes, walkers, crutches, dog	9.93%	87.94%	0.21%	1.00%	0.64%	0.28%	100%
Wheelchairs, scooters	4.35%	90.10%	0.48%	3.14%	0.00%	1.93%	100%
Other	11.94%	85.56%	0.20%	1.30%	0.80%	0.20%	100%
Grand Total	10.96%	87.31%	0.38%	0.80%	0.28%	0.27%	100%
	Age 85+						
None	12.33%	86.23%	0.37%	0.58%	0.28%	0.21%	100%
Canes, walkers, crutches, dog	13.77%	82.30%	0.66%	2.03%	0.54%	0.72%	100%
Wheelchairs, scooters	7.53%	84.68%	0.00%	2.69%	0.00%	5.11%	100%
Other	13.32%	84.87%	0.00%	0.66%	0.66%	0.49%	100%
Grand Total	12.47%	85.32%	0.39%	0.95%	0.34%	0.53%	100%

	Walk & Bicycle	POVs	Golf cars/ Segway	Transit	Taxi, Rental cars, Zip cars	Other	GT
	Mode Shares by Location						
AAD	Urban						
None	21.15%	75.17%	0.04%	2.89%	0.52%	0.22%	100%
Canes, walkers, crutches, dog	20.42%	72.66%	0.22%	5.58%	1.12%	0.00%	100%
Wheelchairs, scooters	7.14%	77.23%	0.00%	10.27%	0.00%	5.36%	100%
Other	20.45%	74.77%	0.27%	3.98%	0.53%	0.00%	100%
Grand Total	20.83%	75.01%	0.06%	3.26%	0.55%	0.28%	100%
	Suburban						
None	12.59%	86.10%	0.22%	0.59%	0.32%	0.17%	100%
Canes, walkers, crutches, dog	12.74%	84.60%	0.09%	1.51%	0.47%	0.59%	100%
Wheelchairs, scooters	5.21%	88.49%	0.00%	2.93%	0.11%	3.26%	100%
Other	13.01%	84.83%	0.24%	0.96%	0.72%	0.24%	100%
Grand Total	12.50%	86.00%	0.21%	0.70%	0.34%	0.25%	100%
	Rural						
None	10.19%	88.51%	0.46%	0.35%	0.23%	0.27%	100%
Canes, walkers, crutches, dog	8.09%	90.11%	0.44%	0.69%	0.39%	0.28%	100%
Wheelchairs, scooters	4.90%	91.70%	0.63%	0.71%	0.00%	2.06%	100%
Other	10.37%	88.47%	0.20%	0.60%	0.13%	0.23%	100%
Grand Total	10.00%	88.64%	0.45%	0.38%	0.23%	0.30%	100%

The 2017 NHTS incorporated several questions intending to find out alternative transportation modes available to the respondents. These alternatives include combinations of public

transportation, taxi, Uber, Lyft, getting a ride from family or friends, rental cars, Zipcars, Car2Go, bicycle, and walk. We examined the three-way relationship among income levels, locations, and availability of alternative modes.

Table 4-8 shows that public transit is only physically present and available in approximately 10% of rural and 30% of suburban communities in the U.S. Older adults with income level lower than $25,000 had to dealt with lower transit availability than those in other income levels of the same environments, likely owing to both the respondents' financial difficulty and insufficient services in low-income neighborhoods. In urban areas, high transit availability is associated with big cities, where there are also higher proportions of residents with higher income levels. The same pattern also applies to commercial ride share services, which also tend to be available more in high income areas in urban and suburban environments. Older adults in rural and suburban where public transit and commercial ride share services were not available made up the lack of alternatives by sharing rides with family members and friends, which was also the alternative most available for older adults with income level lower than $25,000.

Table 4-8 Alternative Mode Availability by Income levels and Locations

	Urban		**Suburban**		**Rural**	
	No	Yes	No	Yes	No	Yes
Income Level	*Public Transit Available as an Alternative Mode*					
<$25,000	69.9%	30.1%	73.7%	26.3%	88.7%	11.3%
$25000 to $49,999	56.9%	43.1%	70.1%	29.9%	89.1%	10.9%
$50,000 to $74,999	58.1%	41.9%	68.9%	31.1%	88.6%	11.4%
$75,000 to $99,999	54.6%	45.4%	68.9%	31.1%	89.1%	10.9%
$100,000 to $149,999	49.5%	50.5%	68.2%	31.8%	88.5%	11.5%
>$150,000	50.2%	49.8%	68.9%	31.1%	88.2%	11.8%
Grand Total	58.9%	41.1%	70.3%	29.7%	89.0%	11.0%
	Commercial Ride Share as an Alternative Mode (Taxi, Uber, Lyft, and Zip cars)					
<$25,000	83.8%	16.2%	76.7%	23.3%	84.2%	15.8%
$25000 to $49,999	69.2%	30.8%	64.0%	36.0%	76.6%	23.4%
$50,000 to $74,999	64.9%	35.1%	58.9%	41.1%	70.9%	29.1%
$75,000 to $99,999	56.9%	43.1%	55.1%	44.9%	66.9%	33.1%
$100,000 to $149,999	52.8%	47.2%	50.5%	49.5%	62.8%	37.2%
>$150,000	44.9%	55.1%	47.9%	52.1%	59.3%	40.7%
Grand Total	66.4%	33.6%	61.2%	38.8%	73.5%	26.5%
	Rides from Family and Friends as an Alternative Mode					
<$25,000	69.0%	31.0%	57.0%	43.0%	47.7%	52.3%
$25000 to $49,999	60.6%	39.4%	49.6%	50.4%	48.4%	51.6%
$50,000 to $74,999	58.4%	41.6%	48.7%	51.3%	47.8%	52.2%
$75,000 to $99,999	58.2%	41.8%	47.8%	52.2%	49.2%	50.8%
$100,000 to $149,999	57.0%	43.0%	49.0%	51.0%	48.3%	51.7%
>$150,000	59.6%	40.4%	49.0%	51.0%	51.7%	48.3%
Grand Total	61.8%	38.2%	50.6%	49.4%	48.7%	51.3%

With these findings, we identified several subgroups of the older adult population that are vulnerable for consequences from unmet mobility needs. Older adults age 85 and older, especially those in the lower income brackets, living in urban areas had a significantly lower daily personal trip rates and miles traveled than any other groups. For those without access to POVs, they had to rely on walking and fixed-route transit. Deteriorating streetscape in the urban neighborhoods and diminished physical abilities can significantly impact the mobility and quality of life for urban seniors (Loukaitou-Sideris, Wachs, and Pinski, 2019). Older adults in rural areas and remote suburbs face mobility challenge in long distance between destinations. They have to travel longer distance for medical care than urban and suburban seniors. Most of the older adults in the rural areas rely entirely on POVs for mobility. Upon cessation of driving, getting rides from family or friends appears to be the primary alternative mode for them.

4.3.2. Attitude Analysis

4.3.2.1 Survey and Sample Attribute

For the attitude analysis this study used data obtained from an online survey conducted in Florida and ten other major metropolitan areas in the U.S. in spring 2017. The metro areas were selected based on their population size and geographical locations. The survey was implemented through a survey firm that maintains a large panel throughout the country. Stratified sampling approach was adopted to ensure sample representativeness based on age, gender, ethnicity, education, and household income. The national 2010 Census data and the Florida 2010 Census data were used to design the sampling plan for the national sample and the Florida sample, respectively. More information about the survey design can be found in previous studies (Asgari et al., 2018).

After data cleaning, information was obtained for 1,198 respondents, including 1,017 young adults (age 64 or below), and 181 older adults (age 65 or above).

Table 4-9 presents the sample attributes for the two groups. In this sample, older adults had higher percentages of male, White, Hispanic, African American, and smaller proportion in the lowest income bracket ($0-$25).

Table 4-9 Sample Attributes

Attribute		**Age 18- 64 (1,017)**	**Age 65 and Older (181)**
Gender	Male	52.2%	63.0%
	Female	47.8%	37.0%
Have Driver license	No	12.4%	5.5%
	Yes	87.6%	94.5%
Ethnicity	White	71.6%	91.7%
	Hispanic/Latino	14.7%	3.9%
	Asian/Pacific Islander	1.8%	1.1%
	Native American/American Indian	0.4%	0.6%
	Black or African American	11.0%	2.8%
	Other	0.6%	0.0%
Education	Less than 9th grade	0.8%	0.0%
	9th to 12th grade, no diploma	3.8%	0.6%
	High school graduate	26.5%	28.7%
	Some college, no degree	30.0%	25.4%
	Associate degree	7.3%	5.5%
	Bachelor's degree	26.7%	33.1%
	Graduate or professional degree	4.9%	6.6%
HH Income	0-$25k	20.6%	16.0%
	$25k-$50k	32.3%	34.3%
	$50k-$75k	22.8%	27.1%
	$75k-$100k	14.7%	13.3%
	$100k-$125k	3.1%	3.3%
	$125k-$150k	2.7%	3.3%
	$150k-$175k	1.5%	0.6%
	$175k-$200k	0.9%	1.1%
	$200 and above	1.4%	1.1%
Employment	Full-time employed	48.6%	6.6%

Attribute		Age 18- 64 (1,017)	Age 65 and Older (181)
	Part-time employed	14.2%	8.8%
	Unemployed	16.0%	1.1%
	Student	6.1%	0.6%
	Retired	9.6%	81.8%
	Others	5.5%	1.1%
Online shopping frequency	Never	3.8%	9.4%
	Less than once a month	17.3%	33.7%
	Once a month	17.1%	22.1%
	Once per two weeks	18.3%	12.2%
	Once a week	19.3%	9.9%
	More than once a week	24.2%	12.7%
Ever used ride-sourcing	No	52.7%	84.5%
	Yes	47.3%	15.5%

About 82% of the seniors were retired. They were also less likely to shop online than the younger group. About 85% of the older adults had not used ridesourcing before compared to 53% of the younger group.

4.3.2.2 Attitudes

Furthermore, the following four sets of questions focusing on attitudinal questions (question type was indicated in the parentheses) were included in the survey:

i. General mobility preferences (Likert scale from strongly disagree to strongly agree)

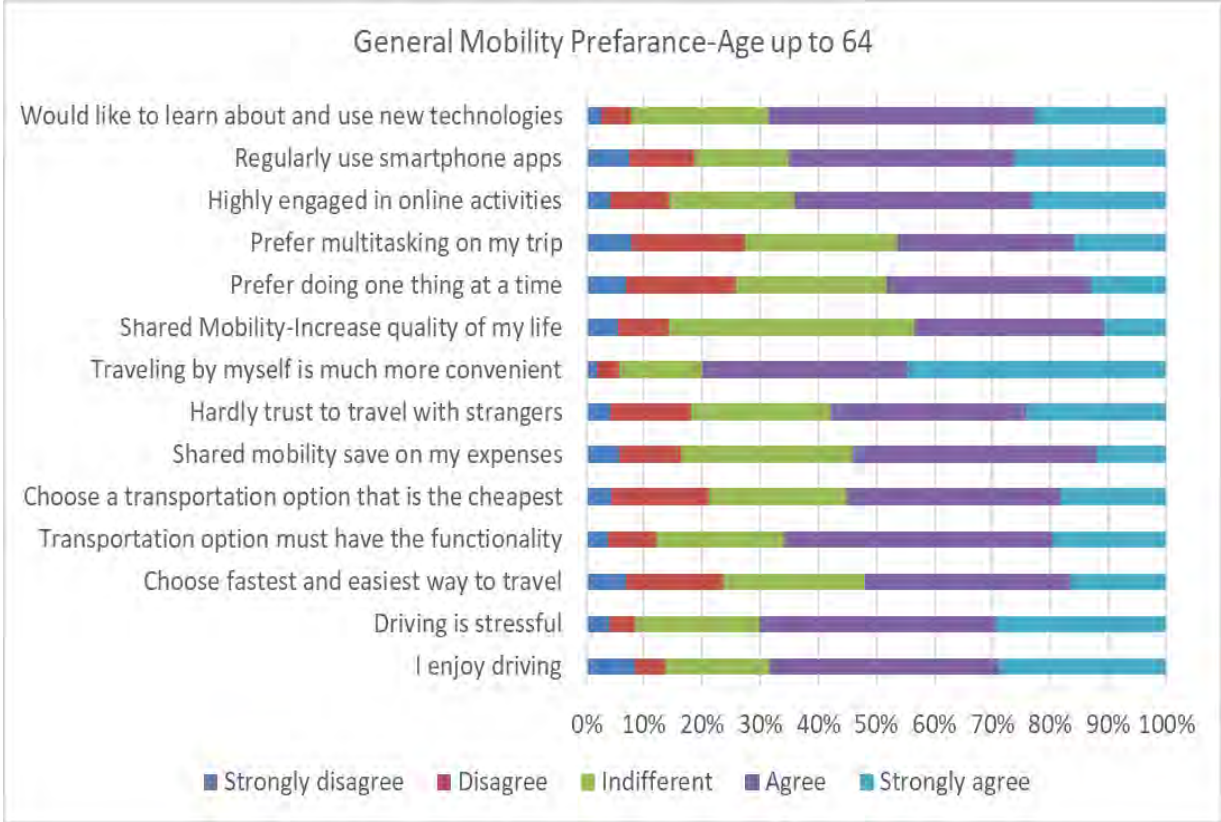
ii. User's perceptions on the benefits and concerns of shared mobility (ranking)

iii. The reasons for owning or not owning private vehicles (all that apply)

iv. Motivations for using automated vehicles (AV) (all that apply)

Figure 4-1 through Figure 4-4 present the responses to the attitude questions for the two groups.

Figure 4-1 shows a summary of responses for general mobility preferences. Compared to the younger group, older adults were less likely to adopt technologies, and use mobile apps (e.g., more than 65% of the younger group agree or strongly agreed that they regularly use smartphone apps, while less than 30% of the older adults stated so). Much fewer older adults (25% vs. 45% of younger adults) preferred multitasking when traveling. Compared to younger adults, older adults were also less likely to choose the cheapest travel mode or perceive that shared mobility help save travel expenses. Interestingly, more than 80% of the respondents (both older and younger adults) believed that traveling by themselves was much more convenient.



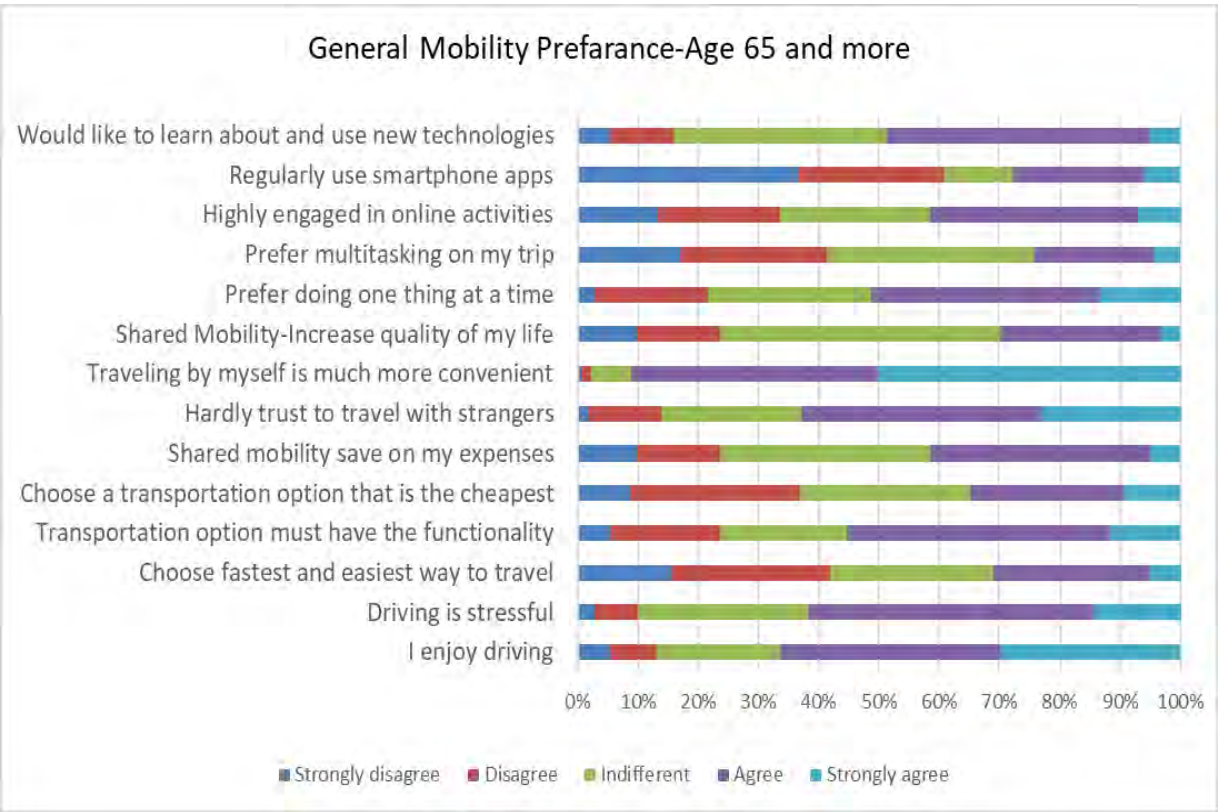


Figure 4-1 General Mobility Preferences for Age up to 64 and Age 65 and more

In view of the perceived benefits and concerns of shared mobility, Figure 4-2 shows that both groups showed similar patterns – cost-effectiveness and less driving stress were ranked as the top benefits, although on-demand service was more likely to be valued by older adults (38% ranked it as high or the highest priority) compared to younger adults (28%). Notably, for both groups, data privacy and unreasonable fares showed “bipolar” effect – a significant portion of the respondents didn’t care about these issues at all (no priority), while another significant portion ranked them as the highest priority. This indicates mixed perceptions in the population regarding data privacy and fare issues of shared mobility services.

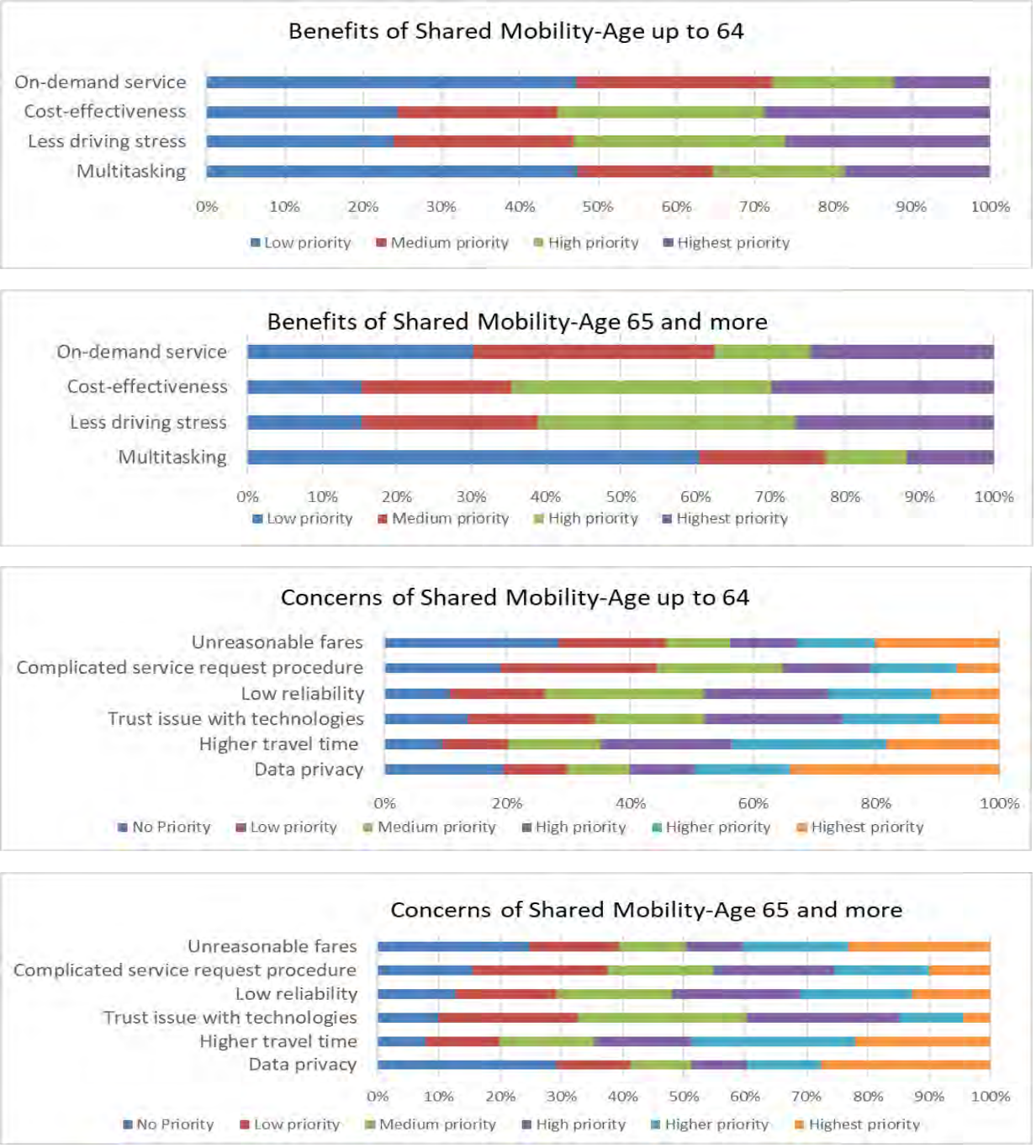
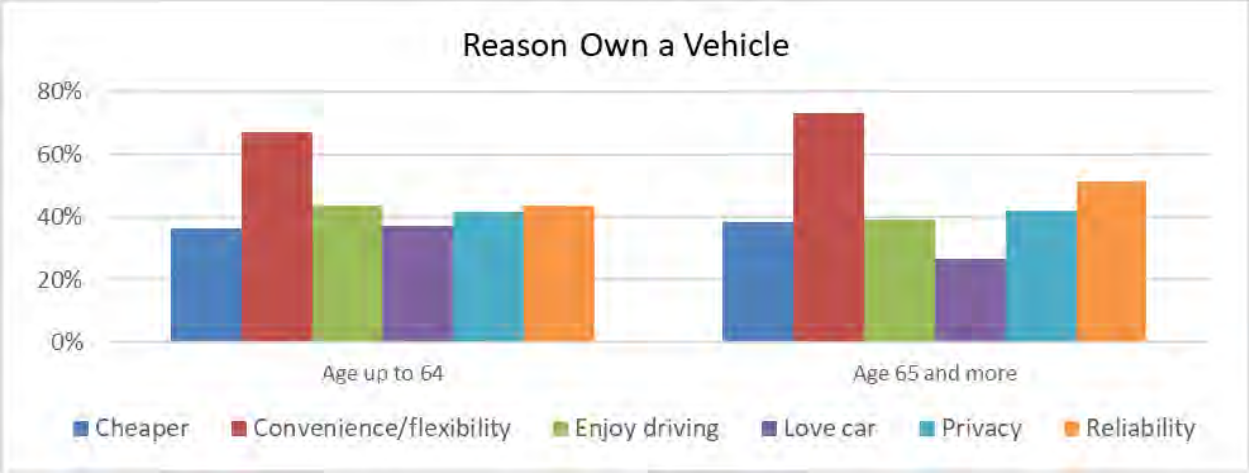


Figure 4-2 Perceived Benefits and Concerns of Shared Mobility for Older and Younger Adults

When asked about the reasons to own or not to own a vehicle, Figure 4-3 shows similar patterns for older adults and younger adults. For both groups, convenience/flexibility and reliability were the top reasons for owning a vehicle. On the other hand, affordability and maintenance costs were the top reasons for not owning a vehicle.



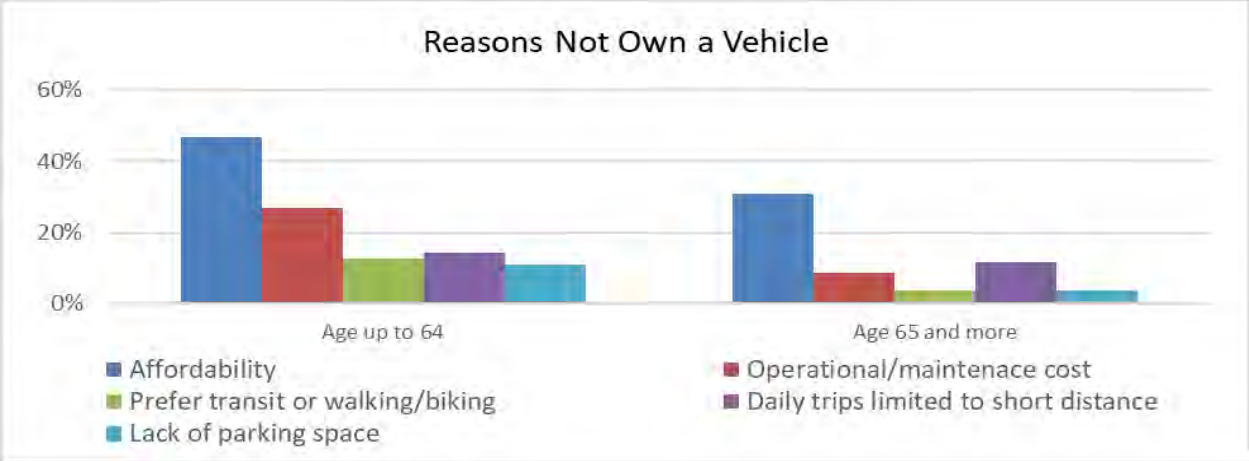
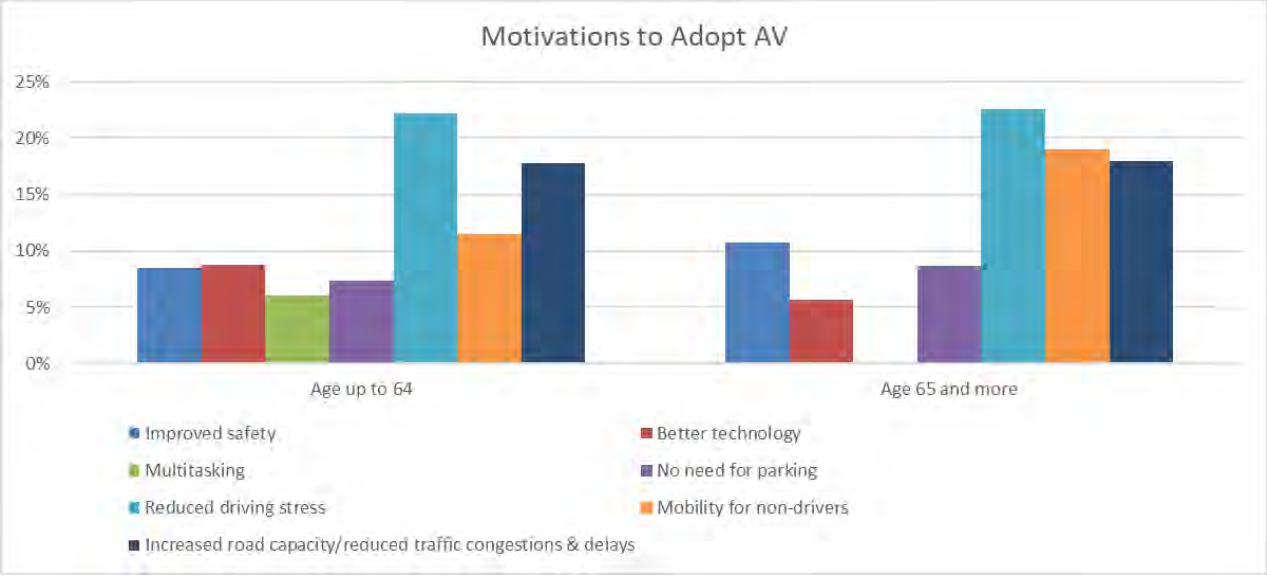


Figure 4-3. Reasons Behind Private Vehicle Ownership.

Figure 4-4 shows the outputs of the younger and older adults' motivations to ride or drive in an AV and the most cherished AV features. Like vehicle ownership choices, here each respondent was allowed to select multiple options. In the context of motivations, reduced driving stress (older 23%, younger 22%), and increased capacity of roadways/reduced traffic congestions (18% for both age group) were the top reasons for both groups. Moreover, mobility for non-drivers was the most likely motivation for older adults (19%) than younger adults (12%) to adopt AV as aging forces people to stop driving. Older adults did not show any interest in multitasking to adopt AV. Concerning the desired features, compared to the younger adults self-parking assistance (30% older adults), lane-keeping assistance (22% older adults), and avoid collision assistance (12% older adults) was the most cherished features for older adults. Lastly, improved fuel efficiency was more desired for younger adults (%) than older adults (%). These were the top-selected features by both age groups.



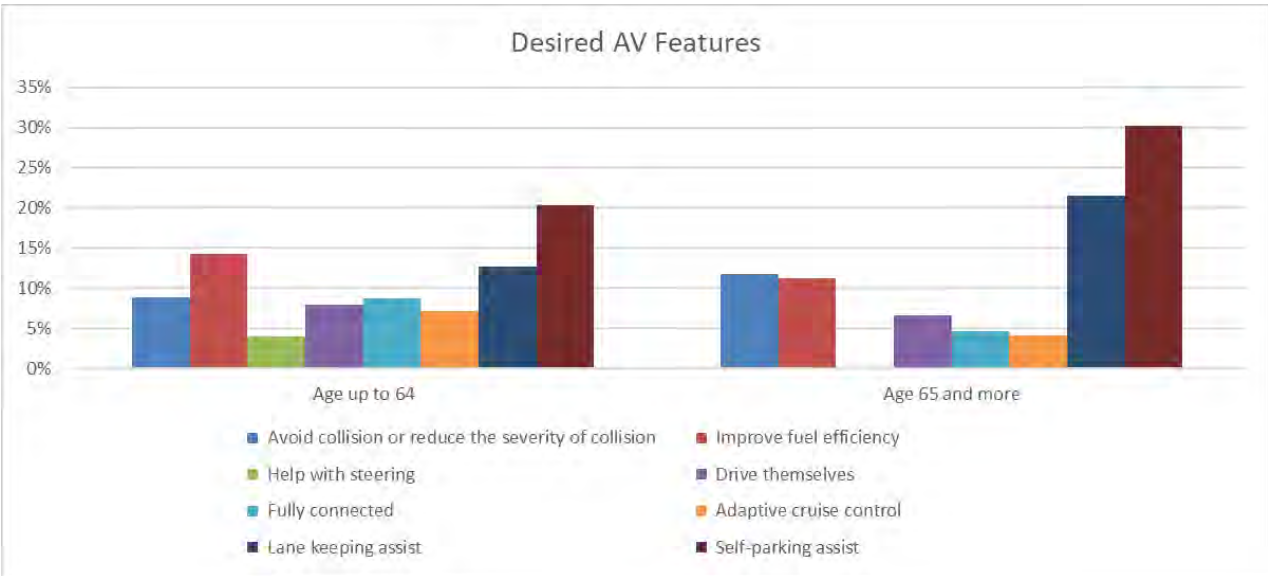


Figure 4-4 Motivations for and Desired Features of Automated Vehicles (AV)

4.3.3. Shared Mobility Analysis

The same survey data described above were also used to explore older adults' propensity to adopt ridesourcing services. To gauge the economic motivation to adopt ridesourcing, the respondents were presented with the following valuation question:

I would use ridesourcing if driving cost increases by dollars per month (e.g., you can think of fuel cost, parking cost, or fare):

a) $50, b) $100, c) $150, d) $200, or e) $250 or more

Figure 4-5 presents the distribution of desired monthly travel cost savings to switch to ridesourcing for the two age groups (Age up to 64 and age 65 and older). It indicates that older adults were more likely to require higher cost savings to switch to ridesourcing services compared to the younger group, in other words they were harder to persuade. Specifically, 21% of the older adults needed monthly savings of $250 or more to give up private vehicles compared to 13% of the younger group.

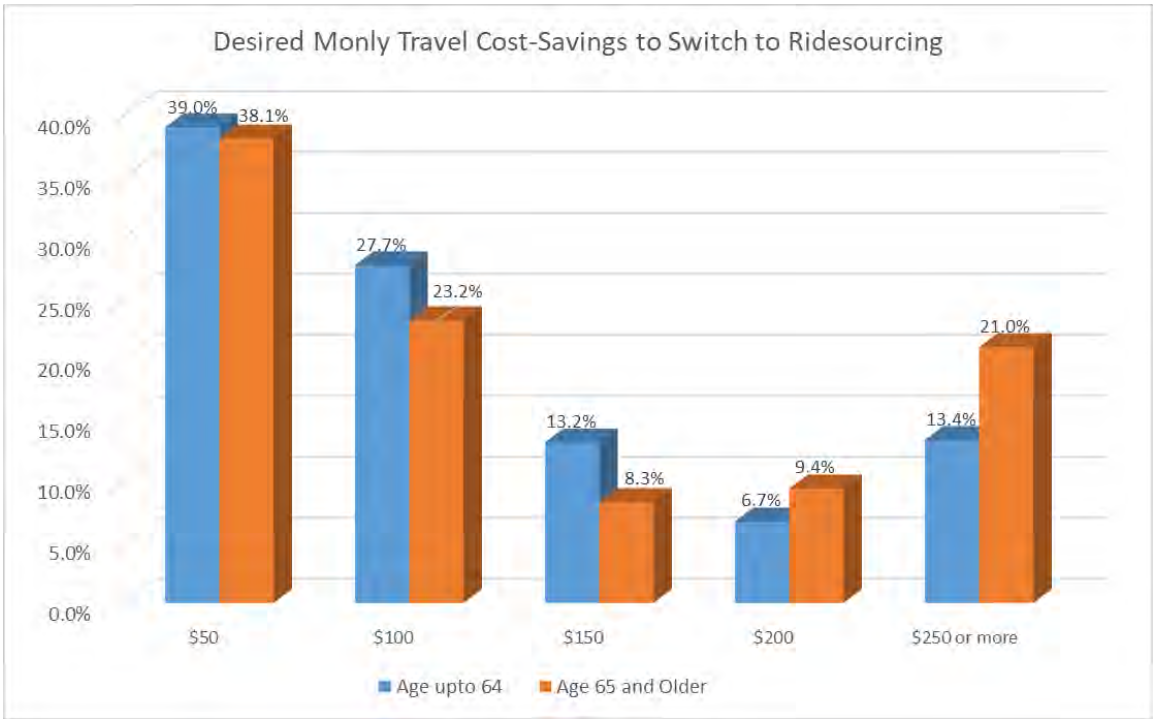


Figure 4-5 Comparisons of the desired monthly savings to switch to ridesourcing services.

4.3.3.1 Identifying Attitude Factors

An exploratory factor analysis (EFA) was conducted to extract underlying attitudinal factors. Factor analysis is a method that converts a large number of observed correlated parameters into a potentially small number of uncorrelated parameters called factors (Taherdoost et al., 2014; Mair, 2014). This method has been widely used to investigate people's attitudes and choices (Rahimi et al., 2020; Wang et al., 2020; Haboucha et al., 2017). Separate factor analysis was performed for each attitudinal aspect (shown in Figure 4-1 to Figure 4-3), where the eigenvalue was used as a metric to identify the number of factors. The eigenvalue reflects how much of the variance of the parameters a factor explains. Any factor having an eigenvalue greater than one elucidates more variance than an individual indicator (Cliff, 1988). Table 4-10 presents the results of the EFA. The analysis was conducted using the Python factor_analyzer package. A brief description of each factor that speaks for an individual's attitude was included.

The percentage of variance that each factor explains, the cumulative percentage of variance that each category explains, and the eigenvalues for each factor are also presented.

Table 4-10. Identified latent factors

Category	Factors	Description	Eigen-values	% of Variance Explained	Cumulative % of Variance Explained
General Mobility Preferences	F1: Rational Choice	Involves the deliberation of service quality (e.g., travel time, cost, and convenience) in mobility choice.	3.710	14.0%	14.0%
	F2: Tech-savvy	Alludes to engagement with online activities, smartphone use, and familiarity with technology.	1.804	12.8%	26.7%
	F3: Trust Issue with Strangers	Refers to the concerns regarding traveling with strangers.	1.237	8.1%	34.8%
	F4: Anti-Multitask	Represents the disinterest in multitasking during travel.	1.040	7.5%	42.3%
Perceptions of Shared Mobility	R1: Pro-On-Demand Service	Refers to the interest in on-demand services and lack of interest in multitasking.	2.278	13.6%	13.6%
	R2: Cost-Effectiveness	Refers to the interest in the effectiveness of ridesourcing in terms of cost.	1.289	13.5%	27.1%
	R3: Fare and Procedure Concerns	Indicates the concerns with unreasonable fares and complex service request procedure; negatively associated with data privacy and technology trust issues.	1.255	12.5%	39.6%
	R4: Stress Relief	Indicates the belief in stress relief while using ridesourcing services.	1.215	12.4%	52.1%
	R5: Travel Time Concerns	Refers to the concerns on higher travel time due to waiting time and multiple pickups.	1.137	11.2%	63.2%
	R6: Reliability Concerns	Refers to the concerns on service reliability of shared mobility.	1.087	11.2%	74.4%

Category	Factors	Description	Eigen-values	% of Variance Explained	Cumulative % of Variance Explained
Vehicle Ownership	P1: Private Vehicle Utility	Represents the fondness for a private vehicle because of privacy, flexibility, reliability.	2.303	12.3%	12.3%
	P2: Pro-Driving	Indicates the attachment with private vehicles due to the joy of driving and love of cars.	1.310	12.0%	24.3%
	P3: Maintenance Cost	Indicates the concern on maintenance cost as the main reason for not owning a vehicle.	1.111	11.2%	35.5%
	P4: Cost-Sensitive	Refers to the consideration of travel cost as a main reason in vehicle ownership choice.	1.058	3%	38.5%

4.3.3.2 Methodology

For this study, an ordered logit structure was employed to reflect the ordered nature of the dependent variable (i.e., cost savings). The literature has documented the advantage of ordered logit models, including parsimoniousness, higher detection capability, high flexibility, and more straightforward interpretations, etc. (Zheng et al., 2014). Following the methodology presented in Washington et al. (2011), Azimi et al. (2020), Zheng et al. (2014), the latent variable, Z_{ni}^* (coded as 1, 2, 3, 4, 5 respectively for \$50, \$100, \$150, \$200, and \$250 or more) that determines the measure of cost savings can be illustrated as follows:

$$Z_{ni}^* = \boldsymbol{\beta_{ni} X_n} + \varepsilon_{ni} \quad (1)$$

Where Z_{ni}^* is the latent continuous variable related to cost saving level i for observation n, β_{ni} = vector of coefficients to be estimated, X_n = vector of explanatory variables, ε_{ni} = random error term which is assumed to be normally distributed with zero mean and unit standard deviation.

Under the ordered logit model framework and the latent continuous function, the observed cost savings Z_{ni}^* is the discernment of a latent cost savings propensity for each respondent, z_{ni}^*. the association between the categories of Z_{ni}^* and the values of z_{ni}^* can be defined as follows (Washington et al., 2011).

$$Z_i = \begin{cases} 1 \rightarrow \text{ if } z_{ni}^* \leq \mu_1 \\ 2 \rightarrow \text{ if } \mu_1 \leq z_{ni}^* \leq \mu_2 \\ \dots\dots\dots \\ i \rightarrow \text{ if } z_{ni}^* \geq \mu_{i-1} \end{cases} \quad (2)$$

Where μ_i is the set of thresholds of the continuous scale for z_{ni}^*. For this study, μ_1 is equal to 0, and only μ_2 , μ_3 , μ_4 need to be estimated

To estimate the probabilities of i, the ordered logit model selection probabilities are illustrated as follows (Washington et al., 2011; Azimi et al., 2020):

$$
\begin{aligned}
&P(Z_i = 1) = \Phi(\mu_1 - \boldsymbol{\beta_{ni} X_n}) \\
&P(Z_i = 2) = \Phi(\mu_2 - \boldsymbol{\beta_{ni} X_n}) - \Phi(\mu_0 - \boldsymbol{\beta_{ni} X_n}) \\
&P(Z_i = 3) = \Phi(\mu_3 - \boldsymbol{\beta_{ni} X_n}) - \Phi(\mu_1 - \boldsymbol{\beta_{ni} X_n}) \\
&\ldots \\
&P(Z_i = i) = 1 - \Phi(\mu_{i-1} - \boldsymbol{\beta_{ni} X_n})
\end{aligned}
\tag{3}
$$

To further examine potential heterogeneity in the impacts of independent variables, random parameters were introduced. The RPOL model assumes that variables are distributed randomly with potential heterogeneous variables produced from particular probability distributions such as normal, lognormal, uniform (Greene, 2012). Moreover, to determine the potential sources of heterogeneity, interaction effects were introduced into the model. In this regard, random parameters were interacted with various socioeconomic and demographic attributes to identify the sources of variations. Introducing interaction effects could improve the model's goodness of fit and provide more clear insights into the presence of heterogeneity. An error term is introduced to randomize the parameters that is correlated with both unobserved and observed factors. It transforms individual's heterogeneity to parameter heterogeneity that can be formulated as follows:

$$\beta_{ni} = \beta + \tau Y_n + P w_{ni} \tag{4}$$

Where β is the fixed part of coefficient, τ is the interaction effects' matrix, Y_n is the vector of interaction coefficients, *P* is the matrix of standard deviation, and w_{ni} is the vector of random draws from a normal standard distribution function.

4.3.3.3 Model Results

Separate RPOL models were developed for older adults and younger adults, which provides a means to examine whether and how their decisions in switching to ridesourcing services may differ. Table 4-11 presents the model results for both groups. The model was estimated in R. All variables that were statistically significant at the 90% confidence level (p-value <0.1) were kept in the model. A positive coefficient indicates that higher cost savings were required to motivate the switch to ridesourcing services. In contrast, a negative coefficient means a lower economic motivation would suffice.

Table 4-11 RPOL Model Results

			Age 65 and older				Age up to 64			
			RPOL model		RPOL model with interaction effects		RPOL model		RPOL model with interaction effects	
			Estimate	Z-value	Estimate	Z-value	Estimate	Z-value	Estimate	Z-value
Constants	μ_2		2.55	4.03	2.61	4.37	1.66	11.63	1.73	10.67
	μ_3		3.55	4.18	3.65	4.58	2.65	12.49	2.76	11.33
	μ_4		4.92	4.15	5.08	4.59	3.35	12.69	3.48	11.52
	Constant		-1.23	-1.87	-1.66	-2.47	-0.20	-0.72	-0.29	-1.01
Socioeconomic and demographic factors	Age 25 to 39						0.42	2.60	0.39	2.37
	HH Income: $0-$25k						-0.98	-4.32	-0.94	-4.09
	HH Income: $25-$50k						-0.43	-2.41	-0.38	-2.11
	HH Income: $125k-$150k						0.95	2.17	1.17	2.51
	High school graduate		-1.17	-1.73	-1.09	-1.70				
Driver's license	Yes						0.85	3.11	0.84	2.96
Online shopping	More than once a week		1.59	2.15	1.83	2.48	0.35	1.93	0.39	2.06
Regular travel mode	Private Vehicle		0.48	2.71	0.54	2.96				
Attitudinal variables	Trust Issue with Strangers		1.11	2.67	0.95	2.32	0.20	2.05	0.21	2.03
	Cost-Effectiveness						-0.19	-2.53	-0.19	-2.47
	Private Vehicle Utility		1.82	3.49	1.87	3.90	0.37	3.46	0.38	3.45

			Age 65 and older				Age up to 64			
			RPOL model		RPOL model with interaction effects		RPOL model		RPOL model with interaction effects	
			Estimate	Z-value	Estimate	Z-value	Estimate	Z-value	Estimate	Z-value
	Pro-Driving						0.25	2.40	0.22	2.03
	Cost-Sensitive		-1.59	-2.79	-1.51	-2.72				
Random parameters	Rational Choice	Mean	-0.77	-1.86	-1.32	-2.26	-0.56	-4.88	-0.48	-3.68
		SD	1.68	2.11	1.84	2.29	0.56	1.78	0.84	2.78
	Tech savvy	Mean	-0.78	-1.96	-1.19	-2.50				
		SD	2.72	2.48	2.60	2.68				
	Fare and Procedure Concerns	Mean					0.19	1.84	0.19	1.73
		SD					1.12	3.34	1.17	3.57
Interaction effects	Rational Choice	HH Income: $150k and above			1.78	1.93			2.10	2.21
		Online shopping: Less than once a month							-1.18	-3.57
	Tech-savvy	Cost-Effectiveness			0.53	1.83				
	Fare and Procedure Concerns	Cost-Sensitive							0.44	2.07
goodness of fit	Log-likelihood		-212.3		-209.3		-1371		-1355	

4.3.3.3.1 OLDER ADULTS

For the results in Table 4-11, three attitudinal factors, including “Trust Issue with Strangers”, “Private Vehicle Utility”, and “Cost-Sensitive” were found to have significant impacts on older adults’ decision on ridesourcing adoption. Those who had concerns about traveling with strangers and those who believed that private vehicles provide better utilities in terms of convenience, reliability, and flexibility required higher cost-saving incentives to switch to ridesourcing services. In other words, these individuals were harder to convince and less likely to adopt ridesourcing. This finding is consistent with the literature (Asgari et al., 2020; Alemi et al., 2018). On the other hand, those who were sensitive to travel costs were easier to persuade to adopt ridesourcing as they needed lower cost savings, reflected by the negative impact of “Cost-Sensitive.”

Regarding socioeconomic and demographic characteristics, only two variables exhibited significant impacts: education level and online shopping frequency. Older adults with only high school degrees were interested in switching to ridesourcing with lower cost savings compared to those with higher degrees. Past study has shown that less-educated individuals were less likely to adopt ridesourcing. This finding suggests that economic incentives might help motivate low-educated older adults to adopt ridesourcing. Interestingly, older adults who shopped online more than once a week expected more cost-savings to switch to ridesourcing. Those who shop online frequently must have access to the internet and be comfortable with new technologies. Nonetheless, they were still less likely to use ridesourcing. This may be associated with their higher economic status, which relates to higher economic incentives.

Considering individuals' mobility habits, the model shows that older adults who used private vehicles regularly required higher cost-savings to choose ridesourcing. It seems logical that people who were used to private mobility were more reluctant to try other modes.

To further test potential heterogeneity in the impacts of the attitudes, we tested each of the attitude factors as a random parameter. Results show that two attitudinal factors showed significant mean and standard deviation at the 90% confidence interval, implying the existence of heterogeneity. These two factors are “Rational Choice” and “Tech-Savvy.” The negative mean values of the two parameters indicated that, on average, those who were more focused on service quality (e.g., travel cost, travel time, functionality, etc.) in their mobility decisions and those who were more tech-savvy were easier to convince to switch to ridesourcing with less economic incentives compared to those who weren’t. However, the large standard deviation of these two random parameters indicates that for some individuals, these factors might have positive effects, therefore needed higher economic incentives.

To determine the potential sources of the variation of the impacts among the observations, various socioeconomic and demographic, and attitudinal variables were tested as interaction

variables. The results showed that two variables had significant interaction effects. It shows that rational users with high income ($150k and above) would require higher cost-savings to change their mobility preferences to ridesourcing. This seems logical that higher economic incentives are needed to motivate individuals with higher income levels. Similarly, tech-savvy rational users who valued the cost-effectiveness of shared mobility also needed high economic incentives. This may indicate that ridesourcing services at their current state may still be viewed as less economical compared to other modes such as driving. A past study also showed that auto users with a positive attitude about the cost-effectiveness of ridesourcing were less likely to use exclusive rides (Azimi et el., 2020). Shared rides may be viewed as an attractive alternative for these individuals.

4.3.3.3.2 YOUNG ADULTS

Compared to older adults, “Trust Issues with Strangers” and “Private Vehicle Utility” also had positive effects for young adults (age 64 or younger). Interestingly, two more attitudinal factors were at play for young adults in their decisions to adopt ridesourcing. “Pro-Driving” did not affect older adults’ choice behavior but showed a significant positive effect for young adults, indicating higher economic incentives needed to switch to ridesourcing. This is an interesting finding that although the shares of people who enjoy driving were the same between the two groups (as shown in Figure 4-1 and Figure 4-3), this attitude was not a decisive factor when it comes to ridesourcing adoption for older adults. To some degree, this implies that ridesourcing does stand a chance to break the attachment with private vehicles for older adults, as long as it provides the same or even better utilities as private vehicles (diminishing the impacts of “Private Vehicle Utility”).

Another attitude that only affected young adults is “Cost-Effectiveness,” which indicates that those who believed that cost-effectiveness was an important benefit of shared mobility required less cost-savings to adopt ridesourcing. Again, although Figure 4-2 shows that the older and young adults had similar views on the cost-effectiveness of shared mobility, this attitude does not play a role in older adults’ decision-making, which implies that cost-effectiveness was not an important feature in their mobility choice decisions.

Considering socioeconomic and demographic characteristics, household income played an essential role in young adults’ decision to switch to ridesourcing. But it did not impact older adults’ decisions; instead, education attainment was a more important indicator for older adults in terms of ridesourcing adoption. Younger adults who hold a driver’s license needed higher economic incentives to switch to ridesourcing, while again, this is not a decisive factor for older adults. It may imply that the younger generation may own fewer vehicles and less likely to hold a driver’s license, but for those who do, it may be an indicator of attachment to the car or the joy of driving, which means it’s less likely to persuade these individuals to give up

private vehicles and switch to ridesourcing. This is similar to the impacts of the "Pro-Driving" attitude, which only affected the decisions of young adults.

4.3.3.3.3 MARGINAL EFFECTS AND DIRECT ELASTICITIES

To further facilitate the interpretation of the impacts of the influential variables, marginal effects for and direct elasticities were calculated and shown in Table 4-12. Marginal effects tell how the estimated probability of a binary outcome changes when the estimated explanatory variables change from zero to one (Norton et al., 2018). Direct elasticities explain the instantaneous rate of change in the outcome because of a 1% change in the estimated parameters (Yang et al., 2013). Here, marginal effects and direct elasticities were calculated for SED (dummy variables) and attitudinal (continuous variables) factors, respectively.

Figure 4-6 presents the marginal effects and direct elasticities for cost-savings of $50 per month. Similar graphs can be produced for other cost-saving categories. We use the lowest cost-saving category to demonstrate the relative impacts among the influential factors. A monthly cost-saving of $50 represents those who are easiest to persuade to adopt ridesourcing. Positive effects reflect factors that help motivate the switch to ridesourcing, while negative effects reflect factors that hinder the switch.

One interesting observation from Figure 4-6 is that while young adults' decisions were highly influenced by demographic attributes, older adults' choices to switch to ridesourcing were mostly affected by attitudes. Specifically, "Private Vehicle Utility" and "Cost-Sensitive" were the most influential attitudes that prevent and promote older adults to switch to ridesourcing, respectively. "Private Vehicle Utility" and "Trust Issue with Strangers" had negative impacts for both young and older adults, but the effects on older adults were much larger than that on young adults. "Tech-Savvy" and "Cost-Sensitive" showed large positive impacts for older adults but had no effect for young adults. Specifically, older adults that were more technology embracing were more likely to switch to ridesourcing with lower economic incentives, and those who considered travel cost as the main reason to own or not own a vehicle were also easier to persuade to switch with less economic incentives.

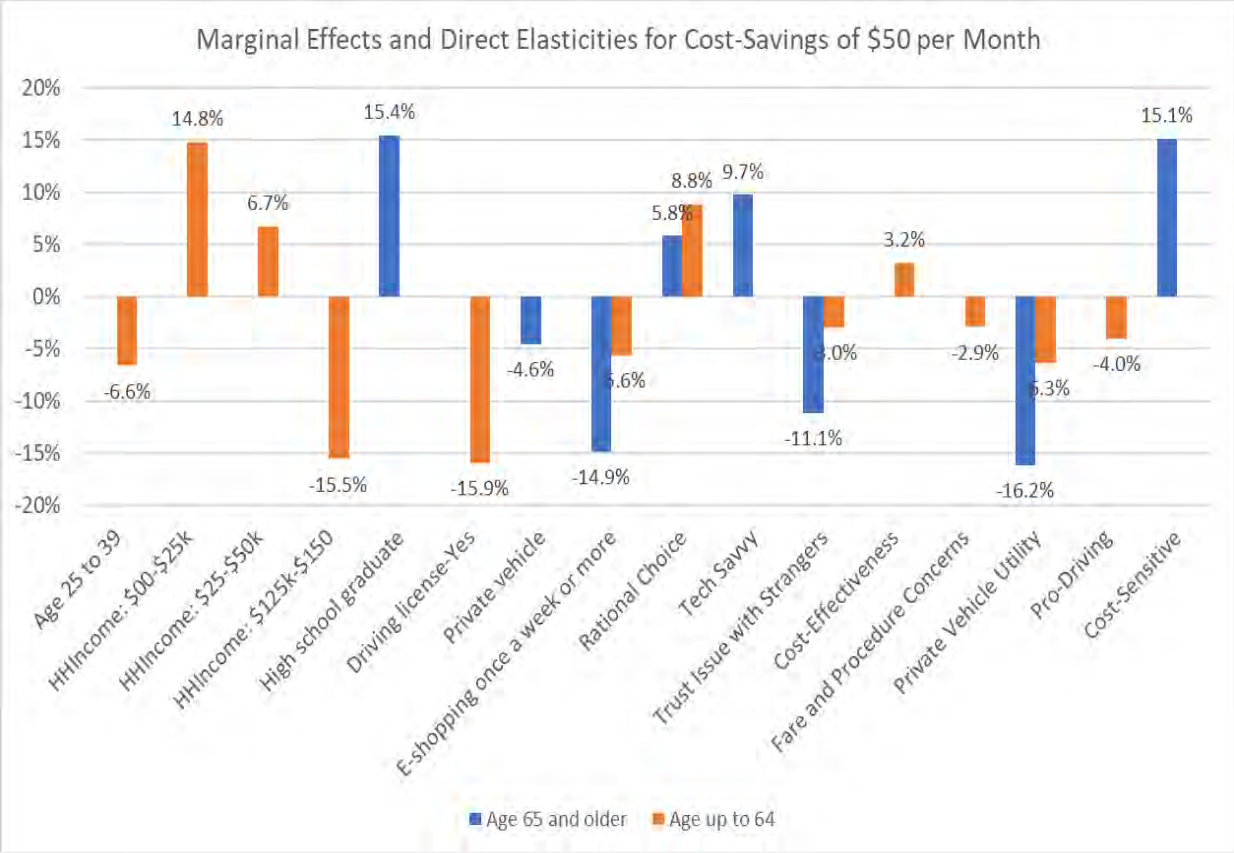


Figure 4-6 Marginal effects and direct elasticities for desired monthly cost-savings of $50.

In terms of socioeconomic and demographic attributes, frequent online shopping (i.e., more than once a week) was an indicator for higher economic incentives to adopt ridesourcing for both young and older adults, with much larger impacts for older adults. While age, income, and driver's license were highly influential in young adults' decisions to switch to ridesourcing, education level was the dominant personal attribute that contributed to older adult's decisions

Table 4-12 Marginal Effects and Direct Elasticities

		Age 65 and older					**Age up to 64**				
Category	Variable	$50	$100	$150	$200	$250 or more	$50	$100	$150	$200	$250 or more
Socioeconomic and demographic factors	Age 25 to 39						-6.6%	0.3%	1.6%	1.3%	3.5%
	HH Income: $00-$25k						14.8%	-0.7%	-3.6%	-2.8%	-7.7%
	HH Income: $25-$50k						6.7%	-0.3%	-1.6%	-1.3%	-3.5%
	HH Income: $125k-$150						-15.5%	0.7%	3.8%	2.9%	8.2%
	High school graduate	15.4%	0.8%	-1.2%	-2.5%	-12.5%					
Driver's License	Yes						-15.9%	0.7%	3.9%	3.0%	8.4%
Regular Travel Mode	Private vehicle	-4.6%	-0.2%	0.4%	0.7%	3.7%					
Online Shopping	More than once a week	-14.9%	-0.7%	1.1%	2.4%	12.1%	-5.6%	0.3%	1.4%	1.1%	3.0%
Attitudinal Variables	Rational Choice	5.8%	0.3%	-0.4%	-0.9%	-4.7%	8.8%	-0.4%	-2.1%	-1.7%	-4.6%
	Tech savvy	9.7%	0.5%	-0.7%	-1.6%	-7.9%					
	Trust Issue with Strangers	-11.1%	-0.6%	0.9%	1.8%	9.0%	-3.0%	0.1%	0.7%	0.6%	1.6%
	Cost-Effectiveness						3.2%	-0.1%	-0.8%	-0.6%	-1.7%
	Fare and Procedure Concerns						-2.9%	0.1%	0.7%	0.5%	1.5%
	Private Vehicle Utility	-16.2%	-0.8%	1.2%	2.6%	13.1%	-6.3%	0.3%	1.5%	1.2%	3.3%
	Pro-Driving						-4.0%	0.2%	1.0%	0.8%	2.1%
	Cost-Sensitive	15.1%	0.7%	-1.2%	-2.5%	-12.2%					

4.4. CONCLUSIONS

In this study, we described findings from a comprehensive examination of the 2017 NHTS data for identification of mobility needs and challenges faced by older adults in urban, suburban, and rural environments. Urbanization and income level were found to be significant factors for mobility patterns of older adults in the U.S. Overall, with decreasing urbanization of the environment, the average number of daily person trips generally decreased, while average daily person miles increased. Across all locations, the average number of daily person trip and daily person miles both increased as income levels increased from low to medium-high levels (i.e., < $100,000/year). High availability of public transit and commercial share ride services was identified in areas with higher income levels. Older adults with income level lower than $25,000 had reported lower transit availability than those in other income levels of the same environments. For older adults requiring ambulation assistance, respondents on wheelchairs or scooters made less trips a day than those who ambulated without limitations. Despite longer average distance required for reaching destinations for essential services, rural older adults with disabilities had less daily mileage than their counterparts in the urban areas, suggesting unmet mobility needs by this group of older adults.

Emerging mobility options for older adults that are available now include dynamic, for-profit ride-share services (e.g., Uber and Lyft) and non-profit ride-share services. Subsidized services by Uber or Lyft appear to be feasible options for authorities seeking cost-effective solution to providing mobility to seniors. Non-profit ride-share services have also been taking advantage of Internet and smartphone technologies to make their services more convenient for seniors. Ride-share services can offer scheduling flexibility, ambulation assistance, and comfort and convenience close to what POVs can offer. Based on the findings of this study, there is a great market potential and needs for ride-share services to fill the mobility needs of older adults in a way that cannot be filled by typical fixed route or on-demand paratransit. There is an urgent need for future research and practice to find out financially feasible and operationally effective strategies and programs of ride-share services that serve the mobility needs and challenges of older adults in the U.S.

In the aims to evaluate older adults' inclination toward shared mobility services, this study further investigated the magnitude of cost-saving per month that would encourage travelers to switch from their current mode to ridesourcing services. Data from an online SP survey conducted in Florida and ten other major metropolitan areas in the U.S. were used for this study. Separate RPOL models were developed for two age groups, young adults (age 64 or below) and older adults (age 65 or above). The impacts of SED attributes, trip patterns, and attitudinal factors on the desired economic incentives were examined.

The model results suggest that SED attributes highly impacted young adults' mode decisions, while for older adults, the choice to switch to ridesourcing was mainly affected by attitudinal

factors. Specifically, older adults who had concerns about traveling with strangers, or believed that private mobility provide better utilities in terms of convenience, reliability, and flexibility required higher cost-saving incentives to switch to ridesourcing services. These two attitudes showed the same impacts for young adults but with much smaller magnitude. Interestingly, although both groups had similar attitudes toward joy of driving, the "Pro-Driving" attitude was not a decisive factor for older adults. This may indicate that ridesourcing does stand a chance to break the attachment with private vehicles for older adults, as long as it provides the same or even better utilities as private vehicles. Ridesourcing services for older adults may focus on service quality, especially privacy, reliability, convenience, and flexibility. Additional measures ensuring security, privacy and driver selection process would also be beneficial. Outreach programs that highlight these features of the ridersoucing services as well as free trial programs would be more helpful in encouraging older adults to use ridesourcing services.

In addition, older adults who were rational choice makers or those who consider cost to be the main factor when making mobility choices, less economic incentives were needed to encourage the switch to ridesourcing. This indicates a potential market for ridesourcing among older adults who would value the mobility option that could provide faster, cheaper, and functional services that suit their traveling needs. Again, outreach programs and trial programs may help travelers realize the benefit and advantage of ridesourcing services in terms of reducing travel time (parking time or waiting time for transit) and travel cost (fuel, parking, and toll costs), and improving convenience (door to door service), therefore encourage the adoption and use of ridersoucing among older adults.

Older adults who were "Tech-Savvy" also required less economic motivations to switch to ridesourcing, and interestingly concerns on unreasonable fares or complicated service request procedures did not impact older adults' decision on ridesourcing adoption. Educational campaigns focusing on introducing the operation, process, communication, and level of efforts involved in using ridesourcing services could help those who are less tech-savvy to get familiar and comfortable with the services.

The findings of this research provide valuable insights into factors affecting older adults' decisions toward ridesourcing services and highlight the unique attitudes that influence their decisions. This study advances our understanding of the propensity toward ridesourcing among older adults in terms of their preferences and motivations. This knowledge would lead to better estimation of their mobility choices and better design of policies and services that meet the mobility needs of older adults.

Findings of this study were limited geographically to the survey data collected in the state of Florida and ten other metropolitan areas. Future research in other locations or wider geographic coverage could help verify the findings of this study. This study also did not consider built environment factors in individuals' mobility choices. Future work extending from the context of this study can investigate the impacts of land use and urban environments.

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5.0 HEALTH CARE VISITS DURING THE COVID-19 PANDEMIC: A SPATIAL AND TEMPORAL ANALYSIS OF MOBILE DEVICE DATA

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5.1. INTRODUCTION

Transportation is widely recognized as critical factor in health care access (Syed et al., 2013). Nearly 5.8 million Americans in 2017 reported delaying medical care because of a lack of transportation options (Wolfe et al., 2020). COVID-19 has significantly disrupted transport and health systems. Early indications are that these changes, combined with lockdown requirements and a desire to limit exposure, reduced access to health care. For example, 35% of US adults reported delaying health care because of COVID-19 (Household Pulse Survey, 2020, May) and many news outlets have reported decreases in preventive services (e.g., Smith, 2020; Martin et al., 2021).

In response to COVID-19, health care systems implemented policies that made accessing care both harder and easier. During the initial months of the pandemic, most systems eliminated or significantly reduced access to elective or non-emergency services. Hospitals also placed restrictions on whether patients could have individuals accompany them to appointments. While these policies reduced access to in-person health care, providers and insurers increased support for telemedicine visits (Chen et al., 2021; Medicare Telemedicine, 2020). COVID-19 also disrupted transportation options. Shared mobility options including fixed-route transit, paratransit, and ride-hailing, became less available as agencies and firms decreased service in response to safety concerns and ridership declines (Hu & Chen, 2021; APTA, 2021).

The purpose of this study is to assess the impacts of COVID-19 on health care access in North Carolina (NC). We do this by using mobile device data from SafeGraph to identify visits to health care facilities and then use time-series clustering to identify Census Block Groups (CBGs) exhibiting similar medical visit patterns during 2020. We then examine the association between these temporal patterns and the socio-demographic and spatial characteristics of CBGs in NC. The findings reveal social and spatial inequalities in health care use before and during the COVID-19 pandemic. As part of our work, we also assess the reliability of the mobile device data.

The research contributes to existing studies on the impacts of the pandemic on activity-travel behavior in two aspects. First, mobile phone data provides a viable data source to capture large-scaled human mobility and has been widely used to map mobility patterns and identify activity hotspots during the COVID-19 pandemic. However, few studies (e.g., Atkinson et al., 2020) have checked the quality of mobile phone data to measure mobility during the COVID-19

pandemic. As a result, it is difficult to know the validity of these findings. Our study validates the use of mobile phone data to measure mobility patterns and activities by using weekly pattern data from SafeGraph, specifically for health care related activities. Second, the research examines the correlation between socio-demographic and spatial characteristics and medical visits during the pandemic. A better understanding of these associations could inform the design of appropriate policies to deliver health care service in a safe, equitable, and timely manner.

5.2 BACKGROUND

5.2.1 Health care services during COVID-19

The COVID-19 pandemic drastically changed peoples' access to and use of health care services. These changes include health insurance loss, health facility closure, and the increasing use of telemedicine (Chen et al., 2021). During the pandemic, more than 40 million Americans lost their jobs, which further caused many of them to lose their employer-based health insurance (Blumenthal et al., 2020). As a result, they may have been forced to delay necessary but noncritical treatments (Blumenthal et al., 2020). These impacts also tend to be disproportionately distributed. Minorities and people with low educational attainment and low incomes have experienced disproportionate job loss and delayed care (Kurtzleben, 2020).

The pandemic also caused significant economic threats to the viability of some health care providers, especially those located in rural and poor communities (Blumenthal et al., 2020; Chen et al., 2021). The pre-existing accessibility to health care facilities in rural and poor communities is comparatively lower (Ghorbanzadeh et al., 2021; Guida & Carpentieri, 2021). Many providers were temporarily closed during the pandemic, which may have further decreased geographic access to local health care and further influenced health care use.

Telemedicine is another key change in health care services. Many health care systems increased telemedicine options for patients during the pandemic. Health insurers also expanded their coverage to include telemedicine. With these changes, the use of telemedicine increased significantly during the pandemic to replace in-person care (Mann et al., 2020). However, not everyone has equal access to telemedicine. People with limited internet access, language barriers, and cognitive limitations may not be able to use telemedicine, and telemedicine is not suitable for all medical services (Chen et al., 2021).

5.2.2 Transportation during COVID-19

Transportation provides access to health care. Despite the increasing popularity of telemedicine, transportation is still important for people who need in-person care. Thus, the pandemic's disruptions of travel demand and transportation services may influence health care access and use. In response to stay-at-home orders and social distancing regulations, travel demand decreased (Dasgupta et al., 2020; Pepe et al., 2020). Some people may also have reduced their health care trips, delayed medical visits, or used telemedicine to meet critical

health care needs (Cochran, 2020). Others may have had more time and flexibility to commit to conducting health care activities because of their flexible work schedules. Mobility reduction also varies among different socio-demographic groups and geographic locations (Dasgupta, 2020; Pepe et al., 2020; McLaren 2020). Thus, the ability to conduct medical trips may also vary among people with different socio-demographic characteristics and living in different geographic locations. Neighborhoods with higher percentages of minorities and people with low incomes and low educational attainment tended to show less reduction in mobility perhaps due to reduced options for remote work (Dasgupta, 2020; Pepe et al., 2020; McLaren 2020). Jones (2021) documented that 54% of urban residents, 42% of suburban residents, and 27% of rural residents viewed COVID-19 as a major threat. The disparities in COVID-19 threat awareness may partially contribute to the geographic differences in mobility change. Scholsser et al. (2020) revealed that mobility declined more in large cities in Germany compared to less dense population areas. Lee et al. (2020) found that population density is positively associated with more mobility reduction in the United States.

Transportation services also changed. Nationally, public transit ridership dropped by 80% at the start of the pandemic and remained approximately 60% below 2019 levels (APTA, 2021). Public transit agencies cut service because of reduced ridership and revenues. For example, in response to reduced revenues, Los Angeles' transit agency (LA Metro) cut their budget by 1.2 billion and service by 20% (Los Angeles Times, 2020). MARTA, in the Atlanta region, cut most of its bus routes in April and is still operating at low capacity, and King County Metro in Seattle cut service by 15% in September (Bellis, 2020). Ride-sourcing programs, such as Uber and Lyft, suspended their pooled and shared ride options in response to the spread of COVID-19. Changes in public transit and ride-hailing programs left some people, particularly those who rely more on transit and shared rides, such as individuals with disabilities, facing greater challenges accessing transportation and health care (Cochran, 2020).

5.2.3 Mobile phone data and measuring mobility

Mobile phone data, which consist of Call Detail Records (CDR) or Global Position System (GPS) data, have been widely used in transportation research. These data offer a rich source of information on continuous space–time geography in urban areas. These data have been used to develop human mobility models (e.g., Deville et al., 2016), to develop traffic models (e.g., Demissie et al., 2018; Breyer et al., 2018), and to estimate trip rates (e.g., Çolak et al., 2015).

Given the popularity of mobile device data in mobility studies, its representativeness has attracted increasing attention. Ranjan et al. (2012) assessed the accuracy of CDR data in measuring human mobility. They revealed that sparsely sampled CDRs have biases, which are associated with the ratio of CDRs in an individual's trajectory. GPS data comparatively have fine granularity in spatial and temporal aspects (Fang et al., 2017). However, because people's phone activities in space and time are uneven, mobile phone location data also suffers from the problem of sparse sampling (Becker et al., 2013). As a result, mobile device data based on GPS locations also introduces biases in measuring human mobility. For example, Lu et al. (2017)

analyzed the representativeness of mobile phone location data on the estimation of human mobility. They revealed that mobile phone location data underestimates human mobility as mobile phone location data is incomplete.

Because mobile phone data can capture large-scale human mobility patterns, it also has been used in COVID-19 related studies to map human mobility patterns (e.g., Gao et al., 2020), identify activity hotspots (e.g., Li et al., 2021), and set parameters for disease transmission models (e.g., Chang et al., 2020). Chang et al. (2020) and Kang et al. (2020) demonstrated that the aggregate trends derived from SafeGraph data match the aggregate trends revealed in Google Mobility Data in the US.

5.3 Study area and data

5.3.1 Study area

Our study area is North Carolina (NC), consisting of three large metropolitan areas, Charlotte Metro, Research Triangle Area, and Piedmont Triad. In response to COVID-19, NC declared a state of emergency on March 10, 2020, and issued stay-at-home orders on March 14, 2020, to close all K–12 public schools and ban gatherings of more than 100 people. Additional stay-at-home orders were implemented continually over March to close non-essential businesses and enforce social distancing measures. On May 8, 2020, NC moved to phase 1, reopening retail businesses and childcare facilities. On May 22, 2020, NC moved to phase 2, reopening restaurant dine-in services; bars and nightclubs with capacity limits; and allowing gatherings of 10 people. On September 1, 2020, NC moved to phase 2.5, reopening indoor exercise facilities and increasing mass gathering limits to 25 people indoors and 50 people outdoors. On October 2, 2020, NC moved to phase 3, allowing the reopening of bars, entertainment venues, and movie theaters with capacity restrictions. On December 8, 2020, NC further lifted stay-at-home orders, but continued encouraging people to stay home between 10 p.m. and 5 a.m.; and required restaurants, bars, entertainment venues, personal care businesses, and other businesses to close at 10:00 p.m.

5.3.2 Data

We obtained data on visits to medical facilities in NC from SafeGraph, a data company that aggregates anonymized location data from mobile device applications. SafeGraph data is a type of GPS data, tracking devices which opted in via apps with GPS. It tracks the movement of mobile devices from their home CBGs to points of interest (POIs) across the United States. SafeGraph defines each device's home CBG as the most common nighttime location over the previous six weeks. The study period spans 52 weeks from January 6, 2020, to the week starting on December 28, 2020.

Specifically, we used SafeGraph's Core Places and Weekly Patterns datasets to identify trips to health care facilities. For each POI, these datasets provide the North American Industry Classification System (NAICS) code as well as estimates of weekly visits and visitors and the

home CBG of each visitor. Weekly visits are the aggregated raw counts of visits with the duration at least 4 minutes to the POI per week, and weekly visitors are the aggregated number of unique devices to the POI per week.

We aggregated estimates of weekly visitors from each home CBG to all medical POIs. Medical facilities are POIs with the designation "office of physicians (NAICS code 621111)", "office of dentists (NAICS code 621210), "office of other health practitioners (NAICS code 6213), "office of outpatient care centers" (NAICS code 6214), and "general medical and surgical hospitals" (NAICS code 622110) (Table S-1 in Supplementary Materials). Medical facility POIs are usually concentrated spatially, especially in urban areas. It is challenging to measure visitors to each medical POI accurately. Furthermore, multiple medical POIs are usually identified for a large medical facility. For example, POIs of the office of physicians are inaccurately identified within the building boundary of the Duke University Hospital. These POI data issues further challenge the accuracy of assigning visits to each medical POI and differentiating visits to different types of medical facilities. Thus, for each CBG, we aggregated the estimates of weekly visitors to all these types of health care facilities.

We used American Community Survey (ACS) 2019 5-Year Estimates to measure socio-demographic and economic characteristics at the CBG level. We included metrics in five domains: (1) age; (2) race and ethnicity; (3) education; (4) economic status; and (5) transportation disadvantage. We also derived percent of the population without internet access, and percent of commuters working at home as proxy measures for the potential of using telemedicine from ACS 2019 5-Year Estimates.

For spatial variables, we used the urban-rural classification scheme from the National Center for Health Statistics to categorize CBGs into six types: large central metropolitan, large fringe metropolitan, medium metropolitan, small metropolitan, micropolitan, or noncore county. We also calculated population density for each CBG, defined as the number of people per square mile. We further used the medical POI data from SafeGraph to derive the measure of density of health care facilities, defined as the count of the number of health care facilities per square mile for each CBG.

5.4 Methods

Our study aimed to assess the reliability of SafeGraph data for analyzing trips to medical facilities and patterns of travel to medical facilities during 2020.

5.4.1 Reliability of SafeGraph data

To assess the reliability of SafeGraph data, we used three approaches. First, we estimated sample geographic representativeness by comparing the number of sampled devices with 2019 Census Bureau population counts at different geographic levels, from the CBG, Census Tract, county, and state levels. Census Tracts are designed to be relatively homogeneous units in terms of population characteristics, economic status, and living conditions and has a population of 4,000 (U.S. Census Bureau Definition, 2021). A CBG is a subdivision of a Census Tract and is a

geographic unit that typically has a population of 600 and 3000 people. The CBG is also the smallest geographic entity for which the sample data from the decennial census is available. Using American Community Survey 2019 5-year estimates, we also estimated the expected demographic characteristics of sampled devices and compared to state averages. Second, we compared SafeGraph medical facility POIs with the Centers for Medicare and Medicaid Services (CMS) list of health care providers (CMS, 2020) to check the accuracy and representativeness of medical facility POIs. Third, we compared and correlated SafeGraph estimates of medical facility visit volumes with the in-person outpatient visit volume to facilities under the UNC Health Care system. The in-person encounter visit volume data was obtained from Carolina Data Warehouse for Health. Data analysis was primarily conducted in R. Some text responses to open-ended questions were imported and analyzed in Dedoose.

5.4.2 Analysis of temporal travel trends to medical facilities

5.4.2.1 Data preprocessing

We conducted several preprocessing steps on the medical visitor flow data to ensure that CBGs contained sufficient and valid records to derive stable estimates of visitors for analyzing temporal patterns. We removed CBGs with zero population, as sampled devices in CBGs with zero population are likely to be misidentified. The number of devices in some CBGs dropped significantly across 2020 from thousands or hundreds to only a few. To address this, we included CBGs where weekly counts of sampled devices were at least 2% of the CBG's population and removed CBGs with fewer than 10 sampling devices. The analysis results are not sensitive to our selection of cut points. Our final preprocessing yielded 52 weeks of data for 5,565 of the 6,155 NC CBGs. The number of devices sampled for each CBG in the SafeGraph data varies each week. Because of this, we normalized aggregated number of visitors from each CBG to medical facility POIs by the reported number of sampled devices in the CBG and focused our analysis on the number of medical visitors per device per week from each CBG.

5.4.2.2 Time-Series Clustering

After preprocessing, each CBG has a time series sequence with a length of 52, representing the number of medical care visitors per device per week across 52 weeks in 2020. We have 5,655 (CBGs) time series sequences. We employed time-series clustering to group CBGs with similar temporal patterns in medical care visitors per device together. Time-series clustering partitions time series datasets into clusters based on a similarity measure (Das et al., 1998; Aghabozorgi et al., 2015).

We experimented with two common distance measures for determining the similarity, Euclidean distance, and Dynamic Time Warping (DTW) distance. Euclidean distance is a common measure of similarity in clustering analysis (Keogh and Pazzani, 1999; 2001. However, Euclidean distance for time-series datasets requires the exact alignment of the time axis and is very sensitive to small distortion in the time axis (Keogh and Pazzani, 1999; 2001) (See Equation (1)); Euclidean distance requires that the ith point in one sequence is exactly aligned with i^{th} point in the other. Thus, we chose a distance measure based on dynamic time warping, with a

window size of 2 for warping, which allows us to compare the similarity in the absolute number of medical visitors per device in time and therefore allows for small distortions of the time axis (See Figure 5-S-1). Equation (2) represents the DTW distance between any two time-series sequences.

$$Dist(Euclidean) = \sqrt{\sum_{i=0}^{n} (p_i - q_i)^2} \quad (1)$$

Where p and q are two time-series sequences of length n (n=52 here); i is time index, representing the week number.

$$Dist(DTW) = min\sqrt{\sum_{k=1}^{k} (w_k)} \quad (2)$$

To determine the DTW distance for p and q, we firstly derive a n by n distance matrix between p and q, D. The value of individual cell (d_{ij}) in the matrix D is calculated as $\sqrt{(p_i - q_j)^2}$. w_k is the cell $(i,j)_k$ in matrix D that is also the kth element of a wraping path, $W = \{w_1, w_2, \dots w_k\}$. A wraping path is a series of neighboring elements in the distance matrix, D that links the bottom left cell ($w_1 = d_{11}$) with the top right cell ($w_k = d_{nn}$). There would be many wraping paths from the bottom left cell to the top right cell. We are interested in the wrapping path with the minimized length. DTW uses the following dynamic programming to find the shortest path (See Equation (3) (4)).

$$D^{p,q}\ (i,j) = \sqrt{(p_i - q_j)^2} + \min\ (D^{p,q}\ (i-1, j-1), D^{p,q}\ (i-1, j), D^{p,q}\ (i, j-1)) \quad (3)$$

$$|i - j| \leq \Delta t \quad (4)$$

Where $D^{p,q}\ (i,j)$ is the sum of current cell (d_{ij}) and the minimum of the cumulative distances of the adjacent cells. The resulting $D^{p,q}\ (i,j)$ denotes the DTW distance between p and q. Δt is the wrapping window. It is a constraint on the wrapping path searching. Euclidean distance has a wrapping window size of 0. Unconstrainted DTW has a wrapping window size of n-1. In the study, we choose a window size of 2.

Various clustering algorithms are available (Aghabozorgi et al., 2015). K-means and K-medoid are mostly commonly used. K-means is often used in conjunction with the Euclidean distance, and K-medoid is more appropriate for time-series clustering with DTW (Aghabozorgi et al., 2015). Thus, we adopted the K-medoid clustering algorithm. The core steps of k-medoid clustering are as following: (1) specify the number of clusters k; (2) select k samples from time-series objects as the initial center of the k clusters; (3) assign each object to the nearest center

based on the DTW distance; (4) find the center within each cluster, the object with the minimum average DTW distance to the remaining objects; and (5) repeat steps (3) and (4) until none of the objects change their cluster memberships.

In this study, we present results with three clusters. We selected k=3 by running the DTW distance-based K-Medoid clustering algorithm with values of k from 2 to 7. The clustering outcomes of different numbers of clusters were visually compared and explored (see Supplementary Materials for details). We selected the value of k=3 based on our exploration.

5.4.2.3 Statistical analysis

We characterized differences across time-series clusters by comparing socioeconomic characteristics using unadjusted (ANOVA) and adjusted (multinomial logit regression) approaches.

5.5 Results

5.5.1 Reliability of SafeGraph medical facilities data

The SafeGraph sample averaged 631,835 devices in NC during 2020. The proportion of population sampled (sampled device counts/state population) ranged from 4.5-8% 2020 (Figure 5-1). The number of sampling devices decreased significantly during the lockdown period (from Mid-March to May). SafeGraph sources data from phone applications, such as navigation and social media apps, where people could opt into location tracking. Thus, stay-at-home orders may decrease the use of apps with location tracking and therefore decrease the number of sampled devices. At the county level, the sample averaged 6,318 devices (6% of population; IQR 5%-7%). At the census tract level, the sample averaged 287 devices (6% of total population; IQR 5%-7%). At the CBG level, the sample averaged 102 devices (6% of total population; IQR 4%-8%). The correlation coefficients between average device counts and Census population estimates ranged from 0.98 to 0.99 at the county level, 0.77 to 0.85 at the census tract level, and 0.72 to 0.83 at the CBG level. The ratio of devices to census population also varied spatially with the ratio being higher in metropolitan areas compared to non-metropolitan areas (Figure 5-2).

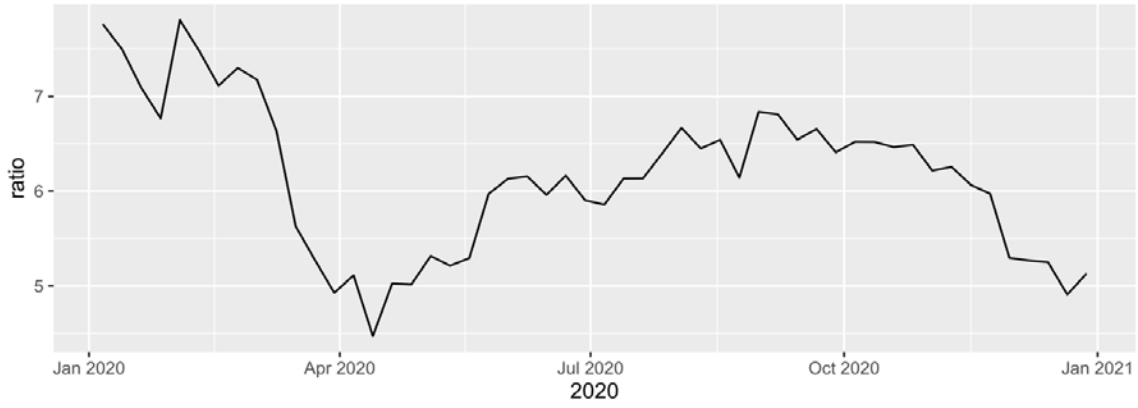

Figure 5-1: Weekly sampled device counts vs. state population from ACS 2015-2019

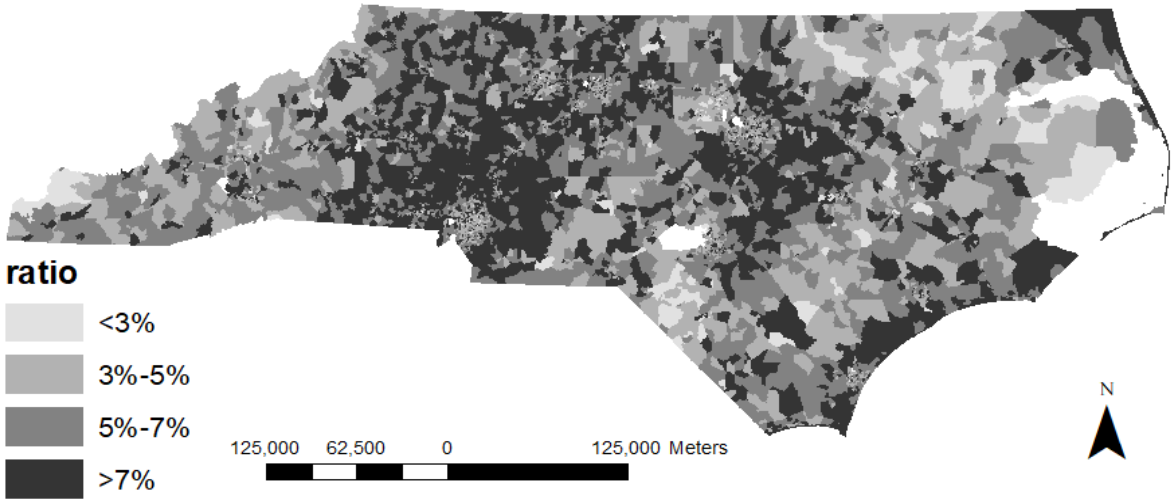

Figure 5-2: Ratio of mean weekly sampled device counts in 2020 to the population from the ACS 2019 estimates at CBG level. NA represents zero population.

We analyzed how closely the device data matched state demographic averages by assuming that sampled devices in a CBG have the same demographic characteristics as the CBG. In terms of age composition, the weekly device sample across 2020 is slightly over-represented for the over age 45 population while under-represented for those under age 45. But overall, the device sample is well-sampled across age groups. The sample is generally over-represented on Whites but under-represented on non-Whites (those identifying as Black and Hispanic). The sample is generally well-sampled for educational attainment categories. It is slightly over-represented for those with higher education levels and under-represented for those with high school degrees or below. The sample is under-represented for lower household income categories (annual income between $15,000 and $35,000, and less than $15,000) and over-represented for higher household income categories (income between $50,000 and $100,000, and higher than $100,000).

Table 5-1: Comparison of device demographics to Census demographics for NC

	Sample Mean (range across 52 weeks)	Census Bureau	Ratio (sample/census)
% Female	51.3 (51.2-51.4)	51.3	1.00 (1.00-1.00)
Age groups			
% Under 18	22.1 (21.9-22.4)	22.4	0.99 (0.98-1.00)
% 18-44	34.5 (33.9-35.3)	35.5	0.97 (0.95-0.97)
% 45-65	27.0 (26.6-27.3)	26.3	1.03 (1.01-1.04)
% Over 65	16.2 (15.8-16.6)	15.9	1.02 (1.00-1.04)
Race and ethnicity			
% White	66.6 (65.1-67.8)	63.1	1.06 (1.03-1.07)
% Black	18.7 (17.9-19.8)	21.1	0.89 (0.85-0.94)
% Hispanic	8.6 (8.4-8.9)	9.4	0.92 (0.89-0.95)
Education			
% High school or below	37.2 (36.7-37.7)	37.9	0.98(0.97-1.00)
% BA or more	31.5 (30.8-32.2)	31.3	1.01 (0.99-1.03)
Household income ($)			
% Less than 15k	10.9 (10.6-11.1)	11.4	0.95 (0.93-0.97)
% 15k-35k	20.1 (19.9-20.3)	20.6	0.98 (0.97-0.99)
% 35k-50k	13.7 (13.6-13.8)	13.9	0.98 (0.98-0.99)
% 50k-100k	30.7 (30.5-30.9)	30.4	1.01 (1.00-1.01)
% 100k+	24.7 (24.0-25.1)	23.7	1.04 (1.03-1.06)

Note: Calculation of sample demographics assumes sampled devices in a CBG have the same demographic characteristics as the CBG.

Compared with the CMS list of medical facilities, the spatial distribution of medical POIs from SafeGraph is well-balanced. The distribution of medical facilities at the county level derived from both datasets is similar; counties with a higher number of CMS providers also have a higher number of medical facility POI from the SafeGraph dataset (Pearson correlation coefficient=0.89). There are no medical facilities in 594 census tracts (27%), based on the two datasets. 42 tracts have one or two CMS providers, which are not identified in the SafeGraph POI. There are no medical facilities in 3,316 CBGs (54%), based on both datasets. 107 CBGs have one or two CMS providers, which are not identified in SafeGraph POI. The correlation coefficients at the census tract and CBG levels are moderate, at 0.58 and 0.54, respectively. As mentioned before, medical POIs are usually concentrated spatially, and multiple POI points are

often identified for large medical facilities. For example, POIs of offices of physicians in SafeGraph are often identified within the boundary of medical centers. Thus, one provider in the CMS list often corresponds to several POIs in SafeGraph POI data. The data issues may contribute to the moderate correlation coefficients (0.58 at the tract level and 0.54 at the CBG level) at the tract and CBG levels.

Overall, trends of medical facility visits from SafeGraph and the UNC Health Care system are comparable, exhibiting similar temporal patterns (Figure 5-3). The number of medical visits started to drop in the middle of March when NC's governor declared a State of Emergency and reached their lowest values in early April. Visits to facilities in the UNC Health Care system dropped more (over 70%) during the lockdown period than visits measured from SafeGraph data. The gaps may result from the disparities in what types of visits were recorded in the two datasets. SafeGraph captures all visits to health care facilities in NC, including inpatient visits, outpatient visits, and all other types of visits such as those by employees. The in-person encounter volume to clinics in the UNC Health Care system data only contains outpatient care visits. Compared to inpatient and employee visits, outpatient visits were more likely to be deferred during the lockdown. Furthermore, most medical facilities in the UNC Health Care system are in central urban areas where declines in travel during the lockdown were greater than in more outlying and rural areas (Lee et al., 2020; Scholsser et al., 2020) (Figure 5-S-2). In May, when the stay-at-home order was lifted and NC entered Phase 2, medical visits recovered, as revealed by both datasets. The correlation coefficient between the two groups is strong, at 0.83.

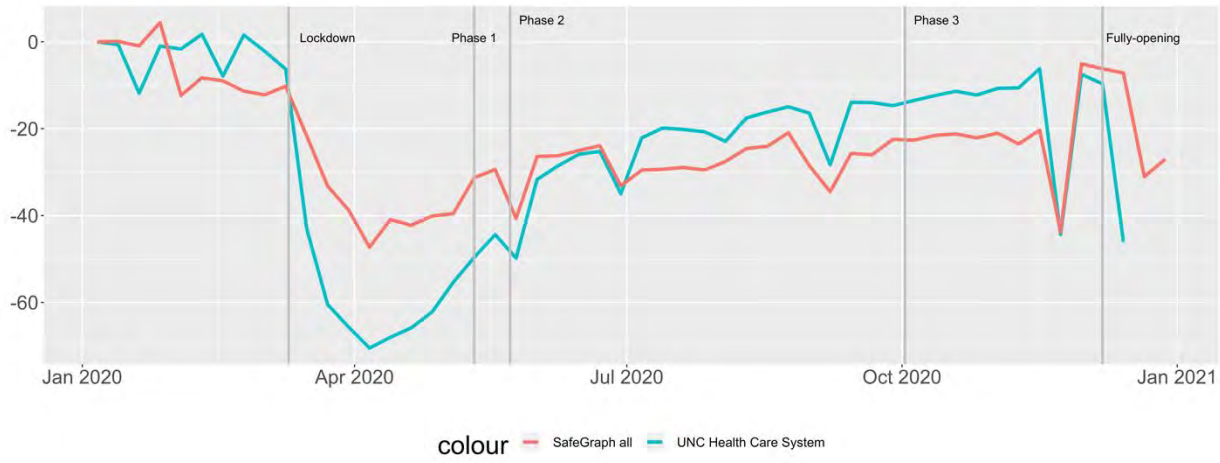

Figure 5-3: Temporal trends of medical facility visit change.

Note: Visits to facilities under UNC health Care system are available until the week starting on 12/7/2020. Two lines represent the percent change in visits (UNC Health Care system) and visits per device (SafeGraph) since the first week of 2020.

Based on these assessments, we concluded that, overall, SafeGraph data are well-balanced in terms of geographic and demographic representativeness of population but slightly under-represented in minority and low-income groups and have a well-balanced sampling of POIs. The aggregated trends in medical visits revealed in SafeGraph data somewhat matched up to the aggregated trends in patient volumes to facilities in the UNC Health Care system. However, we still need to be cautious that SafeGraph data have a limited coverage in outlying and rural areas; limited representativeness in low-income populations who often have limited access to smartphones with GPS; limited accuracy of POI location identification; and limited coverage for POIs of small size. As a result, medical visits derived from SafeGraph by low-income people, and medical visits to small size hospital POIs, especially in rural areas, may not be accurately recorded in SafeGraph data.

5.5.2 Temporal patterns of medical facility visits

We identified three clusters of CBGs that exhibited similar temporal trends for trips to medical facilities. Medical care visits of CBGs in all three clusters dropped at the start of the pandemic and did not return to pre-pandemic levels by the end of 2020.

- *Cluster 1.* CBGs in this cluster (n=1,899) have lower medical visits all the time. These CBGs also responded to the lockdown in April with a strong reduction in medical visits. As the COVID-19 restrictions were gradually lifted, these CBGs experienced a moderate and slow increase in medical visits.
- *Cluster 2.* CBGs in this cluster (n=1,208) have higher numbers of medical visits per device per week and responded to the stay-at-home orders implemented in March and April strongly; CBGs in this cluster saw a significant decrease in medical visits during the lockdown period. Compared to CBGs in cluster 1, medical visits bounced back sooner but were lower than pre-pandemic levels when NC implemented a re-opening phase in mid-May.
- *Cluster 3.* Compared to CBGs in cluster 2, CBGs in this cluster (n=2,458) have a medium level of medical visits. CBGs in this cluster also experienced a moderate decrease in medical visits during the lockdown period and a moderate and low increase after.

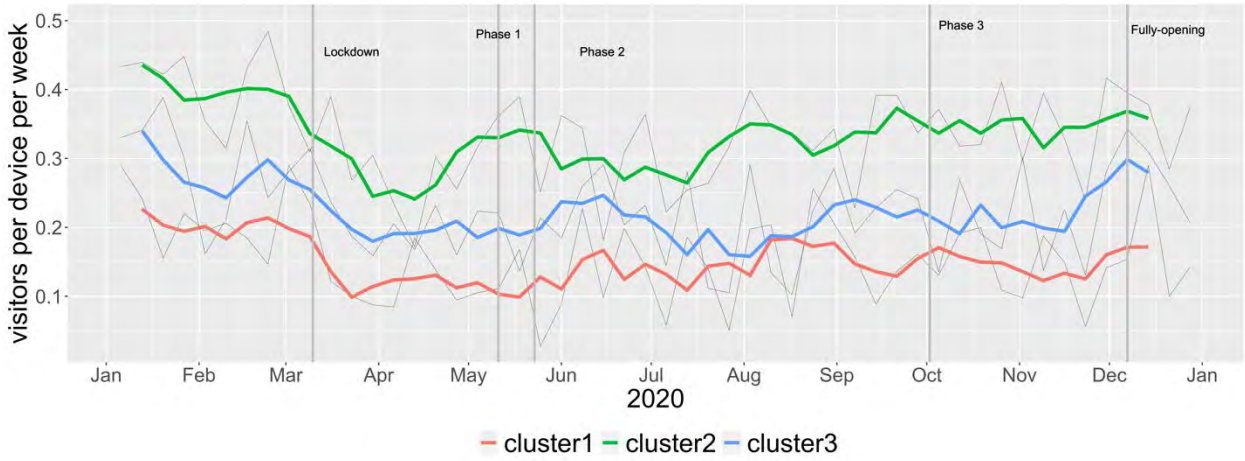

Figure 5-4: Clustering Results (Smoothed Lines) of DTW K-Medoid Clustering Algorithms: Three Identified Clusters.

Note: grey lines represent the medoids of the three identified clusters.

5.5.3 Spatial distribution of clusters

Figure 5 shows the spatial distribution of the three clusters across NC. CBGs in cluster 1 are more likely to be in central urban core and outlying rural areas. CBGs in cluster 2 are more concentrated in the suburban areas of large metropolitan areas. CBGs in cluster 3 are more spatially dispersed. The spatial patterns imply that socio-demographic and spatial variables may explain observed disparities in medical care-seeking before and during the pandemic.

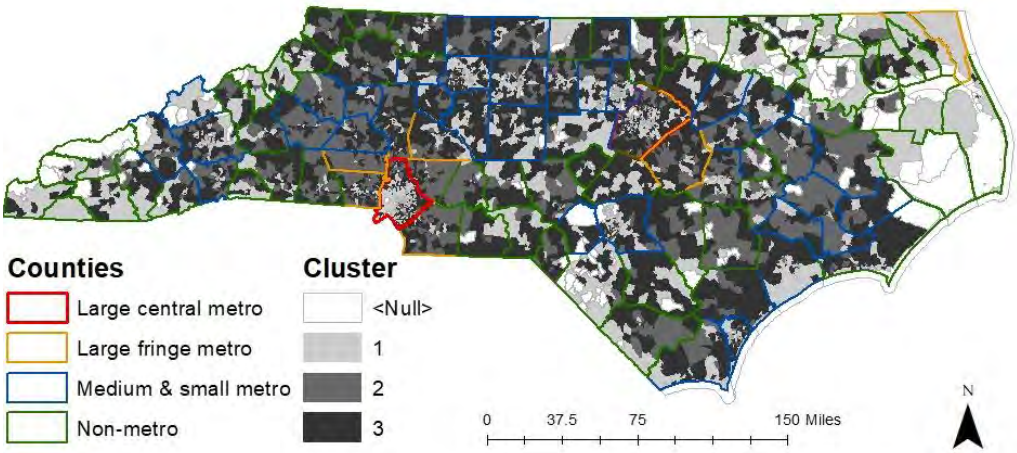

Figure 5-5: Spatial Distribution of the Three Clusters

5.5.4 Descriptive analysis

(Table 5-3). CBGs in cluster 2 comparatively have a higher percentage of persons over age 65. For racial composition, CBGs in clusters 2 and 3 have higher percentages of Whites. CBGs in clusters 1 and 3 have higher percentages of Blacks and Hispanics. As for education, compared to CBGs in cluster 1, CBGs in cluster 2 and 3 have high percentages of adults with higher

educational attainment. In terms of household income, CBGs in cluster 2 and 3 show a similar distribution of a lower percentage of low-income households and a higher percentage of high-income households, while CBGs in cluster 2 have a comparatively higher percentage of households with annual incomes greater than $100,000. Compared to CBGs in cluster 2 and 3, CBGs in cluster 1 have a higher percentage of zero-car households and households without internet access.

Significant disparities in all spatial variables (except non-metro variables) are revealed among CBGs in the three clusters. 20% of CBGs in cluster 1 are in large central areas, and 48% of CBGs in cluster 1 are in medium and small metros. 21% of CBGs in cluster 2 are in fringe areas of large metros. In periphery non-metro areas (micropolitan and noncore), the distribution of CBGs in the three clusters is similar. CBGs in cluster 1 and 3 tend to have a higher population density.

Table 5-3: Socio-demographics characteristics by the three clusters.

	Cluster 1		Cluster 2		Cluster 3		ANOVA	
	mean	std	mean	std	mean	std	P-value	Sig
	Socio-demographics							
% Age over 65	17.1	10.6	18.5	7.8	17.9	8.8	0.000	***
% White	54.1	29.9	77.0	19.1	68.8	23.1	0.000	***
% Black	29.3	26.6	12.4	15.4	17.6	18.6	0.000	***
% Hispanic	10.7	12.2	6.2	8.0	8.2	9.5	0.000	***
% Below high school	42.3	18.3	38.9	16.7	39.2	17.4	0.000	***
% Bachelor and above	26.7	19.7	29.0	19.7	29.2	19.6	0.000	***
% Income<35k	40.5	18.9	29.6	14.4	31.2	15.7	0.000	***
% Income 35-50k	14.9	8.6	13.3	7.3	14.2	7.8	0.000	***
% Income 50k-100k	27.9	12.0	31.2	10.3	31.2	10.3	0.000	***
% Income 100k+	16.7	15.1	25.9	17.3	23.4	17.2	0.000	***
% No vehicle households	9.1	10.3	4.2	5.1	4.8	5.9	0.000	***
% No internet access	19.8	14.0	16.0	11.5	16.2	11.8	0.000	***
% Work from home	5.0	5.9	5.0	5.4	5.4	5.5	0.065	
	Spatial Characteristics							
Large central metro	20.1		9.6		16.7		0.000	***
Large fringe metro	6.8		21.1		14.8		0.000	***
Medium & small metro	47.5		43.7		42.8		0.007	**
non-metro	25.6		25.6		25.7		0.994	
Population density (1,000 residents/sq.miles)	1.7	1.9	0.8	1.1	1.1	1.5	0.000	***
Health care facility density	4.1	11.7	4.5	25.6	3.3	12.0	0.076	

Note: *** significance at p<0.001; ** significance at p<0.01; * significance at p<0.05

5.5.5 Regression results

We estimated a multinomial logit model to examine how socio-demographic and spatial characteristics at the CBG level are associated with cluster types (Table 5-4). We chose cluster 2 as the reference cluster because CBGs in cluster 2 comparatively have higher medical visits, and

CBGs in cluster 2 exhibit a typical pattern of medical visits, decreasing significantly during the lockdown and recovering after. The socio-demographic variables are strongly correlated, and thus we presented our final model without any multicollinearity issues. The model overall has a moderate fit (Pseudo R^2=0.10).

CBGs in cluster 1- the cluster with the lowest rate of medical visits and slowest recovery in rate of visits -- have a higher proportion of residents over age 65, with incomes under 35,000, without household vehicles, and with higher pre-pandemic rates of telework. These CBGs also have a lower proportion of residents that self-identify as White.

CBGs in cluster 3, compared to those in cluster 2-the cluster with slower recovery in rate of in-person visits during the re-opening stages, have a lower proportion of residents with incomes over $100,000 and who identify as White.

Table 5-4: Modeling Results

	Cluster 1 (vs. Cluster 2)				Cluster 3 (vs. Cluster 2)			
	Coef.	SE	Sig.		Coef.	SE	Sig.	
	Socio-demographics							
% Age over 65	0.020	0.005	0.000	***	0.010	0.005	0.034	*
% White	-0.025	0.002	0.000	***	-0.014	0.002	0.000	***
% Income<35k	0.013	0.004	0.001	***	-0.004	0.004	0.340	
% Income 100k+	-0.026	0.004	0.000	***	-0.017	0.003	0.000	***
% No vehicle households	0.024	0.008	0.002	**	-0.003	0.008	0.707	
% Work from home	0.050	0.009	0.000	***	0.030	0.008	0.000	***
	Spatial Characteristics							
Spatial locations (ref.=non-metro)								
Large central metro	0.766	0.184	0.000	***	0.502	0.168	0.003	**
Large fringe metro	-0.894	0.144	0.000	***	-0.300	0.115	0.009	**
Medium-small metro	0.055	0.103	0.590		-0.052	0.093	0.576	
Pop density	0.297	0.042	0.000	***	0.159	0.040	0.000	***
Health care facility density	-0.012	0.003	0.000	***	-0.010	0.003	0.000	***
Constant	1.159	0.270	0.000	***	1.851	0.250	0.000	***
Log Likelihood	-5326							
Pseudo R2	0.100							

Note: *** significance at p<0.001; ** significance at p<0.01; * significance at p<0.05; % blacks and % Hispanics are strongly correlated with % Whites (correlation coefficient>0.75). Four measures of household income are strongly correlated. We kept the percentage of income less than 35k and income greater than 100k. Measures of education attainment and internet access are strongly correlated with measures of household income (correlation coefficient>0.75). Thus, these measures were removed from the final model

Table 5-5: Elasticities

	Cluster 1	Cluster 2	Cluster 3
		Socio-demographics	
% Age 65+	0.16***	-0.19***	-0.02
% White	-0.72***	0.89***	-0.05
% Income less than 35k	0.31***	-0.13	-0.25***
% Income 100k+	-0.25***	0.32***	-0.03
% No vehicle households	0.08***	-0.07	-0.09***
% Work from home	0.10***	-0.16***	0.003
		Spatial variables	
Spatial locations (ref.=non-metro)			
Large central metro	0.28***	-0.48***	0.02
Large fringe metro	-0.46	0.44***	0.14*
Medium-small metro	0.06	0.004	-0.05
Pop density	0.12***	-0.25***	-0.05**
Health care facility density	-0.02*	0.03***	-0.006

Note: *** significance at p<0.001; ** significance at p<0.01; * significance at p<0.05.

Spatial variables play an important role in determining temporal patterns of visits to medical POIs. CBGs in cluster 1 are more likely to be in large central metros and less likely to be located in large fringe metros. These CBGs also tend to have higher population density and less geographic proximity to health care POIs. Compared to CBGs in Cluster 2, CBGs in cluster 3 are less likely to be located in large fringe metros and are generally located in areas with fewer number of health care POIs.

5.6 Discussion

Our study aimed to analyze patterns of travel to medical facilities during 2020 and assess the reliability of SafeGraph data for analyzing trips to medical facilities.

5.6.1 Disparate patterns of visits to medical facilities

We found three distinct clusters of temporal patterns of visits to medical POI during 2020. All three clusters experienced a reduction in medical care visits during the lockdown but differed in their extent and recovery patterns.

CBGs with lower medical visits before the pandemic (cluster 1) experienced a slower recovery. CBGs with higher percentages of elderly persons, minorities, low-income individuals, and people without vehicle access (cluster 1) had limited use of health care before and during the pandemic and experienced a slower recovery after the lockdown. These socio-demographic

disparities confirm the necessity of health systems to care adequately for these groups under normal conditions and during a pandemic.

CBGs with higher population density and in central areas are more likely to be in cluster 1. Higher population density areas and central areas are usually areas with higher public transit use (Taylor & Fink, 2003), but public transit is also highly likely to be affected by the pandemic. As a result, people living in these areas may be more likely to have difficulty accessing health care during COVID-19 and experience a lower recovery after the lockdown. The positive association between a lower facility density and the likelihood of being in cluster 1 also suggests the limited physical access to health care resources for CBGs in cluster 1, highlighting the importance of ensuring equal accessibility to health care resources (Guida & Carpenteri, 2021).

CBGs in the other two clusters with comparably higher medical visits (cluster 2 and cluster 3); cluster 3 has a relatively slower and modest recovery. The socio-demographic and spatial characteristic variables also explain the disparities in recovery patterns between cluster 2 and cluster 3. It is important to note that these significant associations tend to be small in magnitude, suggesting recovery patterns of medical care visits after the lockdown are not sensitive to socio-demographic and spatial characteristics. However, the effect sizes of two variables, percentages of White individuals and highest income individuals are still comparable. CBGs with higher percentages of Whites and people in the highest income class (greater than $100,000) have highest medical visits and reduced their medical visits during the lockdown but increased their visits soon after the lockdown.

Taken together, these results suggest that areas most at-risk for decreased health care access during a pandemic are the same neighborhoods where residents exhibited lower health care access prior to the pandemic.

5.6.2 Using mobile phone data to measure medical trips

Our assessment of the accuracy and reliability of mobile device data from SafeGraph to analyze visits to medical facilities shows that the data has good geographic representativeness of population at different geographic scales (county, tract, and CBG). The data was spatially balanced when sampling health care facility POIs and could measure the overall temporal patterns of visits to medical facility POIs at the state level. However, the study limits the comparison between outpatient visits to clinics in the UNC Health Care system and medical care visits of SafeGraph, which calls for more research on assessing the accuracy in using mobile device data on measuring visits to POIs. Furthermore, the data still suffers from a slight under-representativeness of low-income people and non-White individuals. The data issues may indicate that SafeGraph data does not accurately record medical visits by low-income people, especially in rural areas. The study's focus on longitudinal analysis and spatially balanced distribution of health care POI would help alleviate potential sampling bias.

Our assessment also showed a significant decrease in sampled devices, which may be attributed to the inability of mobile phone data to track a population staying at home not using phone apps with GPS tracking. However, SafeGraph data does not reveal the information about which phone apps with GPS tracking are recorded in the data collection process. Different socio-demographic groups may use their phone apps differently. Without data transparency about phone apps, it would be difficult for us to evaluate and correct the potential bias of the sampling.

5.6.3 Strengths and Limitations

Timely delivery and access to health care are essential under normal circumstances and during a pandemic. This study is among the few to examine medical care visits during COVID-19. Distinct from other studies, ours is based on a geographically extensive sample of mobile devices across the state of NC, allowing for interpretation beyond the context of a single geographic setting and a small sample of patients.

Several caveats should be considered when interpreting the research results. The data suffers from some under-representativeness issues revealed in our assessment. The data tracks a device instead of an individual, and thus it could not distinguish multiple people traveling with one sampled device. These data issues are still unclear, and this study does not differ from most studies using mobile device data. The data also cannot capture sub-CBG without individual information. This study focuses on area-level associations rather than individual-level associations; however, area-level characteristics are significantly associated with health behavior independent of individual characteristics (Turrell et al., 2010), suggesting the value of considering area-level characteristics. This study only examined the data of year 2020 and may conflate the seasonality with the impacts of COVID-19, which calls for future studies with the incorporation of data of previous years. We only considered the state-wide restrictions and did not consider the disparities in restrictions across counties. Counties may have had different levels of restrictions during COVID-19, and future studies could benefit from considering more fine scale restriction disparities.

While our focus on NC was useful for understanding broader geographic disparities, especially urban and rural disparities, it could also mask variation within metropolitan areas which usually have more apparent disparities in the distribution of socio-demographic characteristics. It would be interesting to conduct similar research in a single metropolitan area as a supplement to this study's findings.

5.7 Conclusion and policy implications

Analysis of the temporal patterns of visits to medical POI across 2020 and their associations with socio-demographic and spatial characteristics at CBG level reveals two key findings. The findings may be useful for policymakers seeking to improve health care delivery and access.

CBGs with higher percentages of elderly persons, minorities, low-income individuals, and people without vehicle access (cluster 1) had lower use of health care before the pandemic and experienced a slower recovery in medical visits after the lockdown. Health policymakers and transportation planners need to develop appropriate strategies to address persistent inequalities in health care use by these social groups. First, health policymakers need to make telemedicine a viable option for people living in these less-advantaged CBGs. Historically vulnerable populations, such as racial minorities, adults over age 65, and low-income households, have limited digital literacy and access (Smith, 2020). Community health centers, which provide safety-net care for low-income and uninsured people, have financial constraints to implement telemedicine (Kim J-H et al., 2020). Health care providers need to develop training programs to teach populations in these areas the digital skills to use telemedicine and offer language interpreter access. Health care systems may also need to provide community health centers located in less-advantaged areas with funding to support telemedicine.

Second, public transportation agencies, private transportation providers, health care providers, and governments should work together to provide low-cost and reliable transportation options for people living in these less advantaged CBGs. Transportation agencies should ensure that transit and paratransit options for health care are still operating for these CBGs. People may also be less willing to use transit to conduct health care visits because of safety concerns. Thus, transportation and health care agencies may need to make efforts to partner with private transportation providers, like ride-hailing services (e.g., Uber), to provide low-cost ride-hailing options for vulnerable populations to access care.

CBGs in the central areas of large metropolitans or with higher population density tend to have a slow recovery of health care visits (cluster 1 and 3 vs. cluster 2). The results may be attributed to significant disruptions in transportation in these areas. When transit services become unavailable in these dense and central areas, transportation agencies, health care providers, and private transportation providers should support alternate transportation options for people living in central and dense areas. Ride-hailing companies like Uber and Lyft have provided Non-Emergency Medical Transportation (NEMT) since 2018 in select geographies. Studies have shown that using ridesharing NEMT has produced positive results, such as fewer missed appointments (Power et al., 2016). Health care providers and insurers could continue partnerships with ride-hailing companies for people living in these areas to access health care. Transportation agencies could also collaborate with bike-share companies to provide free or low-cost bike-share in these areas. Bike share in Chicago, Boston, and New York have offered free access for health-care workers during the pandemic (BicycleRetailer, 2021). Bicycling may not be a good transportation option for all people who need care. However, the availability of bike-share programs could expand mode options and reduce the number of transit transfers for people who live in the central areas and rely on transit to access health care.

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6.0 EVALUATING CHANGES IN TRANSIT ACCESSIBILITY FOR TRANSPORTATION-DISADVANTAGED POPULATIONS IN THE CITY OF GAINESVILLE

Research conducted by Dr. Ruth Steiner, Dr. Ilir Bejleri, Dr. Xiang Yan, Xueyin Bai, Juan Suarez, Liang Zhai, Andre Soucy, and Larissa Krinos, University of Florida.

6.1. INTRODUCTION

Transportation-disadvantaged populations, including older adults, individuals with disabilities, and low-income people, often lack convenient access to a personal vehicle or are unable to drive. Therefore, they tend to be more dependent on public transit to reach essential places (Lucas, 2012; Steiner et al., 2021). For transportation-disadvantaged populations, inadequate transportation services can lead to unemployment or underemployment, inaccessible health care, or a lack of available nutritious food sources. This can further result in social isolation, and physical and mental health ailments (Lichter and Johnson, 2007; Stanley and Lucas, 2008).

When considering methods for improving transportation services for transportation-disadvantaged populations, one should differentiate between the concept of mobility and spatial accessibility. Mobility is facilitated by the physical infrastructure, while spatial accessibility is the ease of accessing destinations including the time it takes to get to the destination using different methods of travel (Shay et al., 2016). Federal laws and regulations, such as the Americans with Disabilities Act (ADA) and the Transportation Equity Act for the 21st Century (TEA-21), require all transportation projects to be reviewed for their effect on transportation-disadvantaged populations (Combs et al., 2016; Carleton and Porter, 2018). Transportation planners must be especially considerate of the needs and the placement of these members of the community in the development of new transportation services. However, the laws and regulations do not require differentiation between mobility and spatial accessibility and providing mobility options is typically viewed as adequate. Available public transit can be hindered by transportation planners and service providers who limit themselves to one viewpoint.

The provision of public transit services in the United States is under great pressure. National transit ridership, both in total and per-capita, has been declining ever since 2014 (Higashide and Buchanan, 2019). The Covid-19 pandemic is aggravating the situation. Public transit agencies are facing additional challenges due to the loss of ridership and revenue, and the increased cost of operating safe service. Due to this situation, transportation-disadvantaged populations can be most susceptible to the effects of changes in transit services, whether they be service reductions during the pandemic or service developments in the future. Research examining how the Covid-19 pandemic and future transit development has affected and may affect the

transit accessibility for transportation-disadvantages populations is currently limited (Chen et al., 2021; Wilbur et al., 2020; Tilahun and Fan, 2014; Guthrie, Fan, and Das, 2017).

This study contributes a methodology to evaluate changes in transit accessibility for transportation-disadvantaged populations using a case study in the city of Gainesville, Florida. In collaboration with the Gainesville Regional Transit System (RTS), we assessed the performance of the RTS system and identified neighborhoods that have large numbers and high proportions of transportation-disadvantaged populations across the city. We then developed three scenarios involving transit-service changes during Covid-19, and in a future development plan. We evaluated how these changes have affected and may affect the transit accessibility to different types of destinations for transportation-disadvantaged populations. These analyses provide an effective way to help public transit agencies reduce transit deficiencies and identify additional options for transportation services to meet the needs of transportation-disadvantaged populations.

6.2. METHODOLOGY

6.2.1 Technical Analysis

Figure 6-1 shows the technical details of our research, which contains the data and method used, analysis process, and the results we obtained. First, we applied the data envelopment analysis (DEA) to evaluate the operational efficiency and spatial effectiveness of each transit route in Gainesville. We then presented these results to RTS staff to discuss how RTS could revamp the transit system to improve performance. These inputs from RTS contributed to our later scenario development designed to investigate transit-accessibility changes during the next five years. In addition to this scenario of transit development in the next five years, we also developed two other scenarios, which are the “Impact of the Covid-19 Pandemic” and “Recovery from the Covid-19 Pandemic,” respectively. In addition, we mapped the distribution of transportation-disadvantaged populations based on a transportation vulnerability index that we developed.

While discussing these issues with RTS staff, we identified four neighborhoods with a large concentration of transportation-disadvantaged populations. Finally, we applied a geospatial tool that the research team previously developed to evaluate how transit accessibility of the four transportation-disadvantage neighborhoods changes with the three scenarios. Our evaluation could further help inform RTS to revamp their transit system to better serve transportation-disadvantaged populations. We used Python, ArcGIS Pro, and a customized transit accessibility tool in modifying GTFS files, creating scenarios from different sets of GTFS files, and calculating the transit accessibility scores under the created scenarios. The data, method, and analysis processes are explained in detail in the following paragraphs.

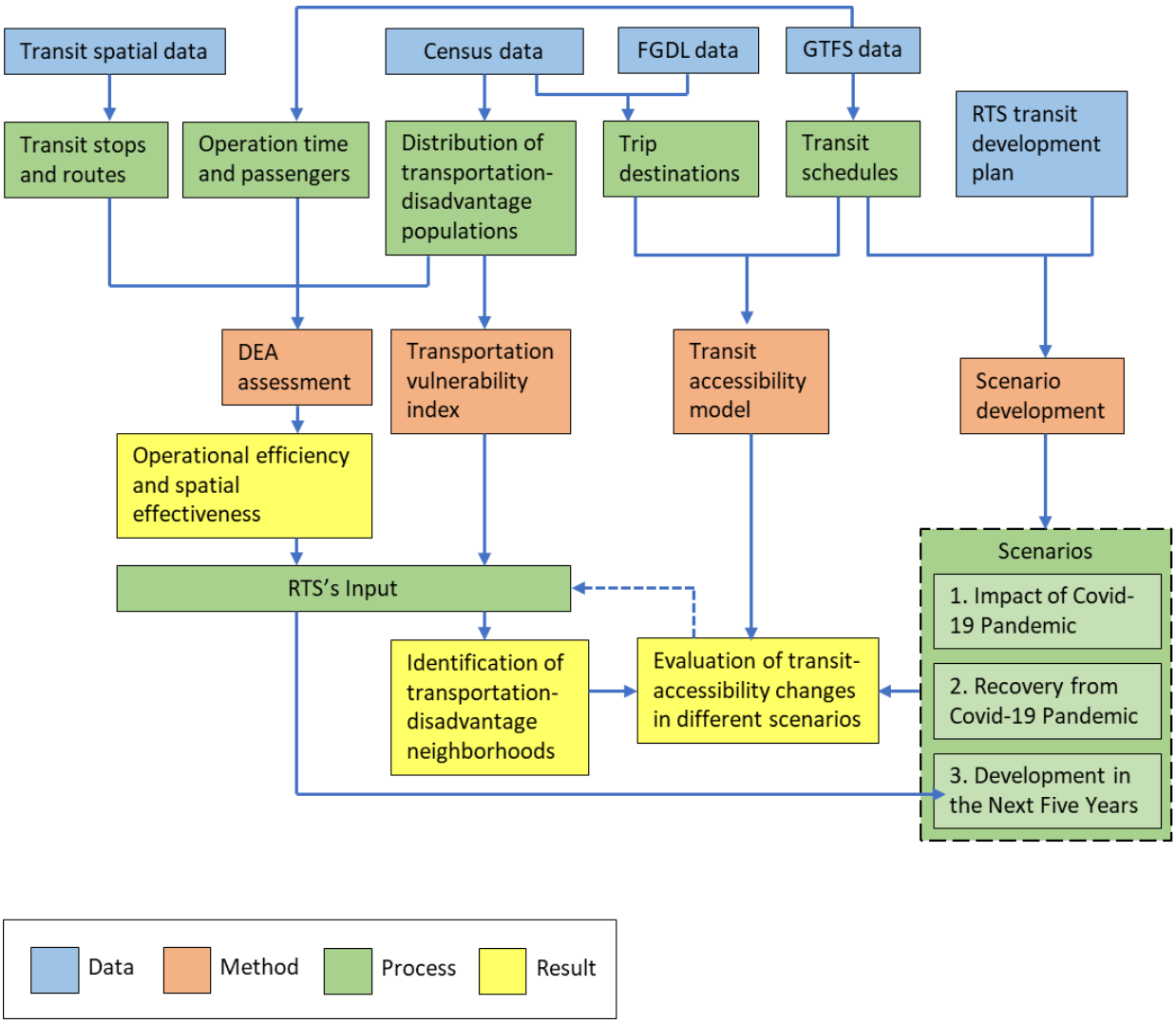

Figure 6-1. Technical Route.

6.2.2 Data Envelopment Analysis (DEA) of RTS System

We used the Data Envelopment Analysis (DEA) to assess the operational efficiency and spatial effectiveness of the transit system in Gainesville. DEA involves the development of multiple models to evaluate the efficiency of particular Decision-Making Units (DMUs) as compared to a "most efficient" virtual DMU, created by consolidating the outputs of all other DMUs being examined. In our analysis, individual bus lines were considered as DMUs. Analyzing operational efficiency provides a measure of the productivity of the supply while analyzing spatial effectiveness provides a measure of the benefits of demand for each bus line.

6.2.2.1 Data

DEA calls for a set of input and output indicators to be used for calculations. For operational efficiency, input variables include operation time, round-trip distance, and the number of bus stops, while the output variable is the average number of passengers per year. For spatial

effectiveness, input variables included (within 0.25 miles (400 m) of each bus stop) older adults (aged 65 and above), individuals with disabilities, and low-income people (below the poverty line). The output variable is the average number of transportation-disadvantaged passengers per year (Table 6-1).

Three types of data were used for the DEA model: General Transit Feed Specification (GTFS) data, transit spatial data, and census data. GTFS data and transit spatial data were used for the calculation of operational efficiency inputs. Transit spatial data and census data were used for the calculation of spatial effectiveness inputs. GTFS is a standardized data specification that allows public transit agencies to publish their transit schedules. We collected the GTFS datasets from the Florida Transit Data Exchange (FTDE) and RTS. Transit spatial data were obtained from RTS, and census data were obtained from the U.S. Census Bureau website. The average daily ridership counts for each bus line were also retrieved from RTS. Some of the spatial data were prepared in the Geographic Information Systems (GIS), with transit spatial data in the form of bus routes (lines) and stops (points) and census spatial data in the form of block groups (polygons). Attributes of these data prepared in the GIS are listed in Table 6-2.

Table 6-1. Input and Output Indicators for DEA.

	Input Variable	Output Variable
Operational Efficiency	• Operation time • Round-trip distance • Number of stops	Average number of passengers
Spatial Effectiveness	Within 0.25 miles (400 m) of each stop: • Older adults (aged 65 and above) • Individuals with disabilities • Low-income people (below poverty line)	Average number of transportation-disadvantaged passengers

Table 6-2. GIS database for analysis.

Categories	Spatial Data	Feature Class	Attributes
Transit Data	Bus Stops	Points	• Name • Latitude • Longitude
	Bus Routes	Lines	• Name • Round-trip distance • Speed limit

Categories	Spatial Data	Feature Class	Attributes
			• Direction • Number of stops • Annual number of passengers
Census Data	Census Block group	Polygons	• Total population • Population density • Population over 65 and older • Individuals with disabilities • Median household income • Automobile ownership • Commuters who use buses

6.2.2.2 Calculation of Operational Efficiency and Spatial Effectiveness

The DEA model was applied to 55 routes within the Gainesville RTS system. The process for calculating operational efficiency involved the use of Excel functions and VBA programs for calculating input values from the GTFS and GIS data. The following inputs were calculated as follows:

Operation Time: An Excel VBA program was implemented to output all stop times for each route; Excel functions were used to calculate the total daily operating time (in hours) for each bus route.

Round-trip Distance: GTFS bus route line data was output in GIS; GIS tools were used to calculate the length of bus line features for each heading of each bus line; total round-trip distance values were calculated with Excel functions.

Number of Stops: An Excel VBA program was implemented to add all stops corresponding to each trip heading of each bus route and output total stop counts for each route.

The process of calculating spatial effectiveness involves the use of GIS analysis and an Excel VBA program for calculating input values. The following three inputs, older adults (aged 65 and above), individuals with disabilities, and low-income people (below poverty line), were calculated as follows:

GIS: GTFS stop data was used to generate 0.25-mile (400 m) radius buffer polygon features for each stop in the system;

Stop buffer layer was intersected with census block group data;

Census counts were recalculated based on the ratio between intersect feature areas and original block group feature areas;

The attribute table was exported to Excel.

Excel: A program was implemented to calculate total census data counts for each stop and subsequently for each bus route;

The data was output as the spatial effectiveness inputs.

DEA Model Variables:

j: index of decision-making units, j = 1, … , n,

i: index of input, i = 1, … , m,

r: index of output, r = 1, … , s,

x_ij: the ith input for DMU_j,

y_rj: the rth output for DMU_j,

λ_j: the nonnegative scalars (weight) for DMU_j,

μ: the optimal output level.

DEA Parameters:

$$Max\ \mu$$

$$s.t. \quad x_{io} \geq \Sigma^{n}{}_{j=1}\, x_{ij}\lambda_j \qquad i = 1,\ldots,m$$

$$y_{ro}\mu \leq \Sigma^{n}{}_{j=1}\, y_{rj}\lambda_j \quad r = 1,\ldots,s$$

$$\Sigma^{n}{}_{j=1}\lambda_j = 1$$

$$\lambda_j \geq 0 \quad j = 1,\ldots,n$$

6.2.3 Identification of Transportation-Disadvantaged Neighborhoods

As defined previously, transportation-disadvantaged populations include older adults (aged 65 and above), individuals with disabilities, and low-income people (below poverty line). Using socio-economic data from the American Community Survey (2014-2018), we mapped the distribution of different groups of transportation-disadvantaged populations and applied the transportation vulnerability index to identify neighborhoods with large concentrations of transportation-disadvantaged populations.

6.2.3.1 Distribution of Transportation-disadvantaged Populations

Figure 6-2 displays the percentage of older adults, individuals with disabilities, and low-income people, respectively, in Gainesville. The darkest areas on each map shows the highest

concentration for each group of travelers. Older adults reside in areas away from the center with a concentration in an area in the southwest (left). Persons with disabilities similarly reside in areas away from the center with a concentration in the Northeast where the Tacachale Disability Center is located. For low-income people below the poverty line, while the federal poverty line is approximately $11,000 a year for one adult individual, the cost of living in Gainesville is closer to $20,000. The darkest areas on the map (right) have more than forty percent of the populations below the poverty line. The darkest areas in the central section have high concentrations of students. Many students are considered dependents or work part-time, and thus reported their income as below the poverty line.

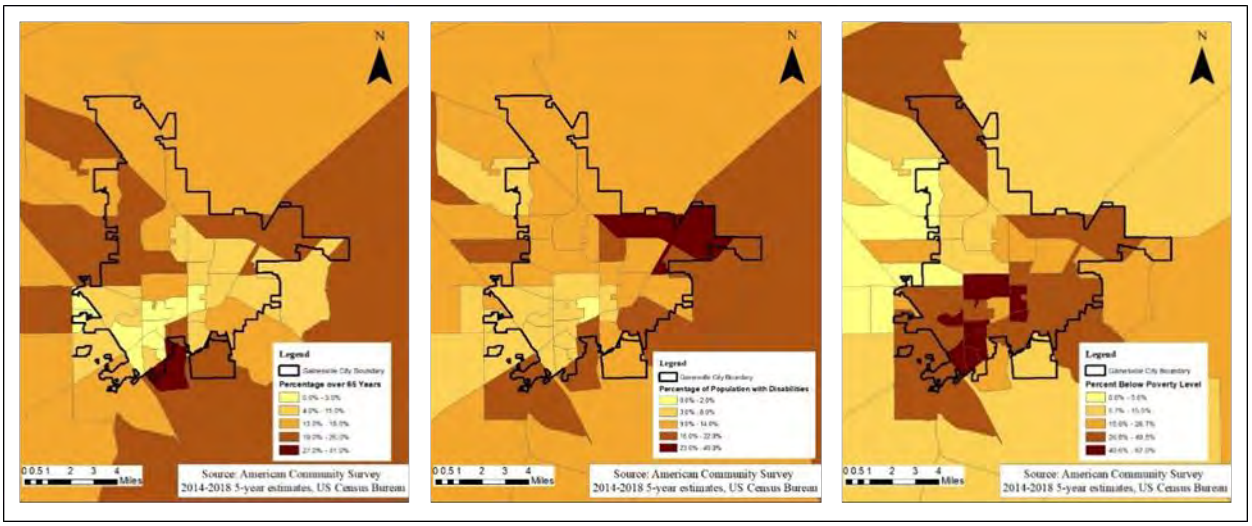

Figure 6-2. Percentage of Older Adults (Left), Individuals with Disabilities (Middle), and Low-income People (Right) in Gainesville, 2014-2018.

6.2.3.2 Transportation Vulnerability index

For each census tract, we developed a transportation vulnerability index based on the z-scores of the percentage of transportation-disadvantaged populations (Figure 6-3, Left) and the raw number of transportation-disadvantaged populations (Figure 6-3, Right), respectively. A z-score tells where the concentration of transportation-disadvantaged populations is in a particular census tract compared to the average of the entire city. The formula is as follows:

$$Z_i = \frac{x_i - \overline{x}}{s}$$

Z_i is the z-score of a census tract i, x_i is the percentage or counts of transportation-disadvantaged populations in the census tract i, $\overline{x}$ is the average percentage or counts of transportation-disadvantage populations of the entire city, and s is the standard deviation of the entire city. A higher z-score represents a higher concentration of transportation-disadvantaged populations. A z-score greater than one is considered to show an area significantly different from the average. The darkest areas in these two maps mark the areas where the z-score is greater than two.

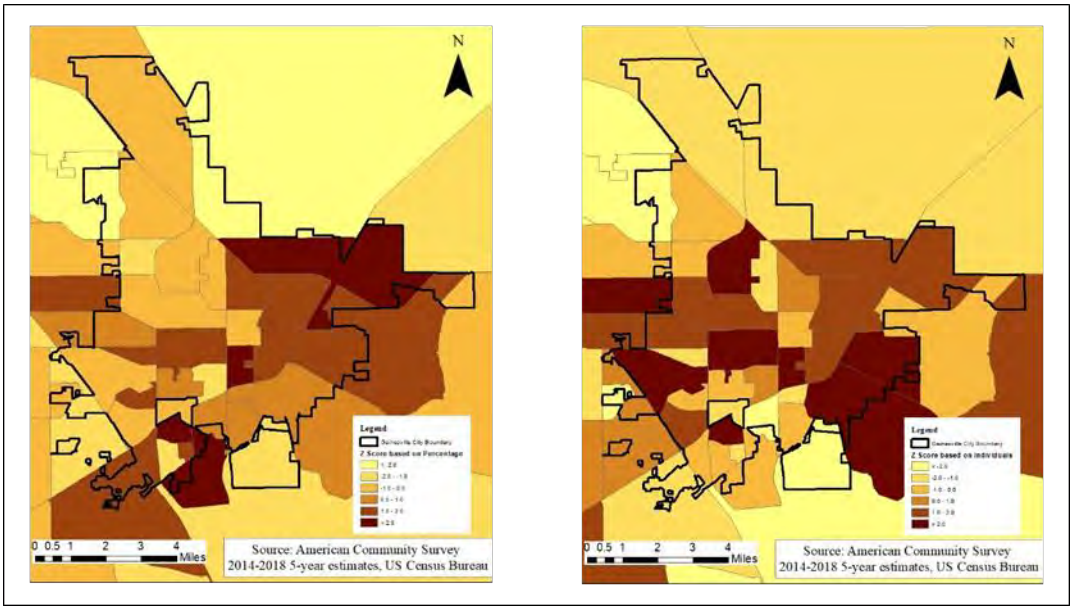

Figure 6-3. Transportation vulnerability index: 1) based on the z-scores of the percentages of transportation-disadvantaged populations (Left), and 2) based on the z-scores of counts of transportation-disadvantaged populations (Right).

6.2.4 Evaluation of Transit-Accessibility Changes in Different Scenarios

6.2.4.1 Scenario Development

The average daily ridership across the RTS bus system in Gainesville changes drastically at the turn of every academic semester. Changes in ridership over the course of a year follow a similar annual pattern, which is that there is higher ridership in the Fall, followed by high ridership in the Spring and a low number in Summer, as well as dips in ridership during December. However, the Covid-19 pandemic that began in early spring 2020 in Florida brought a lot of changes to the transit systems that are reflected by the ridership plunge and reduced transit services. To explore how the Covid-19 pandemic has influenced the transit services for transportation-disadvantaged neighborhoods, we developed two scenarios (Scenario 1 and Scenario 2) to evaluate changes in service levels. Scenario 1 represents the "Impact of the Covid-19 Pandemic" and Scenario 2 shows the "Recovery from the Covid-19 Pandemic." To evaluate the impact of future transit development on transportation-disadvantaged neighborhoods, we also developed Scenario 3, which consists of "Development in the Next Five Years," which is based upon the RTS Transit Development Plan.

The above three scenarios were defined by comparison between transit services during six different time periods: Spring 2019, Summer 2019, Spring 2020, Summer 2020, Fall 2020, and the next five years (Table 6-3 and Table 6-4). For the "Impact of Covid-19 Pandemic" (Scenario 1), although we could find a decrease in transit service from Spring 2020 to Summer 2020, this was not a reasonable reflection of the pandemic impact because overall transit service in Gainesville during the summer is always reduced compared with that in the spring. Thus, to truly reflect the impact of the pandemic, we compared the service decrease from Spring 2020

to Summer 2020 and the service decrease from Spring 2019 to Summer 2019. To reflect the scenario, "Recovery from Covid-19 Pandemic" (Scenario 2), we compared transit service in Fall 2020 and Spring 2020. To reflect "Development in the Next Five years" (Scenario 3), we compared projected transit service during the next five years and during Fall 2020.

Table 6-3. Selection of Time Periods for Scenario Development

Time Period	Code	Meaning
Time Period 1	T1	Spring 2019
Time Period 2	T2	Summer 2019
Time Period 3	T3	Spring 2020
Time Period 4	T4	Summer 2020
Time Period 5	T5	Fall 2020
Time Period 6	T6	The next five years

Table 6-4. Definition of Scenarios

Scenario	Code	Meaning	Definition
Scenario 1	S1	Impact of Covid-19 Pandemic	(T3 – T4) – (T1 – T2)
Scenario 2	S2	Recovery from Covid-19 Pandemic	T5 – T3
Scenario 3	S3	Development in the Next Five Years	T6 – T5

6.2.4.2 Transit Accessibility Model

We applied a geospatial tool that the research team had previously developed to evaluate how the level of transit accessibility in transportation-disadvantaged neighborhoods changed among the three different scenarios. We evaluated the transit accessibility of a census block based on the travel time from the census block to different types of destinations (work, medical, grocery, education, and social) by transit, as shown in the following equation:

$$A_{transit\_i} = \sum_{j=0}^{n} e^{-kt_{j,90min}}/n\,, i = work, medical, grocery, education, or\ social, j = 1,2, \dots n$$

Where $A_{transit\_i}$ is the transit accessibility score in terms of destination i; $t_{j,90min}$ is the transit time from a census block group to the jth opportunity of destination i given a time limit of 90 minutes; k is the decay parameter for the type of trips used in the specific study area; and n is the total number of destinations.

Figure 6-4 shows the process of deciding the origin where people start a transit trip in a census block. We assumed that most transit users started their trips from home, so we treated median centers of the residential parcels inside each block group as origins. To calculate the transit time cost of an origin to a destination, we created a transit-enabled network using the GTFS files corresponding to the scenario we defined (Figure 6-5). For example, the transit-enabled network that was created based on Fall 2020 GTFS data was different from the one created

based on 2019 GTFS data. Although those two networks look similar, routes and schedules could be different. This transit-enabled network includes a walk mode and a transit mode, which means that the network considers the walking time to and from the bus stops as well as transfer time. If an origin or destination (opportunity) is too far from a bus stop that a person cannot reach it within 10 minutes by walking, the model would consider the trip not accessible.

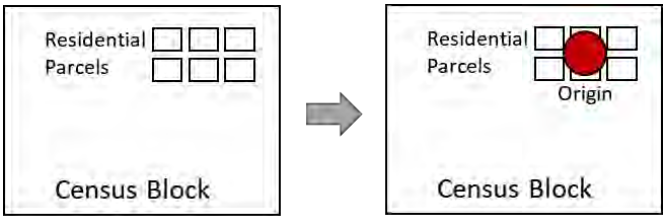

Figure 6-4. Deciding the Origin of a Census Block.

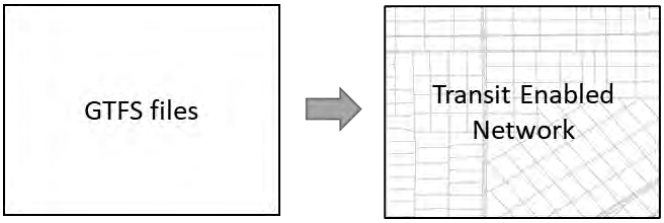

Figure 6-5. Creating a Transit-Enabled Network Using GTFS Files.

Figure 6-6 demonstrates how the transit time was calculated for one origin. For one origin or one census block, there would potentially be multiple destinations (opportunities). For example, when calculating transit accessibility to work destinations, the opportunities include census blocks where jobs are available. Then the model counts the total transit time, which includes a person's time leaving home at 7 am (for the job), walking to a bus stop (the best route), waiting for the bus, traveling on the bus, potential transferring that includes more walking and waiting, and walking to the job location after the bus reaches the last stop. If a trip takes more than 90 minutes, the model treats the opportunity as not accessible by transit. In the end, the model summarizes the total time cost of all trips from that origin and converts the time to an accessibility score. Longer trips contribute less to the final accessibility score of the origin. A decay parameter in the model controls this contributing process.

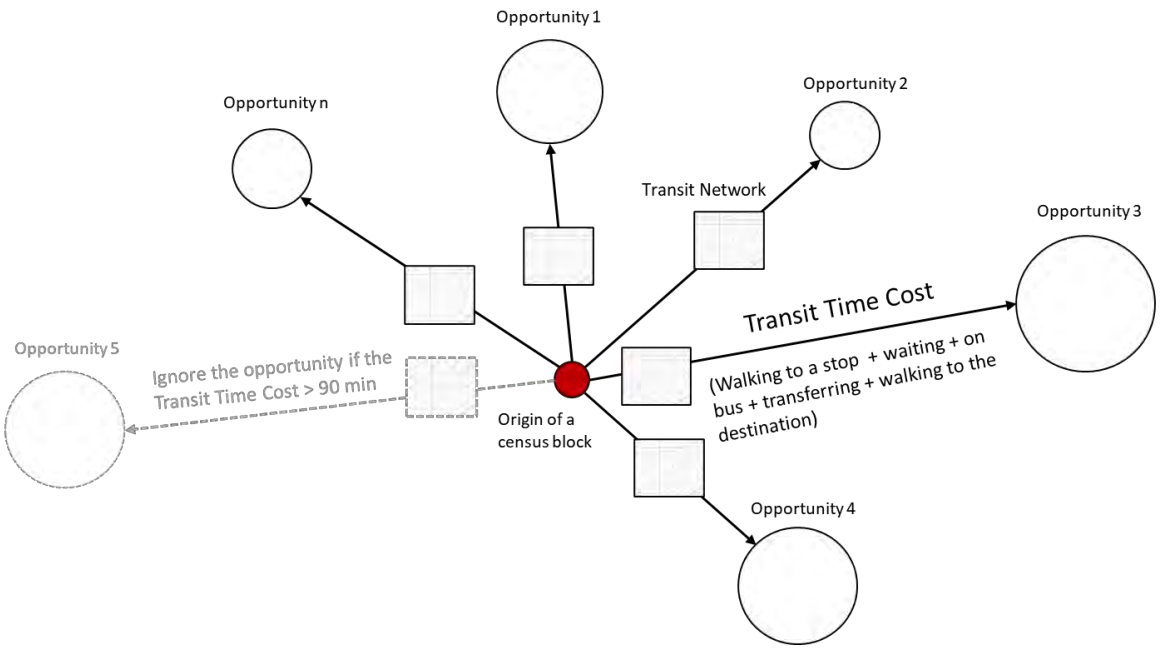

Figure 6-6. Calculating Travel Time from One Origin to Potential Opportunities (Destinations).

6.2.4.3 Data Processing

Three types of data were used to measure transit accessibility: GTFS data, residential parcel data, and census data.

GTFS Data

To calculate transit time across different time periods, we collected GTFS data with transit schedules from the Florida Transit Data Exchange (FTDE) and RTS. As mentioned above, these GTFS data included the following time periods: Fall 2020, Spring 2020, Fall 2019, Spring 2019, and Summer 2019. Unfortunately, GTFS data for Summer 2020, when most of the public transit system schedules were impacted by Covid-19, was not officially published, and we could not expect GTFS data in the next five years to be published ahead of time. To represent the transit schedules of these two time periods, we developed a GTFS editor that can modify the GTFS files as needed. The editor has three functions: 1) suspending routes, 2) decreasing/increasing the frequencies of routes, and 3) increasing or decreasing the service span of routes.

By manually comparing the summer 2020 bus schedule published by RTS as a documentation with the 2019 summer schedule, we created a Summer 2020 GTFS dataset based on the officially published GTFS dataset. By summarizing the future changes in the RTS Ten-year Transit Development Plan documentation, we created a GTFS dataset to reflect the transit service schedule in the next five years. Although a ten-year plan was proposed in the RTS documentation, only the most recent five years include detailed plans, such as the increase of frequencies and service spans for some routes. Therefore, we implemented these plans to build a five-year improvement GTFS dataset, instead of a ten-year one, based on the current Fall

2020 GTFS dataset. The GTFS datasets were then used to create transit-enabled networks as one of the required parameters of the transit accessibility model.

Parcel Data

The residential parcel data in 2017 were collected from FGDL. The parcel data were used for two purposes. First, they were used to adjust the location of the centroid of a census block to the weighted center using residential parcels in the block (Figure 6-7). The reason for adjusting is that people usually travel from residential areas, but some census blocks have their residential parcels clustered at places that are far from the centroids.

The second use of the parcel data was to generate different types of destinations (medical, grocery, education, and social) based on the parcel description. Medical destinations are the centroids of the following parcels: hospitals, clinics, medical doctors, and nursing homes. Grocery destinations are the centroids of supermarket parcels. Education destinations are the centroids of private and public school facilities. Social destinations are the centroids of parcels with the following labels: drive-in theaters, open stadiums; enclosed theaters, enclosed auditoriums; nightclubs, cocktail lounges, bars; bowling alleys, skating rinks, pool halls, enclosed arenas; tourist attractions, permanent exhibits, other entertainment facilities, fairgrounds (privately owned); clubs, lodges, union halls; and cultural organizations, facilities; forest, parks, and recreational areas.

Census Data

We used census data to identify work destinations. Specifically, work destinations are the centroids of census blocks, and every destination was weighted by the number of jobs. Job numbers by census blocks were obtained from the Longitudinal Employer-Household Dynamics (LEHD) program by the Center for Economic Studies at the U.S. Census Bureau.

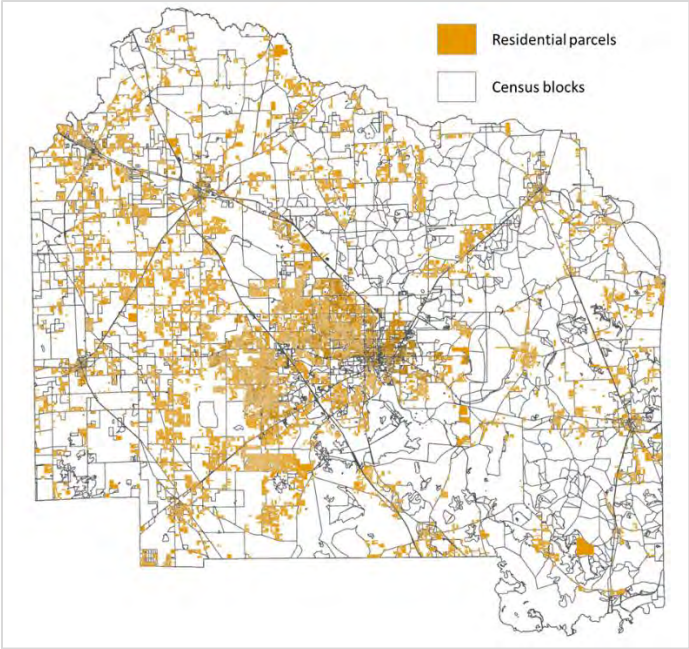

Figure 6-7. Overlaying Census Blocks and Residential Parcels

6.3. RESULTS

6.3.1 Operational Efficiency and Spatial Effectiveness of the RTS System

6.3.1.1 Operational Efficiency

The data and results for the DEA model for Operational Efficiency are shown in Appendix 6.A. The routes are ranked and sorted based on the relative efficiency values, which is a maximum of 1 for those technically efficient. Based on the results, six routes are determined as technically efficient ($1/\mu = 1$), three routes are fairly efficient ($1/\mu > 0.6$), and 46 routes are inefficient ($1/\mu < 0.6$). The results generally showed that the most efficient routes are the most compact, including those serving the University of Florida campus core areas (120, 127, 118), microtransit serving East Gainesville Neighborhoods (600, 601), and routes connecting major student housing areas to the university campus (19, 38, 20, 21). The most inefficient routes ($1/\mu < 0.6$) are generally express routes used by commuters connecting Gainesville to other cities (901, 902), night and weekend service routes (300s, 711, 128) and routes serving parts of North, Northeast, and East Gainesville (24, 27, 2, 3, etc.).

The on-campus routes are expected to perform well considering that they serve a small but critical area with a disproportionate number of daily travelers, including many commuters to the campus. The microtransit routes are outliers in the analysis based on their few registered fixed stops as compared to a variable amount of on-demand pickups and drop-offs by users, which provided a disproportionate ridership as compared to the GTFS data. However, considering the on-demand nature of microtransit, the score may hold some value. Routes connecting the campus and major student housing hubs are also expected to perform well, with Route 38 being a clear example. A notable feature of Route 19 is that it serves during a

relatively short period of time for high-demand areas, which contributes to its high performance.

Most Efficient Routes: 120, 127, 600, 601, 19, 38.

120 (Frat row to Hub Circulator) — major on-campus route.

127 (East [Campus] Circulator) — major on-campus/housing route.

600, 601 (East Gainesville Microtransit) — microtransit, so expected to meet specific demand.

19 (Reitz Union to SW 35th/23rd Terrace) — serves a major campus-to-student-housing area connection for a short time.

38 (Hub to Gainesville Place) — major route connecting core campus area to large student housing developments, relatively direct routing.

118 (Hub to Cultural Plaza) — major daytime on-campus route connecting east to west, commuter lots, housing, and gyms.

More Efficient Routes: 118, 20, 21.

Less Efficient Routes: 128, 303, 2, 39, 3, 305, 40, 6, 300, 7, 16, 301, 76, 26, 25, 11, 10, 29, 23, 36,

800, 126, 302, 117, 75, 119, 15, 17, 122, 8, 121.

Least Efficient Routes: 901, 902, 24, 27, 711.

901, 902 (Express to Lake City, Express to Trenton) — Relatively new, long-distance express routes with few stops, likely relatively minimal demand expected; inefficiency may be exaggerated by the algorithm for operating time.

24 (Rosa Parks to Job Corps) — daytime route connecting northeast areas to downtown, very long headways (~120 min based on 2018 schedule).

6.3.1.2 Spatial Effectiveness

The data and results for the DEA model for Spatial Effectiveness are shown in Appendix 6.B. The routes are ranked and sorted based on the relative effectiveness values, which is a maximum of 1 for those technically effective. Based on the results, six routes are determined to be technically effective ($1/\mu = 1$), five routes are fairly effective ($1/\mu > 0.6$), and 44 routes are ineffective ($1/\mu < 0.6$). The results generally show that the most effective routes are the most compact, serving the University of Florida campus core areas (120, 127, 118), microtransit serving East Gainesville Neighborhoods (600, 601), express routes (901, 902), and routes with many stops along major housing corridors (38, 15, 46, 20, 13). The most ineffective routes ($1/\mu$

< 0.6) are generally night, weekend, and special service routes (300s, 711, 128, 19), and routes serving parts of North, Northeast, and East Gainesville (24, 27, 39, 3, 40, 36).

Most Effective Routes: 118, 120, 127, 901, 600.

118 — Compact campus route, commuter lot connection, used by many commuters and others not living within stop range, 3-digit (free).

120 (Frat row to Hub Circulator) — Compact campus route – used by many, even those who do not live on campus, 3-digit (free).

127 (East [Campus] Circulator) — Compact route connecting most dense off-campus housing to campus core, 3-digit (free).

901 (Express to Lake City) — Express route, few stops, low supply meets relatively low demand.

600 (East Gainesville Microtransit) — microtransit, generally expected to match demand.

More Effective Routes: 601, 15, 46, 20, 13, 38.

Less Effective Routes: 300, 302, 27, 24, 39, 711, 3, 40, 36, 119, 121, 76, 25, 16, 2, 126, 122, 6, 29,

117, 10, 17.

300 (Later Gator A) — Night/Weekend route, runs through midtown, campus core, frat row, and sorority row.

302 (Later Gator C) — Night/Weekend route, runs through midtown, frat row, southwest campus, west student housing, oaks mall.

27 (Downtown to NE Walmart) — NE Gainesville route, less student housing.

Least Effective Routes: 128, 303, 19, 305, 301.

128 (Reitz Union to Lake Wauburg) — Weekend service, many on-campus stops, but relatively low demand unless for recreation (going to Lake Wauburg).

303 (Later Gator D) — Night/Weekend route, runs mostly on SW 13th Street, relatively fewer young students than other Later Gator routes.

19 (Reitz Union to SW 35th/23rd Terrace) — Connects major student housing area to campus, but for a short time.

305 (Later Gator F) — Night/Weekend route, runs north of southwest student housing area to Butler Plaza.

301 (Later Gator B) — Night/Weekend route, runs directly through southwest student housing area.

6.3.2 Transportation-Disadvantaged Neighborhoods

By showing our previously developed maps of the transportation vulnerability index and discussing the results with Gainesville RTS, we identified four neighborhoods (census tracts) with large concentrations of transportation-disadvantaged populations (Figure 6-8). Table 6-5 summarizes the socio-economic attributes of these four transportation-disadvantaged neighborhoods.

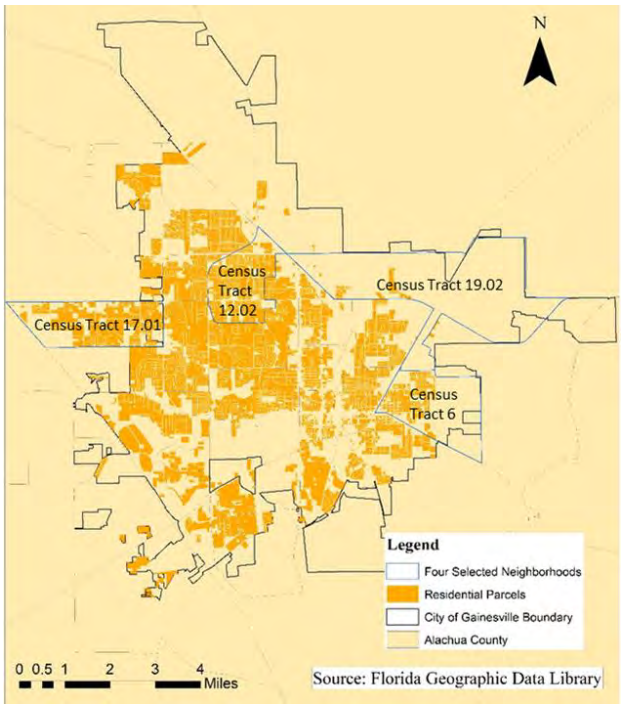

Figure 6-8. Selected Transportation-disadvantaged Neighborhoods.

Table 6-5. Socio-economic Attributes of Four Transportation-disadvantaged Neighborhoods

	Tract 17.01	**Tract 12.02**	**Tract 19.02**	**Tract 6**
Population	5622	7309	3192	5195
Low-income people	304 (5.41%)	624 (8.54%)	1201 (37.63%)	1777 (34.21%)
Older adults	1159 (20.62%)	1054 (14.42%)	502 (15.74%)	290 (5.58%)

	Tract 17.01	Tract 12.02	Tract 19.02	Tract 6
Individuals with disabilities	558 (9.93%)	819 (11.21%)	1247 (39.07%)	N/A
White population	90%	75%	53%	<10%

Tract 17.01 is located in the western side of Gainesville and encompasses a large swath of unincorporated land (Figure 6-9). There are numerous points of interest in this tract including Santa Fe College and a few student housing apartments such as The Crossings. Along 83rd Street, various assisted living and retirement homes exist, such as The Village, contributing to a reported larger presence of older adults than in other parts of the Gainesville area, as seen in Figure 6-2 (Left). In addition, the many of the subdivisions in this area were developed in the 1970s and 1980s and the residents may be aging in place. These communities may also contribute to a larger number of disabled citizens in the area, as seen in Figure 6-2 (Middle). A large portion of the tract is developed with single family homes, but perhaps the tract's ranking in terms of number of people living below the poverty line can be attributed to the presence of students at Santa Fe, as well as the presence of communities for older adults. Large parts of the tract are distant from the city's major commercial sectors, and the area includes large numbers of dead ends and cul-de-sacs that are typical of suburban areas but can limit accessibility to more desired parts of Gainesville. Currently five bus routes serve the area: 10, 23, 39, 43 and 76.

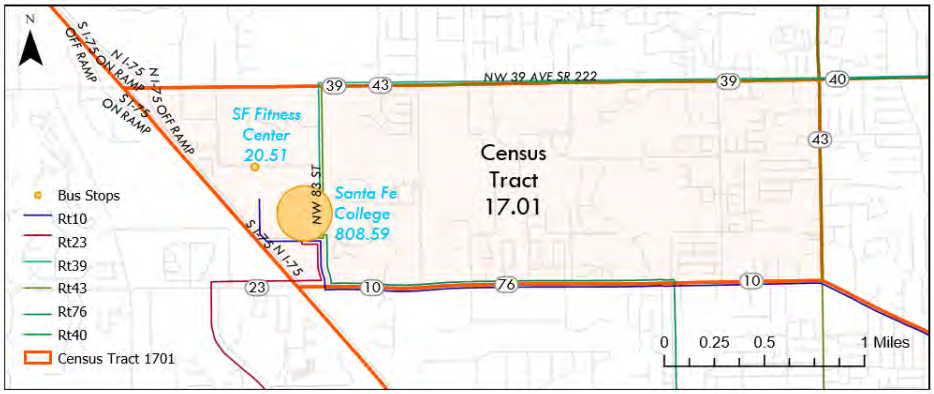

Figure 6-9. Bus Routes and Stops in Tract 17.01.

6.3.2.2 Transit Services in Tract 12.02

Tract 12.02 is located in the northwestern section of Gainesville (Figure 6-10). A vast majority of the tract is composed of single-family homes in communities such as Northwood and Spring Hill. These are near the North Gainesville Walmart and the surrounding commercial center. Within the tract, a senior recreation center can be found next to Northside Park. Additionally,

these stores and centers are next to two large apartment complexes, Deerwood and Creekwood. Currently four bus routes serve the area: 6, 8, 29 and 40.

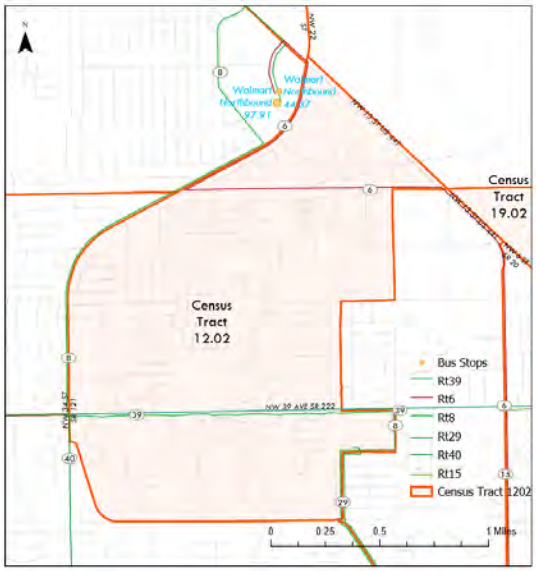

Figure 6-10. Bus Routes and Stops in Tract 12.02.

6.3.2.3 Transit Services in Tract 19.02

Tract 19.02 is located in the northeastern section of Gainesville (Figure 6-11). These residential areas are dense but small. Most of these are trailer parks, including Bella Vista Village, Brittany Estates (which is a 55+ community) and Lamplighter, which is the most distant and removed neighborhood in this tract. Surrounding Ironwood Golf Course are a few single-family homes and an apartment complex. The tract is composed of a large amount of industrial type warehouses north of the Gainesville Airport as well as on the north end of 6th Avenue. Car dealerships are also present at the end of Main Street. The presence of the Tacachale Disability Center in the tract, which is designated for people with developmental disabilities, is the reason why this tract has a high level of disabled citizens, as observable in Figure 6-2 (Middle). Currently five routes serve the area: 15, 24, 25, 26 and 39.

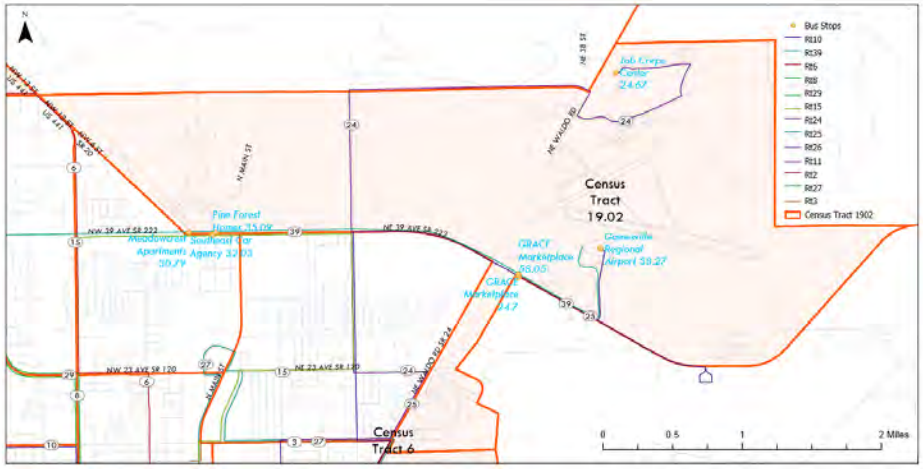

Figure 6-11. Bus Routes and Stops in Tract 19.02.

6.3.2.4 Transit Services in Tract 6

Tract 6 is located in Gainesville's Eastside, encompassing a neighborhood known as Duval Heights (Figure 6-12). Many single-family homes cover the area with several multifamily complexes such as Gardenia Gardens, mixed in throughout. The presence of the Clarence Clark Community Center and numerous daycare centers indicate the presence of working families and youth. This contrasts with the lack of services for older adults as noted in the previously discussed tracts. Figure 6-2 (Right) indicates that this tract has a large presence of people living below the poverty line. The Duval Heights Walmart in the tract is the single largest commercial presence and compensates for a lack of other commercial services. There are currently seven routes serving Tract 6: routes 2, 3, 7, 11, 24, 25, 26 and 27.

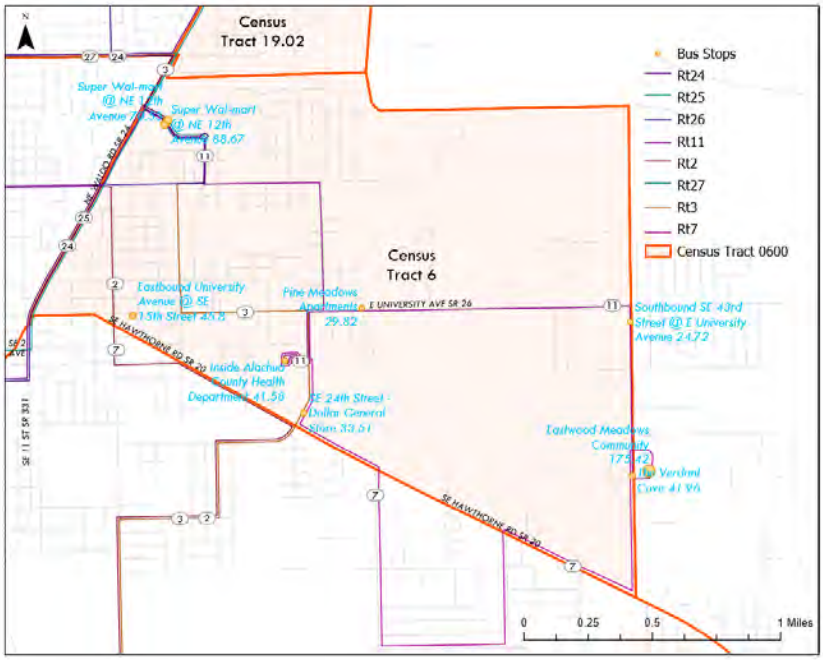

Figure 6-12. Bus Routes and Stops in Tract 6.

6.3.3 Transit-accessibility Changes for Transportation-disadvantaged Neighborhoods in Different Scenarios

6.3.3.1 Scenario 1: Impact of Covid-19 Pandemic

Work trips

Figure 6-13. Impact of Covid-19 on Transit Accessibility for Work Trips

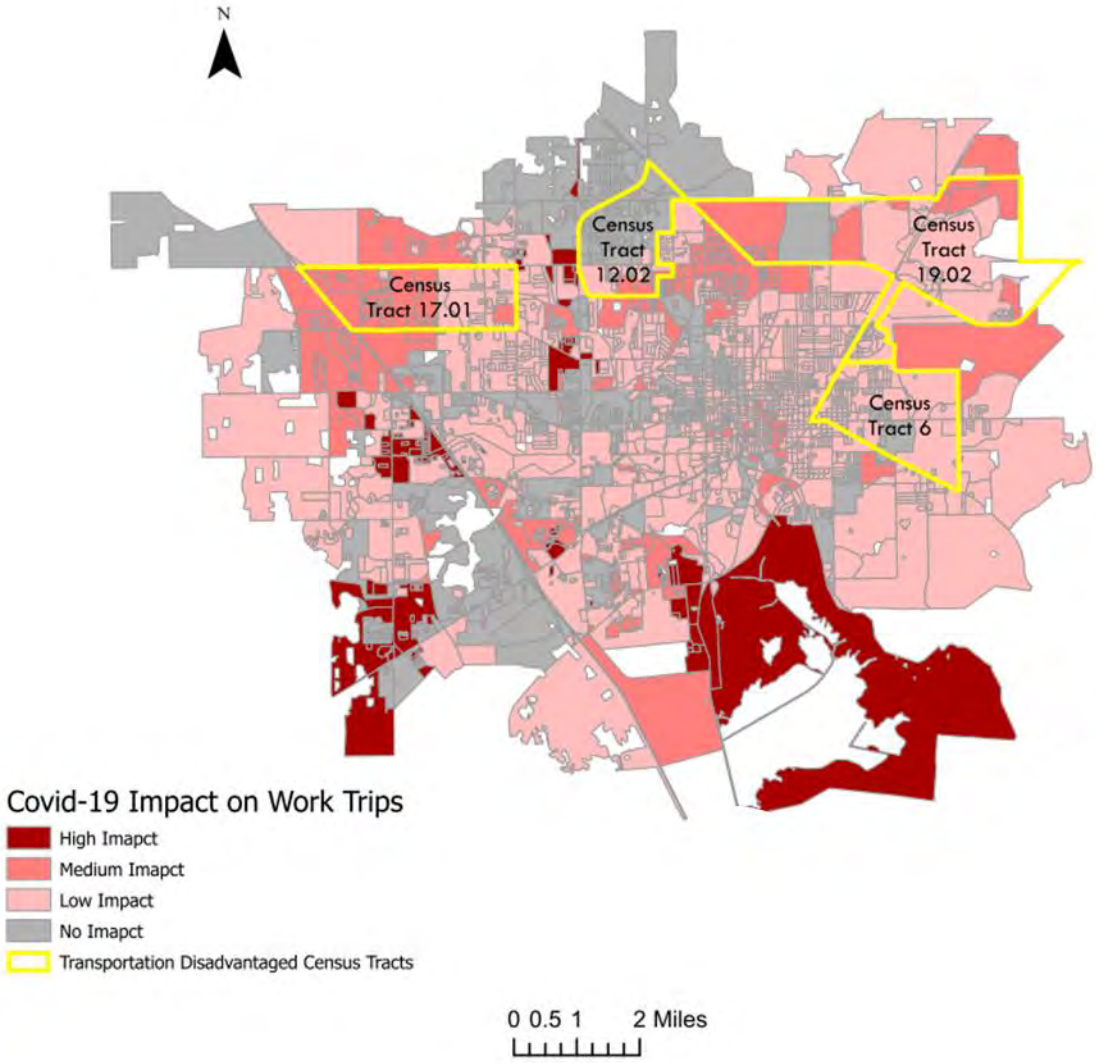

Figure 6-13. Impact of Covid-19 on Transit Accessibility for Work Trips

The impact of Covid-19 on transit accessibility for work trips was low to medium across the four transportation-disadvantaged neighborhoods compared with other neighborhoods in the city (Figure 6-13). Tract 17.01 has 304 people (5.41%) living under the line of poverty – the lowest absolute number and percentage among the four neighborhoods. Transit changes have had a relatively low impact on the population that benefits from accessing transit for work in the eastern part of this neighborhood. The impact of transit changes is greater in the western part

of this neighborhood. The reason could be the extension of headway from 35 minutes to 70 minutes on Route 10 since it runs through a few activity centers along the way, such as the NW 16 Avenue and NW 43rd Street activity center, which generates numerous work trips.

Our model results show no impact from transit changes on work trips in most of Tract 12.02. In this neighborhood, Routes 6 and 8 remained in service through the pandemic period, allowing people to access many workplaces, from the North Walmart down towards downtown and UF Health, respectively. Additionally, numerous developments under construction along these two routes closer to University Avenue maintained low impacts for workers living in Tract 12.02 who were trying to access these more distant worksites. The southern end of this neighborhood shows low to medium impacts on work trips, which can be attributable to the suspension of Routes 39 and 29. However, because our model applies weights to employment sites, it was sensitive to the large number of attraction points at either end of the termini of these two routes: Route 39 which ends at Santa Fe College in the west and the Airport in the east, and Route 29 which runs down to the UF campus core.

Tract 19.02 demonstrates similar impacts on work trips along Route 39 as previously discussed, as well as along Route 24 which leads into the Job Corps Center north of the Airport. The suspension of these routes, which took a long time to be restored, bring challenges related to connecting workers to jobs in the northeastern sector of Gainesville. Although Route 15 runs through parts of Tract 19.02 and provides access to multiple workplaces, such as around the NW 13 Street and 23 Avenue activity center, there are more widespread medium impacts of transit changes on work trips in this neighborhood. Reduction in operation hours to combat the spread of the pandemic could be responsible for many of these widespread impacts in a zone with a substantial portion of people living under the poverty line. The residents, who might otherwise wish to take jobs with inconvenient schedules which were accommodated prior to the pandemic, may have found them severely curtailed at the onset of the outbreak.

Tract 6 experienced low impacts on work trips due to strict maintenance of transit services, including microtransit services and fixed-route services, which remained almost intact at the onset of the pandemic. The only impact could be the change in operation hours which were also curtailed. Late-night essential workers may have experienced the impact more severely in this area, although the model demonstrates a low impact overall.

Medical trips

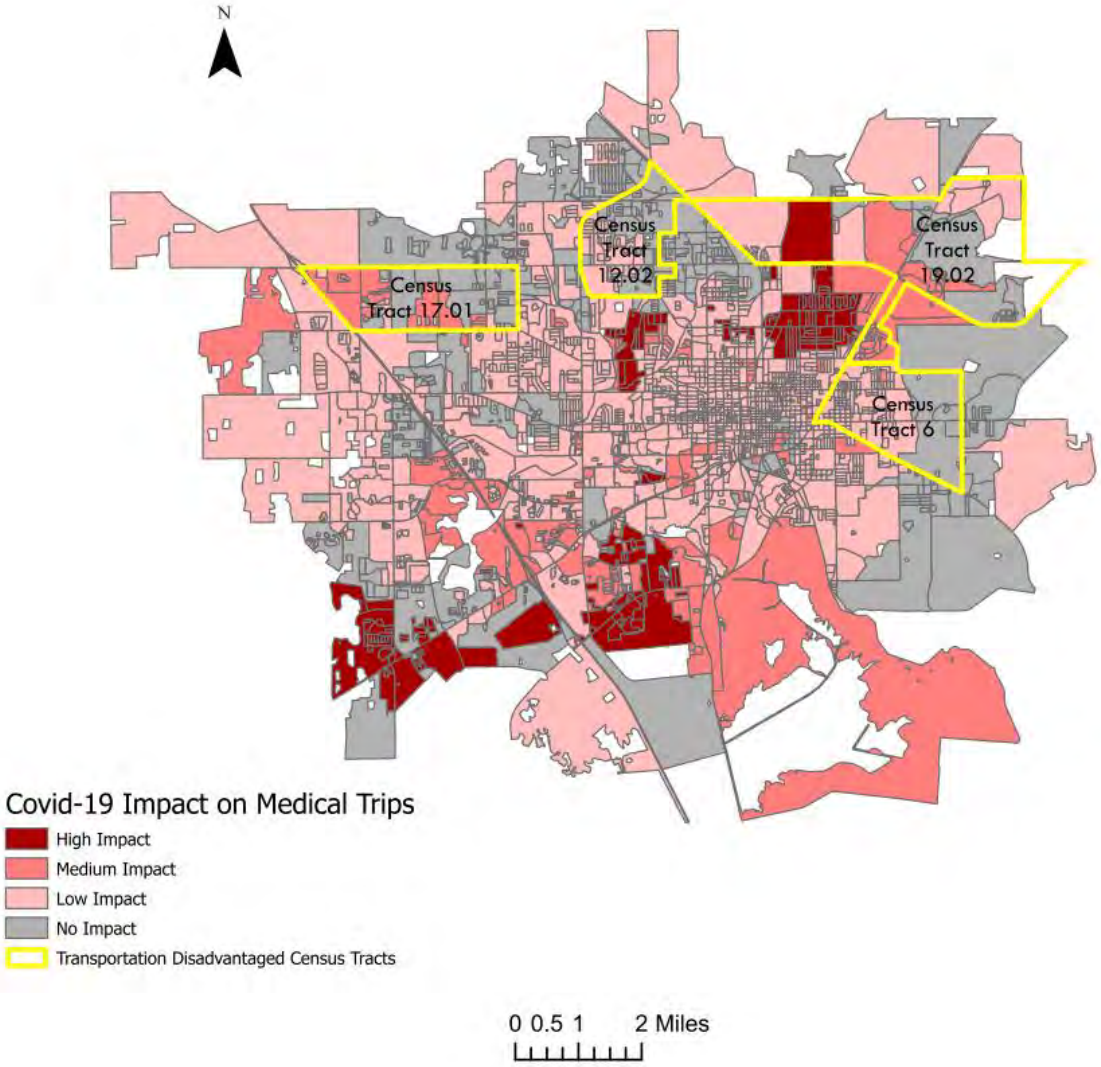

Figure 3-7. Impact of Covid-19 on Transit Accessibility for Medical Trips

Transit changes during Covid-19 affected trips for medical purposes at a medium level in about half of Tract 17.01 (Figure 6-14). This impact can be attributed to the changes in operation hours of Route 23, which ceased to operate after 5pm. Route 23 connects the western blocks of the neighborhood to many medical destinations surrounding the North Florida Regional Hospital. In addition, Route 43 connects to the Shands Hospital complex. The extension of headway from 35 minutes to 70 minutes on Route 10 significantly altered the ability for travelers in the central part of this neighborhood to access medical centers located at NW 16th Avenue and NW 43rd Street as well as on University Avenue in Downtown. This area has the highest number (1159) and percentage (20.62%) of adults over 65 years old. Therefore, older

adults dependent on transit in Tract 17.01 could have been the most impacted group in terms of access to medical services among all four transportation-disadvantage neighborhoods.

Medical trips in Tract 12.02 have not been affected by transit changes. The suspension of Routes 39 and 29, which occurred about 3 weeks into the pandemic period, did not bring many extra changes because the suspension of these two routes was common during the summer schedule. Additionally, no changes were recorded on Routes 6 and 8, which meant that residents in this neighborhood living near these two routes maintained access to Shands and other medical destinations across Gainesville.

We observed medium to high impacts in parts of Tract 19.02. The highly impacted zone corresponds to a multi-family development, Eden Park. While there were no major schedule changes as a result of COVID-19, the suspension of Route 39, which connects this neighborhood to medical destinations close to Santa Fe College, was partly responsible for the resulting severe impact. Specifically, travel times for medical purposes greatly increased because trips to a plethora of other medical destinations required a bus transfer on all other routes. Given that this neighborhood has the highest number (1201) and percentage (37.63%) of people living below the poverty line, it is possible that this group of people who make use of public health services could be the most impacted and needed to make selective considerations about medical access.

Tract 6 experienced low to no impacts on transit trips for medical services during the pandemic period. Although distant from the major clusters of medical services in Gainesville, trips to these services were expedited through connections at the Rosa Parks Transfer station in Downtown Gainesville. Additionally, Route 25 connects the neighborhood directly to Shands and other medical destinations along the way. It is worth mentioning that, even though the operation times were not extensive, microtransit buses in East Gainesville helped to connect some transportation-disadvantaged people with medical services.

Grocery trips

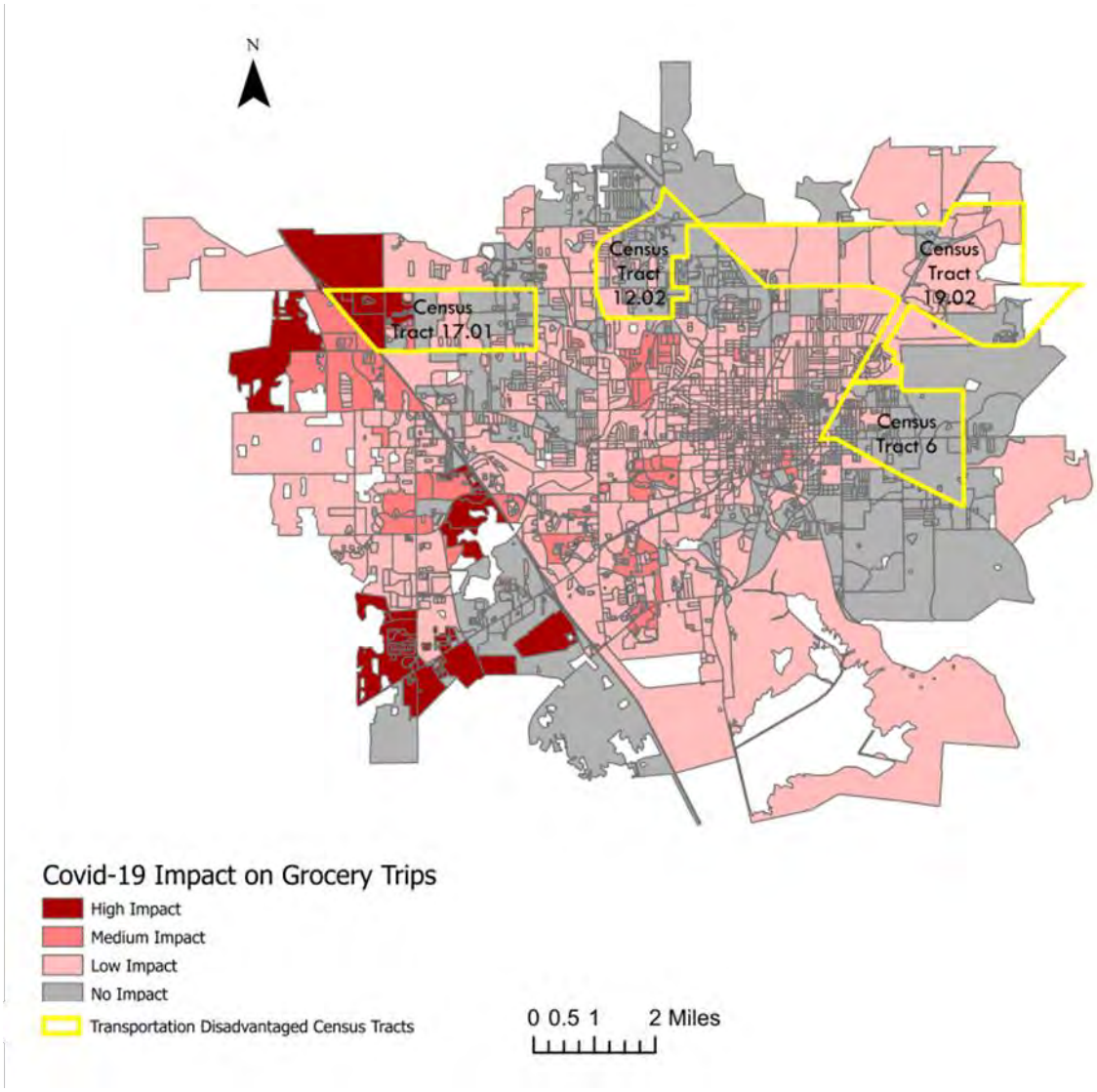

Figure 6-15 Impact of Covid-19 on Transit Accessibility for Grocery Trips

Transit changes during the pandemic had modest impacts on grocery trips in the four transportation-disadvantaged neighborhoods (Figure 6-15), except for the northwesternmost sector of Tract 17.01, which demonstrated a high level of impact. The single grocery store in that part of the neighborhood was rendered inaccessible since our model was sensitive to walking distances that were longer than 10 minutes. Given the suspension of Route 39 operations, the level of disconnection was extensive in this area.

The other three transportation-disadvantaged neighborhoods all experienced low to no impacts on transit trips for grocery shopping. Tract 12.02 enjoys reasonable connectivity to local grocery stores via transit, and the service operations on Routes 6 and 8 were maintained during the

pandemic. Tract 19.02 demonstrates widespread low impacts across the board. The impact of Route 39's suspension was remediated in part by Route 15's connection to multiple grocery destinations. As for Tract 6, despite the fact that there were no grocery destinations located within this neighborhood, accessibility via bus and walking did not seem to be substantially affected given that route frequencies were never curtailed in this area during the pandemic.

Education trips

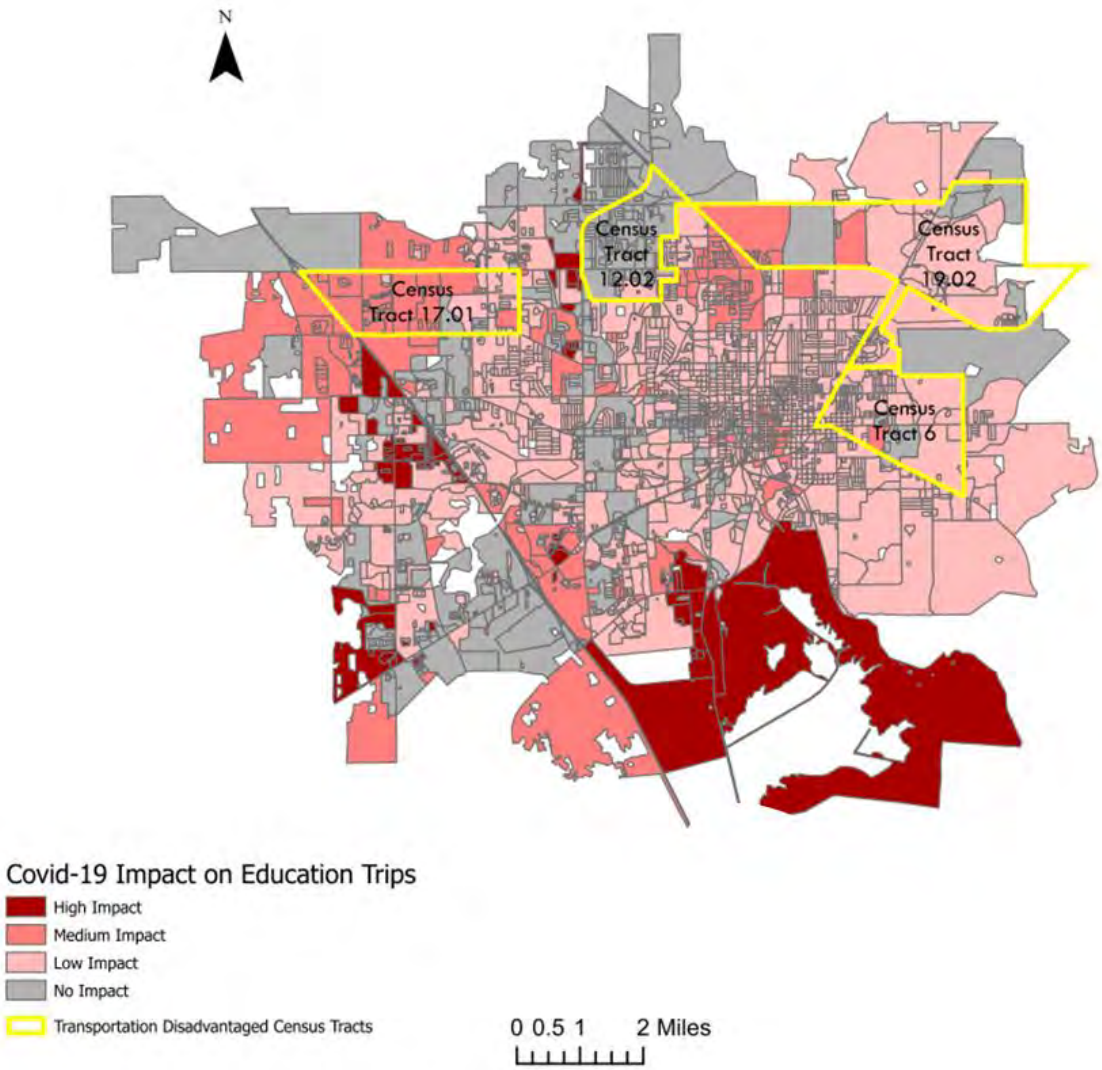

Figure 6-16. Impact of Covid-19 on Transit Accessibility for Education Trips

The impacts of the Covid-19 pandemic on trips for education purposes were larger in Tract 17.01, the transportation-disadvantaged neighborhood with a relatively higher percentage of students (Figure 6-16). The presence of more schools further away from the neighborhood could also be responsible for this impact, because our model is more sensitive to the sum of

longer trip times due to distance, which effectively lowers the level of accessibility. Tracts 19.02 and 6 show lower levels of impact, presumably for similar reasons to Tract 17.01, except that these two tracks are closer to a larger number of educational destinations. This lowers the level of impact since trips could potentially be made within the 90-minute time frame. Finally, Tract 12.02 demonstrates a widespread level of no impact. However, our model results of impact on trips for education purposes are only figurative because students began coursework online at the onset of the pandemic and there were almost no trips for education purposes.

Social trips

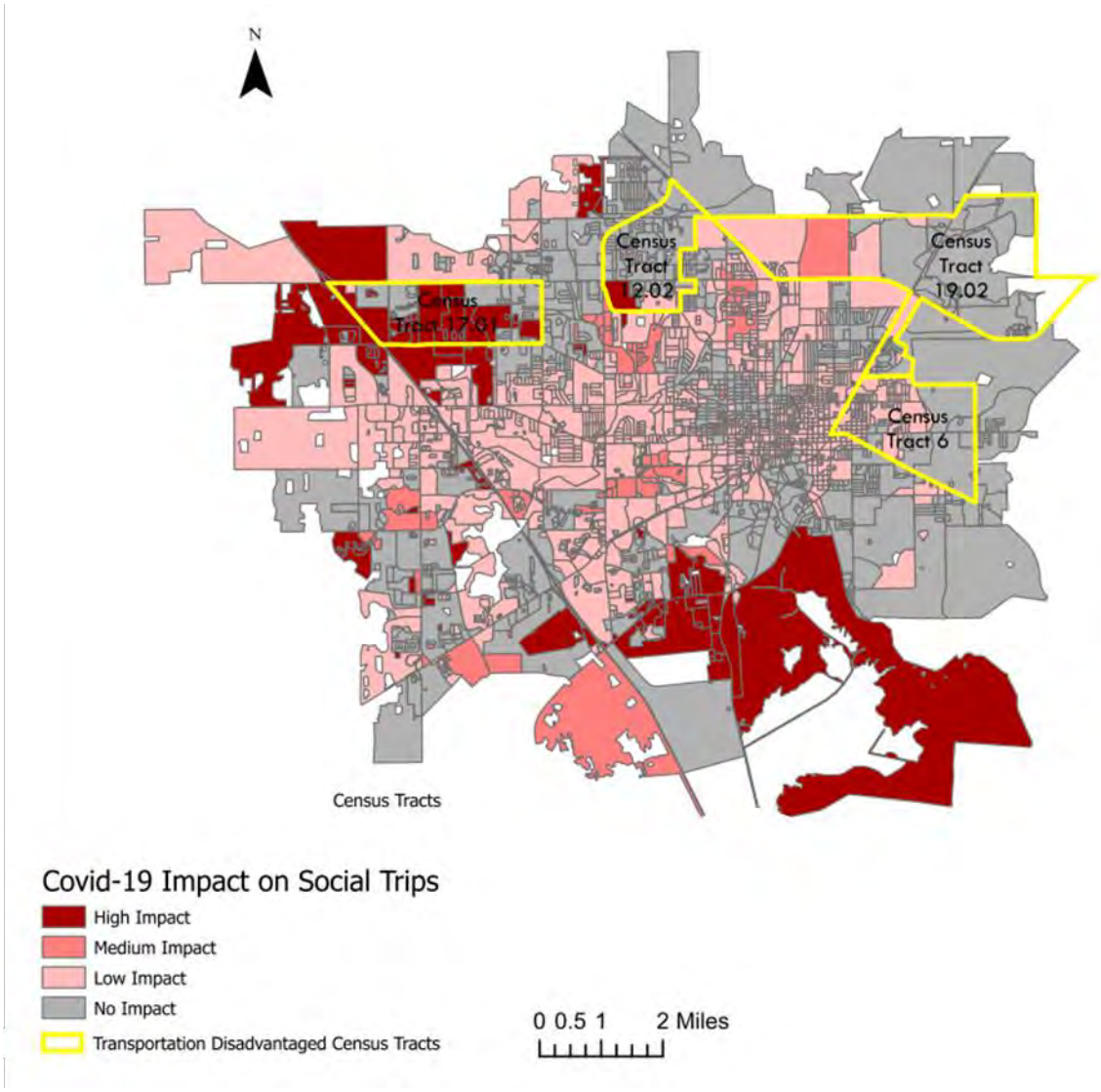

Figure 6-17. Impact of Covid-19 on Transit Accessibility for Social Trips

The impact of Covid-19 on social trips was especially heavy in Tract 17.01 where the reduction in transit services decreased the accessibility to the already distant and small number of social destinations (Figure 6-17). Tract 12.02 showed no impacts on social trips, indicating that none

of the changes were really affecting access to these destinations. Social trips in the western part of Tract 19.02 tend to be more impacted by the transit changes due to the lack of direct connection in these areas to some social destinations. Tract 6 showed low to no impacts, presumably due to its proximity to many social destinations in the downtown area and the connection to these via bus.

6.3.3.2 Scenario 2: Recovery from Covid-19 Pandemic

Work trips

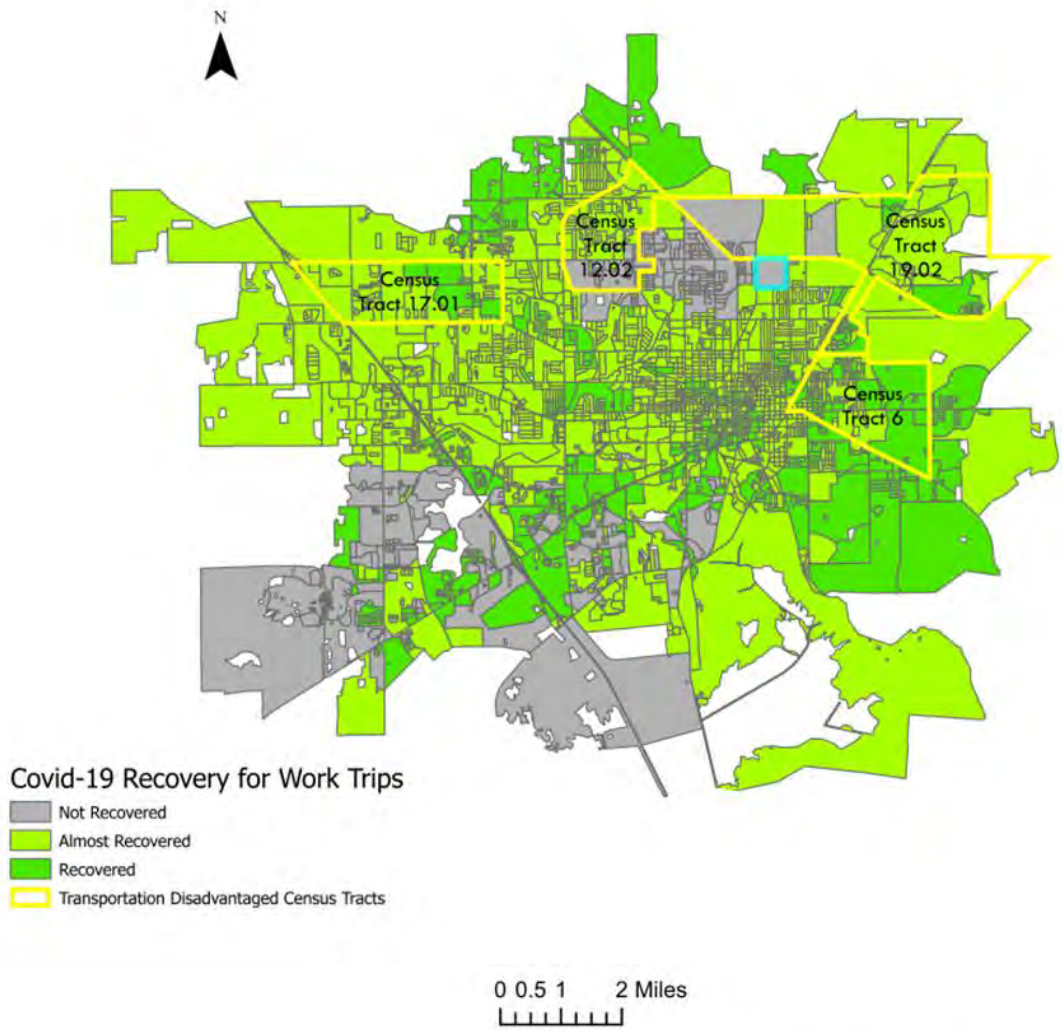

Figure 6-18. Transit-accessibility Recovery from Covid-19 for Work Trips

The level of Covid-19 recovery in terms of trips to access work varies across the four transportation-disadvantaged neighborhoods (Figure 6-18). Most parts of Tract 17.01 are almost recovered while some have fully recovered. The partial resumption of some routes has made a major difference in increasing accessibility to jobs along 39th Avenue in particular.

Similarly, Route 76 connecting to the Oaks Mall can be a major source of recovery for workers who were left disconnected during the pandemic period. However, Tracts 12.02 and 19.02 still have many areas that have not recovered in terms of trips to work. These areas are found along NW 39th Avenue. These results can be attributed to reduced trips from Route 39 in the recovery period. As for Tract 6, the recovery of trips for work was favorable mainly due to the capacity to maintain its schedule even during the pandemic period.

Medical trips

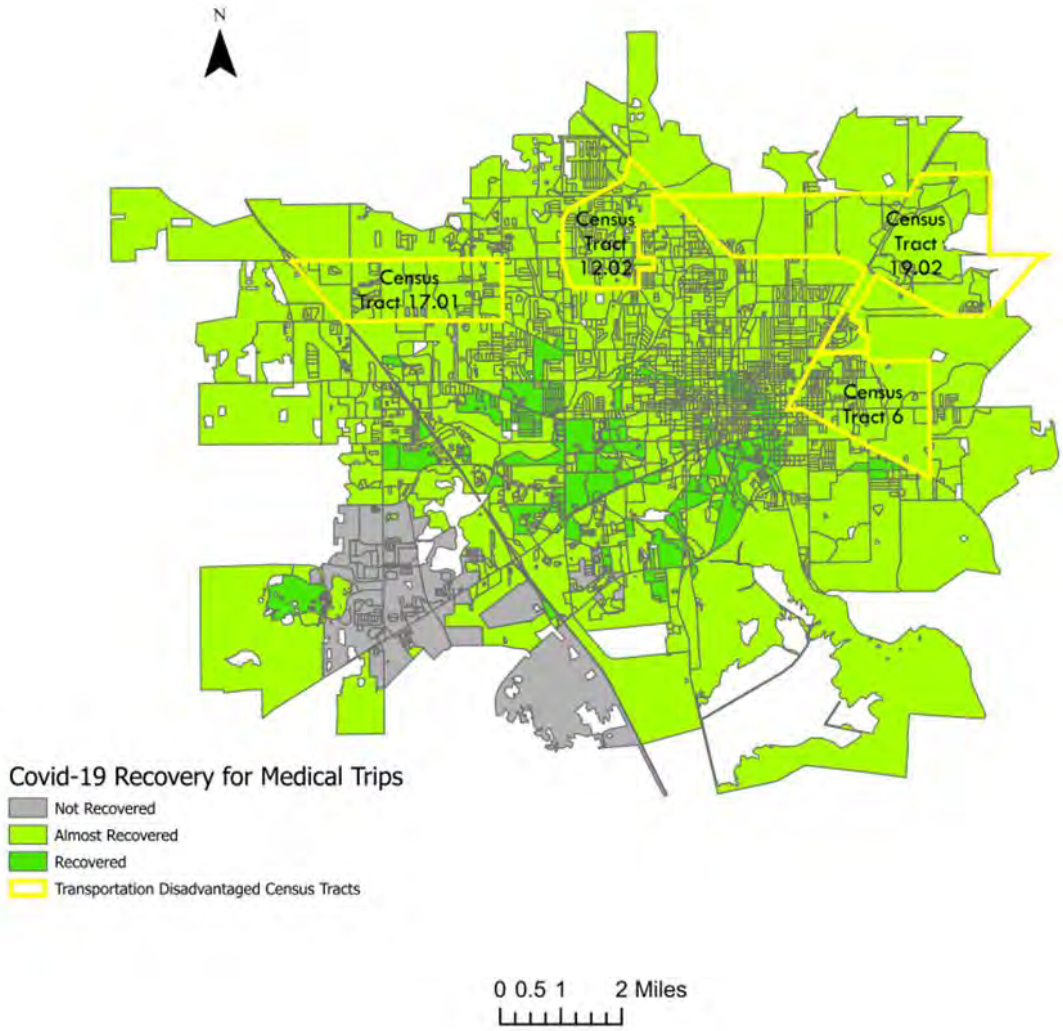

Figure 6-19. Transit-accessibility Recovery from Covid-19 for Medical Trips

During the Covid-19 recovery period, the resumption of previously reduced transit services demonstrates an almost recovered status across the board (Figure 6-19). The four transportation-disadvantaged neighborhoods all share Route 39, which, although having a low frequency of 60 minutes and short operation hours (8AM – 4PM), connects these

neighborhoods to multiple medical institutions in North Gainesville, while serving a large number of older adults and customers who live below the poverty level.

Grocery trips

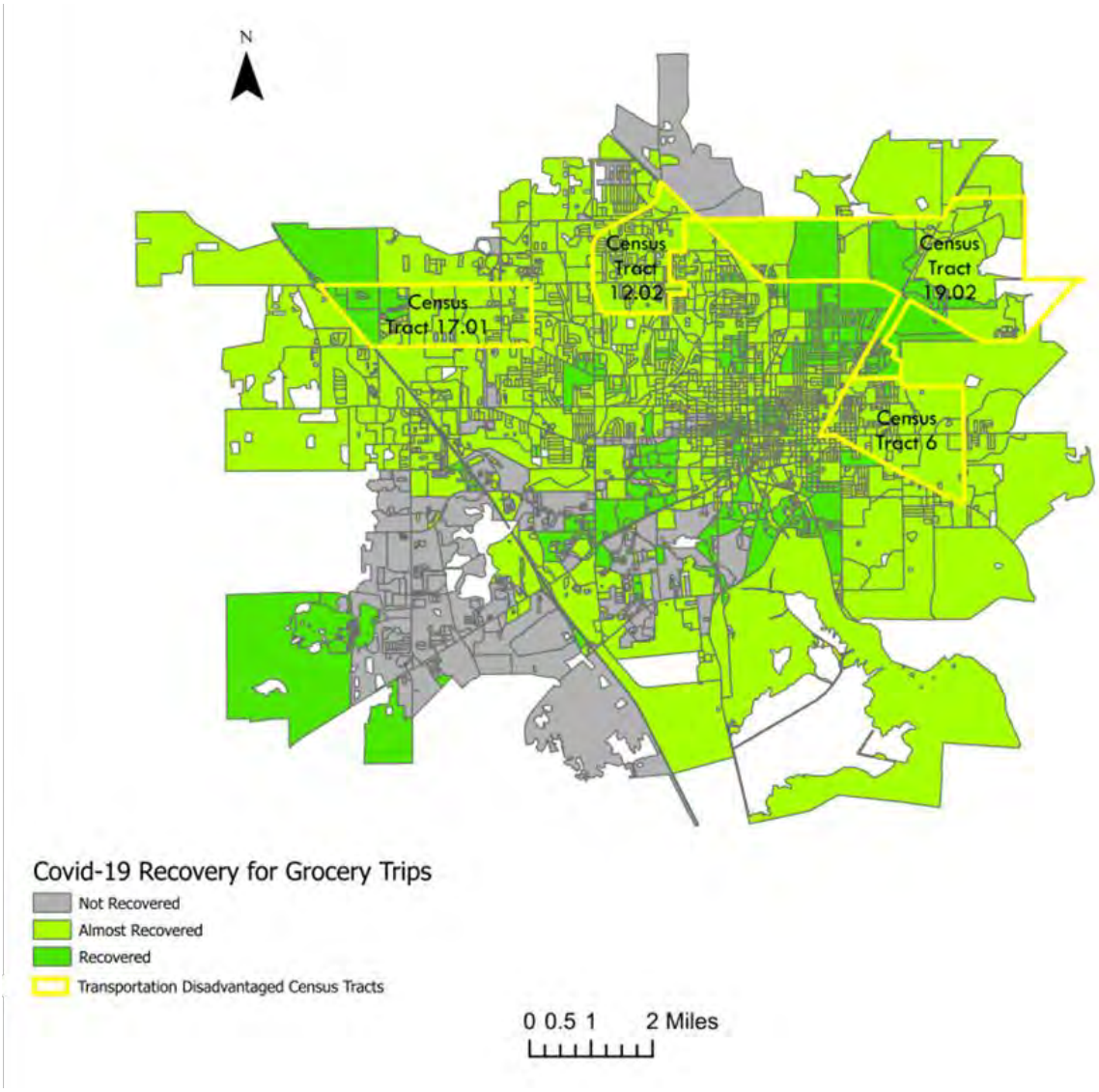

Figure 6-20. Transit-accessibility Recovery from Covid-19 for Grocery Trips

Transit accessibility for grocery trips has experienced positive recovery across the four transportation-disadvantaged neighborhoods (Figure 6-20). Specifically, both Tract 12.02 and 6 have almost recovered. We see that the previously highly impacted zone in the northwestern portion of Tract 17.01 has fully recovered. Tract 19.02 shows higher recovery levels. This is in part because the recovery period has allowed for the resumption of most bus trips. The relative convenient location of transit in relation to grocery destinations helps to maintain a relatively large number of trips that represent recovery.

Education trips

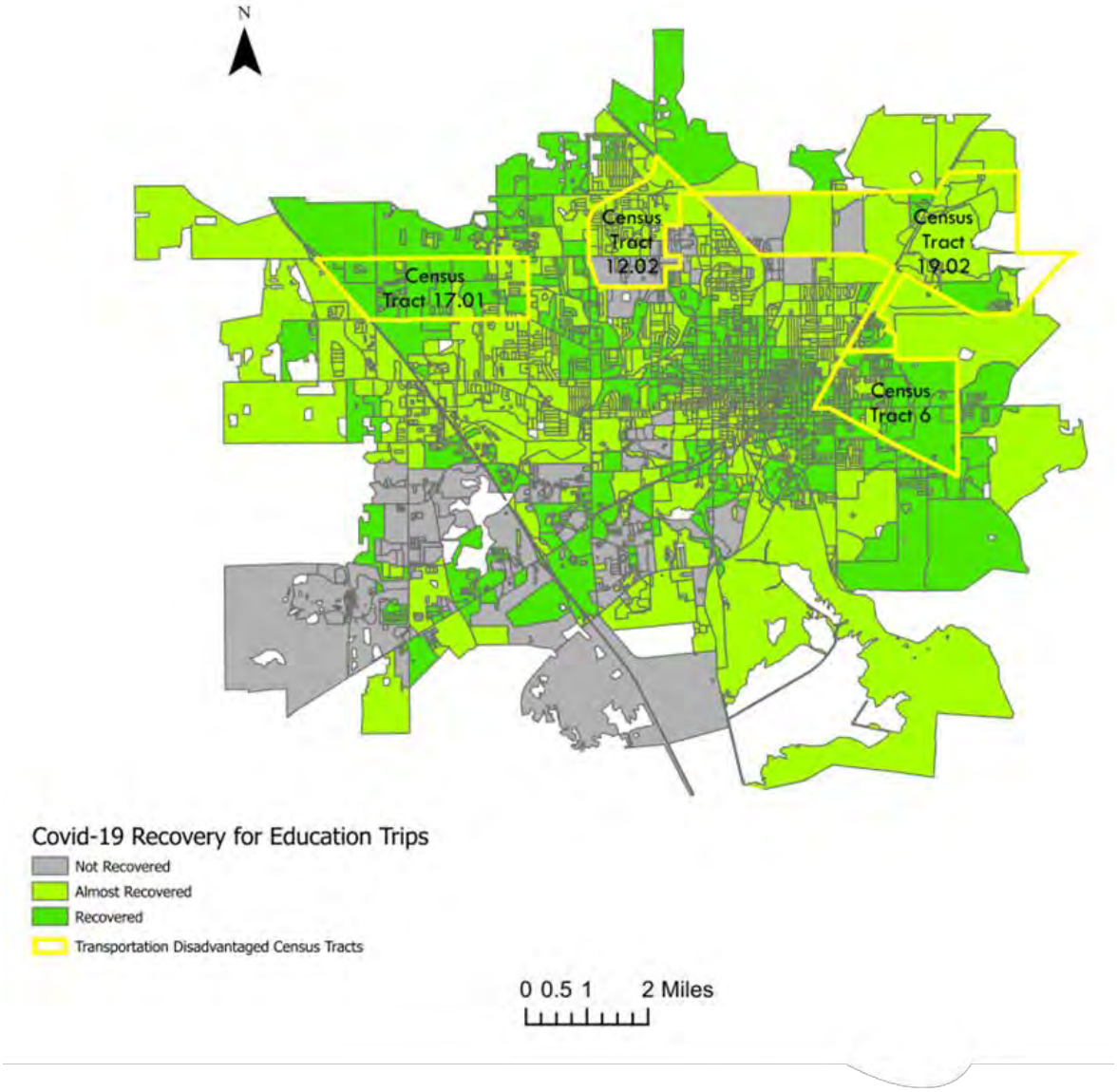

Figure 6-21. Transit-accessibility Recovery from Covid-19 for Education Trips

The level of Covid-19 recovery in terms of trips to school varies across the four transportation-disadvantaged neighborhoods (Figure 6-21). Tract 17.01 demonstrated an overall high level of recovery despite Routes 39 and 76 remaining suspended during the recovery period, and reductions in Route 10 frequencies. Routes 43 and 10 are both highly effective in distributing trips to both Santa Fe College and the University of Florida, as well as numerous elementary and high schools along their alignments. Low recovery rates in Tract 12.02 can be attributed to the combined suspension of Routes 29 and 39 that connect many to the University of Florida and to Santa Fe, respectively. Areas in Tract 19.02 that are not recovered can be attributed to the small number of schools inside these areas and the suspension of Route 39.

Social trips

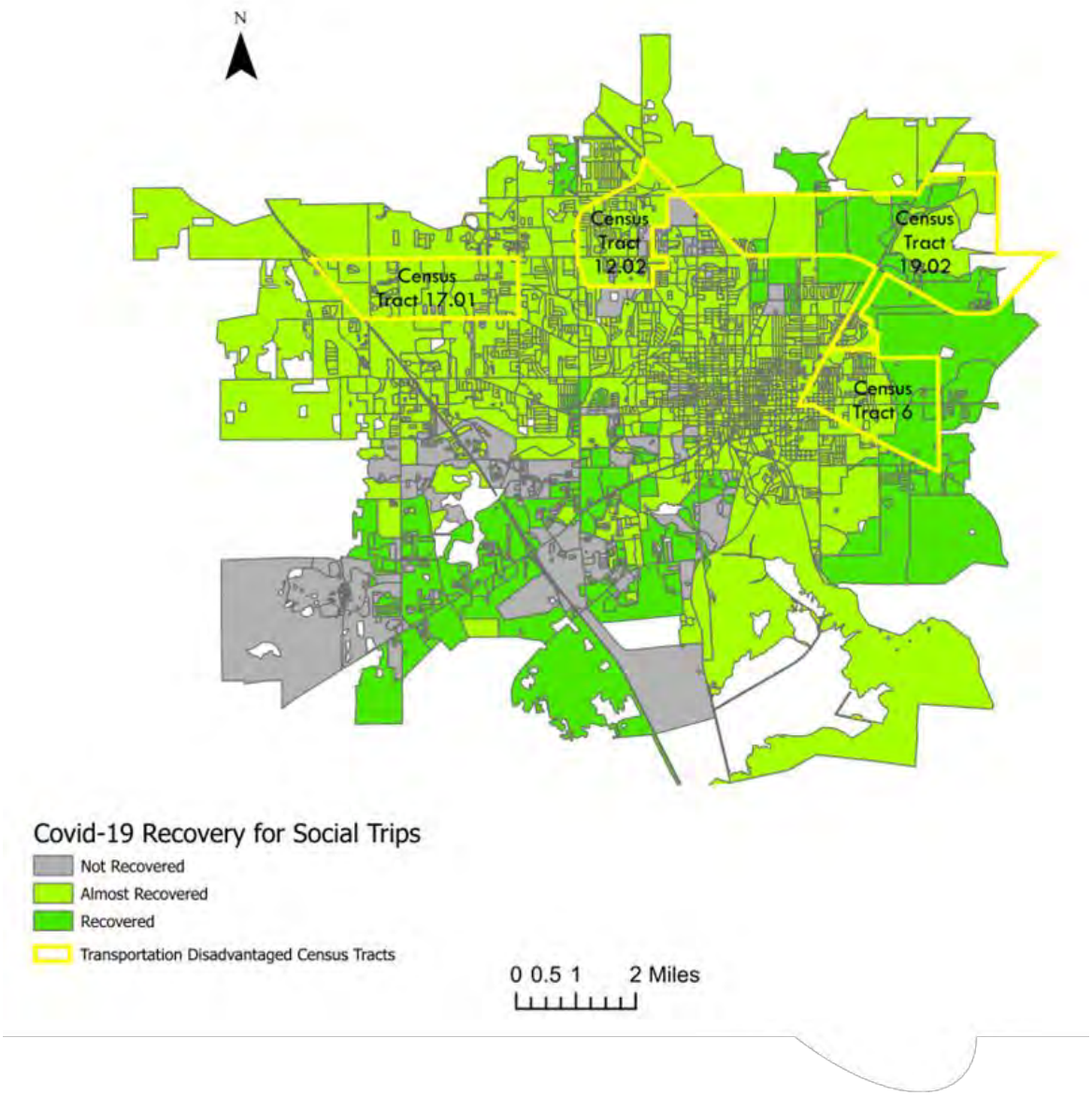

Figure 6-22. Transit-accessibility Recovery from Covid-19 for Social Trips

Trips for social purposes have almost recovered or fully recovered across the four transportation-disadvantaged neighborhoods (Figure 6-22).

6.3.3.3 Scenario 3: Development During the Next Five Years

Work trips

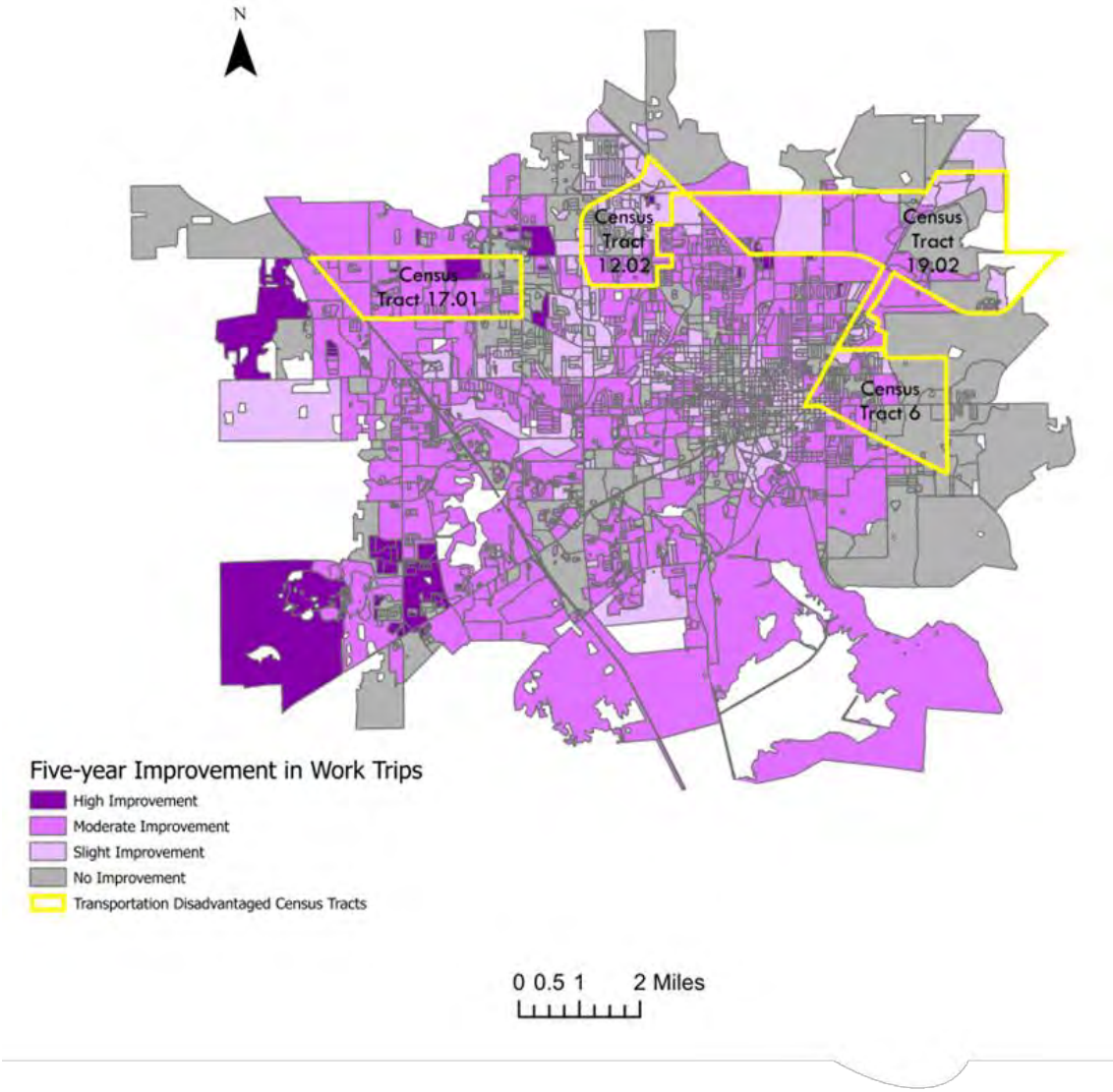

Figure 6-23. Five-year Improvement in Transit Accessibility for Work Trips

Over a five-year period, we saw an overall moderate improvement in the transit accessibility for work trips in Tract 17.01 (Figure 6-23). This was due in part to additional improvements to Route 43 which connected more people in this neighborhood to many work opportunities across the city of Gainesville. These opportunities included Santa Fe College down through several activity centers such as the Millhopper and Thornebrook Shopping Centers, NW 34th Street and University Avenue, and all the way across the University of Florida and ultimately to Shands. However, the north-easternmost portion of this neighborhood showed no improvements. This can be attributed to the model's sensitivity to the perceived improvements contributed by individual routes, because Routes 39 and 40 did not potentially contribute to

any improvements in the overall transit system. Therefore, the model demonstrates the combined level of improvement as low to none. Most parts of Tract 12.02 show slight or no improvements in terms of trips for work purposes. This could be an indication that the improvements listed in the RTS Ten-year Transit Development Plan were not sufficient to address connectivity to more workplaces.

Tract 19.02 was expected to show moderate improvements overall, which was attributable to an increase in frequency on Route 15 that has been responsible for connecting residents of this neighborhood to the rest of the city. With services extended until midnight as proposed the RTS Ten-year Transit Development Plan, the 1201 residents living under the poverty line in this neighborhood would benefit from the opportunity to use transit for work during late hours. Additionally, investments in Mobility on Demand (MOD) could be expected to create greater impacts on this neighborhood. Tract 19.02 falls under MOD Zone 3, which ranks second in terms of investments among the seven MOD Zones detailed in the Transit Development Plan. This can be attributed to demographics and geospatial relationships that have been discussed previously. The challenge that residents of this neighborhood face in getting reasonable access to transit service might be more easily remediated by the addition of on-demand services, such as microtransit.

The easternmost part of Tract 6 shows no improvements over the next five years. These areas have accounted very lightly for the microtransit service which has the potential to improve connectivity under the Transit Development Plan. While the suggestion to increase microtransit service along Route 7 would be responsible for higher levels of expected transit improvements in the neighborhood, additional considerations for microtransit service on the easternmost side of the neighborhood past SE 43rd Street, which remains severely disconnected, may be necessary.

Medical trips

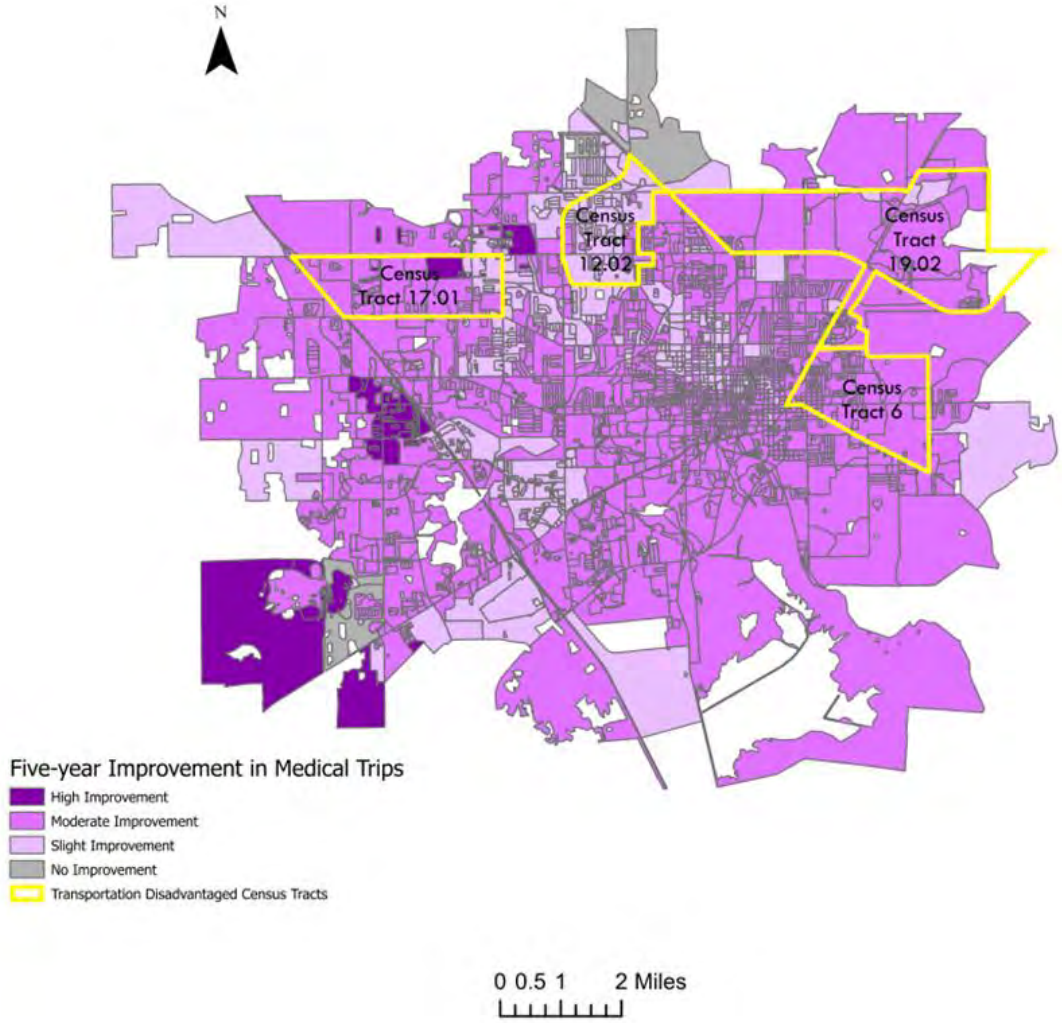

Figure 6-24. Five-year Improvement in Transit Accessibility for Medical Trips

Over the next five years, we expect moderate improvements in transit accessibility for medical trips in Tract 17.01, 19,02, and 6, and a slight improvement in Tract 12.02 (Figure 6-24). Particularly beneficial to Tract 17.01 would be an increase in frequency and expanded hours of service on Route 43. Transportation disadvantaged populations who live close to the route's alignment along 39th Avenue would benefit by connecting them to medical services at NW 16th Avenue and 43rd Street as well as to the Shands Medical Complex.

Despite a higher frequency and later hours of service planned on Route 6, these changes tend to show minimal improvements in the connection between residents in Tract 12.02 and medical destinations. This can be attributed to a lack of direct connection to medical services along the route, which requires either long walks or transfers to other routes to reach medical destinations.

Tracts 19.02 and 6 demonstrate moderate improvements on trips to access medical services due to extended hours of operation for microtransit services projected in Tract 6, and higher frequencies on Route 15 proposed in Tract 19.02. It is worth noting that our model is sensitive to the total number of destinations, and it is possible that expected transit changes would not yield dramatic improvements because medical hotspots like Shands or North Florida Regional remain a transfer away from either one of these two neighborhoods. Nonetheless, greater frequency and expanded hours of service will increase connectivity and reduce waiting times at transfer points for customers.

Grocery trips

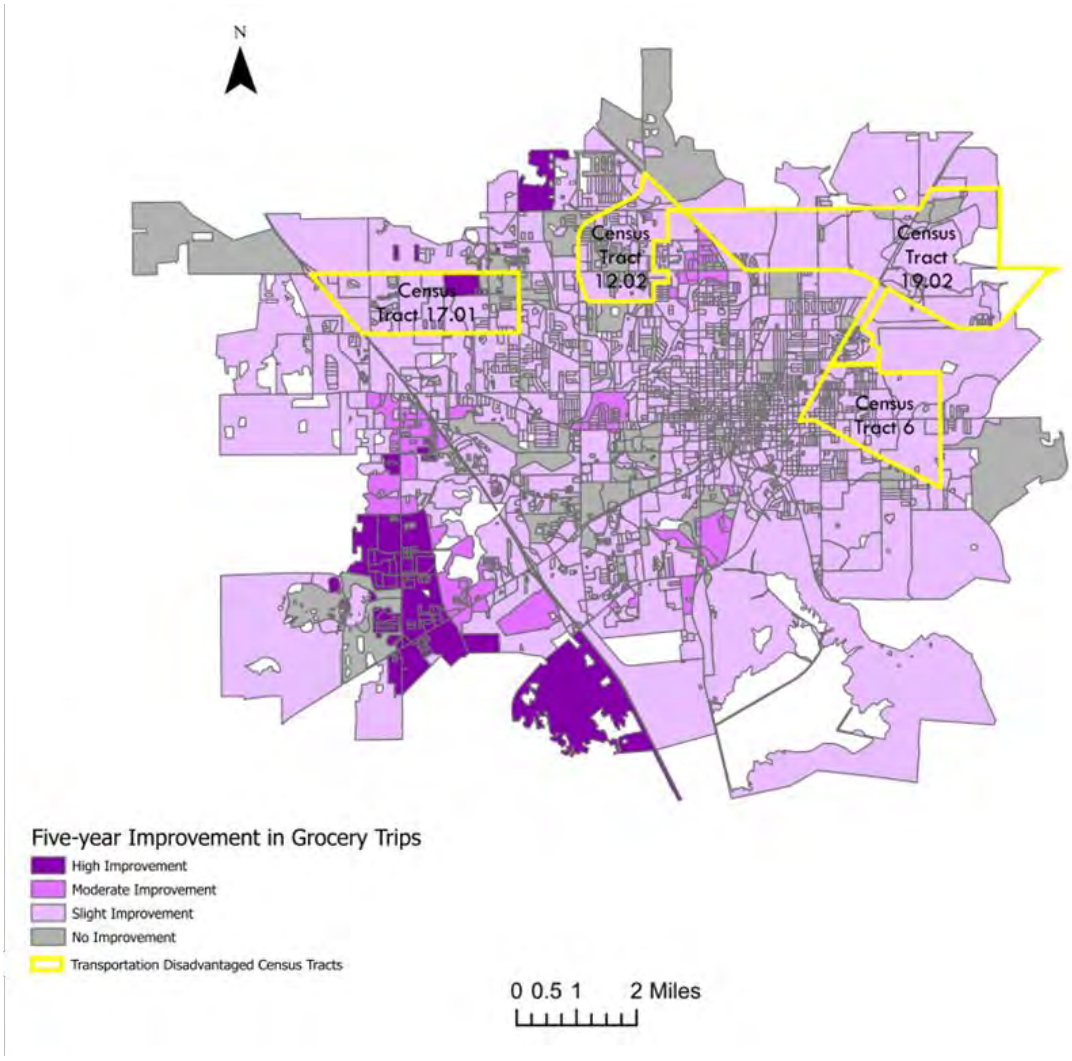

Figure 6-25. Five-year Improvement in Transit Accessibility for Grocery Trips

The current five-year outlook promises only slight improvements in transit accessibility to grocery stores in transportation-disadvantaged neighborhoods (Figure 6-25). It is possible that the relatively small number of grocery destinations are already strategically placed in such a way that proposed improvements in transit services would not make very noticeable changes in the accessibility to these destinations.

Education trips

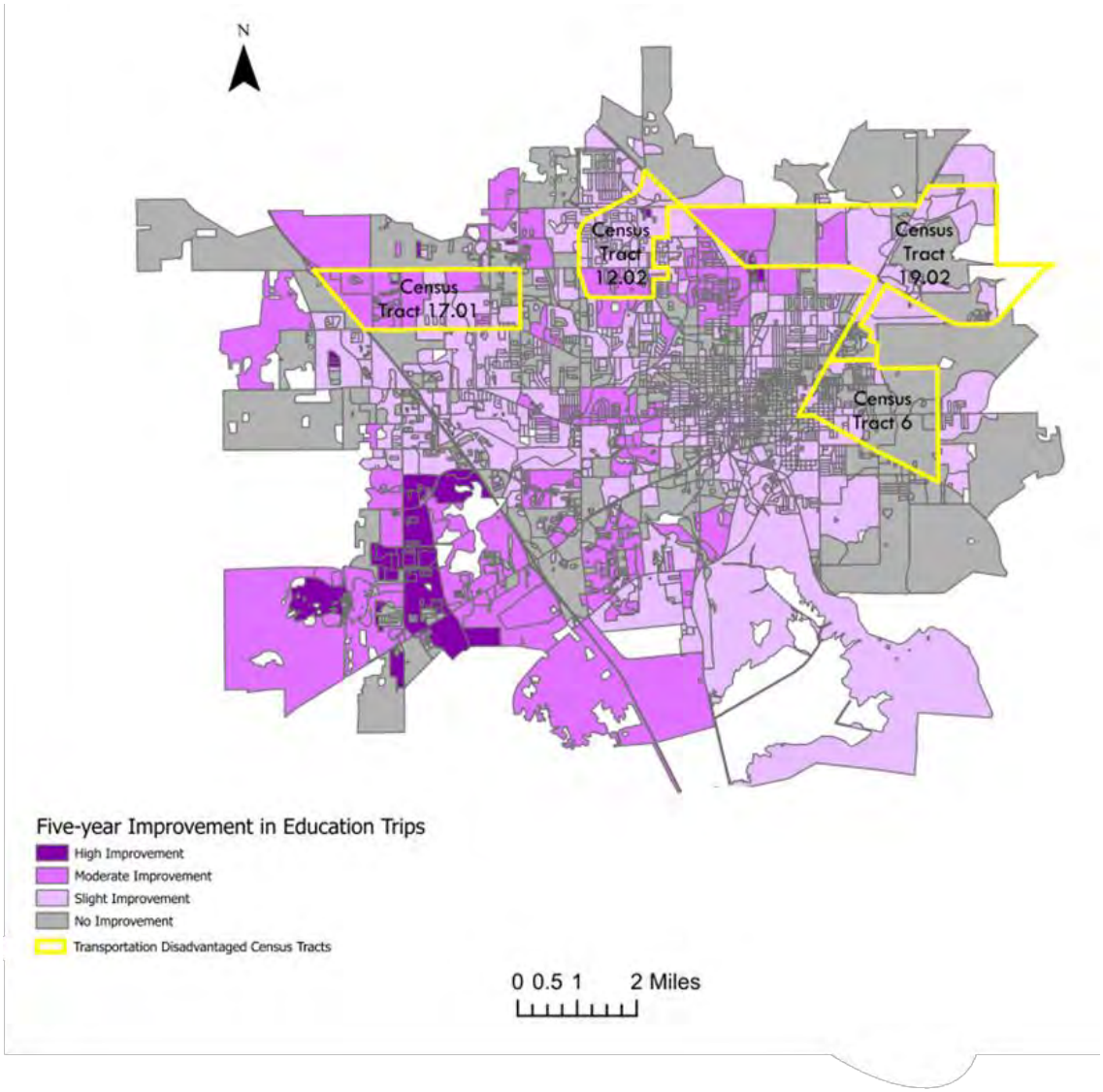

Figure 6-26. Five-year Improvement in Transit Accessibility for Education Trips

Improving transit services for education trips has been emphasized in the RTS Ten-year Transit Development Plan because the largest share of trips would be for the purpose of going from home to school and from school to home. However, the expected service improvements vary across the four transportation-disadvantaged neighborhoods (Figure 6-26).

Tracts 17.01 and 12.02 demonstrate widespread slight-to-moderate transit improvements designed to cater to students. Improvements on Route 43 will be highly favorable to users in Tract 17.01 to connect to the University of Florida and Santa Fe College. Improvements on Route 6 for those in Tract 12.02 will better connect users to Santa Fe College in downtown Gainesville. Most areas in Tract 19.02 also show slight-to-moderate improvements. The addition of Lite Bus Rapid Transit between Tract 19.02 and the UF campus, as well as improvements on Route 15, will serve to increase trips to Santa Fe College in downtown.

However, we found a disparity of service improvements in Tract 6, which remains widely lacking in improvements for transit accessibility for education trips. None of the proposed improvements would significantly enhance the connection between schools and transportation-disadvantaged populations in this neighborhood.

Social trips

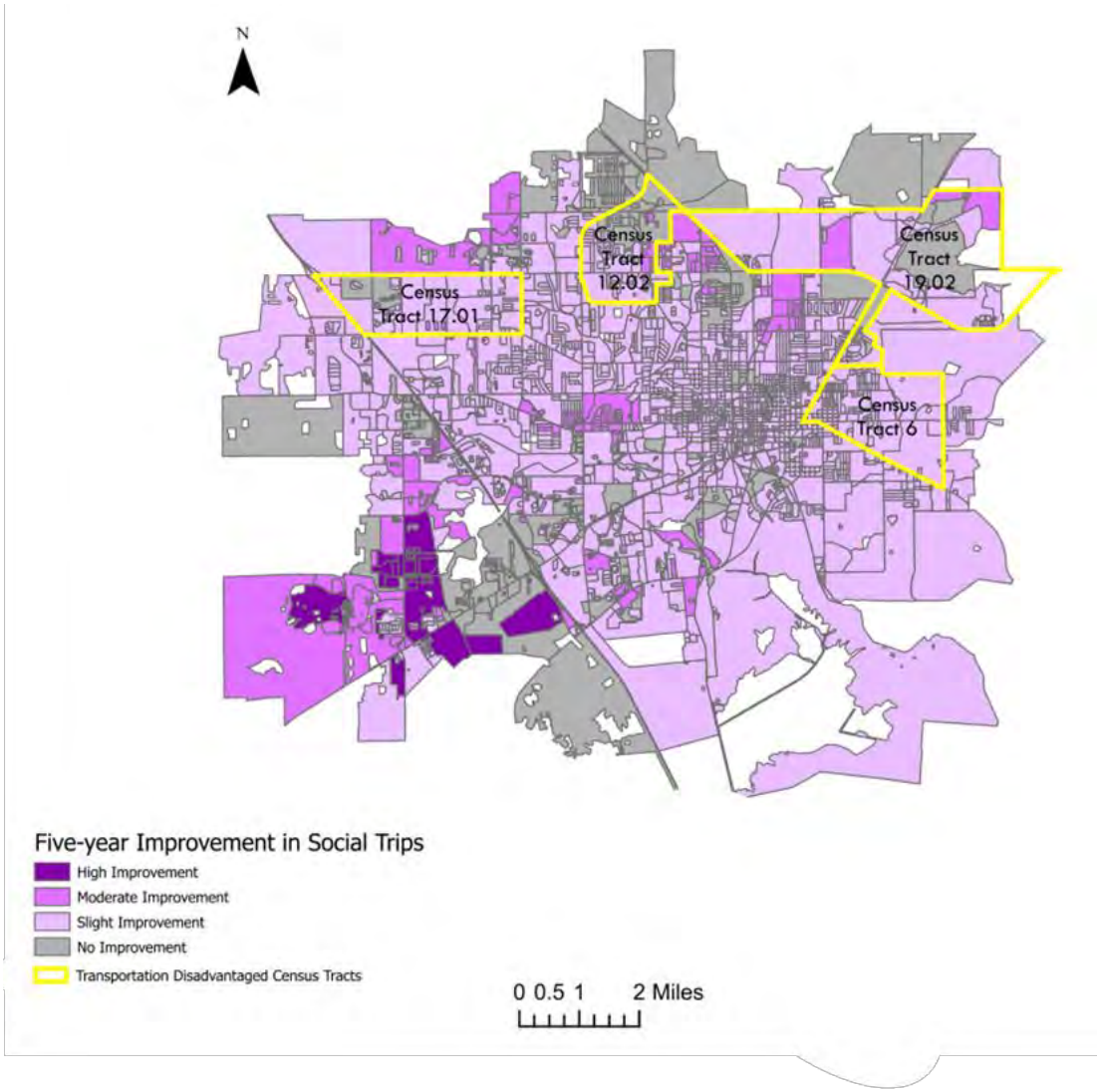

Figure 6.27. Five-year Improvement in Transit Accessibility for Social Trips

As for trips for social purposes, slight improvements are projected in Tract 17.01, potentially a result of increasing operation hours and frequency on Route 43, as well as its direct connection to a large number of destinations for social activities in the central part of Gainesville (Figure 6-27). Similar slight improvements are expected in the other transportation-disadvantaged neighborhoods. In Tract 12.02, a higher level of frequency is proposed for Route 6, and its connection to downtown Gainesville's multiple social destinations can be responsible for enhancing residents' social trips. Like Tract 12.02, transit improvements in Tract 19.02, particularly in Route 15, will favorably increase the potential for trips to downtown Gainesville. Finally, the projected on-demand investments will create direct connections for transportation-disadvantaged populations living in Tract 6 to access downtown Gainesville for social purposes.

6.3.3.4 Summary of Findings

Our model results reflect changes in the transit accessibility for different types of destinations under different scenarios. By comparing Scenario 1 and Scenario 2, we find how transit service changes during Covid-19 pandemic have affected the transportation-disadvantaged neighborhoods and how well transit services for these neighborhoods have recovered. Regarding transit trips for the purpose of work, the impacts of Covid-19 were overall low to medium, but the recovery varies across the four transportation-disadvantaged neighborhoods. Specifically, Tracts 12.02 and 19.02 still have many areas that have not recovered. As for medical trips, the pandemic posed a greater impact on Tract 17.01 and 19.02, with some parts of Tract 19.02 highly affected. However, the resumption of previously reduced transit services demonstrates an almost recovered status across the board. As for grocery trips, although the Covid-19 pandemic had a high-level impact on the northwesternmost part of Tract 17.01, the four transportation-disadvantaged neighborhoods all recovered well during Fall 2020. When evaluating transit accessibility for education and social trips, our model results only figuratively show the degree of impact and recovery. In our modeling analysis, we did not evaluate the plunge in transit demand for education and social purposes during the pandemic due to the stay-at-home order, or the shutdown of nonessential businesses.

Our model results also display the improvements that are projected to occur because of proposed transit changes in the coming years. The current five-year outlook promises slight improvements in transit accessibility for grocery and social trips in all the four transportation-disadvantaged neighborhoods. As for the access to jobs, medical institutions, and schools, we see greater improvements in Tract 17.01 compared with the other three transportation-disadvantaged neighborhoods. Tract 12.02 shows slight to moderate improvements for medical and education trips but shows limited improvements in terms of trips for work. Tract 19.02 is expected to see moderate improvements in work and medical trips overall, and slight to moderate improvements in education trips for most areas. In Tract 6, we observed a moderate improvement in medical trips, but limited improvements in work and education trips.

6.4. CONCLUSION

By evaluating transit accessibility in the scenarios of Covid-19 and the projected 5-year improvements, our model results show how transportation-disadvantaged populations could be affected due to changes in transit services and reflects the transportation needs that deserve priority attention. For example, the reduction in transit operation hours during the pandemic may have posed a greater impact on low-income people who may have to take jobs with inconvenient schedules, and who would be unable to so with fewer transit options. Additionally, older adults and individuals with disabilities dependent on transit could have been the most impacted group in terms of access to medical services. Thus, the development of alignments and configurations of routes and services need to be considered thoroughly to bridge the gap that can be generated by demand justification.

Our findings also help identify additional options for transportation services. Microtransit, or transportation network companies (TNCs), are possible alternative types of transit services that may represent cost-effective solutions to fulfill the needs of transportation-disadvantaged populations. Take one of the four transportation-disadvantaged neighborhoods in Gainesville, Tract 19.02, as an example. This neighborhood has a low population density and the housing developments and job areas are more insular compared to other parts of the city. Transportation needs in this transportation-disadvantaged neighborhood would likely be best addressed by microtransit, which has the potential to operate efficiently in low-density areas.

Some limitations need to be addressed in our future research. First, this study identified four neighborhoods with large concentrations of transportation-disadvantaged populations based on American Community Survey (ACS) data. We only used information about age, income, and physical condition to calculate the number of older adults, low-income people, and individuals with disabilities. Further investigation of residents' living conditions is necessary to reflect realistic transit demands of transportation-disadvantaged populations. Second, as mentioned above, our model did not take changes in the internal transit demands due to external environment, including the Covid-19 pandemic and the coming five years, into consideration. Third, although we conducted a DEA assessment of operational efficiency for each transit route, route efficiency was not accounted for in our transit accessibility model. For example, our model shows the significance of Route 39 in connecting transportation-disadvantage populations to various destinations. However, in practice, Route 39 has a relatively low operational efficiency. Improvements of the model are needed to better reflect the service level of transit routes.

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6.6 APPENDICES

Table 6.A: Operational Efficiency Data

Route	Operation Time	Round-trip Distance	Number of Stops	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
120	12.08	2.36	15	1037	1.00	1.000
127	12.47	2.20	18	1566	1.00	1.000
600	14.50	8.13	4	43	1.00	1.000
601	14.50	7.93	4	32	1.00	1.000
19	2.38	5.78	25	50	1.00	1.000
38	15.80	7.45	35	3771	1.00	1.000
118	14.27	4.82	25	2377	1.05	0.956
20	19.90	11.46	51	2477	1.52	0.657
21	13.17	9.05	41	1843	1.65	0.606
9	19.38	7.66	45	2177	1.73	0.577
28	10.42	9.80	48	1165	1.96	0.511
46	10.68	4.35	25	865	1.97	0.509
35	19.52	10.13	49	1796	2.10	0.476
33	18.97	9.82	25	1206	2.13	0.469
125	10.42	4.61	27	749	2.27	0.440

Route	Operation Time	Round-trip Distance	Number of Stops	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
13	17.92	6.47	37	1461	2.30	0.435
1	17.20	11.70	59	1556	2.42	0.413
12	20.73	9.30	47	1518	2.48	0.403
37	14.03	11.22	53	992	3.31	0.302
34	18.25	10.44	48	1088	3.47	0.289
5	20.38	12.77	65	1000	3.77	0.265
43	13.58	20.60	95	795	3.97	0.252
121	11.40	2.88	30	327	4.55	0.220
8	17.40	17.91	92	823	4.58	0.218
122	10.00	10.78	54	461	4.69	0.213
17	13.32	5.71	26	442	5.54	0.180
15	17.48	14.34	74	666	5.67	0.176
119	10.40	4.83	29	308	5.71	0.175
75	16.72	28.80	122	656	5.75	0.174
117	12.22	5.03	28	377	5.98	0.167
302	6.85	15.85	79	194	6.64	0.151

Route	Operation Time	Round-trip Distance	Number of Stops	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
126	16.30	6.31	38	485	6.78	0.147
800	9.92	18.00	16	92	6.95	0.144
36	11.42	11.06	56	341	7.49	0.134
23	14.80	13.37	31	426	7.53	0.133
29	10.68	7.33	44	298	7.89	0.127
10	12.50	17.12	76	340	8.40	0.119
11	14.33	12.85	62	387	8.70	0.115
25	10.57	8.91	51	251	9.25	0.108
26	15.40	16.30	53	391	9.36	0.107
76	9.97	16.45	55	216	9.95	0.100
301	6.48	14.08	80	119	9.98	0.100
16	18.27	7.42	33	329	10.73	0.093
7	13.83	12.01	66	256	12.60	0.079
300	7.00	9.36	50	103	12.94	0.077
6	14.07	15.53	67	246	13.37	0.075
40	11.70	13.61	55	196	13.43	0.074

Route	Operation Time	Round-trip Distance	Number of Stops	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
305	6.90	11.18	64	86	15.07	0.066
3	7.88	14.64	64	103	15.26	0.066
39	9.03	22.05	79	105	18.02	0.055
2	14.32	13.07	54	175	19.25	0.052
303	6.37	11.82	64	48	23.86	0.042
128	7.92	21.94	51	47	33.63	0.030
711	16.87	14.27	72	102	37.15	0.027
27	10.92	12.50	54	50	48.21	0.021
24	11.87	18.63	67	48	55.98	0.018
902	14.12	56.77	10	4	166.00	0.006
901	14.85	81.47	10	4	197.37	0.005

Table 6.B: Spatial Effectiveness Data

Route	Bus Commuters	Persons aged 65 and older	Persons with Disabilities	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
118	588	9	76	2377	1.00	1.000
120	400	19	36	1037	1.00	1.000
127	317	36	156	1566	1.00	1.000
901	15	41	27	4	1.00	1.000
600	20	76	81	43	1.00	1.000
38	1165	163	485	3771	1.00	1.000
601	20	76	81	32	1.35	0.742
15	203	1878	2802	666	1.48	0.678
46	265	412	672	865	1.50	0.666
20	1363	455	764	2477	1.52	0.657
13	594	455	632	1461	1.64	0.611
9	1740	499	1440	2177	1.73	0.577
26	150	1307	1836	391	1.81	0.552
35	1060	429	1035	1796	1.96	0.511
902	16	47	28	4	1.98	0.505
21	1250	229	544	1843	2.05	0.489

Route	Bus Commuters	Persons aged 65 and older	Persons with Disabilities	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
1	926	647	1054	1556	2.05	0.487
33	750	191	596	1206	2.30	0.436
12	1275	304	551	1518	2.48	0.403
125	564	26	62	749	2.58	0.388
5	687	1308	1550	1000	2.61	0.382
23	237	768	681	426	2.72	0.368
8	580	2926	2532	823	2.86	0.350
11	237	1560	1533	387	2.99	0.334
28	1492	236	625	1165	3.24	0.309
800	70	675	382	92	3.27	0.306
43	709	2756	2078	795	3.36	0.298
34	2044	565	1354	1088	3.47	0.289
75	567	2023	3135	656	3.53	0.284
37	1654	626	1379	992	3.80	0.263
7	202	1006	1333	256	3.81	0.263
17	440	334	486	442	4.37	0.229

Route	Bus Commuters	Persons aged 65 and older	Persons with Disabilities	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
10	351	3288	2388	340	4.90	0.204
117	471	37	197	377	5.37	0.186
29	330	1176	1165	298	5.38	0.186
6	276	2178	2569	246	5.51	0.181
122	671	300	687	461	5.59	0.179
126	935	46	217	485	5.59	0.179
2	210	1085	1355	175	5.81	0.172
16	439	452	496	329	5.87	0.170
25	323	1099	1671	251	6.31	0.158
76	292	1543	905	216	6.63	0.151
121	559	24	218	327	7.01	0.143
119	759	45	125	308	8.26	0.121
36	1521	270	551	341	11.05	0.090
40	541	2162	1360	196	11.39	0.088
3	246	1531	1688	103	11.61	0.086
711	272	1967	2003	102	13.13	0.076

Route	Bus Commuters	Persons aged 65 and older	Persons with Disabilities	Total Number of Passengers	Efficiency (μ)	Relative Efficiency (1/μ)
39	291	2787	2123	105	13.62	0.073
24	146	1679	2243	48	14.42	0.069
27	197	1852	2244	50	19.00	0.053
302	1623	912	1668	194	19.44	0.051
300	888	529	1121	103	30.15	0.033
301	2162	1013	2158	119	31.71	0.032
305	938	583	963	86	37.26	0.027
19	472	207	406	50	40.56	0.025
303	828	823	1372	48	61.09	0.016
128	1056	432	534	47	74.44	0.013

THE ROLE OF MAAS IN SUPPORTING RURAL COMMUNITIES' NEED TO ACCESS URBAN AREAS

Research conducted by Dr. Jeffrey LaMondia, Mitchell Fisher, and Jacob McGhee, Auburn University.

7.1 INTRODUCTION

Over the past decade, cities of all sizes have seen the growth of new modes to support daily activities. Many of these modes fall under the category of Mobility as a Service (MaaS), which include bikeshare/escooters (where patrons may rent a bicycle or scooter for a period of time), rideshare (where patrons may request a ride in the vehicle someone else is driving, most often seen as an Uber or Lyft), and carshare (where patrons may rent a vehicle for a period of time). These modes benefit travelers as they provide access and mobility without having to own or maintain these vehicles. They also benefit communities as they optimize available transportation systems and infrastructure.

However, while MaaS adoption and impacts in urban settings has being studied quite significantly, there is notably less research considering how MaaS can be implemented in rural communities. These communities are significantly different than their urban counterparts, with more dispersed geographies, less dense population densities, further separation between home/work/leisure locations, and populations different lower socioeconomic characteristics. Additionally, previous research highlights that MaaS mode adoption is heavily dependent on trip distances, which is of critical importance to rural communities. As such, the role of MaaS modes in supporting the mobility of rural areas (and specifically accessing urban areas) can be significantly different as well.

Therefore, this research seeks to understand how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to be utilized to support existing travel patterns through comparisons to urban MaaS use. Additionally, this research seeks to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity in rural areas. It is important to recognize that this work cannot consider latent demand for travel supported by MaaS; rather, it focuses on existing travel that could be converted to MaaS modes.

Therefore, there are two main objectives of this work: (a) determine the relative influence household and trip characteristics have on MaaS mode choices in rural areas and document how these differ from urban areas, and (b) determine the relative influence household and trip characteristics have on how far rural residents need to travel for different purposes and document how these differ from urban areas as well as which trips are most likely to support

MaaS adoption. Both objectives are completed using travel pattern data from the 2017 National Household Travel Survey. The first objective is addressed through an examination of the trends in MaaS trip mode choices considering a variety of characteristics as well as estimating multinomial logistic regressions of MaaS trip mode choices for rural and urban residents. The second objective is addressed through an examination of the trends in trip distances considering a variety of characteristics as well as estimating logarithm regressions of trip distances for rural and urban residents.

7.2. URBAN AND RURAL TRIP DATA FROM THE 2017 NATIONAL HOUSEHOLD TRAVEL SURVEY

This project utilizes the 2017 National Household Travel Survey (NHTS), conducted by FHWA, to measure how mode choice and trip distance influences differ between rural and urban settings. Overall, a total of 923,572 person trips were captured in this dataset completed by 263,991 individuals. This work focuses on 13 regional, trip, and sociodemographic variables that (a) provide detailed information to best capture trip characteristics and respondent sociodemographic groups, (b) build off previous research that has already identified known significant influencing factors, and (c) limit known correlating variable pairs (ex. income levels and education, or trip distance and trip duration). Table 7-1 lists each variable and its categories if not continuous. In this work, MaaS is identified as Carshare (e.g. rental vehicles) and Rideshare (e.g. Uber, Lyft, Taxis). The urban/rural designation developed by NHTS was adopted in this study.

To help limit modeling error, the final dataset was cleaned of distance outliers (any trip 1.5 times the interquartile range over the third quartile), trips with a trip distance of zero, and trips completed by modes defined as “other”. This reduced the final number of person trips to 894,737 with 191,191 person trips being completed by rural households and 703,546 person trips being completed by urban households. Additionally, trip distance, which heavily skews towards shorter distances, was transformed using a natural log function to better reflect a normal distribution for testing purposes. This helped satisfy regression requirements of assuming normally distributed continuous variables. Two types of models were used for this analysis: linear regression for modeling trip distance influencers and multinomial logistic for modeling mode choice influencers. The software SPSS was used to complete this analysis.

Table 7-2 presents two summaries of urban and rural trips in the dataset: (a) the percentages of trips in each category and (b) the mean trip distances in each category. Additionally, this table presents the results of a two-sample means hypothesis test on the statistical difference between urban and rural trip differences in each category (a p-value less than 0.001 indicates the two mean trip distances are statistically different at a 99.9% confidence level). Across almost all trip classifications, rural and urban trips have statistically different mean trip distances, with rural far exceeding the distances of urban trip (and with wider ranges in

distance), which makes use of MaaS for these trips challenging and only appropriate under specific situations. Interestingly, the only set of trip distances that are statistically similar between urban and rural areas were those associated with MaaS (or equivalent) modes (e.g. taxi, rental car, public transit/paratransit). In rural areas, distances for medical, recreation/social and shopping (important purposes for MaaS) are dramatically higher. While the data indicates that the higher your income, the further someone is likely to travel, on average, in both rural and urban areas, this does not extend to households where transportation is a financial burden. Finally, there were no major differences in trip distances for travelers of all race or age in rural and urban areas.

Figures 7-1 and 7-2 show the distributions of rural trip counts by distance band, trip purpose and mode (with the latter focusing on trips not by personal vehicle). Figure 7-1 shows all rural trips distributed by distance and purpose. Overall, the majority of rural trips are less than 15-miles, with a significant percentage even being less than 6-miles. This is promising for MaaS adoption, as these mid-distance trips are most supportive of MaaS modes. The shortest trips are focused on shopping/errands with social and work trips also represented. Although shopping and errands are a common purpose for travel across all distance bands, further trips of 15+ miles include more work travel compared to shorter trip bands. Additionally, one can see that almost all rural trips, regardless of purpose and distance are completed via personal vehicle. While personal vehicle trips could be converted to MaaS modes, it is important to consider how these modes are currently being utilized. Figure 7-2 focuses on the non-personal vehicle trips to see how these modes are being employed in rural areas. The dominant purpose across all distance bands is social or recreational, followed by work and shopping/errands. This graph highlights that carshare and rental MaaS modes are currently being used for intermediate trip distances of 6 to 50-miles. Paratransit is the most common for the 6 to 15-mi trip, while fixed-route transit is most common for the 15 to 50-mi trip (and even some trips with further distances). Interestingly, carshare and taxi modes are present in trips with intermediate distances, but only carshare is being used for trips over 50-miles. This indicates that taxi MaaS modes currently cannot support the long-distance trips. MaaS is more common for discretionary trips of shopping, social; but it is used for work access as well.

Table 7-1: Dataset Variables

CATEGORY	VARIABLE	TYPE	CATEGORIES	
TRIP CHARACTERISTICS	Trip Distance	Continuous (Miles)		
	Primary Trip Mode	Categorical	Personal Vehicle Walk Bike Public Transportation	Paratransit MaaS (Taxi, Uber, Lyft, etc.) Rental/Carsharing
	Primary Trip Purpose	Categorical	Home Work School/Daycare/Religious Activity Medical/Dental Shopping/Errands	Social/Recreational Transporting Someone Meals Something Else (Other)
HOUSEHOLD/INDIVIDUAL CHARACTERISTICS	Locale Type	Categorical	Urban	Rural
	Household Size	Continuous		
	Count of Household Vehicles	Continuous		
	Household Income	Categorical	Unknown Less than $25,000 $25,000 to $49,999	$50,000 to $99,999 $100,000 to $199,999 $200,000 or Greater
	Household Census Division	Categorical	New England Mid Atlantic East North Central West North Central South Atlantic	East South Central West South Central Mountain Pacific
	Respondent Hispanic Origin	Categorical	Unknown Yes	No
	Respondent Gender	Categorical	Unknown Male	Female
	Travel is a Financial Burden	Categorical	Unknown Strongly Agree Agree	Neither Agree or Disagree Disagree Strongly Disagree
	Respondent Age	Continuous/Categorical	Unknown Generation Z (Under 21) Millennials (21 to 36)	Generation X (37 to 52) Baby Boomer (53 to 71) Silent Generation (72 or Older)
	Respondent Race	Categorical	Unknown White Black of African American Asian	Native or Islander Multiple Races Other

Table 7-2: Trip Characteristic Summary Statistics by Category

	URBAN			RURAL			T-TEST P-VALUE
	Percentage of Trips	Distance		Percentage of Trips	Distance		
		Mean	St. Dev.		Mean	St. Dev.	
ALL TRIPS	100%	7.3	13.9	100%	10.2	14.5	<0.001
MODE							
PERSONAL VEHICLE	87.0%	8	14.3	93.2%	10.8	14.6	<0.001
WALK	9.9%	0.69	1.4	6.0%	0.77	2.1	<0.001
PUBLIC TRANSPORTATION	1.4%	8.7	10.6	0.2%	16.7	21.8	<0.001
PARATRANSIT	0.1%	8.4	11.1	0.0%	14.6	15.1	0.002
TAXI (UBER/LYFT)	0.4%	7.2	10	0.1%	9.3	12.7	0.025
RENTAL CAR (CARSHARING)	0.2%	19.1	30.2	0.1%	15.1	21.6	0.011
BICYCLE	1.0%	2.5	4.5	0.4%	3.7	7.4	<0.001
TRIP PURPOSE							
WORK	24.8%	9.9	13.4	11.6%	13.2	15.2	<0.001
SCHOOL, DAYCARE, OR RELIGIOUS ACTIVITY	8.8%	5.7	10.3	3.9%	8.3	10.5	<0.001
MEDICAL OR DENTAL SERVICES	3.7%	8.9	13.2	2.1%	15.7	17	<0.001
SHOPPING OR ERRANDS	40.2%	5.4	12	23.3%	7.5	11.9	<0.001
SOCIAL OR RECREATIONAL	22.5%	8.98	18.2	10.2%	10.9	17.4	<0.001
DIVISION							
NEW ENGLAND	1.3%	6.9	13	2.2%	9.5	14.4	<0.001
MIDDLE ATLANTIC	12.8%	6.9	13.3	19.4%	9.6	13.6	<0.001
EAST NORTH CENTRAL	10.9%	7.1	13.5	14.8%	10.4	14.8	<0.001
WEST NORTH CENTRAL	4.2%	7	15.3	3.1%	10.5	16.5	<0.001
SOUTH ATLANTIC	19.4%	7.5	13.9	29.9%	10.1	13.5	<0.001
EAST SOUTH CENTRAL	0.7%	8.6	16.9	1.7%	10.5	14.3	<0.001
WEST SOUTH CENTRAL	22.4%	7.4	12.6	14.1%	11	14.4	<0.001
MOUNTAIN	4.0%	6.7	14.1	3.6%	10	16	<0.001
PACIFIC	24.3%	7.3	14.5	11.2%	10.2	15.9	<0.001

Table 7-2 (Continued): Trip Characteristic Summary Statistics by Category

	URBAN			RURAL			T-TEST P-VALUE
	Percentage of Trips	Distance		Percentage of Trips	Distance		
		Mean	St. Dev.		Mean	St. Dev.	
HOUSEHOLD INCOME							
$24,999 OR LESS	13.2%	5.4	11.2	13.8%	9	12.6	<0.001
$25,000 - $49,999	18.4%	6.6	12.8	21.8%	9.7	13.6	<0.001
$50,000 - $99,999	32.0%	7.6	14.2	35.4%	10.5	14.7	<0.001
$100,000 - $199,999	27.7%	8	14.7	23.4%	10.9	15	<0.001
$200,000 OR MORE	8.7%	7.9	14.6	5.6%	10.8	15.9	<0.001
AGE							
GEN Z (20 & UNDER)	11.4%	6.17	13	10.1%	9.2	13.3	<0.001
MILLENNIALS (21-36)	17.8%	7.9	14.1	11.4%	11.34	14.6	<0.001
GEN X (37-52)	22.2%	7.9	13.9	18.4%	11.2	14.7	<0.001
BOOMERS (53-71)	36.3%	7.3	13.9	45.2%	10.2	14.6	<0.001
SILENT (72 & UP)	12.3%	6	12.7	14.9%	8.9	13.5	<0.001
RACE							
WHITE	77.9%	7.3	14	91.4%	10.2	14.4	<0.001
BLACK OR AFRICAN AMERICAN	7.5%	7.1	12.2	4.1%	10.3	13.3	<0.001
ASIAN	5.0%	7.4	12.8	0.6%	10.6	14.7	<0.001
AMERICAN INDIAN OR ALASKA NATIVE	0.4%	8	15.4	0.7%	10.2	14.9	<0.001
HISPANIC	9.3%	7.3	15.5	3.1%	10.4	14	<0.001
TRAVEL IS A FINANCIAL BURDEN							
STRONGLY AGREE	8.1%	7.3	13.2	10.6%	10.8	14.8	<0.001
AGREE	26.3%	7.4	13.9	31.2%	10.6	14.6	<0.001
NEITHER AGREE NOR DISAGREE	34.9%	7.3	13.9	35.1%	9.9	14	<0.001
DISAGREE	23.4%	7.1	13.7	18.1%	10.1	14.7	<0.001
STRONGLY DISAGREE	7.3%	7.1	13.4	5.0%	9.2	13.5	<0.001

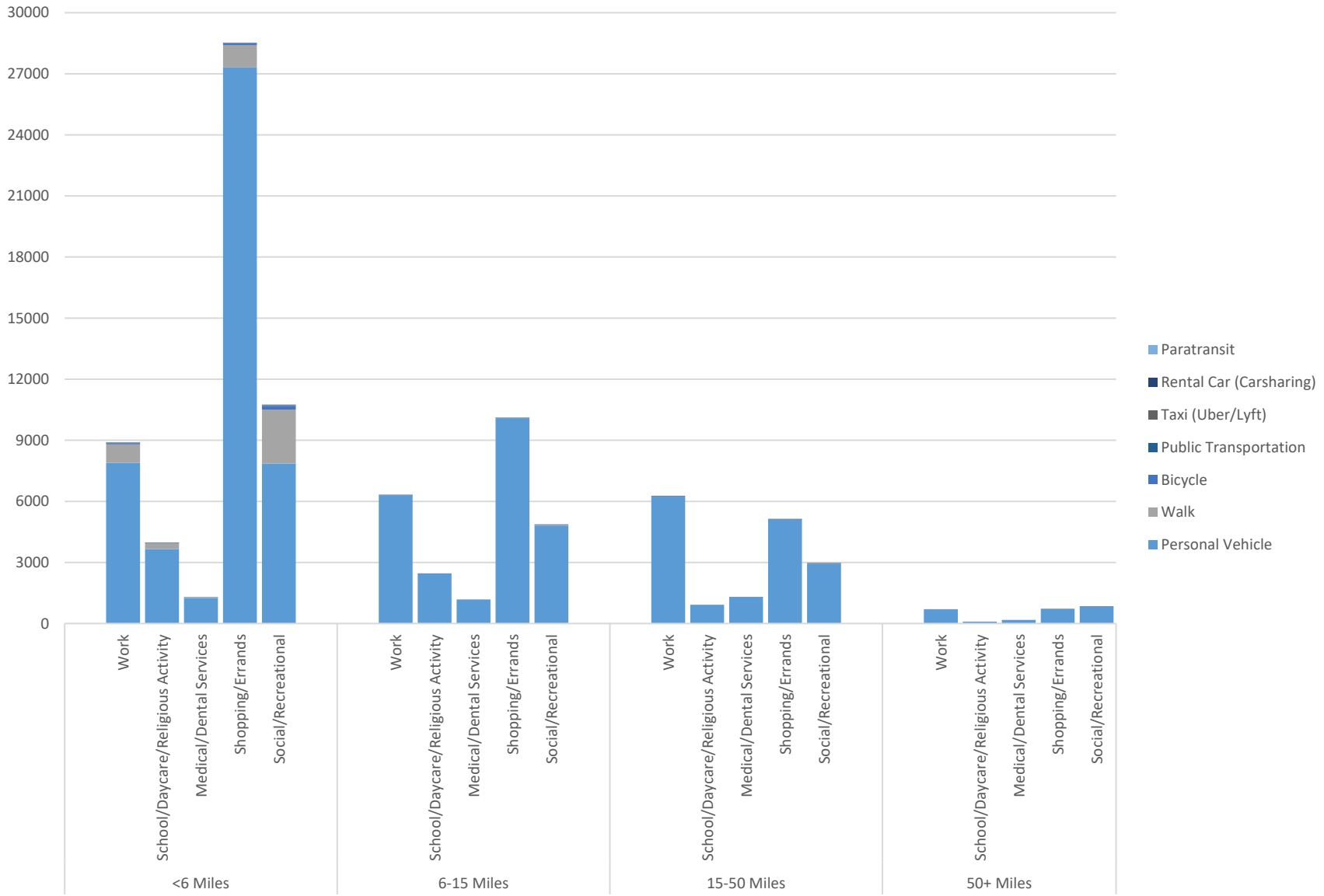


Figure 7-1: Rural Trip Counts by Distance Band, Trip Purpose, and Mode

Figure 7-2: Rural Trip Counts by Distance Band, Trip Purpose, and Mode (excluding Personal Vehicle)

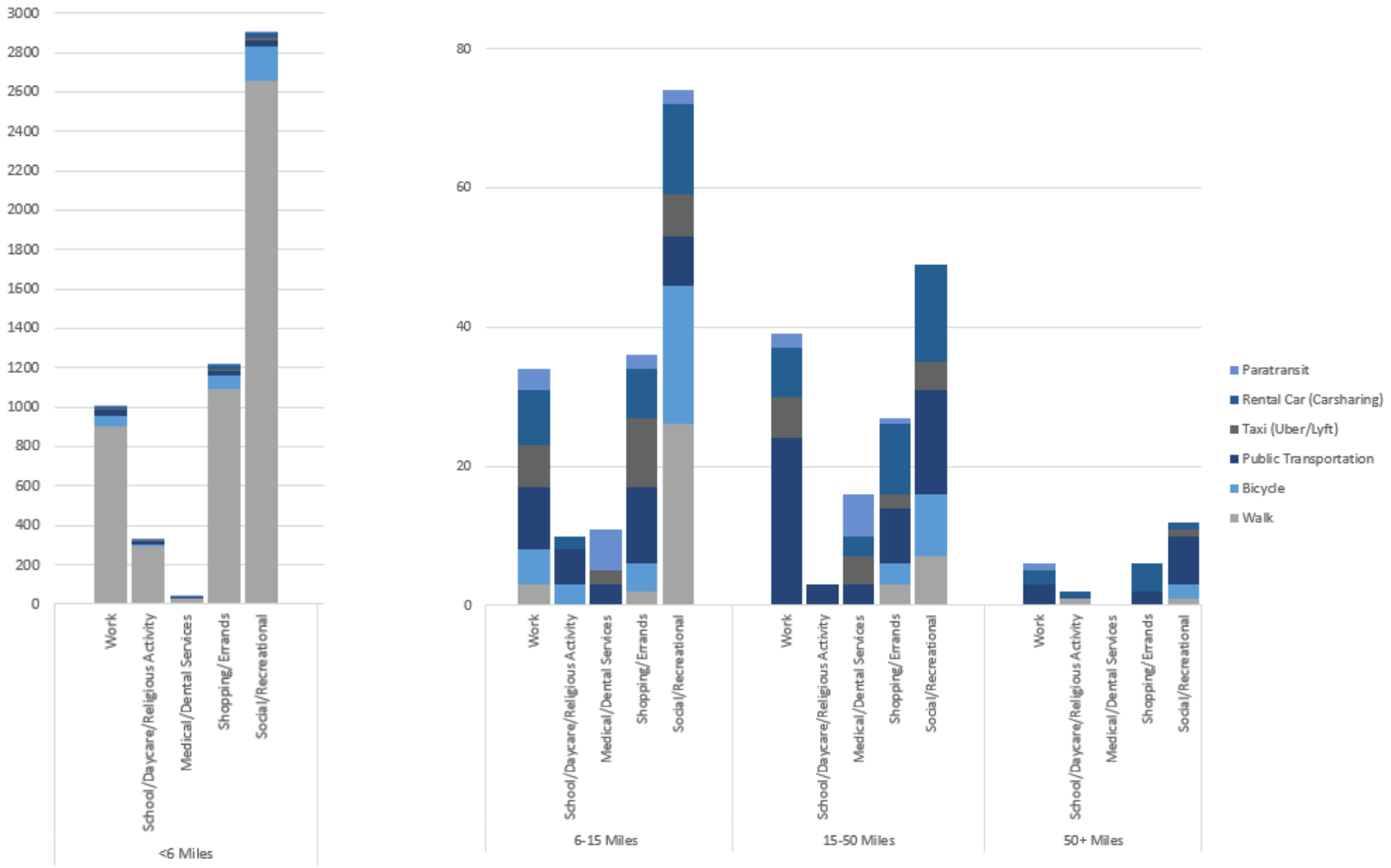


Figure 7-2: Rural Trip Counts by Distance Band, Trip Purpose, and Mode (excluding Personal Vehicle)

7.3. CHARACTERIZING AND MODELING RURAL MAAS MODE CHOICES AND OPPORTUNITIES

This section seeks to determine the relative influence household and trip characteristics have on MaaS mode choices in rural areas and document how these differ from urban areas. First, the trends in MaaS trip mode choices considering a variety of characteristics is examined. Second, two multinomial logistic regressions of MaaS trip mode choices for rural and urban residents are estimated. Survey weights were not used in the model estimation, as they are not needed for regressions when the relative coefficients for each factor/variable are being estimated and the sample size is large.

7.3.1 Trends in Mode Shares

Trips recorded in the National Household Travel Survey were analyzed with the goal of determining if the current use of MaaS modes (and modes that would translate into MaaS, should it be offered or expanded) differ between rural and urban areas. Specifically, we considered mode choices by (a) trip purposes, (b) trip distances, (c) census divisions, (d) household income, (e) household age, and (f) whether transportation is a financial burden for households. These breakdowns are important, as they offer insight into the different factors influencing mode adoption and opportunities for involvement.

First, Figure 7-3 compares mode uses by trip purpose. As we saw previously, most trips in both rural and urban areas are completed by personal vehicle, but these figures indicate this is true regardless of trip purpose. Across all purposes, public transit has a larger mode share in urban areas than rural areas, with the most use for work trips (2.4% and 0.3%, respectively) and medical trips (2.7% and 0.2%, respectively). MaaS modes (carshare and rideshare options) is about the same in urban and rural areas, with very low participation for every purpose. However, there is one notable difference in medical trips, where the largest shares are 1.0% in urban areas and 0.4% in rural areas.

Second, Figure 7-4 compares mode uses by trip distance. Personal vehicle dominates travel between 6 and 50 miles away, (about 96% in rural and 94% in urban) but MaaS mode more common in that distance in urban (0.9%) and transit (2.3%) than rural (only 0.2 and 0.4% respectively). This represents a meaningful opportunity for expansion of MaaS in rural areas, if other personal and geographic conditions are similar to urban areas. For short distances, there is a similar use of MaaS modes between urban and rural communities. Urban areas have a higher amount of public transit use (1.2% compared to 0.2% in rural areas). This distance band, however, is not the most efficient for MaaS modes (except for specialty options like escooters). Longer distance trips (of 50 miles or more) sees a major difference in mode choices. In rural areas, 89.6% of these trips are completed by personal vehicles and 0.8% are completed by MaaS modes. In urban areas, 84.2% of these trips are completed by personal vehicle and 1.5% are completed by MaaS modes (predominantly carshare).

Third, Figure 7-5 compares mode uses by census division. The NHTS data shows there are some regional preferences for mode choices. Rural to urban differences in personal vehicle use range between a 9.1% difference in the Middle Atlantic to 1.1% difference in the West North Central. The percentage of trips completed by personal is relatively consistent across the country (around 90%). For rural areas, East and West South Central census divisions have the most trips by personal vehicle (92.45%), and the Middle Atlantic census division has the least trips by personal vehicle (88.0%). Rural to urban differences in MaaS mode use range between a 0.1% difference in the West North Central (which was the only census region to have more MaaS use in the rural communities) to -0.5% difference in the Pacific. The percentage of trips completed by personal is relatively consistent across the country (all less than 1.0%). For rural areas, Middle Atlantic and West North Central census divisions have the most trips by MaaS (0.4%), and the rest of the census divisions have fewer trips using MaaS (0.2% or less).

Fourth, Figure 7-6 compares mode uses by traveler age. Interestingly, there are minimal differences in mode choices by traveler age. In rural areas, this was especially true for MaaS or transit use. In urban areas, MaaS use was present in each age group, but it was most common in millennials (0.9%), gen X (0.7%) and Boomers (0.6%). Transit use was the highest for millennials (2.1% of all trips), and use drops off as age increases.

Finally, Figure 7-7 compares mode uses by traveler income, and Figure 7-8 compares mode uses by whether the household feels transportation costs are a financial burden. In rural areas, MaaS is currently mostly used by households with income of $50 to 99.99k (0.7% of all trips) and those with $200k+ (0.4%). The rest of the households have fewer than 0.2% of their tripmaking done by MaaS. Additionally, households with the lowest and highest incomes recorded the highest amount of personal vehicle use. These results are rather consistent with the urban counterparts, where the most use of MaaS also comes from households with income of $50 to 99.99k (1.0% of all trips). Perhaps this is indicative of how MaaS serves the needs of a specific type of household and socioeconomic class. These results are consistent with whether transportation costs represent a significant financial burden for a household: the percentage of trips by MaaS are similar regardless of financial burden in both rural (0.3% on average) and urban (0.6% on average). Again, this points to the important role that MaaS can play in mobility for households that outweighs costs.

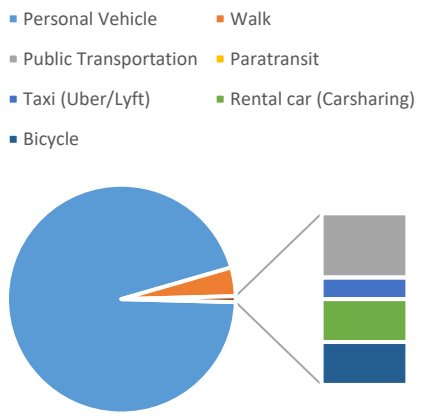
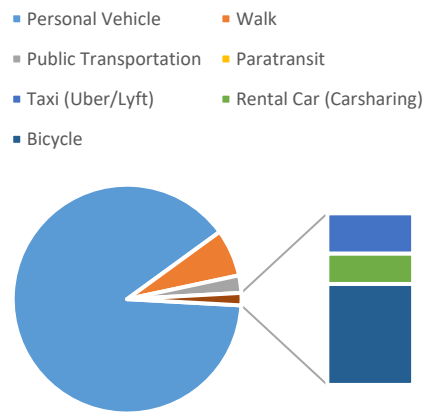
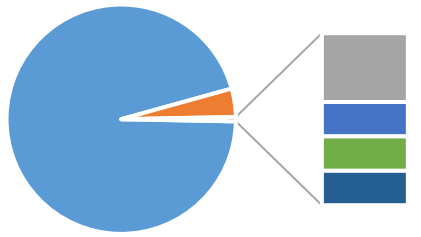
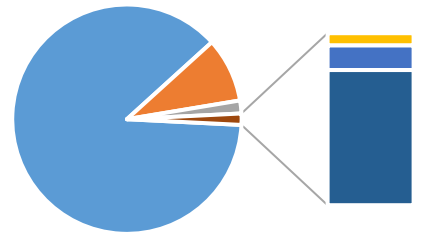
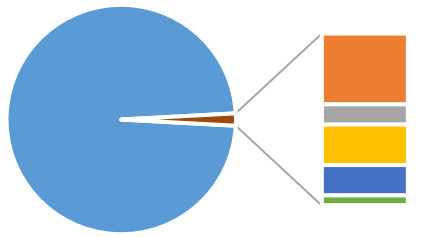
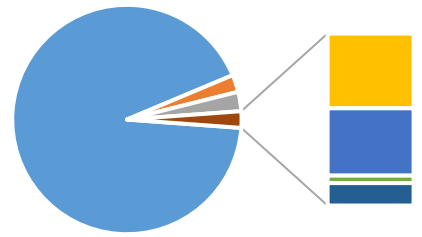
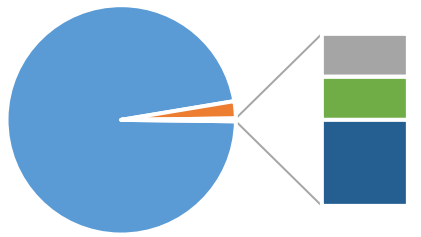
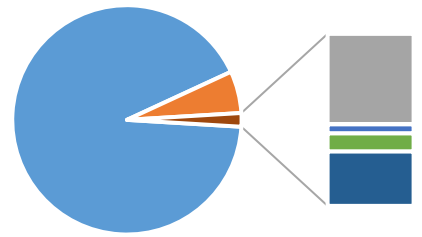
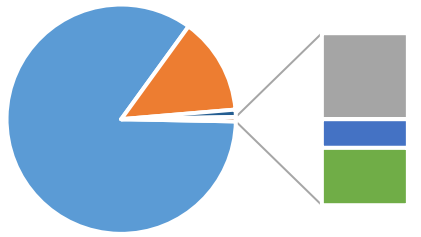
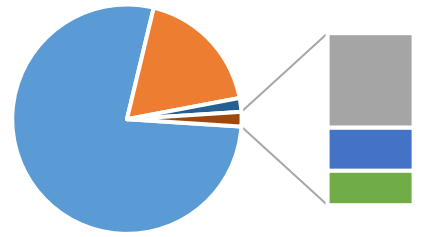
TRIP PURPOSE	RURAL	URBAN
Work		
School, Daycare, or Religious Activity		
Medical or Dental Services		
Shopping or Errands		
Social or Recreational		

Figure 7-3: Urban vs. Rural Trip Mode Share by Trip Purpose

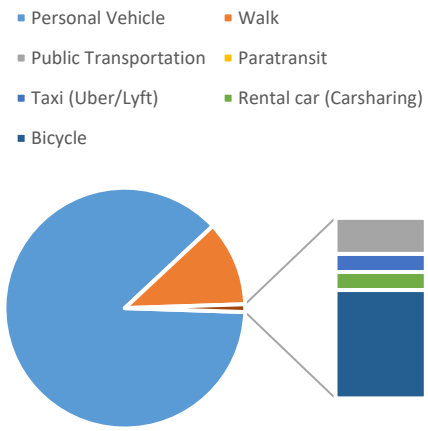
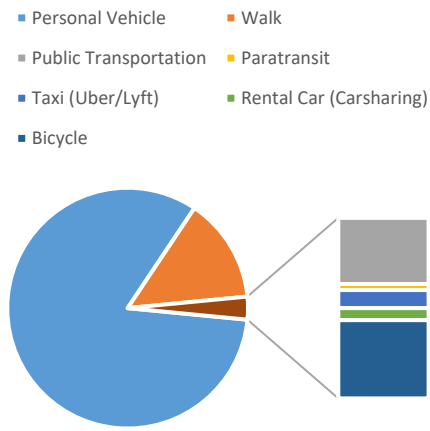
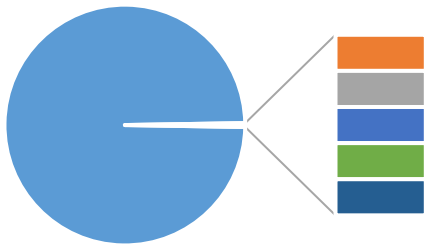
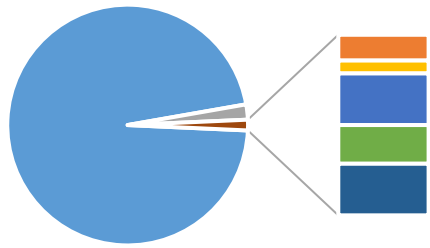
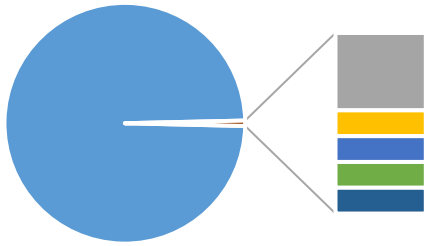
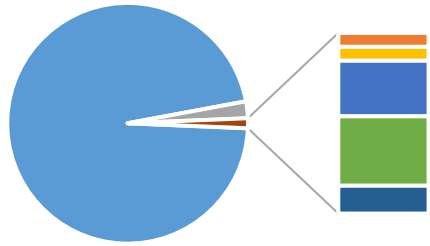
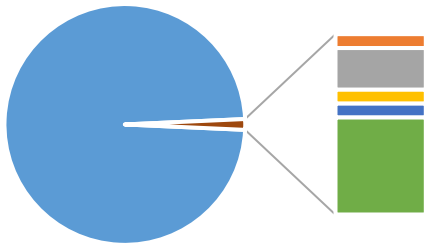
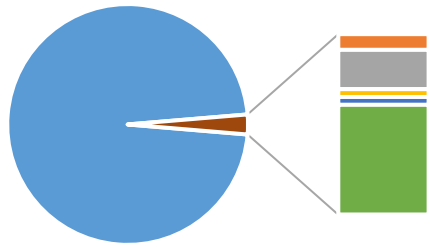
DISTANCE BAND	RURAL	URBAN
0-6 Miles		
6-15 Miles		
15-50 Miles		
50+ Miles		

Figure 7-4: Urban vs. Rural Trip Mode Share by Distance Band

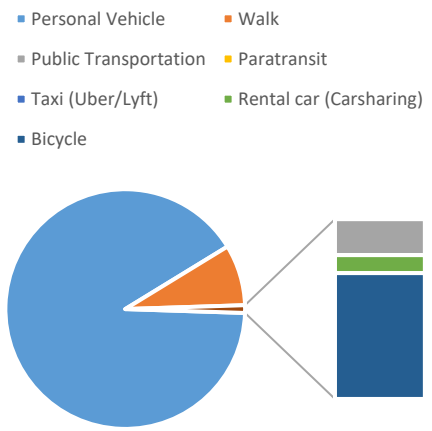
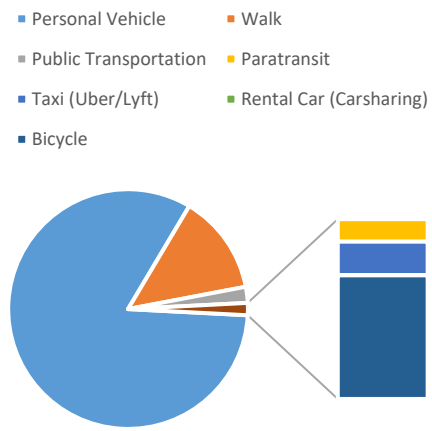
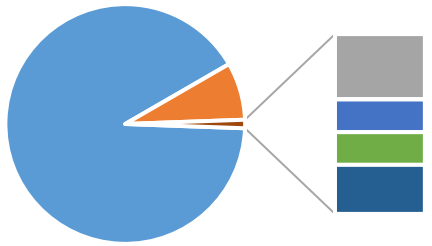
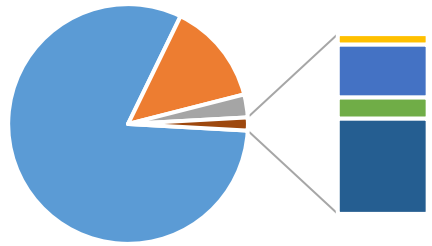
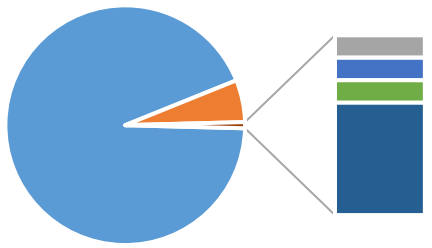
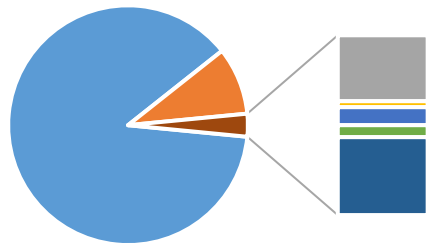
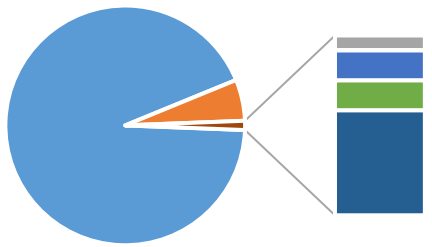
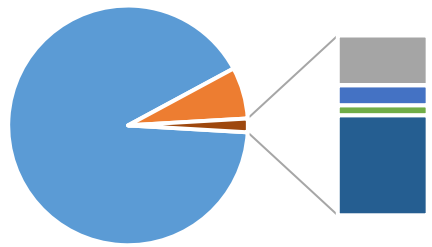
DIVISION	RURAL	URBAN
New England		
Middle Atlantic		
East North Central		
West North Central		

Figure 7-5: Urban vs. Rural Trip Mode Share by Census Division

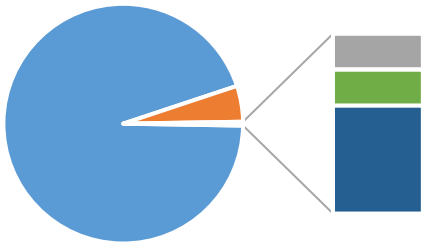
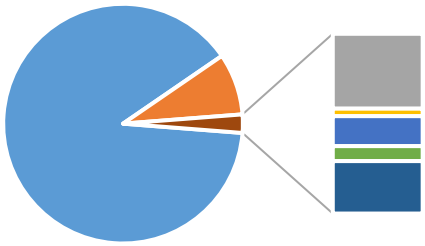
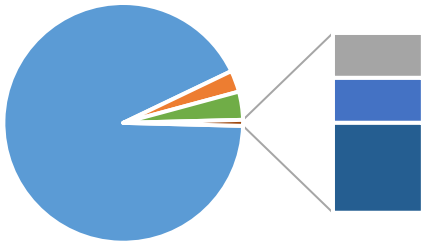
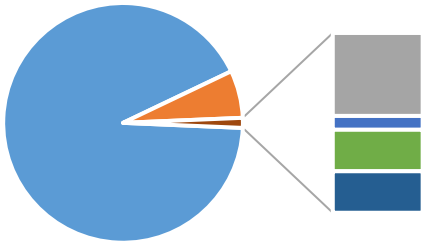
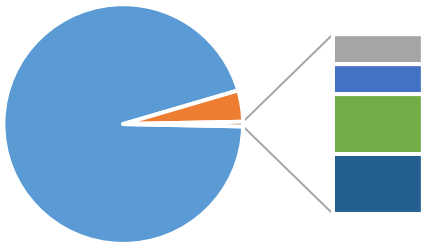
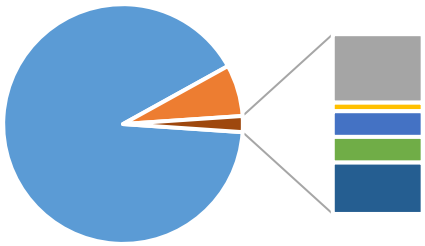
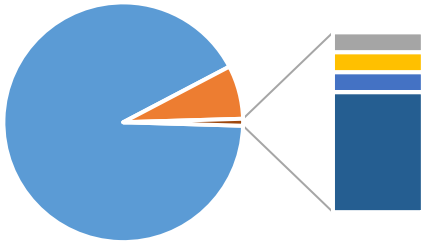
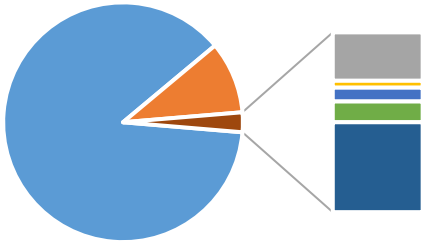
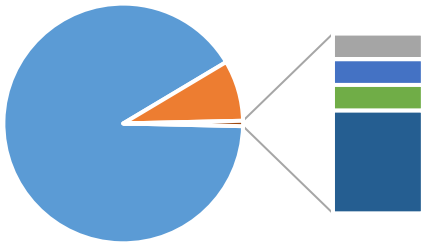
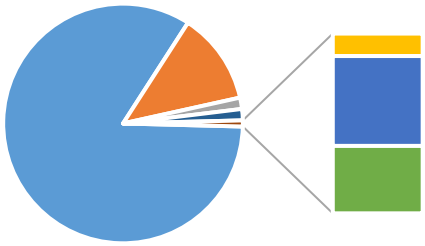
	RURAL	URBAN
South Atlantic		
East South Central		
West South Central		
Mountain		
Pacific		

Figure 7-5 (Continued): Urban vs. Rural Trip Mode Share by Census Division

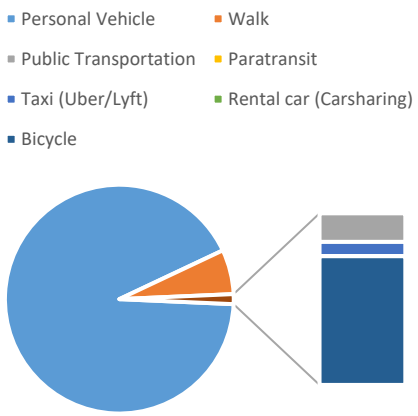
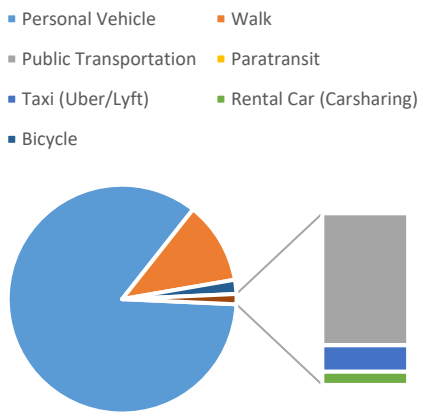
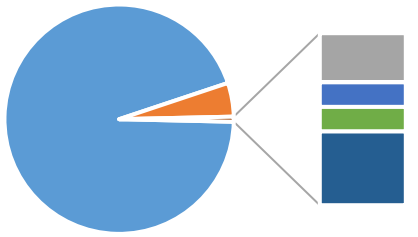
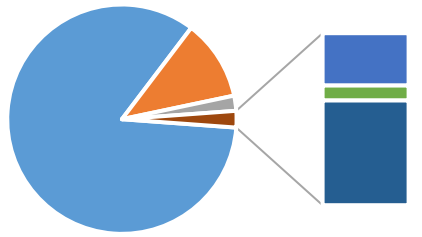
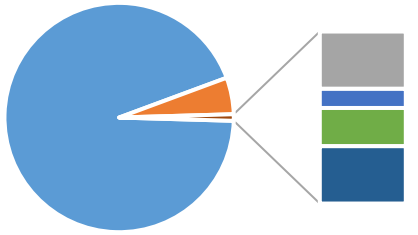
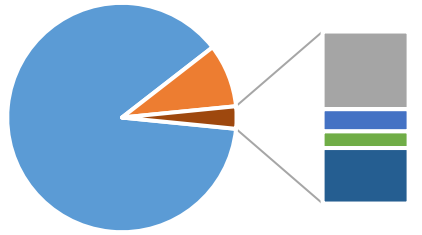
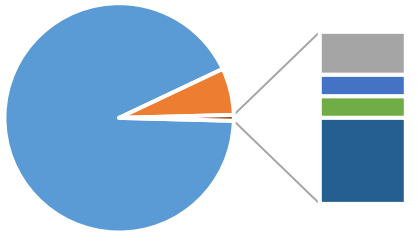
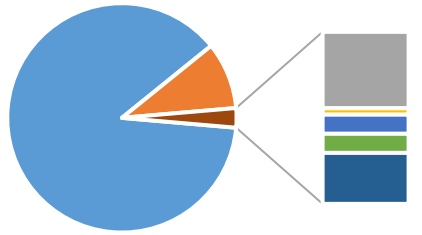
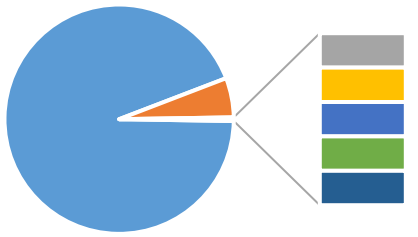
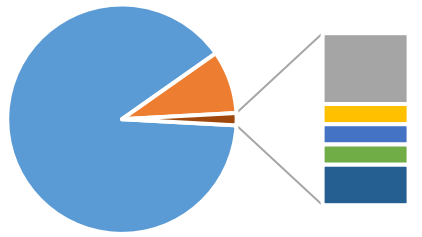
	RURAL	URBAN
Gen Z (20 & Under)		
Millennials (21-36)		
Gen X (37-52)		
Boomers (53-71)		
Silent (72 and up)		

Figure 7-6: Urban vs. Rural Trip Mode Share by Age

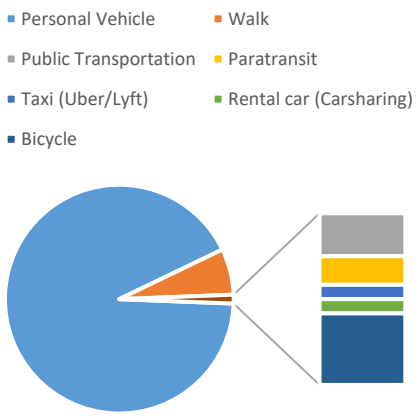
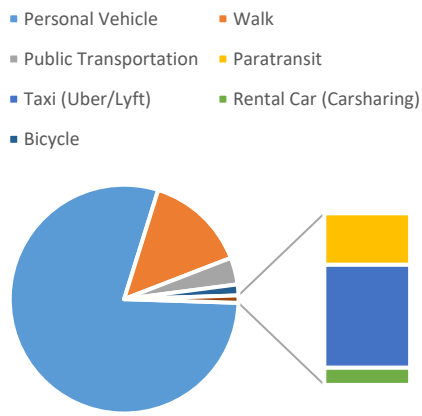
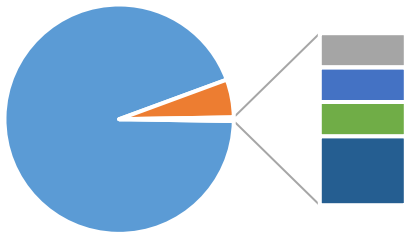
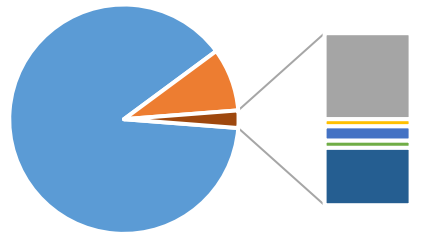
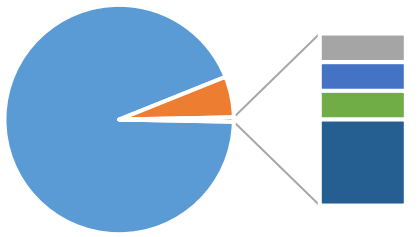
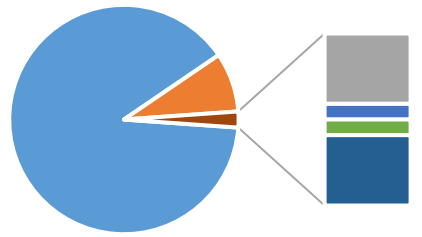
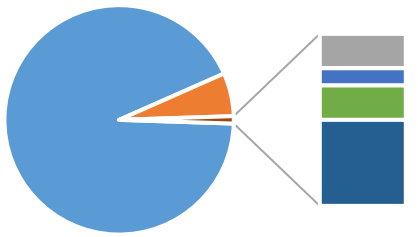
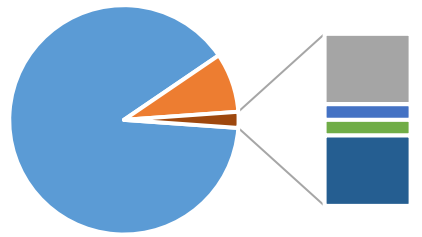
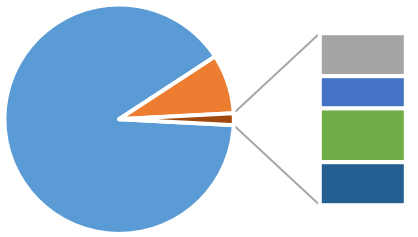
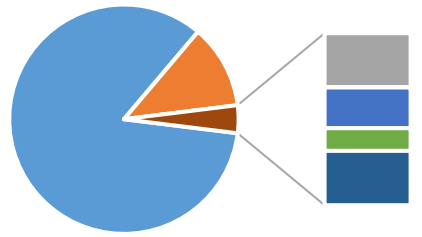
INCOME	RURAL	URBAN
$24,999 or less		
$25,000 - $49,999		
$50,000 - $99,999		
$100,000 - $199,999		
$200,000 or more		

Figure 7-7: Urban vs. Rural Trip Mode Share by Household Income

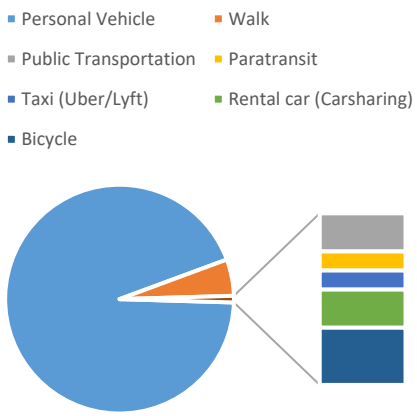
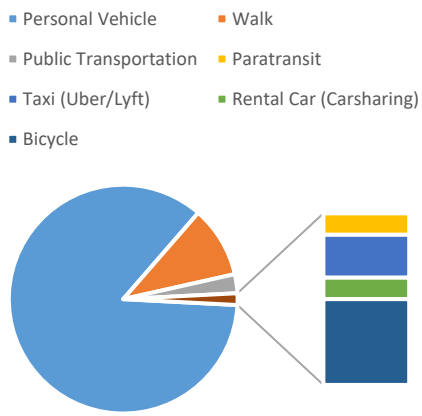
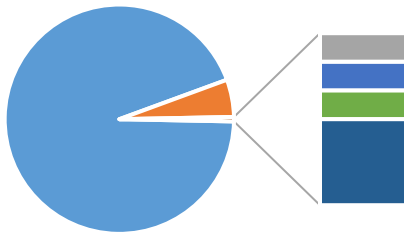
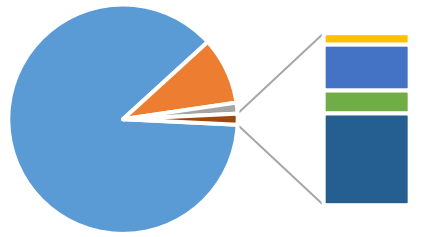
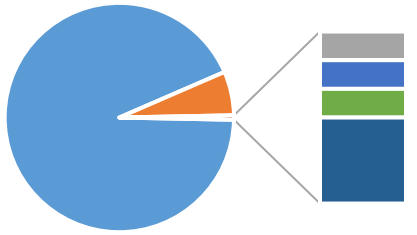
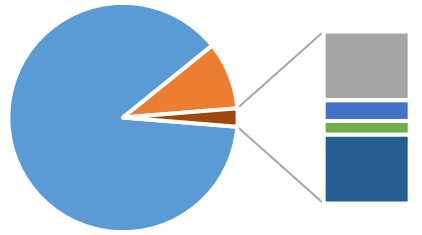
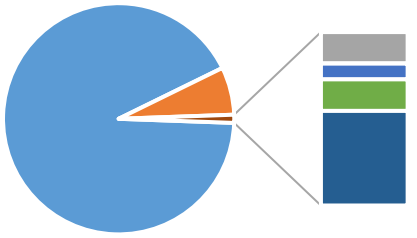
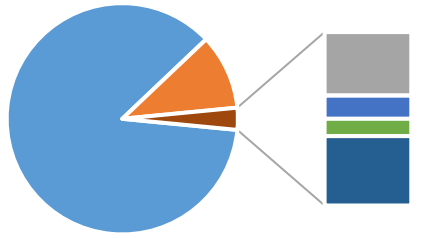
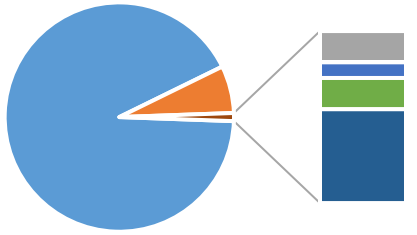
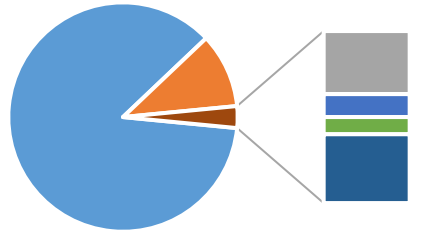
BURDEN?	RURAL	URBAN
Strongly Agree		
Agree		
Neither Agree nor Disagree		
Disagree		
Strongly Disagree		

Figure 7-8: Urban vs. Rural Trip Mode Share by How Much of a Financial Burden Travel Is

7.3.2 Factors Influencing Rural vs. Urban Mode Choices

To best compare alternative mode utility among rural and urban environments, two multinomial logit models were created via R's mlogit packet. Each model assumes personal vehicle as the base mode, so all coefficients are directly comparable to the likelihood, or unlikelihood, of an individual preferring one of the alternative mode choices. The rural model was created using 191,191 individual trips, after outlier and zero-distance trips were removed. Final model log-likelihood was -31,692. Table 7-3 displays the model results.

Trip purpose showed mostly negative coefficients for all alternative mode choices. The only exception was with the paratransit alternative: highlighting all positive coefficients. As this mode had the smallest mode share (62 trips), the potential for less trip/respondent diversity could play a part in coefficient influence. However, paratransit did see a strong positive influence regarding medical/dental purpose trips compared to all other modes alternatives potentially reflecting the more vulnerable populations associated with this mode choice. Other positive purpose variables relative to mode choice included positive influence on choosing walking or biking over personal vehicle with social/recreational trips; possibly capturing exercise activities. Travel distance was modeled both as raw distance (in miles) and the natural log of the distance (as trip distance distribution heavily skews towards smaller trip distances, transforming via natural log creates a more normal distribution pattern). Results reflected expected outcomes as with walking, biking, and MaaS; with these modes losing likelihood as trip distance increased. However, public transportation, paratransit, and rental/carsharing likelihood *increased* with trip distance. The reasoning for this is not immediately apparent and may warrant further research.

Household and respondent characteristics exhibited a wide range of influential variables. Both household size and household vehicle count had a negative influence across all alternative mode choices showing as these variables increased, the likelihood of choosing a non-personal vehicle mode decreased. Household location showed negative influence for walking, biking, and MaaS across all significant Census Division categories relative to the Pacific division, reflecting general favoritism for personal vehicle usage. Public transportation had a positive influence within the Mid Atlantic division and a negative influence within the South Atlantic. This could reflect these regions presence (or lack) of rural public transportation infrastructure. Paratransit use had positive significant coefficients for the New England, East South Central, and Mountain divisions when compared to the Pacific division potentially suggesting higher ridership or modal access in these divisions. Similarly, carsharing/rental had all positive significant coefficients in four divisions (Mid Atlantic, East North Central, South Atlantic, and East South Central) compared to the Pacific division and other mode choices.

Income-related factors, such as household income and identifying if travel is a financial burden, provided some significant insights into mode choice in rural communities. For biking, public transit, and paratransit, all significant responses to "travel is a financial burden" yielded a negative coefficient relative to an "unknown" response base and choosing personal vehicle as

the mode choice. With bike and public transit, generally, the more a respondent agreed that travel was a financial burden, the less likely they were to bike or ride public transit. However, this could reflect households existing in very poor, rural areas where these options may not even be an option. Interestingly, respondents were more likely to choose walking over personal vehicle the more they viewed travel as *not* being a financial burden. A possible explanation for this would be walking trips by these respondents may be more recreational in nature having more time to engage in these types of trips than more burdened individuals. Carsharing/rental choice showed that generally, the more financially burdensome a respondent viewed travel, the more likely they were to choose this mode over personal vehicle. Tying in household income, however, showed an inverse affect where households with incomes $200,000 or greater were more likely to choose carsharing/rental and households making under $50,000 were less likely. Other income findings saw walking trips increased in likelihood as household income increased (further hinting towards the recreational nature of these trips), and biking trips more likely for low income (under $25,000) households. Public transit showed increased likelihood for both income extremes: under $25,000 and $200,000 or greater. This could be capturing commuter trips for higher income households as well as individuals where personal vehicles are not an option. Paratransit and MaaS showed inverse relations with less than $25,000 households having a greater likelihood of choosing paratransit, and households making $200,000 or greater having a higher likelihood of choosing MaaS, relative to an unknown income and to personal vehicle. As both these modes work relatively similarly (with a major difference being cost), this could be illustrating an income divide.

Rural respondent demographics also showed some insights on mode choice habits with respect to gender, generation, and race. Gender results showed all negative coefficients compared to a base of unknown gender and choosing personal vehicle, once again illustrating the dominance personal vehicle travel has in rural communities. However, both generation and race provided some varied insights. Respondents under the age of 21 (Generation Z) had a positive influence on choosing bike over other modes, while those identifying as 72 or older (Silent Generation), had a strong negative influence. This is most likely related to either (a) younger individuals not being able to drive or have easy access to a vehicle, or (b) mobility limitations associated with advanced age. This is partially supported with walking as the older generations (Baby Boomers and the Silent Generation) showed a gradually decreasing likelihood with choosing this mode over personal vehicle. Public transit and paratransit showed inverse influences for Silent Generation respondents; with public transit having a negative influence and paratransit having a positive influence—supporting previous studies identifying older individuals as being the most likely users of paratransit. Carsharing and rental saw a universal negative influence across age categories relative to an unknown age. Testing respondent's identified race listed negative influence for the likelihood of walking for white, black/African American, and multiple-race individuals; and a positive influence for respondents that identified as Asian. Black/African American respondents were more likely to take public transit and paratransit relative to personal vehicle, and less likely to take a MaaS option. For identifying as Hispanic, paratransit

saw similar trends as with gender, where mode utility was negative regardless of identity. However, it was seen that those that did self-identify as Hispanic were more likely to choose biking over personal vehicle.

Table 7-3: Rural Mode Choice Model Having a 95% or Greater Confidence Level (*** > 99.99%, ** = 99.9%, * = 99% CLs)

Log-Likelihood: -31,692 Base Mode: Personal Vehicle			Walk	Bike	Public Transportation	Paratransit	MaaS Taxi (Uber/Lyft)	Rental and Carsharing
Travel Characteristics	Trip Purpose	Home	0.592 ***	0.771 ***	-0.760 ***	0.912 **	-3.197 ***	-0.986 ***
		Work	-0.716 ***	~	~	1.267 **	-3.000 ***	-0.838 ***
		School/Daycare/Religious Activity	-0.614 ***	-0.985 **	~	~	-3.183 ***	~
		Medical/Dental	-2.173 ***	-2.151 *	~	2.501 ***	-2.141 ***	-1.228 *
		Shopping/Errands	-1.963 ***	-0.994 ***	-1.260 ***	~	-4.119 ***	-0.954 ***
		Social/Recreational	0.659 ***	1.303 ***	~	~	-2.614 ***	~
		Transporting Someone	-2.322 ***	-1.987 ***	-2.384 ***	~	-2.854 ***	-1.185 **
		Meals	-1.291 ***	-1.376 ***	-0.860 ***	~	-3.048 ***	~
		Other (Base)	~	~	~	~	~	~
	Travel Distance	Trip Distance	-0.347 ***	-0.017	0.016 ***	~	-0.028 ***	0.010 ***
		LN of Trip Distance	-0.996 ***	-0.678 ***	~	0.235 *	~	~
Household Characteristics	Misc	Household Size	-0.102 ***	-0.169 ***	-0.369 ***	~	~	-0.235 ***
		Household Vehicle Count	-0.083 ***	-0.130 ***	-0.359 ***	-1.237 ***	-1.737 ***	~
	Census Division	New England	~	~	~	1.244	-2.593 *	~
		Mid Atlantic	~	-0.528 ***	1.326 ***	~	~	0.464 **
		East North Central	-0.402 ***	~	~	~	~	0.373
		West North Central	-0.685 ***	~	~	~	~	~
		South Atlantic	-0.414 ***	-0.652 ***	-0.393 *	~	-1.530 ***	0.463 **
		East South Central	-0.775 ***	~	~	1.513 ***	-1.999 *	0.840 *
		West South Central	-0.709 ***	-0.882 ***	~	~	-1.098 ***	~
		Mountain	-0.161 *	~	~	1.779 ***	~	~
		Pacific (Base)	~	~	~	~	~	~
	Hispanic	**Unknown (Base)**	~	~	~	~	~	~
		Yes	~	0.390 *	~	-2.727 **	~	~
		No	~	~	~	-3.649 ***	~	~
	Gender	**Unknown (Base)**	~	~	~	~	~	~
		Male	-0.360 **	-2.953 ***	-2.851 ***	-4.291 ***	~	-3.731 ***
		Female	-0.364 **	-3.979 ***	-2.971 ***	-4.202 ***	~	-4.040 ***
	Travel is a Financial Burden	**Unknown (Base)**	~	~	~	~	~	~
		Strongly Agree	~	-0.841 ***	-1.480 ***	~	~	0.723 ***
		Agree	~	-0.645 ***	-1.715 ***	~	~	0.323 *
		Neither Agree or Disagree	0.160 ***	-0.578 ***	-1.828 ***	-1.915 **	~	~
		Disagree	0.218 ***	~	-1.113 ***	~	~	0.371 *
		Strongly Disagree	0.331 ***	~	-1.173 ***	~	~	~
	Household Income	**Unknown (Base)**	~	~	~	~	~	~
		Less than $25k	-0.161 ***	0.305 **	0.612 ***	1.383 ***	~	-1.193 ***
		$25k to $49,999	-0.244 ***	-0.439 ***	~	~	~	-1.332 ***
		$50k to $99,999	~	~	~	~	~	~
		$100k to $199,999	0.241 ***	~	~	~	~	~
		$200k or Greater	0.644 ***	~	1.314 ***	~	1.721 ***	1.399 ***
	Age (Generation)	**Unknown (Base)**	~	~	~	~	~	~
		Gen Z (Under 21)	~	1.129 ***	~	~	~	-3.656 ***
		Milliennials (21 to 36)	~	~	~	~	~	-2.220 ***
		Gen X (37 to 52)	~	~	~	~	~	-1.968 ***
		Boomers (53 to 71)	-0.083 *	~	-0.740 ***	~	~	-2.208 ***
		Silent (72 or Older)	-0.515 ***	-1.716 ***	-1.690 ***	0.496	~	-2.101 ***
	Race	**Unknown (Base)**	~	~	~	~	~	~
		White	-0.283 **	~	~	~	~	~
		Black or African American	-0.541 ***	~	1.420 ***	1.727 ***	-2.278 *	~
		Asian	0.725 ***	~	~	~	~	1.925 ***
		Native or Islander	~	~	~	~	~	~
		Multiple	-0.200	~	~	~	~	1.631 ***
		Other	~	~	0.864 *	~	~	1.737 ***

The urban model, Table 7-4, had a final log-likelihood of -217,300 based on 703,546 trips. Unlike the rural model, the urban model mode choice distribution was less personal vehicle heavy (93.24% versus 87.07%), but this was still the dominant mode type.

Trip characteristic results (purpose and trip distance) had similar trends as seen in the rural models. For walking and biking modes, all significant trip purpose variables had negative coefficients except for social/recreational trip types, when all other variables were held constant and compared to the likelihood of choosing personal vehicle as the mode. Similarly for distance variables, both walking and biking saw negative likelihoods as distance increased; highlighting the short distances normally associated with these modes. Public transportation and paratransit mode purposes also showed negative coefficients for all significant mode purposes with the exception of medical/dental trips using paratransit. This purpose was also found to be positively significant with the rural model, again potentially reflecting the vulnerable demographic groups most likely associated with this mode. The other two modes, MaaS and rental/carsharing, both had all statistically significant trip purpose categories, but showed negative coefficients for all. This suggests that these modes are less likely to be chosen over personal vehicle regardless of a trip's purpose when all other variables are held constant. For the trip distance variables of public transportation, paratransit, and MaaS, all three modes saw a negative coefficient associated with the raw trip distance but saw a positive coefficient with the natural log of trip distance. This would mean that as a trip's distance increased in milage, the likelihood of a respondent taking one of the modes would *decrease*, however, the natural log of the trip distance would *increase* the likelihood of taking one of these modes. While this may seem contradictory, it actually helps find a more accurate distance threshold for these mode types compared to personal vehicle. Particularly, results suggest that these distance thresholds are roughly 80 miles for public transportation, 120 miles for paratransit, and 30 miles for MaaS; with greater distances decreasing the likelihood of taking these modes and assuming all other model variables are held constant.

Results for household characteristics such as size, vehicle count, and Census Division found some universal trends, but mostly a variety of outcomes. While household vehicle count was found to be negatively associated with each mode alternative (an increase in the number of vehicles resulted in a decrease in mode utility), household size was found to be positively associated with public transportation and paratransit modes (while negative with all other modes). Further investigation may be needed to determine why these modes saw a positive likelihood. Census Division findings saw walking, biking, and MaaS mode choices as being negatively associated with all mode-significant divisions in comparison to the Pacific division; potentially reflecting either the rarity of these mode choice types, or the specific circumstances needed for the modes to be utilized over personal vehicle. Public transportation and paratransit saw positive coefficients for both the New England and Mid Atlantic divisions, and negative coefficients for other divisions, which possibly echoes these divisions' larger public

transportation infrastructure networks. On the other hand, rental/carsharing division results showed positive coefficients for West South Central and Mountain divisions, and negative coefficients for the other significant divisions.

For income-related variables, household income and "if travel is a financial burden", results found walking was more likely to be chosen by those that either indicated that they found travel to not be a financial burden or made $100,000 or more annually. This was similar to biking results; however, biking was found to be more significantly likely if an individual either made above $200,000 annually *or* less than $25,000 annually. These two results could suggest that these two income groups treat these modes differently with more well-off individuals utilizing these modes more for leisure activities and poorer individuals using these modes more for general transportation needs. For public transportation, paratransit, and MaaS, respondents were less likely to choose these modes regardless of if they considered travel to be a financial burden, again reflecting the overwhelming popularity of the personal vehicle. However, rental/carsharing did see a positive coefficient in for this variable when respondents indicated that they disagreed that travel was a financial burden for them, which is further reflected in the household income response category with wealthier individuals indicating a higher likelihood of utilizing this mode. Other household income results saw universal disuse of paratransit but both public transportation and MaaS saw higher likelihoods associated to wealthier ($100,000 or greater) individuals and lower likelihood with other groups, potentially an indication of either high-density urban centers (where car usage would be limited, and income may be higher on average), or that higher income individuals are afforded greater transportation alternatives due to fewer financial hurdles.

Gender, Hispanic origin, age, and race results mostly exhibited an all-or-nothing type of mode utility; where for a particular mode, all significant categories for a demographic variable were either negative or positive, rarely a mix. However, based on the magnitude of the coefficients, general trends could still be inferred. For example, walking results saw negative utility for gender (female in particular), age, and race, but regardless of Hispanic origin an increased likelihood relative to an unknown response. While the Hispanic result may require additional research, the results for females could be a reflection of safety concerns. Age results showed an increasing negative likelihood for walking which could be due to associated loss in physical mobility with age. Other gender and Hispanic origin results saw public transportation, paratransit, MaaS, and rental/carsharing having negative utilities regardless of stated gender or Hispanic origin relative to an unknown response—once again reflecting the overwhelming favoritism towards personal vehicle usage. Age results suggested that older age groups were less likely to favor biking (illustrated by the decreasing coefficient value), public transportation, and MaaS mode options. However, clear trends could not be drawn for paratransit and rental/carsharing results with all significant age groups exhibiting negative coefficients. One note on these age results is the coefficients for MaaS usage. Potentially reflecting the popularities of Uber, Lyft, and other app-based MaaS options, there is a notable spike in likelihood associated with the Millennial generation (21 to 36 years old in 2017) and a smaller,

but still relatively high coefficient for those in Generation X (37 to 52 years old in 2017). In comparison, the Baby Boomer generation (53 to 71 years old in 2017), while still having a positive coefficient, had a smaller value than any younger age group, potentially reflecting the technological savviness of younger individuals. Finally, stated respondent race results offered either all negative or all positive coefficients for a modal alternative. No clear pattern or trend could be determined, potentially warranting future research.

Table 7-4: Urban Mode Choice Model Results Having a 95% or Greater Confidence Level (*** > 99.99%, ** = 99.9%, * = 99%)

Log-Likelihood: -217,300 Base Mode: Personal Vehicle			Walk	Bike	Public Transportation	Paratransit	MaaS Taxi (Uber/Lyft)	Rental and Carsharing
Travel Characteristics	Trip Purpose	Home	~	~	-0.524 ***	-0.432 **	-1.718 ***	-1.799 ***
		Work	-0.566 ***	~	~	-0.873 ***	-1.824 ***	-1.487 ***
		School/Daycare/Religious Activity	-0.489 ***	-0.398 ***	-0.218 ***	~	-2.104 ***	-2.617 ***
		Medical/Dental	-1.484 ***	-1.153 ***	-0.244 ***	1.113 ***	-1.012 ***	-2.760 ***
		Shopping/Errands	-1.705 ***	-1.167 ***	-0.932 ***	-1.692 ***	-2.908 ***	-1.798 ***
		Social/Recreational	0.492 ***	0.615 ***	-0.730 ***	-1.152 ***	-1.352 ***	-0.894 ***
		Transporting Someone	-1.887 ***	-1.793 ***	-1.946 ***	-1.158 ***	-3.818 ***	-1.963 ***
		Meals	-0.991 ***	-1.085 ***	-1.032 ***	-2.059 ***	-1.841 ***	-0.838 ***
		Other	~	~	~	~	~	~
	Travel Distance	Trip Distance	-0.122 ***	-0.019 ***	-0.035 ***	-0.020 ***	-0.027 ***	0.011 ***
		LN of Trip Distance	-1.563 ***	-0.726 ***	0.654 ***	0.498 ***	0.236 ***	0.195 ***
Household Characteristics	Misc	Household Size	-0.024 ***	-0.025 *	0.103 ***	0.210 ***	-0.105 ***	-0.086 ***
		Household Vehicle Count	-0.370 ***	-0.510 ***	-1.774 ***	-1.847 ***	-1.124 ***	-0.400 ***
	Census Division	New England	~	-0.428 ***	0.219 **	0.886 ***	-0.384 *	~
		Mid Atlantic	-0.047 **	-0.641 ***	0.456 ***	0.433 ***	~	-0.163
		East North Central	-0.331 ***	-0.218 ***	-0.353 ***	~	-0.325 ***	-0.543 ***
		West North Central	-0.688 ***	-0.558 ***	-0.976 ***	-0.970 *	-0.926 ***	-0.552 ***
		South Atlantic	-0.371 ***	-0.716 ***	-0.905 ***	~	-0.245 ***	-0.277 ***
		East South Central	-0.644 ***	-1.513 ***	-1.262 ***	~	-1.183 **	~
		West South Central	-0.574 ***	-0.943 ***	-0.854 ***	~	-0.579 ***	0.174 **
		Mountain	-0.210 ***	-0.218 ***	-0.662 ***	~	-0.662 ***	0.216
		Pacific	~	~	~	~	~	~
	Hispanic	**Unknown**	~	~	~	~	~	~
		Yes	0.324 ***	~	~	~	-2.632 ***	-2.846 ***
		No	0.398 ***	~	~	~	-2.781 ***	-2.507 ***
	Gender	**Unknown**	~	~	~	~	~	~
		Male	~	-1.934 ***	-0.573 ***	-2.438 ***	~	-2.150 ***
		Female	-0.195 ***	-2.954 ***	-0.786 ***	-2.456 ***	~	-2.430 ***
	Travel is a Financial Burden	**Unknown**	~	~	~	~	~	~
		Strongly Agree	~	-0.359 ***	-0.294 ***	-0.943 ***	-0.446 ***	~
		Agree	~	-0.303 ***	-0.436 ***	-1.139 ***	-0.464 ***	~
		Neither Agree or Disagree	0.040 **	~	-0.564 ***	-1.328 ***	-0.644 ***	~
		Disagree	0.142 ***	~	-0.390 ***	-1.459 ***	-0.540 ***	0.213 ***
		Strongly Disagree	0.094 ***	0.273 ***	-0.447 ***	-1.169 ***	-0.604 ***	~
	Household Income	**Unknown**	~	~	~	~	~	~
		Less than $25k	~	0.377 ***	~	-0.506 **	~	-1.063 ***
		$25k to $49,999	-0.339 ***	~	-0.586 ***	-1.110 ***	-0.678 ***	-0.428 ***
		$50k to $99,999	-0.149 ***	~	-0.432 ***	-1.485 ***	~	~
		$100k to $199,999	0.189 ***	~	0.063	-1.544 ***	0.522 ***	0.625 ***
		$200k or Greater	0.453 ***	0.331 ***	0.492 ***	-1.106 **	1.812 ***	1.095 ***
	Age (Generation)	**Unknown**	~	~	~	~	~	~
		Gen Z (Under 21)	-0.271 ***	1.972 ***	-0.469 ***	-1.848 ***	0.616 ***	-0.597 ***
		Milliennials (21 to 36)	~	1.653 ***	~	-0.774 ***	1.642 ***	-0.208 **
		Gen X (37 to 52)	-0.324 ***	1.355 ***	-0.373 ***	-0.863 ***	0.939 ***	~
		Boomers (53 to 71)	-0.391 ***	1.017 ***	-0.456 ***	~	0.454 ***	~
		Silent (72 or Older)	-0.883 ***	~	-1.230 ***	~	~	-0.555 ***
	Race	**Unknown**	~	~	~	~	~	~
		White	-0.294 ***	-0.935 ***	~	~	0.838 ***	0.894 ***
		Black or African American	-0.238 ***	-1.764 ***	0.910 ***	0.604 ***	1.240 ***	1.214 ***
		Asian	~	-1.034 ***	0.602 ***	~	0.950 ***	1.195 ***
		Native or Islander	-0.375 ***	-1.000 ***	0.616 ***	~	~	~
		Multiple	-0.244 ***	-0.861 ***	~ ~	0.735 ***	0.977 ***	0.745 *
		Other	~	-1.315 ***	0.761 ***	~	1.462 ***	~

7.3.3 Comparing Rural and Urban Trends

Both mode choice models offered notable insights and trends for how individuals in their respective communities choose their mode, however, comparing the results between models does highlight some differences. Overall, 270 variables were tested by each model with 117 variables being statistically significant in both models. Of these 117 variables, only nine were found to have opposite effects, with the most interesting being with paratransit choice related to household income. Here, the rural model saw a positive association with households making less than $25,000 annually, while urban households in the same income category saw a negative association with paratransit utility. This could be the result of more mode options being readily available to urban respondents, however, further investigation may be needed. Regarding model-specific variables (where a variable was only statistically significant in one model), the urban model saw 74 more unique variables than the rural model—mainly associated with the smaller shared mode choice variables—which most likely reflects the greater number of trips available within the urban model as well as the greater diversity in modal options observed in these trips.

Major trends across both models highlighted the inherent favoritism towards choosing personal vehicle over all other mode alternatives. As observed NHTS 2017 trips indicated personal vehicle as the primary mode choice roughly 88% overall, model results would favor personal vehicle the majority of the time. However, there were still situations where other modes would have a higher likelihood than personal vehicle. For example, social/recreational trips both had a higher likelihood of being completed by walking or biking compared to personal vehicle for both models, while medical/dental purpose trips had a higher likelihood for paratransit utility. Looking at demographic characteristics, respondents that indicated travel as not being a financial burden or having an annual income greater than $100,000 were found to be more likely to walk regardless of model, which may hint to the more leisure-based nature of walking indicated for these groups. Another notable trend for both models was the increased likelihood of individuals having annual incomes of $200,000 or greater choosing public transportation, MaaS, or rental/carsharing over personal vehicle. This could indicate wealth as being a barrier in accessing alternative modes, potentially warranting future research.

7.4. CHARACTERIZING AND MODELING RURAL AND URBAN TRIP DISTANCES TO SUPPORT MAAS USE

This section seeks to determine the relative influence household and trip characteristics have on how far rural residents need to travel for different purposes and document how these differ from urban areas as well as which trips are most likely to support MaaS adoption. First, the trends in urban and rural trip distances considering a variety of characteristics is examined. Second, two logarithmic regressions of trip distances for rural and urban residents are estimated.

7.4.1 Trends in Trip Distances

Trips recorded in the National Household Travel Survey were analyzed with the goal of determining if the current trip distances differ between rural and urban areas. Specifically, we considered distances traveled by (a) mode choice, (b) trip purpose, and (c) household income. These breakdowns are important, as they offer insight into the different factors influencing distances traveled and potential opportunities for MaaS use.

The first pair of Figures 7-9 and 7-10 compare the distributions of trip distances by mode in urban and rural areas. Figure 7-9 presents standard boxplots of trip distance by mode and community type, and Figure 7-10 presents cumulative distribution functions by mode and community type. This comparison highlights three main trends: First, the mean trip distances by mode are relatively similar between urban and rural areas, although rural trips can sometimes have a slightly longer mean trip distance. Examples of this include personal vehicle and MaaS taxi trips. Second, trips made in rural areas include a much wider range of distances for all modes, especially with far longer-distance trips, than urban areas. This highlights how access to urban areas from rural communities can vary greatly across the country. Third, and perhaps most importantly, there seem to be three distinct trip distances in which modes are being used in both urban and rural areas that reveal how MaaS is incorporated into daily travel. Walking and cycling trips are the shortest, with mean trip distances less than 1 mile. Personal vehicles and MaaS taxi trips have a similar distribution of distances traveled (with a mean trip distance around 6 miles in urban and rural areas). This indicates how MaaS taxi trips can be a replacement for personal vehicle trips. Finally, public transportation, paratransit, and MaaS carsharing modes also share a similar distribution of longer distances traveled (especially within the same community type). Interestingly, MaaS carsharing supports the longest mean trip distances for rural areas but stops at 18 miles at the 75% percentile, indicating this option serves a unique market from the MaaS rideshare services. Overall, these results highlight (a) MaaS is being used to serve three distinct trip lengths (short with bikeshare/scooters, medium with rideshare, and long with carshare), (b) MaaS is a direct substitute for specific modes at these trip distances, and (c) there are upper distance limits where MaaS is not a functional option.

The second pair of Figures 7-11 and 7-12 compare the distributions of trip distances by trip purpose in urban and rural areas. Figure 7-11 presents standard boxplots of trip distance by purpose and community type, and Figure 7-12 presents cumulative distribution functions by purpose and community type. These figures demonstrate how rural trips made for all purposes tend to reach destinations further away than those in urban areas. Travel to medical services and schools/daycare/religious activities have the longest trip distances in rural areas, while social/recreational has the widest range of trip distances. Comparing these trip purposes with the distance bands observed in the previous graph, there are many opportunities for MaaS to be utilized to reach each of these different destinations. Shopping/errands and

social/recreational trips in rural areas match closest to rideshare trips, whereas work and medical trips in rural areas match closest to carshare trips.

The third pair of Figures 7-13 and 7-14 compare the distributions of trip distances by household income in urban and rural areas. Figure 7-13 presents standard boxplots of trip distance by income and community type, and Figure 7-14 presents cumulative distribution functions by income and community type. These two graphs support the results of the previous section, where we found that travel behavior in rural areas is not exclusively dependent on household income. In fact, the distributions of trip distances is the same for households in each income group for rural areas. Alternatively, urban households with higher incomes tend to complete shorter trips than households with lower incomes. This is likely due to cost of living, where it is more expensive to live in urban areas with better accessibility (and thus the ability to have shorter trips). Whereas in rural areas, the entire community has a similar level of accessibility and cost.

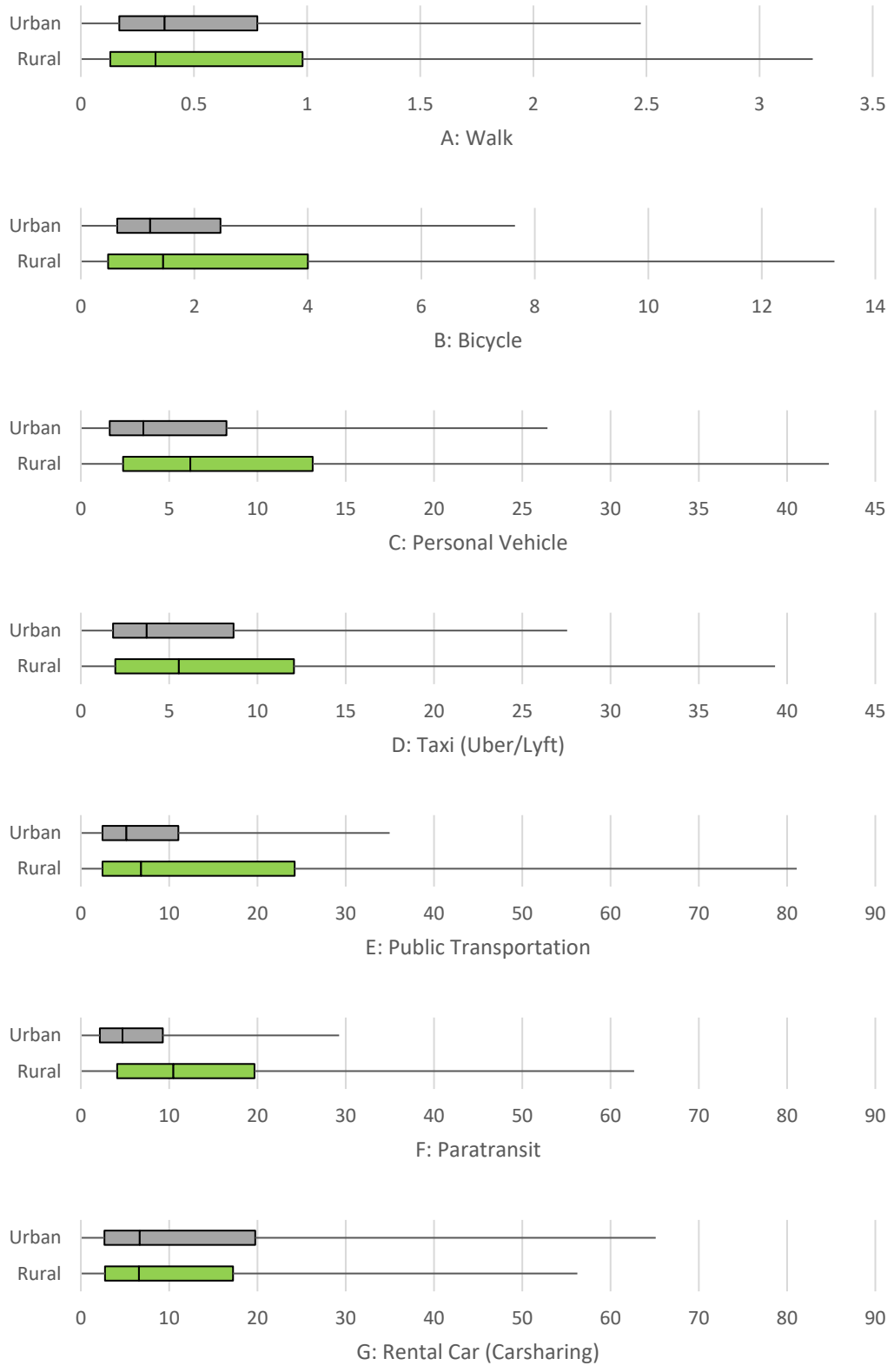
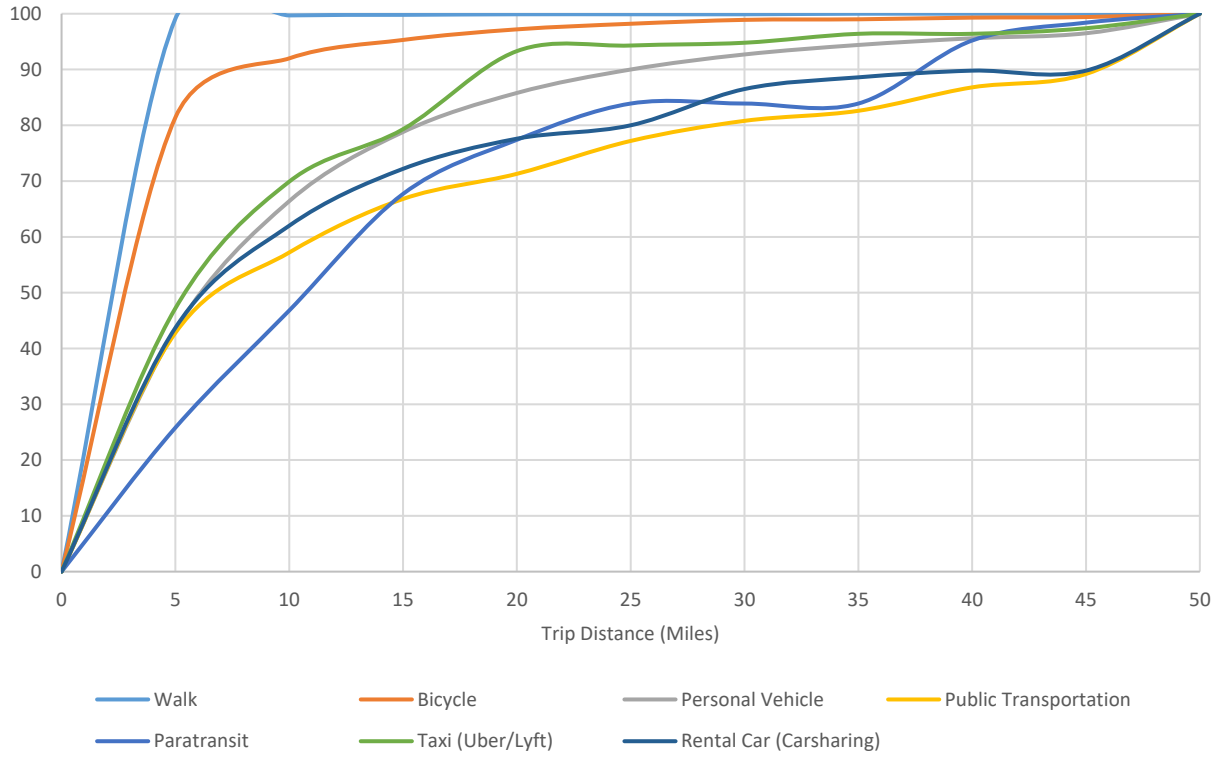


Figure 7-9: Urban vs. Rural Box Plots of Trip Distance by Mode

Figure 7-10: Urban vs. Rural CDFs of Trip Distance by Mode



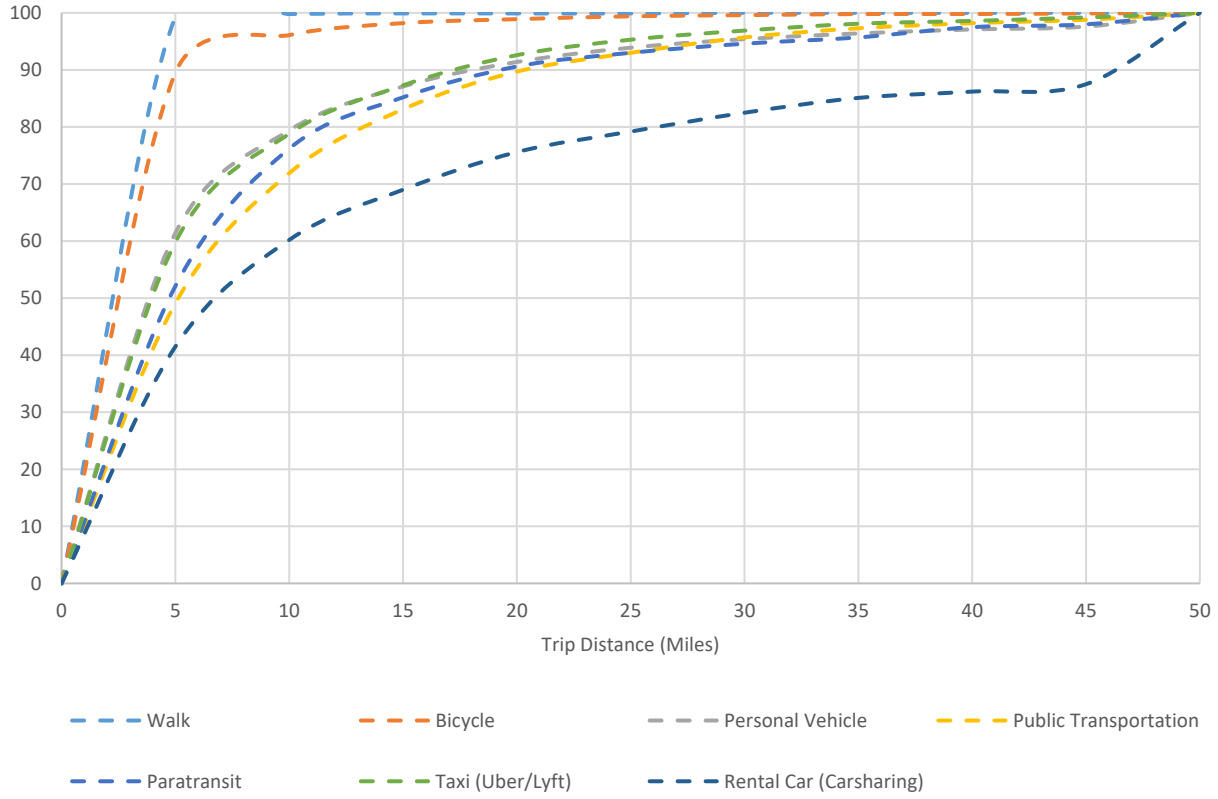


Figure 7-10: Urban vs. Rural CDFs of Trip Distance by Mode

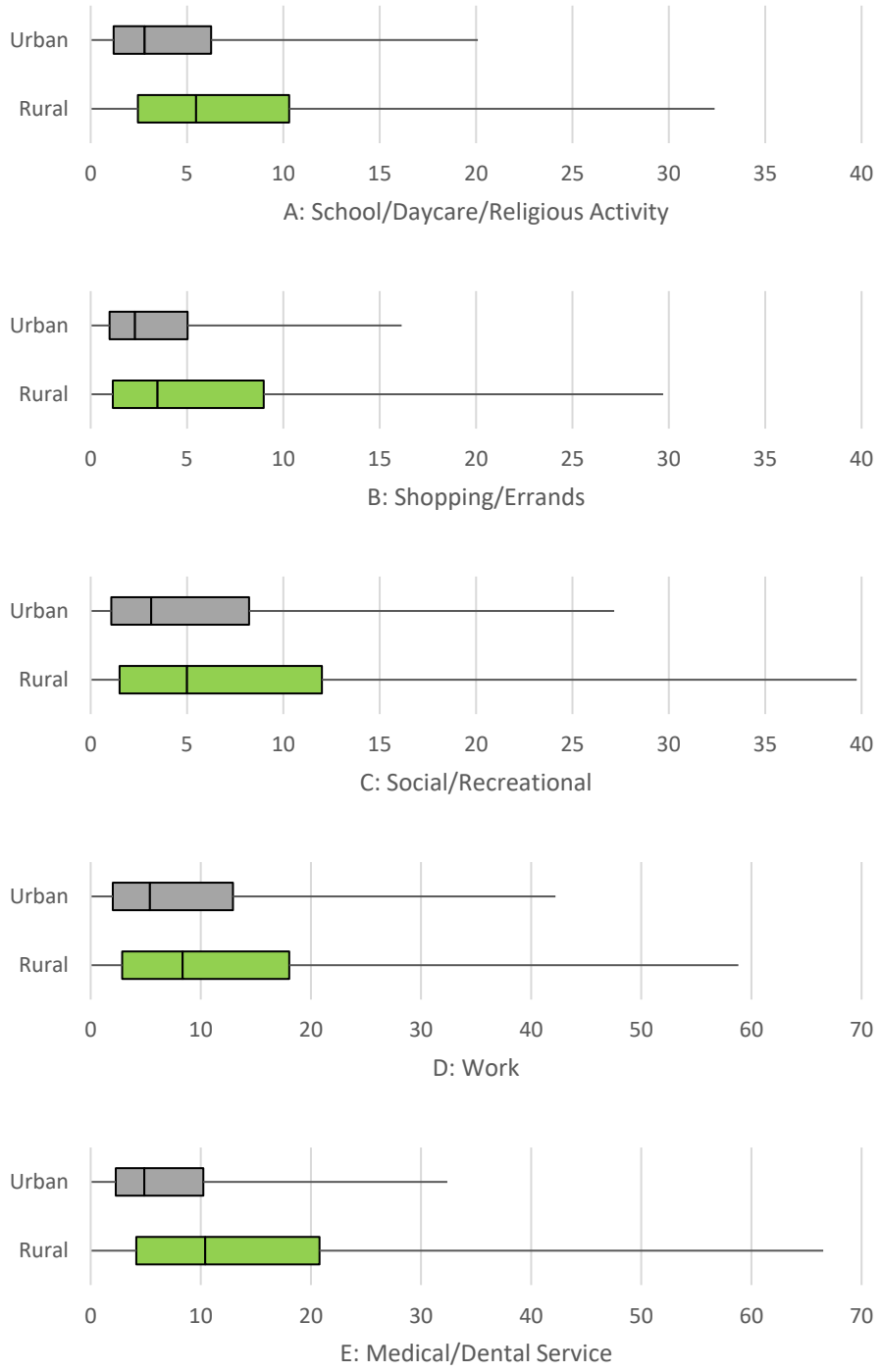
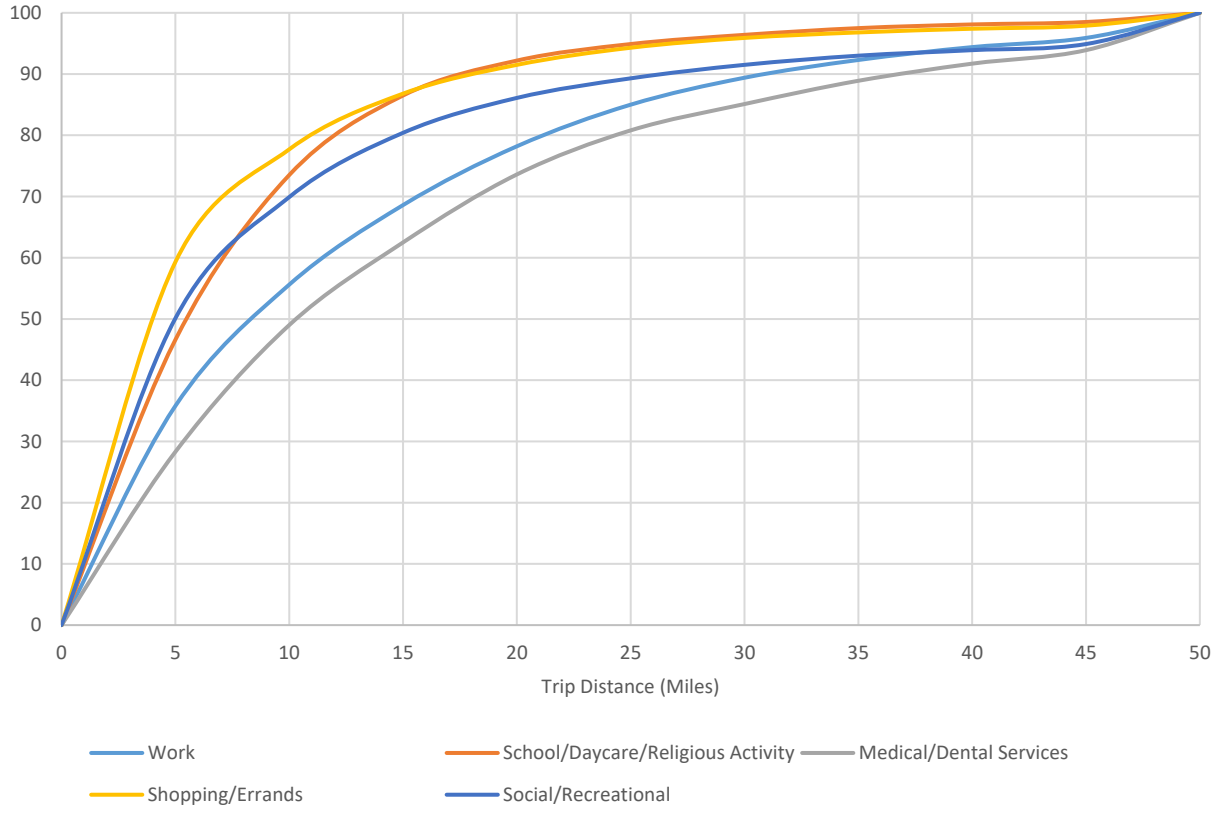


Figure 7-11: Urban vs. Rural Box Plots of Trip Distance by Trip Purpose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Trip Distance (Miles)
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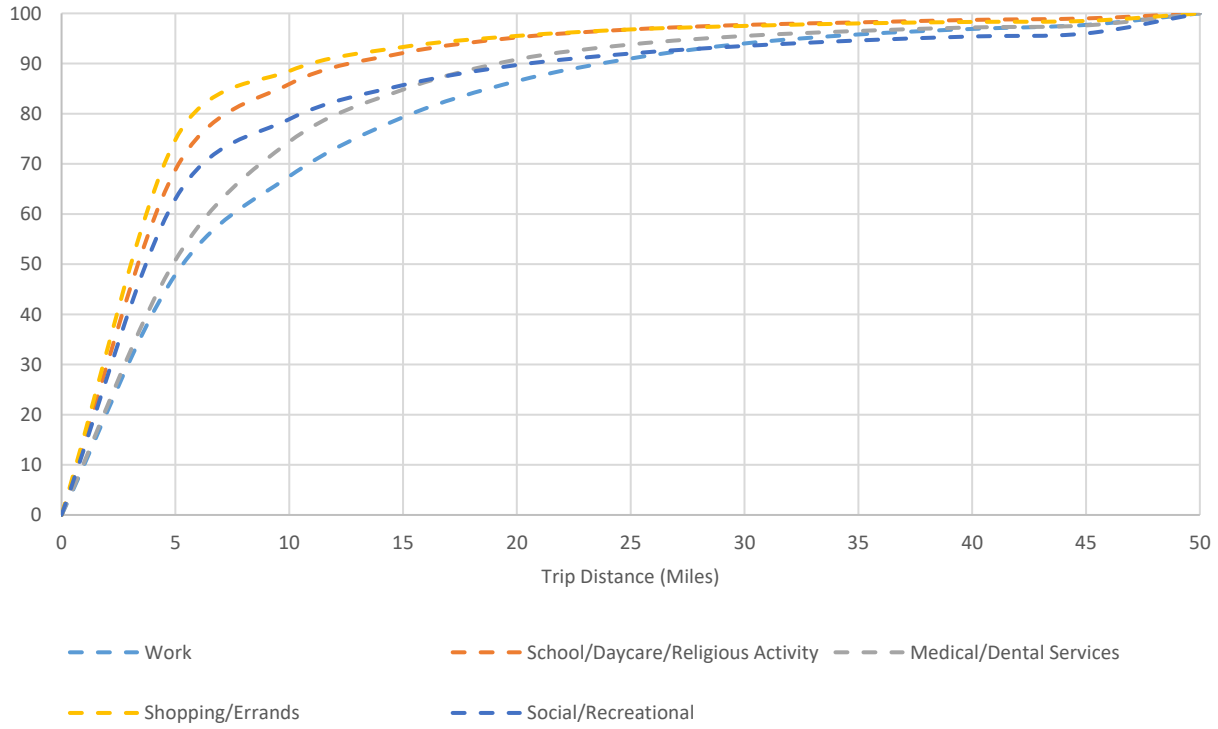
Medical/Dental Services
Shopping/Errands
Social/Recreational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Trip Distance (Miles)
Work
School/Daycare/Religious Activity
Medical/Dental Services
Shopping/Errands
Social/Recreational

Figure 7-12: Urban vs. Rural PDFs of Trip Distance by Trip Purpose

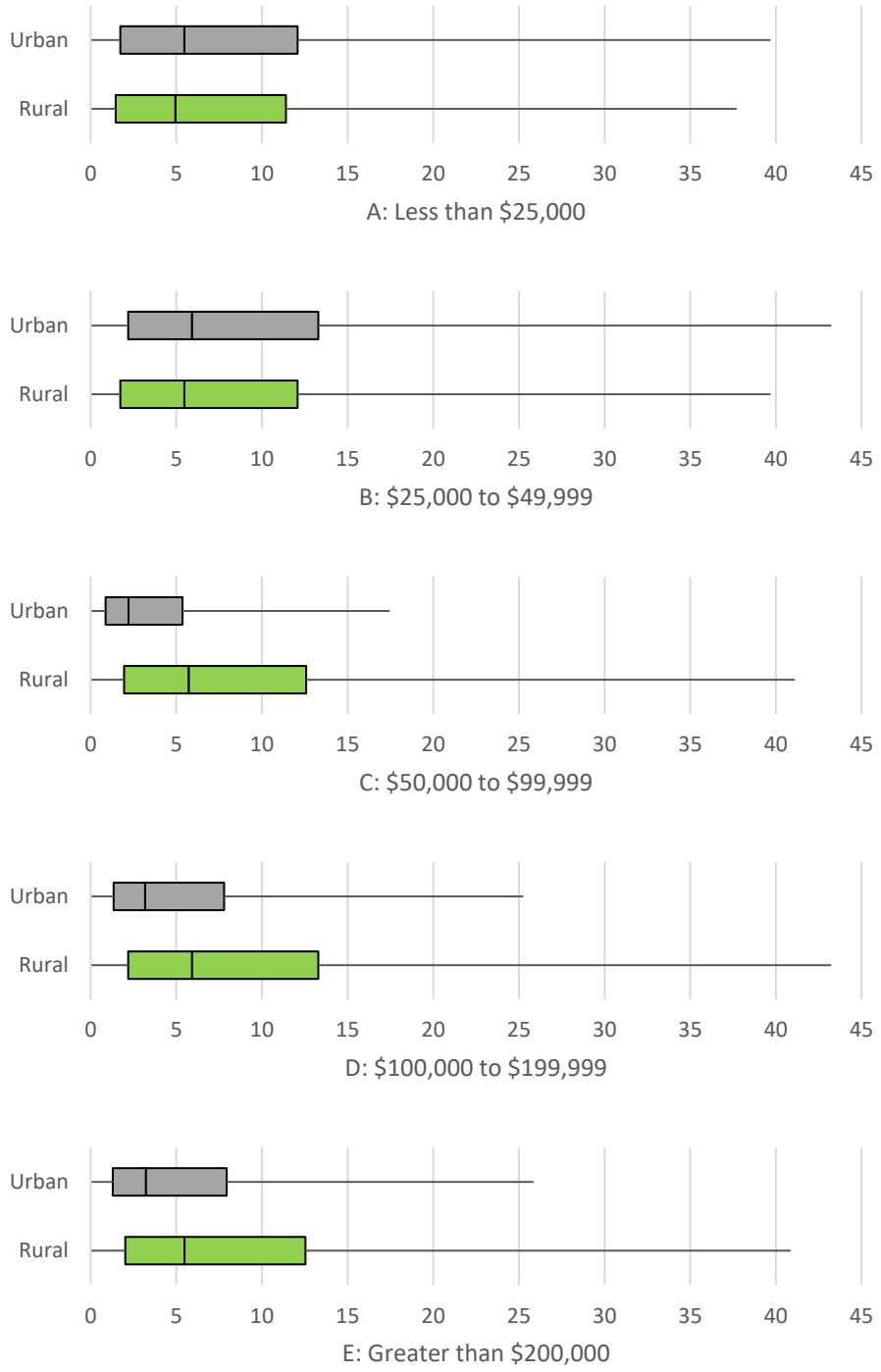
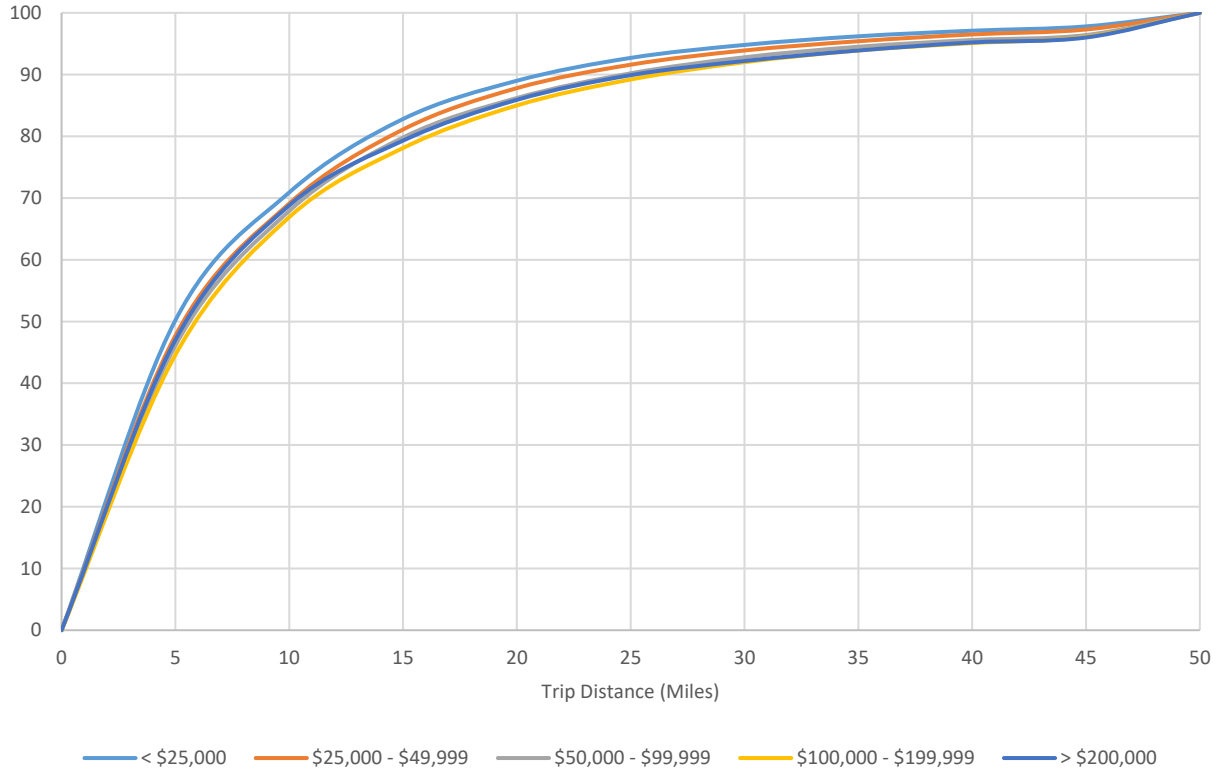


Figure 7-13: Urban vs. Rural Box Plots of Trip Distance by Household Income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Trip Distance (Miles)
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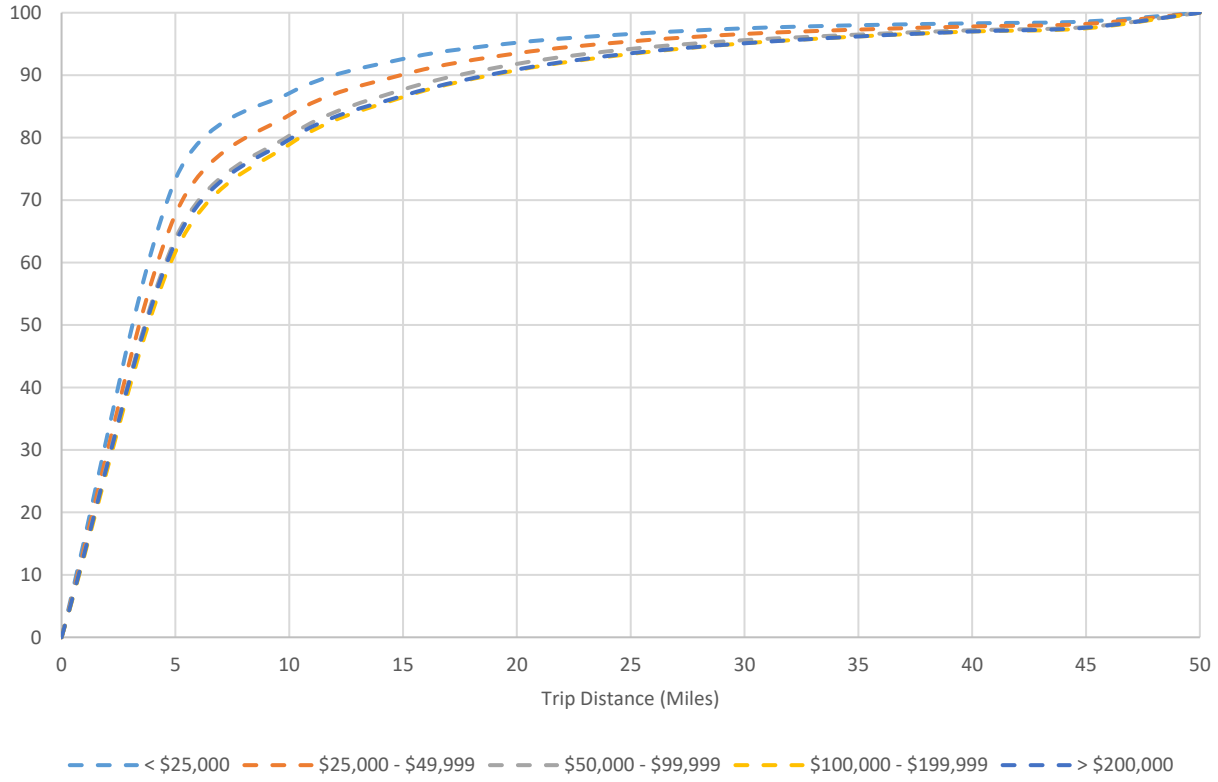
$25,000 - $49,999
$50,000 - $99,999
$100,000 - $199,999
> $200,000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45
50
Trip Distance (Miles)
< $25,000
$25,000 - $49,999
$50,000 - $99,999
$100,000 - $199,999
> $200,000

Figure 7-14: Urban vs. Rural PDFs of Trip Distance by Household Income

7.4.2 Factors Influencing Rural vs. Urban Trip Distances

Two linear regressions, one for rural trips and one for urban trips, were modeled to identify influencing factors on trip distance. For these models, the natural log of each trip's distance was used instead of raw trip distance. This was done to account for data skewing within the trip distance distribution. While model R-squared values were poor, the main purpose of these models was for inference reasons. Both model F-stats were significant above the 99.9% confidence level signifying each model was statistically better than an intercept-only model. Table 7-5 displays distance model results.

Each model was tested with 35 variables with the urban model having 32 statistically significant variables above a 90% confidence level and the rural model having 27 statistically significant variables. Model constants suggest that rural trips, when all other variables are held constant, are greater in distance compared to urban trip constant results. Trip purpose results showed similar negative and positive coefficient influences for both rural and urban trips, with the exception of "transporting someone" which showed rural trips as having lesser distances compared to urban for this trip type. However, both models showed trip distance as increasing when trips were labeled as either work-related or medical/dental, compared to home purpose trips and all other variables held constant. This could be a reflection of long commutes for work-related trips and the relative sparseness of medical destinations a respondent could access. Regarding total trip purpose coefficient magnitudes, urban-based trips saw the greatest influencing trip purpose as medical/dental (with these trips having longer distances) while rural-based trips saw "meal" trips as having the greatest impact (negatively suggesting these trips were completed with shorter trip distances).

Household characteristic results offered relatively similar trends for both urban and rural-based trips regarding trip distance. Both household size and household vehicle counts were tested as raw counts and squared counts as to put more emphasis on larger households. However, results found that household size was statistically significant for only urban trips—negatively in fact, showing larger urban households were completing shorter distance trips—and statistically insignificant for rural trips. Household vehicle count results were similar for both models with the raw number of vehicles available to the household increasing the trip's distance, but the square of this number decreasing this distance. This suggests there is not a linear relationship between household vehicle count and trip distance with higher counts beginning to negatively affect trip distance (that threshold for both urban and rural models being roughly ten vehicles). Results for household Census Division, relative to the New England division, showed that there may not be much regionality in play regarding overall trip distances. This is applicable to the Mid Atlantic, Mountain, and Pacific divisions in both models, and the West North Central division for the rural model; all seeing non-significant coefficients. However, the East North Central, South Atlantic, East South Central, and West South Central divisions all displayed statistically significant and positive coefficients showing trips completed in these divisions,

regardless of urban or rural origin, are longer in distance compared to New England households. Potentially a reflection of the New England division's smaller geographic area and infrastructure connections compared to other, sparser divisions.

Respondent demographic results also showed similar trends between the urban and rural models. For both models, respondents that identified as female took shorter distance trips compared to male respondents, and age results showed older individuals were more likely to take longer trips (however, as age-squared is virtually zero, it cannot be determined if this relationship is truly linear). Respondent race results yielded findings that may warrant further research. For example, compared to respondents that self-identified as white, minority respondents (Black/African American, Asian, or Other) were more likely to take longer distance trips. This could be an indication of racial equity issues regarding destination access and as such need to be further investigated. Finally, household income and the financial burden of travel showed rather contradicting results. As respondents increasingly found travel to *not* be a financial burden, the total trip distance *decreased* compared to the base of "strongly agreeing travel is a financial burden" and holding all other factors constant. This is arguably logically opposite of household income findings which showed that all income categories saw an *increase* in trip distance compared to the base of "household income less than $25,000" and holding all other factors constant. One possible explanation for this could be that while higher income households may complete longer distance (or potentially more frequent trips), low-income households, or those that find travel as a financial burden, may be completing fewer overall trips but trip-chaining (incidentally creating longer trips) to limit the financial impact multiple smaller trips may cost. Further investigation into this may be warranted.

Table 7-5: The Natural Log of Trip Distance by Locale Type (*** = 99.9%, ** = 95.0%, * = 90.0%)

		Dependent Variable: Ln(Trip Distance)	Urban	Rural
Model Information		R^2	0.055	0.05
		F-Stat	1162.71 ***	284.998 ***
		Constant	0.259 ***	1.217 ***
Travel Characteristics	Trip Purpose	**Home**	~	~
		Work	0.360 ***	0.054 ***
		School/Daycare/Religious Activity	-0.056 ***	-0.207 ***
		Medical/Dental	0.487 ***	0.442 ***
		Shopping/Errands	-0.280 ***	-0.566 ***
		Social/Recreational	-0.027 ***	-0.339 ***
		Transporting Someone	0.040 ***	-0.188 ***
		Meals	-0.288 ***	-0.574 ***
		Other	-0.036 ***	-0.347 ***
Household Characteristics	Misc	Household Size	-0.012 ***	0.005
		Household Size (Squared)	-0.003 ***	0.000
		Household Vehicle Count	0.328 ***	0.156 ***
		Household Vehicle Count (Squared)	-0.033 ***	-0.014 ***
	Census Division	**New England**	~	~
		Mid Atlantic	-0.013	0.037
		East North Central	0.072 ***	0.082 ***
		West North Central	0.033 *	-0.047
		South Atlantic	0.167 ***	0.166 ***
		East South Central	0.227 ***	0.223 ***
		West South Central	0.179 ***	0.197 ***
		Mountain	-0.016	-0.023
		Pacific	0.003	-0.012
	Hispanic	**No**	~	~
		Yes	0.037 ***	-0.029
	Gender	**Male**	~	~
		Female	-0.072 ***	-0.087 ***
	Travel is a Financial Burden	**Strongly Agree**	~	~
		Agree	-0.034 ***	-0.041 ***
		Neither Agree or Disagree	-0.073 ***	-0.108 ***
		Disagree	-0.116 ***	-0.132 ***
		Strongly Disagree	-0.120 ***	-0.191 ***
	Household Income	**Less than $25k**	~	~
		$25k to $49,999	0.117 ***	0.048 ***
		$50k to $99,999	0.190 ***	0.073 ***
		$100k to $199,999	0.198 ***	0.124 ***
		$200k or Greater	0.143 ***	0.084 ***
	Age	Age	0.014 ***	0.011 ***
		Age (Squared)	0.000 ***	0.000 ***
	Race	**White**	~	~
		Black or African American	0.112 ***	0.055 ***
		Asian	0.077 ***	0.072 *
		Other	0.023 ***	-0.001

7.5. CONCLUSIONS

This research seeks to understand how MaaS is currently being utilized in rural communities as well as opportunities for MaaS to be utilized to support existing travel patterns through comparisons to urban MaaS use. Additionally, this research seeks to understand the regional, trip, and sociodemographic factors influencing current and future MaaS activity in rural areas.

Therefore, there are two main objectives of this work: (a) determine the relative influence household and trip characteristics have on MaaS mode choices in rural areas and document how these differ from urban areas, and (b) determine the relative influence household and trip characteristics have on how far rural residents need to travel for different purposes and document how these differ from urban areas as well as which trips are most likely to support MaaS adoption. Both objectives are completed using travel pattern data from the 2017 National Household Travel Survey. The first objective is addressed through an examination of the trends in MaaS trip mode choices considering a variety of characteristics as well as estimating multinomial logistic regressions of MaaS trip mode choices for rural and urban residents. The second objective is addressed through an examination of the trends in trip distances considering a variety of characteristics as well as estimating logarithm regressions of trip distances for rural and urban residents.

Results from the mode choice analyses highlighted major barriers for MaaS use in rural areas. For example, only households with higher incomes are likely to utilize MaaS and African American households are significantly less likely to use MaaS. However, there are many opportunities to tap into rural transit user population: less income and predominantly African American. However, tracking MaaS in urban areas shows that there are opportunities for mimicking their behavior, where households with higher incomes, younger, and traveling longer distances are more likely to use MaaS modes. As MaaS becomes more available, it would be logical that these populations would begin to use it more.

Results from the trip distance analyses highlighted (a) MaaS is being used to serve three distinct trip lengths (short with bikeshare/scooters, medium with rideshare, and long with carshare), (b) MaaS is a direct substitute for specific modes at these trip distances, and (c) there are upper distance limits where MaaS is not a functional option. In rural areas, the trips most likely to be supported by MaaS fall into the medical and work purposes and completed by households with middle incomes in the Southeast. Again, we find these trips are also linked to public transit in rural areas, so there are potential collaborations between these modes.

There are many opportunities for future work in this area, including studies of how transit and MaaS can be integrated, individual barriers to adoption, and measuring distances of service.

APPENDICES

8.1 Appendix C – Summary of Accomplishments

Date	Type of Accomplishment	Detailed Description
January 2020	Conference Presentation	2020 TRB Annual Meeting, Paper Presentation: Liu, C., Bardaka, E. Suburbanization of poverty and changes in transit accessibility over time.
January 2020	Conference Presentation	2020 TRB Annual Meeting, Poster Presentation: Wolfe, M.K., McDonald, N.C., and Holmes, G.M. Transportation Barriers to Health Care in the U.S.
June 2020	Presentation	Presented to stakeholder summit on access to health care. Organized with the Orange County (NC) Department for Aging.
January 2021	Presentation	2021 TRB Annual Meeting, Poster Presentation: Lee, M.S., Jin, X., and Tousif, F. Examining the Mobility Needs and Challenges of Older Adults in Urban, Suburban, and Rural Environments.
December 2020	Publication	Manuscript prepared and submitted to special issue of *Transportation Research Part A (Policy and Practice)*: Characterizing Health Pandemic Impacts on Transportation Systems and the Demand for Mobility: Martin Oluyede, Lindsay, Abigail L. Cochran, Mary Wolfe, Lauren Prunkl, and Noreen McDonald. “Addressing Transportation Barriers to Health Care During the COVID-19 Pandemic: Perspectives of Care Coordinators.”
January 2021	Presentation	STRIDE 2021 Student Poster Showcase & Competition, Poster Presentation: Martin Oluyede, Lindsay, Abigail L. Cochran, Mary Wolfe, Lauren Prunkl, and Noreen McDonald. “Addressing Transportation Barriers to Health Care During the COVID-19 Pandemic: Perspectives of Care Coordinators.”

June 2021	Presentation	Abigail L. Cochran, Lindsay Oluyede, Olivia Jueyu Wang, Edward Fishman, and Herb Mullen. "Transportation to Health Care and COVID-19: Exploring Pandemic-Era Travel Trends and Post-Pandemic Challenges and Opportunities" STRIDE Center Webinar, June 2021 (virtual). https://www.youtube.com/watch?v=knsLN_OLZDA&ab_channel=UFTransportation
June 2021	Presentation	Abigail L. Cochran, Noreen McDonald, Mary Wolfe, Kai Monast, and Ryan Brumbaugh. "Transportation's Critical Role in the COVID-19 Vaccine Rollout" Southeastern Transportation Research, Innovation, Development and Education (STRIDE) Center Webinar, June 2021(virtual). https://www.youtube.com/watch?v=xlZydFuCMro&ab_channel=UFTransportation
December 2020	Publication	Liu*, C., and Bardaka, E. (2021). The suburbanization of poverty and changes in access to public transportation in the Triangle Region, NC. *Journal of Transport Geography 90.* https://doi.org/10.1016/j.jtrangeo.2020.102930

October 2021	Presentation	Steiner, R. Panel Discussion on "The Future of Share Mobility. Presented at the Annual Conference of the International Association of China Planners (IACP). Virtual presentation.
October 2021	Presentation	Abigail L. Cochran and Noreen McDonald. 2021. "Transportation barriers to health care access during the COVID-19 pandemic among North Carolina residents" Presented at 2021 NCDOT Research & Innovation Summit. Virtual presentation.