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Prepared by

Ruth L. Steiner, PhD (352-392-0997 ext. 431, rsteiner@ufl.edu),

Heedeok Cho (352-392-0997 ext. 219, hdcho5016@ufl.edu)

Department of Urban and Regional Planning
464 ARCH, P.O. Box 115706
Gainesville, FL 32611

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LIST OF ABBREVIATIONS

AAA	American Automobile Association
BTS	Bureau of Transportation Statistic
CL	Conditional Logit
CUTR	Center for Urban Transportation Research at University of South Florida
DOT	U.S. Department of Transportation
FAA	Federal Aviation Administration
FDOT	Florida Department of Transportation
FRA	Federal Railroad Administration
GDP	Gross Domestic Product
HSR	High Speed Rail
ML	Mixed Logit
MNL	Multinomial Logit
MSA	Metropolitan Statistical Area
NHTS	National Household Travel Survey
RP	Revealed Preference
SP	Stated Preference

ABSTRACT

The overall goal of this project is to enhance the fundamental understanding of Florida long-distance travel characteristics, and to provide policy implications for long-distance transportation planning in the future. To achieve the research goal, this study first conducts a descriptive analysis of long-distance travel with special emphasis on the modes used, distance traveled, and origins and destinations. Then, this study estimates mode choice models for long-distance travel that are sensitive to alternative specific attributes and traveler characteristics. It is important to have appropriate models that are able to provide accurate predictions of travelers' mode choice behavior that consider how people choose one mode or another.

The descriptive analysis shows that nearly 90 percent of trips are made by personal passenger cars, and most are on I-4, I-95, and Turnpike corridors that connect the Tampa, Orlando, and Miami/Fort Lauderdale urbanized areas as defined by Metropolitan Statistical Area (MSA). Among MSAs in Florida, Orlando is the hub for long-distance travel. The estimated model shows that both travel time and travel cost decrease car users' utility, indicating that people will have a greater chance to shift to other modes as travel time and travel costs increase. In contrast, air travel has a positive sign for travel time, and a negative sign for travel cost, while bus has a negative coefficient for travel time and a positive sign for travel cost. Positive signs of these estimated parameters may imply that air travelers and bus users are willing to increase travel time and travel cost, respectively. In addition, residents in rural areas seem to have a higher probability to drive personal cars for long-distance travel. Considering that less air and other public transportation service options are available in rural areas, the sign of this estimated parameter is reasonable.

These results suggest Florida needs to focus more on long-distance travel up to the 200-mile range between MSAs such as Tampa, Orlando, Jacksonville, and Miami/Fort Lauderdale. The I-4 corridor between Daytona and Tampa/Saint Petersburg MSAs, the Turnpike – I-95 corridor that connects the Orlando, Port Saint Lucie, Palm Beach, Fort Lauderdale, and Miami MSAs, and the northern section of I-95 between Jacksonville and Daytona Beach MSAs will need to be planned for in the near future. For this 200-mile travel distance, a new alternative mode may need to be provided at a speed of 150 or more miles per hour, while maintaining a lower cost level than for air travel.

EXECUTIVE SUMMARY

This study examines the questions: (1) what are the existing patterns and trends of the long-distance travel, (2) how do current long-distance travel modes serve people in Florida, (3) what are the factors that affect people's choice of one transportation mode over another, and (4) how can planners and decision makers benefit from this study as they plan for long-distance transportation in the future? In order to answer these research questions, this study first conducts a descriptive analysis of long-distance travel. The descriptive analysis aims to provide a comprehensive understanding of current patterns and characteristics of long-distance travel in Florida with special emphasis on the modes used, distance traveled, and origins and destinations. In addition, this study estimates mode choice models for long-distance travel that are sensitive to both traveler and travel attributes. It is important to have appropriate models that are able to provide accurate predictions of travelers' mode choice behavior based on the reasons people choose one mode or another. For that, this study employs logistic regression models, such as the Conditional Logit (CL) model, and Mixed Logit (ML), that have been developed in previous studies.

This study uses long-distance travel data for Florida residents that were collected as part of the 2009 National Household Travel Survey (NHTS). The Florida dataset contains 2,356 long-distance trips as part of its daily trips. This study transforms such daily trips into personal or household level data because one person can generate multiple daily trips, or, many family members can travel together using the same transportation mode. As a result, this study extracts a total of 1,389 long distance trips that represent either personal trip or household trip. A total 65, out of 67, counties in Florida are involved in generating these long-distance trips. Interestingly, a large portion of long-distance trips, 69 percent, in the 2009 NHTS originated from home, while work accounts for only two percent of origins for long-distance trips.

Findings from descriptive analysis include:

- About 52 percent of long-distance trips are less than 100 miles, while another 23 percent have destinations ranging between 100 and 199 miles.
- Personal cars accounts for nearly 90 percent of total long-distance trips, while about 7 percent of long-distance travelers chose public intercity transportation modes such as bus, train and airplane. Airplane users have the longest average travel distance of 1,266 miles, while car users drive the shortest average distance of 155.3 miles.
- Three quarters of long-distance trips have both the origin and the destination in Florida, averaging about 110 miles in trip length. On the other hand, the origin or the destination of about 16 percent of trips is located in other states, mainly Georgia and Alabama. These interstate trips record an average trip length of approximately 650 miles.
- People make long-distance travel for various reasons, including social and recreational trips, which account for the highest share with a third of total long-distance trips, and this is followed by work and shopping/errands with 15.1 percent and 13.8 percent, respectively.
- People aged 46 to 75 are more likely to generate long-distance travel. The average trip lengths are not significantly different among age groups.

- Income seems to affect the travel distance. Low-income travelers who earn less than $30,000 travel 164.8 miles on average per trip, while mid or high-income travelers are traveling 211.2 and 244.2 miles on average, respectively. However, income does not make a significant difference in the mode choice decision.
- The southwest region of the state captures a relatively small portion of long-distance trips with 4.2 percent, while other regions show similar shares of long-distance trips, ranging between 9.4 and 15.7 percent. The southwest region shows the longest average trip length for both inbound and outbound travel, while the central east region has the lowest in average trip length.
- The personal car is the dominant mode of transportation in central east, northeast, and southeast regions of Florida, while only 31.5 percent of travelers from other states use personal car for their interstate long-distance travel to destinations in Florida.
- Among MSAs in Florida, the Tampa/St Petersburg/Clearwater MSA generates the largest share of long-distance trips at 9.9 percent, and is followed by Orlando MSA at 8.3 percent, Jacksonville at 4.9 percent, and Miami and Daytona MSAs at 4.0 percent.
- Residents of the Daytona Beach MSA have the shortest average trip length for long-distance trips at 76.5 miles, while other large MSAs such as Miami, Orlando, Tampa/St. Petersburg/Clearwater, and Jacksonville MSAs are similar in average trip length ranging from 155.3 to 176.1 miles.
- Among origin and destination pairs for long-distance trips, the top twenty origin and destination region pairs show that four origin and destination pairs are intra-regional trips within central west, northwest, central, and north central region.
- The central, central west, central east, and southeast regions are strongly connected to each other, in addition to high demand for intra-regional long-distance trips. Therefore, highway corridors I-4 (connecting Daytona to Tampa) and Turnpike – I-95 (connecting Orlando – Port Saint Lucie – Palm Beach – Fort Lauderdale – Miami) are considered important for Florida's long-distance transportation.
- The northwest region shows high long-distance travel demand to the destinations in other states, mainly Alabama and Georgia that are geographically close to the region.
- The distributions of destinations from each region show that long-distance trips have a strong geographical propensity. In other words, the travel takes place with adjacent regions. For example, the central region has strong interactions with the southeast region and the central west region, while the southwest region has higher interactions with central west and central regions.
- The Orlando MSA shows the most active interaction with other MSAs such as Tampa/St. Petersburg/Clearwater, Jacksonville, West Palm Beach/Boca Raton, Melbourne/Titusville/Palm Bay, Lakeland, and Daytona Beach.
- The MSA level origin and destination pairs also reinforce the importance of I-4, I-95, and Turnpike in addressing long-distance travel needs.

The estimated conditional logit (CL) model shows that car users are negatively sensitive to both travel time and total travel costs. The ratio of the coefficients of travel time and travel cost indicate that car users are willing to pay 46.15 cents to reduce one minute of travel time. This is equivalent to a $27.69 per hour. This implies that personal car users may change their choice of mode if total monetary savings from using other mode exceeds this money value of $27.69 per hour. Air travelers are positively sensitive to travel time, while travel costs have a negative impact on long-distance travel. In contrast, bus users' utility decreases as travel time increases, while it increases as travel costs increase.

In addition to alternative specific attributes, the estimated mixed logit (ML) model shows that age, income level, and location of residence show positive relationships with mode choice decisions. Residents in rural areas seem to have a higher probability to drive personal cars for long-distance travel. Considering that less air and public transportation services exist in rural areas, the sign of this estimated parameter is reasonable. The estimated model showed that people have a higher probability to choose car as they get older.

Based on finding on long-distance travel patterns, this study has policy implications. First, Florida needs to find solutions to address long-distance travel demand up to a 200-mile range because 75.2 percent of long-distance trips occur within 200 miles. Second, among major corridors in Florida, the I-4 corridor between Daytona and Tampa/Saint Petersburg MSAs, and the Turnpike – I-95 corridor that connects Orlando, Port Saint Lucie, Palm Beach, Fort Lauderdale, and Miami are expected to face problems associated with long-distance trips. The northern section of I-95 between Daytona Beach and Jacksonville MSAs is also expected to encounter growth in long-distance travel demand. Third, coordination with adjacent states like Georgia and Alabama will be critical for some regions, including North West region in Florida, in order to address the needs for long-distance travel to/from those states.

Finally, this study identifies the potential service quality of a new alternative mode by using the coefficients of the travel time and cost from the conditional logit (CL) model. The results show a new alternative is expected to be highly competitive with personal cars and airplanes for the distance range of 100 miles. Meanwhile, it would be competitive when it transports people with a speed of 150 or more miles per hour. In both 300 mile and 400 mile distance ranges, a speed of 200 mile per hour is essential to strengthen competitiveness of a new alternative mode. Even a speed of 200 miles per hour is not sufficient to attract people from other modes in travel distance ranges of 500 miles and 600 miles.

CHAPTER 1 BACKGROUND

1.1. INTRODUCTION

Florida's population grew by 17.6 percent between 2000 and 2010, and is currently the fourth most populous state in the U.S. with 18.8 million residents as of 2010 (U.S. Census Bureau, 2010). In addition, Florida's gross domestic product (GDP) is in fourth place among the 50 states and the District of Columbia in 2011 by growing 4.2 percent to 754 billion dollars between 2000 and 2011 (US DOC, 2012). This extensive population and economic growth has motivated people to engage in extensive activities at both the intra-regional and inter-regional scales. These activities, in turn, have caused rapid increases in both short and long-distance travel demand, and increases in average travel distance as well as congestion and delays on both highway corridors and airports. For instance, Florida's average travel time to work increased from 24.8 minutes in 2002 to 25.4 minutes in 2009 (CUTR, 2010). The Tampa-Orlando I-4 corridor had an average annual daily traffic (AADT) of between 72,000 to 150,000 vehicles per day (vpd) in 2008. Both the Tampa to Plant City and the US 27 to Orlando Downtown segments of I-4 are seriously congested with nearly 140,000 and 150,000 vpd, respectively. Consequently, the level of service at both segments is rated "F" during peak hours (FDOT, 2010). In addition, the Orlando International Airport and Miami International Airport have experienced a continuous increase in delays from 17.8 percent to 20.0 percent, and 19.2 percent to 22.6 percent, respectively, between 2002 and 2010 (BTS, 2011). This declining quality of service can adversely affect both intercity and other travelers.

In solving the growing congestion and delay problems, federal, state and local governments have traditionally attempted to increase the capacity of major highway corridors near the urban areas by spending significant amounts of money. Both state and local governments have, for example, attempted to increase the capacity on interstate corridors such as I-4, I-75, I-95, and Turnpike by widening lanes and implementing an Intelligent Transportation System (ITS) on interstate highway corridors (FDOT, 2002). However, these highway corridors are not expected to accommodate the forecasted demand at an adequate level of service even with these capacity additions. Providing additional capacity of highways and airports near urban areas is increasingly difficult because highways are becoming expensive to build, and geographical limitations tend to prevent airports from providing additional runways and supportive facilities.

These situations have motivated policymakers to acknowledge the needs of a new approach that can respond to current congestion problems as well as the growing future travel demand. In particular, policymakers have emphasized the needs for an efficient and innovative option to control long-distance travel demand because long-distance travel accounts for about 33.2 percent of total trip-miles traveled even though it account for only about 2.1 percent of total trips made (US DOT, 2011). Moreover, long-distance travel by auto and air increasingly takes place under conditions of congestion and delay as the vast majority of long-distance travel is on the highway and airports that are increasingly suffering from capacity problems (FHWA, 2006). Accordingly, both federal and state governments attempted to construct a High Speed Rail (HSR) system connecting Miami, Orlando, and Tampa. The Florida Governor rejected the federal funding due to concerns about the demand for HSR and its cost effectiveness. More importantly, the Florida Department of Transportation (FDOT) has highlighted the importance of rail transportation systems as an alternative mode that can meet with the increased need for mobility as well as rising business and household expectations for safety, security, efficiency, and reliability (Cambridge Systematics, 2009). FDOT also assessed the needs and potentiality of intercity bus that connect between non-urbanized and urbanized areas and non-urbanized and the national intercity bus systems (Tindale-Oliver & Associate Inc., 2009).

However, no systematic attempt has been made to assess the effect of those policy options even though it is necessary to examine whether or not the rail transportation systems or intercity bus service have the potential as a new, efficient, and innovative approach to reduce traffic congestion on major highway corridors and airports. More basically, there have not been enough studies to investigate the patterns and trends of long-distance travel in Florida even though understanding current long-distance travel characteristics is important for future transportation planning. These conditions provide the strong motivations for this study that examines the following questions: what are the existing patterns of the long-distance travel, what are the factors that affect people's choice of one transportation mode or another, what are the desired service quality for a new alternative long-distance mode to meet with traveler's preference, and how the findings in this study can be used to plan in Florida?

1.2. RESEARCH OBJECTIVES

The overall goal of this study is to enhance the fundamental understanding of long-distance travel patterns in Florida, and to provide policy options for long-distance transportation planning in the future. For that, this study conducts descriptive analysis of the 2009 National Household Travel Survey (NHTS) and the Florida add-ons data, develops logistic regression models that are sensitive to alternative specific attributes and travelers' characteristics, test scenarios of travel time and cost combinations where people may change their mode choice behavior, and suggests viable options for Florida. Among various trips by definition, this study focuses on long-distance trips that are defined as trips of 50 miles or more from home to the farthest destination traveled (US DOT, 2011). In particular, this study considers a trip as long-distance trip if at least one segment of the daily trips between each origin and destination is 50 miles or more. This narrows the long-distance trips mostly into intercity trips. In addition, this study takes into account one-way trips from origins to destinations assuming people use the same mode of transportation for their departing or returning trips.

This study first conducts a descriptive analysis of long-distance travel. The descriptive analysis aims to provide a comprehensive understanding of current patterns and the characteristics of long-distance travel in Florida. So far, traditional descriptive studies have focused on the fundamental questions: who is traveling, where people are traveling on long-distance trips, what are the modes used, and why people are making long-distances trips (Bricka, 2001; Mallett, 2001; O'Neill and Brown, 2001; US DOT, 2003; US DOT, 2006)? In addition to these traditional questions, this study focuses more on the origin and destination pairs of long-distance trips that have not been investigated in previous studies. The origin and destination pairs are expected to provide valuable information for policy makers and researchers to measure the interactions between MSAs in Florida, and to identify major corridors in a statewide transportation network that are likely to be affected by current patterns of long-distance travel.

Second, this study develops mode choice models for long-distance travel that can explain the relationship between choices of mode and a set of explanatory variables such as the characteristics of alternative modes (e.g., travel time, travel cost, access/egress time and cost, travel distance and frequency), and traveler characteristics (e.g., income, age, gender, residence area, number of vehicles, education, number of people on that trip, and trip purpose). In order to estimate the choice probabilities of existing alternatives, this study develops logistic regression models such as Conditional Logit (CL) model, and Mixed Logit (ML) model. The CL model explains the interactions of alternative mode-specific variables on choice behaviors, while the ML model includes the characteristics of both individual and alternative modes. These models have relatively simple and closed-form mathematical structures. Therefore, they are straight forward to estimate and interpret the interactions of choice behaviors with the characteristics of alternative modes and individuals making the choices. In turn, they are well suited for the analysis in which the attractiveness of an alternative is affected by government policies.

The empirical models are expected to provide useful information to explain travelers' mode choice behavior with respect to the characteristics of travel mode, travel, and travelers. Among those factors, this study is, especially, interested in the role of the alternative mode-specific characteristics such as travel time and travel cost on long-distance travel mode choice decisions. These factors are considered as the key variables that enable a particular mode to gain a competitive advantage over other alternative modes of transportation in the market.

This study tests various scenarios of travel time and cost combinations to identify the thresholds of service qualities at which long-distance travelers may change mode choice decisions. Then this study attempts to identify a viable alternative option that can satisfy the service quality needs. The thresholds are expected to help policymakers and researchers to predict the potential role of an alternative mode in the transportation market in Florida, and determine the level of service improvement to existing public long-distance travel modes to reduce the use of personal vehicles.

1.3. SCOPE OF STUDY

The first section of Chapter 2 summarizes previous studies that developed mode choice models. Then, this study explains the theoretical frameworks of logistic regression models. The third section provides specification of the logistic regression models that are developed in this study. The final section of Chapter 2 explains the information about the 2009 NHTS and Florida add-ons. This study focuses on long-distance trips used in this project. In Chapter 3, the results of descriptive analysis, mode choice models, measures of marginal effects, and service quality of a new alternative mode are presented. In detail, the assumptions applied for this analysis, descriptive statistics, and travel patterns between origins and destinations are discussed in the first section. The second section of Chapter 3 describes variables used in the models and their operationalization, estimated mode choice models, the measures of marginal effects for travel time and cost, and potential service qualities for a new alternative mode. This study presents marginal effects of travel time and cost in the third section, and this is followed by potential service quality of a new alternative option. Chapter 4 includes conclusions, recommendations, and suggested research. Policy implications and limitations of the study are explored in Chapter 4.

CHAPTER 2 THEORETICAL FRAMEWORK

2.1. REVIEW OF PREVIOUS STUDIES

When a new alternative mode of transportation enters into an existing market or significant improvements are implemented in an existing mode, they will inevitably compete with other modes that provide overlapping services in the market. A portion of other mode use is expected to shift to a new alternative mode. Understanding that portion of modal shift is critical to evaluate the adequacy and efficiency of new transportation investments. Therefore, greater efforts have been given in undertaking demand analysis to lay the foundations of traffic forecasting for future projects. In particular, the focus has been on the mode choice models because travel demand of certain mode of transportation depends largely on the individual's mode choice behavior. This premise is also relevant in the case of long-distance travel or intercity travel.

The multinomial logit models are widely used to describe travelers' mode choice behavior. By developing mode choice models, researchers have attempted to identify the factors that affect long-distance travelers' mode choice decisions, and to predict changes in the market structure with an introduction of a new alternative mode or improvement of an existing mode. The explanatory variables commonly include alternative mode specific characteristics (such as travel time, cost, and frequency), and travelers' characteristics (such as income, gender, age, location of residence, and group size). Exceptionally, some studies focus on spatial characteristics in both origin and destination (such as population density, size of metropolitan area and public transit service quality), and subjective factors (such as comfort, convenience, safety, reliability, and privacy) associated with long-distance travelers' mode choice decisions.

Among the range of variables that have been examined in the previous models, both travel time and cost are the key variables to all of the models. Travel time is often split into in-vehicle time and out-of vehicle time of which the latter includes access and egress time, waiting time, terminal time, and transfer time. The access or egress time is the time taken from place of origin to the airport/the train station, or vice versa, respectively. Therefore, it increases public transportation mode users' total travel time. Travelers are considered to be sensitive to these out-of-vehicle times. Travel cost commonly means cost of driving cars or fare of public transportation modes, even though some exceptional cases include parking cost (Hensher, 1991), differences of fare level by service class (Koppelman, 1989), or access/egress expenses (Kitagawa, 2005; Wardman, Toner and Whelan, 1997).

Travel time and cost are also important variables to predict the impact of a new alternative mode on existing modes in the transportation system. In fact, many countries in both Europe and Asia have developed broad HSR networks such as Shinkansen in Japan, the AVE in Spain, the EUROSTAR between France and the UK, the THALYS between Paris, Brussels and Amsterdam, ICE in Germany, KTX in Korea, and CRHs in China. Thus, models of the impacts of a new intercity mode on existing transportation market and the potential competitiveness of HSR against existing modes such as air, passenger car, bus and conventional rail service have been needed in a variety of contexts. In order to characterize individual preferences in relation to travel alternatives, researchers have developed mode choice models frequently assuming that a new HSR competes with airplane. For example, Gonzalez-Savignat (2004), Lopez-Pita and Robuste (2005), Roman et al., (2007) analyzed the potential competition of high-speed rail with the air transport between Madrid and Barcelona, Spain by adopting disaggregated mode choice models. Ivaldi and Vibes (2005) investigated intermodal competition between aviation and HSR in Europe travel market Kim et al. (2003) and Park and Ha (2006) estimated the air travel demand changes in the Seoul-Busan and Seoul-Daegu routes. Meanwhile, Chang and Chang (2004), Zhang and Xiao-Li (2007), and Ortuzar and Simonetti (2008) estimated the potential mode share of HSR system in competition with aviation, personal car, and conventional train. In those models, travel time and costs are commonly considered as variables that affect travelers' mode choice decisions.

The travel distance is taken into account of its potential influence on the unobserved perception of comfort and convenience of the ground transportation modes (Grayson, 1985; Koppelman 1989; Koppelman and Sethi, 2000; Abdelwahab et al, 1992; Ashiavor et al, 2010, Wilson et al, 1990). In these models, travel distance presents the likelihood of choosing surface modes (such as car, bus, or rail) relative to air. Travel distance is tested in regard to potential thresholds at which travelers' choices may vary. The number of travelers on the same trip is another variable that is directly connected to travel cost, and thus many previous studies included it in the models (Morrison and Winston, 1985; Bhat, 1997a; Koppelman ait Sethi, 2000; Mandel et al, 1997; Swait, 2001; Wardman et al, 1997; LaMondia et al, 2009). This variable assumes that travelers who travel alone prefer airplane more than travelers in a group.

Moreover, the trip purpose is expected to have significant impacts on mode choice (Morrison and Winston, 1985; Wardman et al, 1997; Carlsson, 1999b; Limtanakool et al, 2006). Since travelers' preferences vary with the purpose of their trip, the different trip purpose is an important issue for mode choice decisions. Previous studies have shown that business travelers are expected to be more sensitive to travel time and cost than leisure travelers because their travel costs are subsidized. Service frequency, one of the frequently-employed variables, is mostly defined in terms of departures by time interval or headways (Algers, 1993; Mandel et al, 1997; Kitagawa et al, 2005; Winzer et al, 1990; Wardman et al, 1997; Vrtic and Axhausen, 2002). The effects of service frequency or number of transfer on the mode choice are investigated when the model includes air and/or rail.

In addition to travel mode characteristics, travelers' socioeconomic and demographic attributes such as income, education, car availability, age, gender, education and travel group size are also employed in many mode choice models. Among various forms of traveler-related variables, income has been the most widely used in the models (Bhat, 1997a; Grayson, 1985; Koppelman, 1989; Koppelman and Sethi, 2000; Swait, 2001; Limtanakool et al, 2006; Abdelwhab et al, 1992; LaMondia et al, 2009). Higher-income travelers are generally assumed to choose an alternative mode that provides fast and convenient service even though it is more expensive. It should be noted that some studies focus more on the impacts of these socioeconomic and demographic variables than travel attributes in order to explain mode choice behavior. For example, in addition to income, Limtanakool, Dijst and Schwann (2006) examine the effects of age, gender, education, household type and car availability on mode choice decision. Bhat (1997a) tested whether gender has impact on mode choice decisions, while McFadden (1973) predicted the potential impact of race, occupation and ratio of cars to workers in the household on mode choice decision for shopping trips.

Notably, research has been completed into the interrelations between spatial attributes and travel behavior by means of measuring differences of travel patterns in different types of urban form (size or density) and supply of public transportation services (or infrastructure). With regard to spatial characteristics, some of these studies suggest that travelers in dense and compact cities with mixed land-use use comparatively more public transportation for a large part of their daily trips (Frank and Pivo 1994; Boarnet and Crane, 2001; Timmermans et al., 2003;

Schwanen et al. 2004; Dargay and Hanly 2004; Hickman and Banister, 2005), while other studies concluded that people in larger city are more like to have better public modes such as air and train, and better service quality (Bhat, 1995, 1997, 1998; Limtanakool et al, 2006). MSA size, as a large city indicator, identifies whether a trip originated or/and terminated in a large metropolitan area where there is a preference for the train or bus over air mode. On the other hand, higher population densities are expected to be associated with higher demand for transport, and thus they likely facilitate well-developed public transportation networks resulting in smaller shares for automobile and larger proportions of public transportation trips. Therefore, it is important to measure the impacts of spatial characteristics on travelers' mode choice decisions. For this, it has to be taken into account that spatial characteristics and travel behavior are strongly connected to each other. Travel behavior might be an effect of selective location decisions of individuals or households, but urban form at the place of residence as well as available alternative modes of transportation also affect travel behavior (Scheiner and Holz-Rau, 2007).

Exceptionally, Srinivasan, Bhat and Holguin-Veras (2006) and Winzar, Pidcock and Johnson (1990) concentrate on measuring impacts of perceptions on long-distance travel mode choice decisions. The former study explains the impacts of travelers' perception about security check system and stress level on air travelers' mode choice decisions, while the latter investigates whether comfort, food quality, reliability and convenience are associated with long-distance travel for pleasure. Comfort is expected to have an impact on whether or not travelers have a higher probability of choosing the luxury service class and avoiding the less comfortable alternative, a bus. Reliability is presented as the share of departure/arrival within a certain time from the predetermined service time.

This study employs these potential factors including travel factors such as travel time, travel cost, travel distance, and access cost and time (or distance), and traveler characteristics, such as, number of travelers on the trip, income, age, travel purpose and other characteristics. These factors are then used to explain mode choice behavior for long-distance travel.

2.2. THEORETICAL FRAMEWORK OF LOGISTIC REGRESSION MODEL

This study develops logistic regression choice models that are based on the probabilistic choice theory in which the individual is assumed to choose an alternative if it utility is greater than that of any other alternative (Algers, 1993; Forinash and Koppelman, 1993; Koppelman and Bhat, 2006). In probabilistic choice theory, the utility function for traveler *i* to choose mode *t* includes two components: the deterministic or observable portions that represent the portion of utility observed by the analyst ($V_{i,t}$), and the error or the portion of the utility unknown to the analyst ($\varepsilon_{i,t}$).

$$U_{i,t} = V_{i,t} + \varepsilon_{i,t} \qquad (1)$$

The deterministic or observable portion ($V_{i,t}$) of the model is represented by a linear additive function that parameters, β, and explanatory variables, $Y_{i,t}$, which are predetermined functions of characteristics of individual i and the attributes of alternative t.

$$V_{i,t} = \beta' Y_{i,t} \qquad (2)$$

Therefore, the utility of an individual i to choose alternative t can be represented as:

$$U_{i,t} = \beta' Y_{i,t} + \varepsilon_{i,t} \qquad (3)$$

Error term ($\varepsilon_{i,t}$) is important because it shows that all attributes that affect traveler's mode choice decision are not completely and correctly measured or specified (Koppelman and Bhat, 2006). Thus, researchers have been motivated to develop various mathematical model structures by applying a different set of assumptions to the distribution of the error components of the utility function for each alternative. Among a wide range of assumptions, three specific assumptions, such as 1) the error components are distributed with a Gumbel distribution, 2) the error components are identically and independently distributed across alternatives and 3) the error components are identically and independently distributed across observations/individuals, lead to the multinomial logit (MNL) model structure. The MNL model expresses the choice of probabilities of each alternative as a function of the deterministic (or observable) portion ($V_{i,t}$) of the utility of all the alternatives (Forinash and Koppelman, 1993; Koppelman and Bhat, 2006). The probability of choosing an alternative mode t ($t = 1, 2, 3, \ldots, J$) from a set of J alternatives is generally presented as:

$$P_{i,t} = \frac{exp(V_{i,t})}{\sum_{t=1}^{J} exp(V_{i,t})} \qquad (4)$$

The MNL model has a relatively simple and closed mathematical structure in which the probability of choosing an alternative increases monotonically with an increase in the deterministic utility of that alternative, while it decreases with increases in the deterministic utility of each of the other alternatives. Thus, it has been widely used in many previous studies.

2.3. MODEL SPECIFICATION

As shown in equation (2), the deterministic or observable portion (Vi,t) of the utility function can be expressed as a mathematical function of characteristics of individual i and the attributes of alternative t. This function can include any mathematical form, but it is commonly determined by the types of explanatory variables such as the attributes of the alternative (such as travel time, cost and frequency) and the characteristics of the traveler (such as income, gender, age, and residence location). Three classes of models have been developed such as the generalized logit (GL) models (widely called as multinomial logit (MNL) models), the conditional logit (CL) models and the mixed logit (ML) models (Hoffman and Duncan, 1988). The GL (or MNL) models focuses more on the individuals as the unit of analysis and thus uses the characteristics of individuals as explanatory variables assuming the explanatory variables are constant over the alternatives. In contrast, the CL models focus on the set of alternatives and the attributes of those alternatives. Thus, the CL models allow evaluating the effect of choice-specific variables on the probability of choosing a particular alternative (Hoffman and Duncan, 1988). In the CL models, explanatory variables have different values for each alternative in CL model, and the impact of a unit of explanatory variable is assumed to be constant across alternatives. The ML models include characteristics of both the individual and the alternatives. The choice probabilities in the GL, CL, and ML models are, respectively:

$$V_{i,t} = \beta X_{i,t} + \varepsilon_{i,t} \qquad (5)$$

$$V_{i,t} = \alpha Z_{i,t} + \varepsilon_{i,t} \qquad (6)$$

$$V_{i,t} = \alpha Z_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \qquad (7)$$

Where, Xi,t is the characteristics of individual i

Zi,t is the attributes of the alternatives t, (t = 1, 2, 3, …, J)

Then, the choice probability of the individual *i* to choose the alternative *t* can be expressed as equation (8) – (10):

$$P_{i,t} = \frac{exp(\beta X_{i,t})}{\sum_{t=1}^{J} exp(\beta X_{i,t})} \qquad (8)$$

$$P_{i,t} = \frac{exp(\alpha Z_{i,t})}{\sum_{t=1}^{J} exp(\alpha Z_{i,t})} \qquad (9)$$

$$P_{i,t} = \frac{exp(\beta X_{i,t}+\alpha Z_{i,t})}{\sum_{t=1}^{J} exp(\beta X_{i,t}+\alpha Z_{i,t})} \qquad (10)$$

This study estimates both equations (6) and (7), and then calculates the probabilities of each individual to choose specific alternative among available options. The CL model, equation (6), measures the impacts of alternative-specific attributes on the probability of choosing a particular alternative. Thus, this study is expected to evaluate how government policy affects to the attractiveness of an alternative depending on changes in some relevant characteristics (for example travel time, cost, and frequency). By estimating the ML models, equation (7), this study identifies individual characteristics that affect mode choice decisions for long-distance travel.

2.4. DATA

This study uses the 2009 NHTS and Florida add-on data. The data is expected to form a base for a national coverage of long-distance travel, and thus allow the development of mode choice models for various geographic sectors in order to test the spatial transferability of these models. The 2009 NHTS updated information gathered in the 2001 NHTS and in prior Nationwide Personal Transportation Surveys (NPTS) conducted in 1969, 1977, 1983, 1990 and 1995. In addition, it includes the Florida add-on data that interviewed additional samples to use as a household travel survey for its respective jurisdictions (US DOT, 2011).

Until the 1995 American Travel Survey (ATS), the US Department of Transportation (DOT) defined long-distance travel as trips that are 100 or more miles away from home.

However, the 2001 NHTS redefined it as trips of 50 or more miles from home to the farthest destination traveled. This definition includes the portion of the trip taken to reach the farthest destination, the return trip home, and any overnight stops made along the way or stops to change transportation modes (US DOT, 2011). The 2009 NHTS and the Florida add-on data are not solely designed to collect long-distance travel. In addition, the NHTS has no information on costs of travel, specific travel routes, and the traveler's reason for selecting a specific mode of travel over another mode (NHTS website, 2011). However, it contains valuable information that reflects current patterns and trends, and mode choice behavior of ordinary Americans in their daily lives. In addition, the 2009 NHTS can be representative of national estimates because it provides a weighted dataset that has been adjusted to account for the oversampling in the Add-on areas.

Overall, the dataset includes daily travel patterns of 15,884 households that live in Florida. These households consist of 32,065 individuals, and these individuals generated about 114,910 trips in a day in Florida (US DOT, 2010). More importantly, these daily trips contained 2,356 trips that were longer than 50 miles in Florida. These long-distance trips accounted for 2.1 percent of total daily trips by Florida residents. However, they account for a significantly larger portion of total miles traveled. Long-distance trips represent 33.2 percent of total miles traveled by Floridians. It should be noted that these long-distance trips are likely to affect the highways and airports that are already experiencing capacity constraints because a majority of long-distance trips are on the highways and through airports. Moreover, capacity additions to existing long-distance alternatives are hampered by the high construction costs and limited geographical capability. Long-distance trips in Florida are on average longer than the US average, but they represent a smaller share of long-distance trips and a smaller share of long-distance trip-miles. Table 2-1 summarizes the patterns of the daily trips and trip-miles for both the US and Florida.

Table 2-1 Comparison of daily trips and trip-miles between the US and Florida

Index		US	FL
Trips	Trips	1,148,852	114,910
	Long-distance trips	28,420	2,356
	Share of long-distance trips (%)	2.5	2.1
	Average distance (miles)	143.0	153.9
Trip-miles	Trip-Miles	11,568,714	1,090,497
	Long-distance trip-miles	4,064,060	362,588
	Share of long-distance trip-miles (%)	35.1	33.2

This study operationalizes these daily trip data into household level data by applying four steps: 1) transform 114,910 daily trips into 26,048 personal level trips, 2) identify 1,389 individuals who made one or more long-distance (50 or more miles) trips, 3) identify trip segments that are involved in long-distance trips, and 4) extracts 984 household level samples from 1,389 individual travel data. Table 2-2 present these steps in detail. In step 2, the original 2009 NHTS and Florida add-on include 1,480 individuals who made a total 2,356 long-distance trips averaging 1.6 trips per person. Among these personal level trips, this study, however, excludes 91 individuals because 1) some are not true long-distance trips if their actual distances are calculated based on the origin and destination pairs on the map, and 2) the others' origin and destination pairs are not in Florida, thus they do not fit into the geographical boundaries of this study. As a result, this study uses 1,389 personal level samples. In step 3, this study extracts actual trip segments that comprise long-distance trips among multiple trips made by a household level sample. These samples may include trips of origin – destination or origin – intermediate stop(s) – destination. In most cases, intermediate stop(s) include stops to buy gas, eat meals, get coffee/ice cream/snacks and rest. In step 4, a household trip includes household member(s) who were in the same trip using the same travel mode. Thus a household can form single long-distance trip or multiple long-distance trips. These data transformations are necessary to identify real patterns and trends of long-distance travel.

Table 2-2 Data Operationalization Processes Obtaining Household Level Data Set

Index	Number of Samples
Number of trips in daily trip dataset	114,910
Total individuals in daily trip dataset	26,048
Individuals who have one or more trip segment that is 50 or more miles	1,389
Household level long-distance trip samples	984

CHAPTER 3 RESULTS AND FINDINGS

3.1. DESCRIPTIVE ANALYSIS OF LONG-DISTANCE TRAVEL

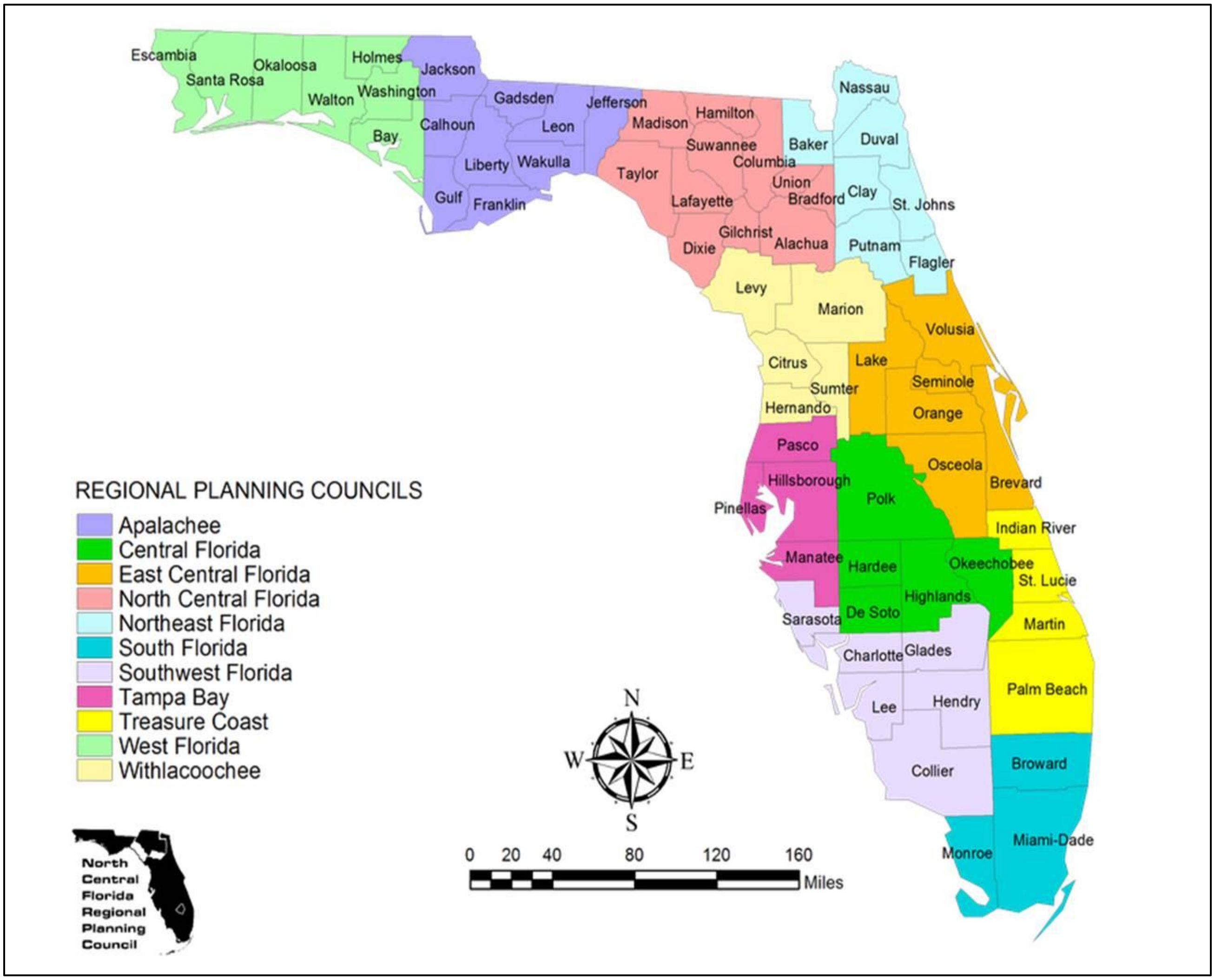
3.1.1. ASSUMPTIONS OF ANALYSIS

As explained in a previous section, this study uses 984 household level samples of long-distance travel. Interestingly, a large portion of long-distance trips, nearly 69 percent, in the 2009 NHTS originate from home, while work accounts for only about 2 percent of origins for long-distance travel (see Table 3-1). On the other hand, home is not a common destination of long-distance travel. It accounts for about 18 percent of destinations of all long-distance trips. The high share of home in all origins is possible because travelers distinctively make long-distance trips from their home, no matter how many trips they generate in a given day of survey. For example, if four trip segments from number 4 to 7 out of 10 trip segments from number 1 to 10 are involved in long-distance travel, then trip number 4 has a very strong possibility to be home while both trips in number 5 and 6 are intermediate stops to rest, or to get a meal or gas. It should be noted that the 2009 NHTS includes many individual-level trips that follow these patterns, and most of these long-distance trips are intercity travel rather than intracity travel.

Table 3-1 Home and Work as Origin and Destination of Long-distance Trips

	Origin of Trips			Destination of Trips		
	Home	Work	Other	Home	Work	Other
Number of Samples	675	23	286	172	93	719
Share (%)	68.6	2.3	29.1	17.5	9.5	73.0

Residents of 65 counties out of 67 counties in Florida generated these long-distance trips. In order to simplify origin and destination analysis, this study categorizes these counties into the twenty-two MSAs in Florida, and eleven regions. In order to facilitate data analysis, this study applies the eleven regions that are classified by the Florida Regional Councils Association (FRCA). Figure 3-1 shows these classifications of geographies. In order to illustrate how long-distance travel affects to the interstate highway systems in Florida, this study attaches origin and destination region pairs with existing highway corridors such as I-4, I-95, I-75, I-10, and Turnpike. For example, travels between the central region and the central west or central east are likely to use the I-4 corridor. In the same context, long-distance travelers from the southeast region to the north east region or north central region are likely to take I-95 or Turnpike/I-75 route, respectively. While multiple federal and state highways (for instance, US 1, US 17, US 27, FL 20, FL 40, and FL 70) comprise major corridors, this study considers only interstate highways or equivalent roadways (e.g., turnpikes). These origin and destination pairs are one of the important aspects of long-distance travel that have not been explored in previous studies.



Source: Florida Regional Planning Councils Association (http://flregionalcouncils.org/)

Figure 3-1 Regions and Counties in Florida

3.1.2. DESCRIPTIVE STATISTICS

About 52.3 percent, or 726 long-distance trips out of a total of 1,389 long-distance trips, are made in the 50 to 100-mile range. Another 318 trips, about 23 percent, have destinations ranging from 100 to 199 miles. Travel distances between 300 and 500 miles, where researchers believe high speed rail can compete with both air and automobile, account for 6.0 percent of total long-distance trips. Table 3-2 presents the distribution of long-distance trips by distance group.

Table 3-2 Long-distance Trips by Trip Distance for Trips within Florida, 2009

Distance Group	50-99	100-199	200-299	300-499	500-999	1000-1499	1500-
Frequency	532	217	76	57	50	34	18
Share (%)	54.1	22.1	7.7	5.8	5.1	3.5	1.8
Cumulative percent	54.1	76.1	83.8	89.6	94.7	98.2	100.0

Approximately 88 percent of long-distance travelers use private cars or trucks, while 8.0 percent chose public intercity transportation modes such as bus, airplane, and train. The share of trips by airplane, 6.1 percent, is relatively higher than the average of the US, which is about 2.4 percent. This may result from Florida's long and narrow peninsula and large population in South Florida. Airplane users have the longest average travel distance of 1,261 miles, while car users drive the shortest average distance of 152.2 miles. Nearly 82 percent of car users traveled less than 200 miles away from their origins, and are responsible for this short average trip length of cars. It should be noted that travelers consider airplane for a trip of 300 miles or more, and air travel is preferred for interstate travel. It should also be noted that airplane's share is higher than that of personal car as travel distance reaches 1,000 miles or more. Table 3-3 and Figure 3-2 show the shares of modes used for long-distance travel by distance.

Table 3-3 Transportation Mode Used for Long-distance Travel

Mode	Frequency	Share (%)	Trip Distance (miles)			
			Mean	Minimum	Maximum	STD
Car	861	87.5	152.2	50	3,018	213.3
Bus	14	1.4	265.1	60	1,100	346.0
Airplane	60	6.1	1261.0	300	3,000	662.9
Train	5	0.5	222.6	120	445	133.0
Others	44	4.5	248.6	53	1,200	276.2
Total	984	100.0	226.1	50	3,018	376.0

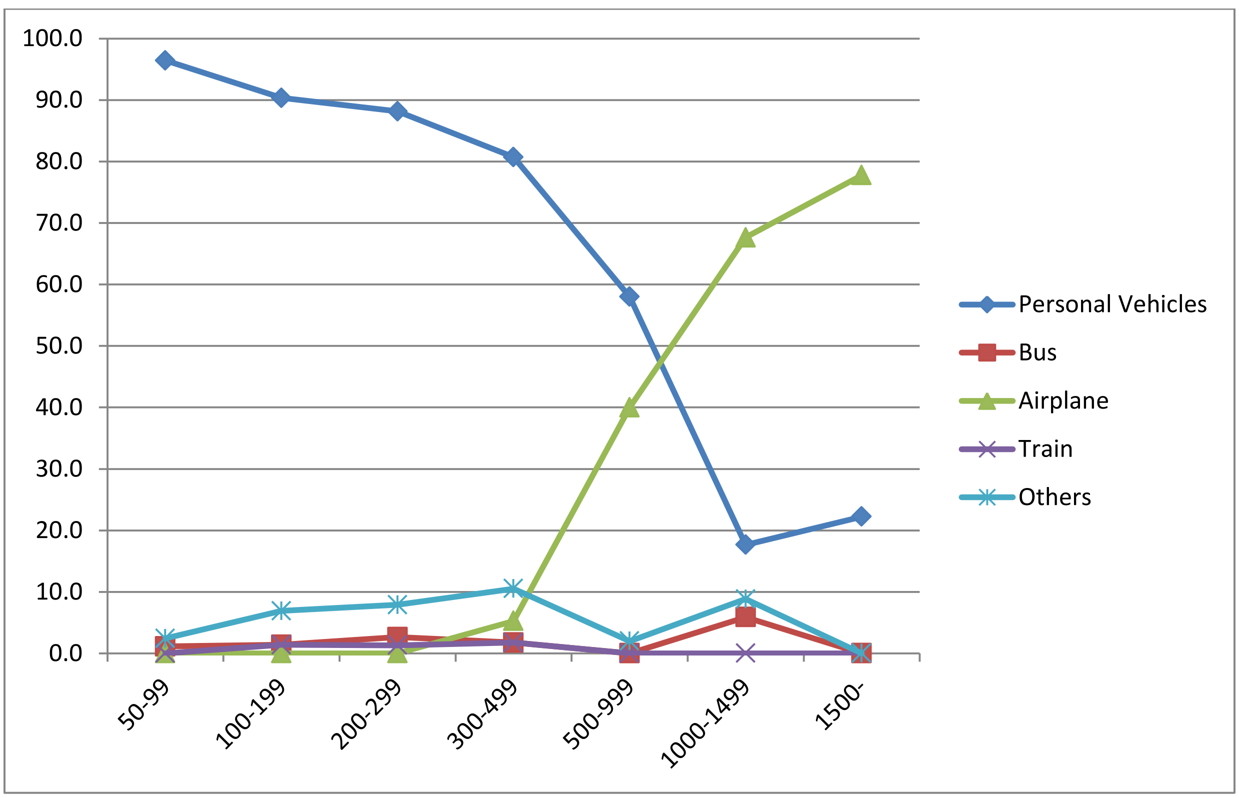


Figure 3-2 Patterns of Travel Mode Choice by Distance

As presented in table 3-4, personal cars carry an average of 1.4 people in a single long-distance trip, while train users travel alone. Personal cars have a maximum number of travelers of 6 people, and show the largest standard deviation of 0.74 persons. Interestingly, airplane users are accompanied by an average of 1.3 persons, which are larger than buses and trains. Considering that number of travelers on that trip affect to the total costs, these numbers of average travelers are acceptable.

Table 3-4 Numbers of People on that Trip by Transportation Mode

Mode	Number of Samples	Share (%)	Mean	Minimum	Maximum	Std Dev
Cars	861	87.5	1.4	1	6	0.74
Bus	14	1.4	1.1	1	2	0.36
Airplane	60	6.1	1.3	1	3	0.49
Train	5	0.5	1.0	1	1	0.00
Other	44	4.5	1.2	1	4	0.54
FL Total	984	100.0	1.4	1	6	0.72

Bus and train trips account for 1.4 percent and 0.5 percent, respectively, of long-distance travel in Florida. Bus and train trips are similar in their average travel length, but the train's minimum travel distance, about 120.0 miles, is twice the minimum trip length of buses. On the other hand, the train trips' maximum trip length of 444.5 miles is less than a half of the maximum distance traveled by buses. This suggests that trains are an alternative for long-distance travel for trips of less than 500 miles. Limited availability of these modes in Florida might be responsible for the low share of train trips in Florida. For example, the shortest distance from the 26,048 sampled households in Florida to airport, Amtrak, and bus terminals are 19.4 miles, 18.5 miles, and 12.0 miles, respectively. Since long-distance travel modes other than the automobile would be a part of a inter or multimodal transportation system, these distances could be long for travelers to access if supportive connections system between stations and other local destinations are not adequately provided. Therefore, services are expected to be of poor quality for producing the desired outcomes. The service quality of these intercity connections should be studied further.

Three quarters of long-distance trips have both of the origin and the destination in Florida, averaging 109.2 miles in trip length. On the other hand, about 16 percent of trips locate either the origin or the destination in other states, mainly Georgia and Alabama. These interstate trips record an average trip length of 621.4 miles, which is much longer than that of intrastate trips. Nearly 90 percent of intrastate travelers stay within less than a 200-mile range from origins using personal car. On the other hand, air travel constitutes about a quarter of the travel by alternative modes in the cases of interstate trips.

About 10 percent of long-distance trips did not specify their destinations in the 2009 NHTS. However, they are considered as interstate trips rather than intrastate trips, because the average trip length of 477.3 mile is close to that of interstate trip. Table 3-5 and Figure 3-3 present distribution of each travel type in total long-distance trips, and their shares by travel distance. Table 3-6 presents the mode distribution by travel type.

Table 3-5 Intra and Interstate Long-distance Trips

Locations of Origins and Destinations	Frequency	Share (%)	Trip Distance (miles)			
			Mean	Minimum	Maximum	STD
Intrastate	730	74.2	107.9	50.3	1389	89.6
Interstate	156	15.9	621.4	51.3	2761	579.3
Unknown	98	10.0	477.3	50.3	3018	645.2
Total	984	100.0	226.1	50.3	3018	376.0

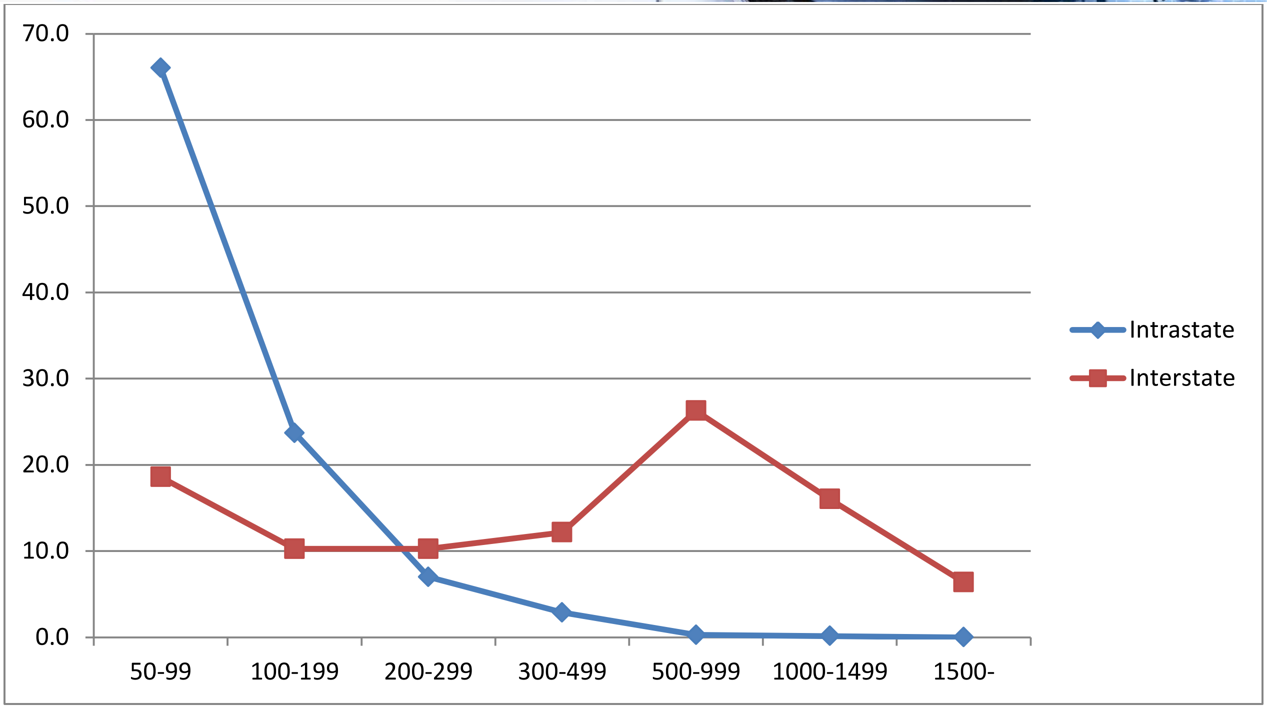


Figure 3-3 Percentage of Intra and Interstate Trips by Distance

Table 3-6 Share of Travel Mode of Intra and Interstate Long-distance Trips

	Cars	Bus	Airplane	Train	Other	Total
Intrastate (%)	684	10	5	4	27	730
	93.7	1.4	0.7	0.6	3.7	100.0
Interstate (%)	99	2	43	0	12	156
	63.5	1.3	27.6	0.0	7.7	100.0
Unknown (%)	78	2	12	1	5	98
	79.6	2.0	12.2	1.0	5.1	100.0
Total (%)	861	14	60	5	44	984
	87.5	1.4	6.1	0.5	4.5	100.0

Among the trip purposes for long-distance travel, social and recreational activities account for the highest share with 30.9 percent of total long-distance trips, followed by work and shopping/errands at 19.7 percent and 12.8 percent, respectively. Interestingly, trips to home show the longest average trip length of 280.4 miles, while trips for medical and dental services have the shortest average trip length of 84.2 miles. Both medical/dental services and school/daycare services are the shortest in maximum trip lengths of 269 miles and 191 miles, respectively, with small standard deviations. This suggests that people choose to locate themselves close to these fundamental service facilities that are essential to maintaining a quality of life. Table 3-7 presents descriptive statistics of trip purposes by travel distance.

Table 3-7 Long-distance Travel by Trip Purpose

Purpose	Number of trips	Share (%)	Trip Distance (miles)			
			Mean	Minimum	Maximum	Std Dev
Home	56	5.7	280.4	50	1997	374.1
Work	194	19.7	143.6	50	2652	292.6
School/Daycare	13	1.3	125.2	50	269	81.3
Medical/Dental	40	4.1	84.2	50	191	39.5
Shopping/Errands	126	12.8	159.1	50	907	179.7
Social/Recreation	304	30.9	241.1	50	3000	376.8
Family/Personal Business	60	6.1	231.0	50	3018	429.4
Transport Someone	70	7.1	115.5	50	1301	159.3
Meal	77	7.8	218.1	50	1389	243.2
Other	44	4.5	950.4	51	2770	738.6
FL Total	984	100.0	226.1	50	3018	376.0

Air travel accounts for relatively higher shares of 10.7 percent and 5.0 percent in trips, respectively, for home and family/personal business purposes. The airplane's share for home trips is high because home trips may include returning trips from other trip purposes such as social/recreation, shopping/errands, and family/personal business. In addition, home trips are more common in distance groups with 300 or more miles at 21.6 percent. Compared to other trip purposes, the personal car’s shares in home and school/day care trips are relatively low at 82.1 percent and 84.6 percent, respectively. This might be caused by the high shares of airplane and bus for home and school/daycare trips, respectively. About 9 percent of long-distance travelers use other modes (mainly trucks) to drive to their work place, while about 15 percent of long-distance travel for school and daycare purpose is by bus. For others purposes, personal car are the most frequent mode used. Interestingly, people use private cars to give ride other to destinations. Figure 3-4 presents mode share by trip purpose.

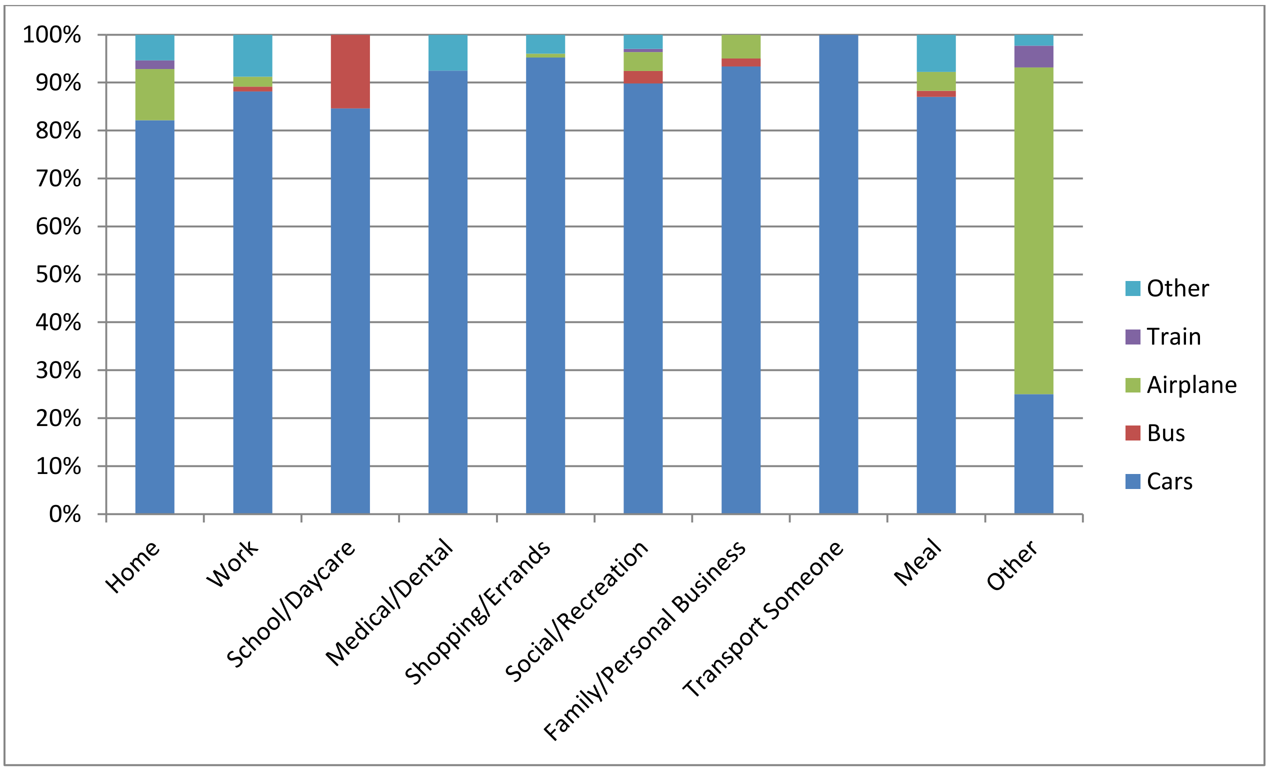


Figure 3-4 Mode Share by Trip Purpose

The location of a residence seems not to have a significant impact on mode choice decisions. As shown in table 3-7, urban area, urban cluster, and non-urban area show similar travel patterns, even though urban cluster has slightly shorter average distance of 196.2 miles. However, there are differences mode choices among residential locations. People residing in an urban area show relatively higher share of airplane at 8.0 percent, while personal cars are used by people in an urban cluster and non-urban area. These patterns might be related to the service availability in each area. For example, it is known that airlines provide more reliable, convenient, and frequent services in an urban area. Table 3-8 presents long-distance travel patterns by urban type, and Figure 3-5 shows the share of mode by urban type.

Table 3-8 Long-distance Trips by Urban Type

Type of Area	Number of Samples	Share (%)	Mean	Minimum	Maximum	Std Dev
In an urban area	566	57.5	242.5	50	3018	396.6
In an urban cluster	120	12.2	196.2	50	1754	301.2
Not in urban area	298	30.3	206.9	50	3000	362.3
FL Total	984	100.0	226.1	50	3018	376.0

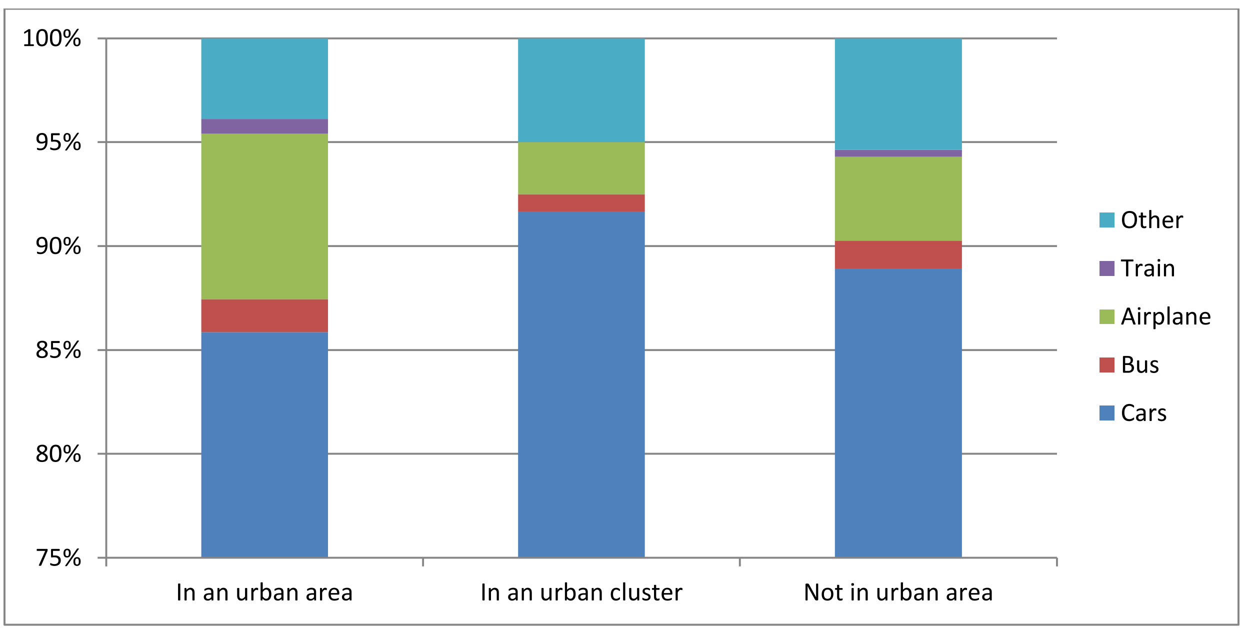


Figure 3-5 Share of Mode by Urban Type

The existence of children or elderly seems to have no effects on average trip distances, even though travelers with children show relatively short maximum distance of 1,022 miles and standard deviation of 260.5 miles. Travelers with children used less personal cars at 66.7 percent compared with other traveler groups. Bus shows relatively higher share of 26.7 percent for travelers with children, possibly because of higher share of charter bus in this traveler group. Table 3-9 presents long-distance trips by the existence of children and elderly, and Figure 3-6 presents variations in mode choice by the existence of children and elderly.

Table 3-9 Long-distance Trips by the Existence of Children and Elderly

		Number of Samples	Share (%)	Mean	Minimum	Maximum	Std Dev
Existence of Child	With Children	15	1.5	208.2	50	1022	260.5
	Without Children	969	98.5	226.3	50	3018	377.6
	FL Total	984	100.0	226.1	50	3018	376.0
Existence of Elderly	With Elderly	282	28.7	224.2	50	2761	350.1
	Without Elderly	702	71.3	226.8	50	3018	386.2
	FL Total	984	100.0	226.1	50	3018	376.0

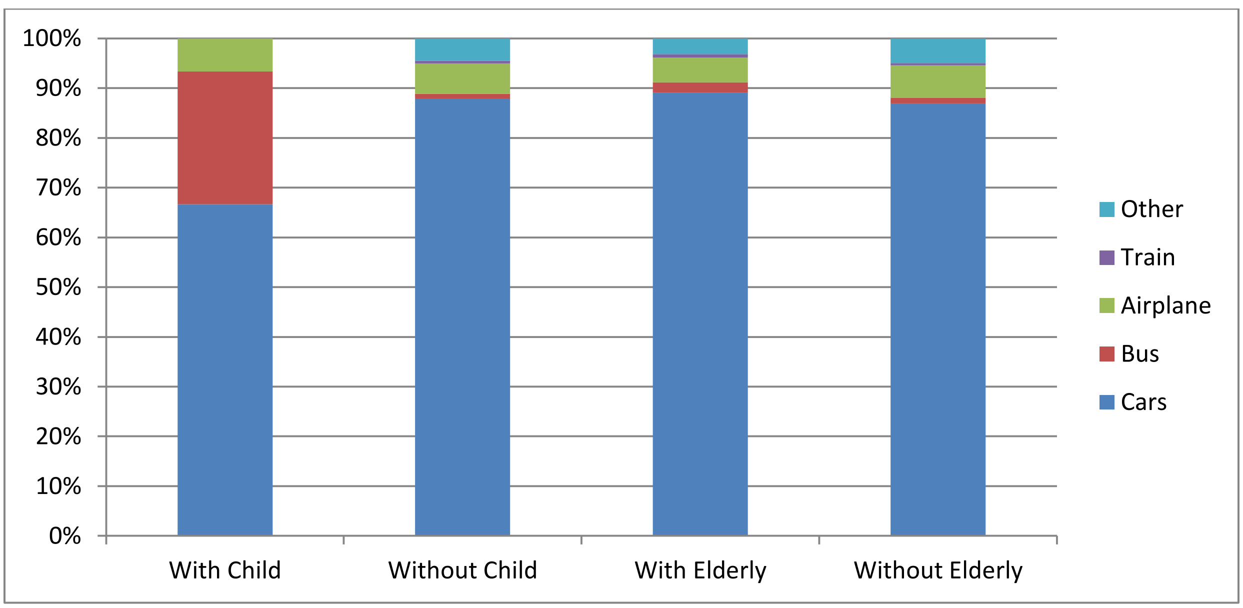


Figure 3-6 Share of Mode by the Existence of Children and the Elderly

As shown in Table 3-10, income seems to affect the average travel distance. Low-income travelers who earn less than $30,000 travel an average of 163.7 miles with a standard deviation of 244.2 miles. Meanwhile, mid or high-income travelers with incomes of $30,000 to $60,000 and over $60,000, are traveling longer distance than low income group at an average of 209.3 miles and 253.9 miles, respectively. These income groups also show relatively larger standard deviations of 331.1 miles and 414.6 miles; thus these groups are likely traveling to a wider variety of geographic locations. This may be due to the low-income group making intrastate trips for medical/dental services, and shopping and errands that are relatively short in trip length. Interestingly, the middle-income group shows relatively higher share of other modes, while high-income group choose airplane slightly higher than other income groups. However, these differences in mode choice among income groups are not significant. Table 3-11 presents the mode choice by income group.

Table 3-10 Average Trip Length by Income Group

Income Group	Frequency	Share (%)	Trip Distance (miles)			
			Mean	Minimum	Maximum	STD
- $29,999	184	18.7	163.7	50	1665	244.2
$30,000 - $59,999	277	28.2	209.3	50	2686	331.1
$60,000 -	456	46.3	253.9	50	3018	414.6
FL Total	984	100.0	226.1	50	3018	376.0

Table 3-11 Mode Choice by Income Group

Income Group	Cars	Bus	Airplane	Train	Other	Total
- $29,999	159	4	9	3	9	184
	86.4	2.2	4.9	1.6	4.9	100.0
$30,000 - $59,999	248	2	10	2	15	277
	89.5	0.7	3.6	0.7	5.4	100.0
$60,000 -	399	7	36	0	14	456
	87.5	1.5	7.9	0.0	3.1	100.0

As shown in Table 3-12 below, the east central, northeast, south and Tampa Bay regions of Florida take the top four positions in accounting for 8.1 to 13.2 percent of outbound trips and 9.6 to 17.5 percent of inbound trips. Inbound trips show more concentration on these four regions that may be caused by long-distance travel demand to large metropolitan areas such as Orlando, Tampa, Jacksonville, and Miami. Among these four regions, the Tampa Bay region shows slightly longer average trip distance at 213.7 miles for outbound trips, while the South region is longer average trips for inbound trips at 222.8 miles. However, they are not significantly different from the average trip lengths of 226.1 miles. In contrast, the Southwest region of Florida represents a relatively small portion with about 6.9 percent share in outbound long-distance trips, but its average trip length of 234.0 miles is the longest among regions of Florida. Similarly, the Withlacoochee region accounts for relatively small portion of inbound long-distance trips at 4.3 percent, but its average trip length of 281.1 miles is the longest among regions of Florida. The statistical tests show that these average trip distances of the southwest and the Withlacoochee region are different from other regions in Florida. This may be possibly because of both regions have relatively smaller portions of intra-regional trips and thus, they are large in the shares of trips 500 or more miles (see Figure 3-7 and Figure 3-8).

It is worth noting that the east central region has the shortest average trip length of 141.7 miles for outbound trips. This is because of the high concentrations on intra-regional trips between 50 to 100 miles. In the same context, the West region and the Central region show relatively short average inbound trip distances at 112.1 miles and 135.5 miles, respectively. This may result from the higher share of long-distance trips between 50 to 200 miles in these regions. Long-distance trips to/from other states show much longer average trip distances at 989.6 miles and 567.2 miles, respectively. Relatively large shares in 500 to 999, 1,000 to 1,499, and 1,500 or more mile distance ranges are considered to be responsible for these travel patterns. In addition, outbound trips whose destinations are not known also have longer average travel distance at 469.9 miles. This may imply that these trips may have destinations in other states.

Table 3-12 Number and Average Trip Length of Long-Distance Trips by Region

	Region	Frequency	Share (%)	Mean	Min.	Max.	STD
Outbound	Apalachee	35	3.6	162.3	53	907	166.5
	Central	66	6.7	157.8	50	1389	243.7
	East Central	130	13.2	141.7	50	2239	233.2
	North Central	65	6.6	168.3	50	1065	224.8
	North East	101	10.3	138.6	50	908	153.6
	South	98	10.0	166.4	50	1512	211.3
	Southwest	68	6.9	234	50	1754	361.4
	Tampa Bay	80	8.1	213.7	50	2652	360.8
	Treasure Coast	74	7.5	145.9	50	1318	209.4
	West	67	6.8	173.8	50	975	211.4
	Withlacoochee	67	6.8	149.7	50	1390	223.9
	Other State	36	3.7	989.6	58	2761	724.9
	Unknown	97	9.9	469.9	50	3018	644.3
	FL Total	984	100.0	226.1	50	3018	376.0

Table 3-12 Continues

	Region	Frequency	Share (%)	Mean	Min.	Max.	STD
Inbound	Apalachee	41	4.2	181.7	52.3	968.2	175.8
	Central	49	5.0	135.5	50.3	1138	175.8
	East Central	172	17.5	168.4	50.3	2454	277.6
	North Central	53	5.4	171	50.3	2686	372.3
	North East	94	9.6	213.3	50.3	3018	444.1
	South	102	10.4	222.8	50.3	2770	426.7
	Southwest	56	5.7	201.9	50.3	1294	317.9
	Tampa Bay	121	12.3	166.8	50.3	2165	310.1
	Treasure Coast	89	9.0	140.5	50.3	1665	210.1
	West	48	4.9	112.1	50.3	439.9	97.94
	Withlacoochee	42	4.3	281.1	50.3	3000	545.8
	Other State	117	11.9	567.2	51.3	2652	498.5
	FL Total	984	100.0	226.1	50	3018	376.0

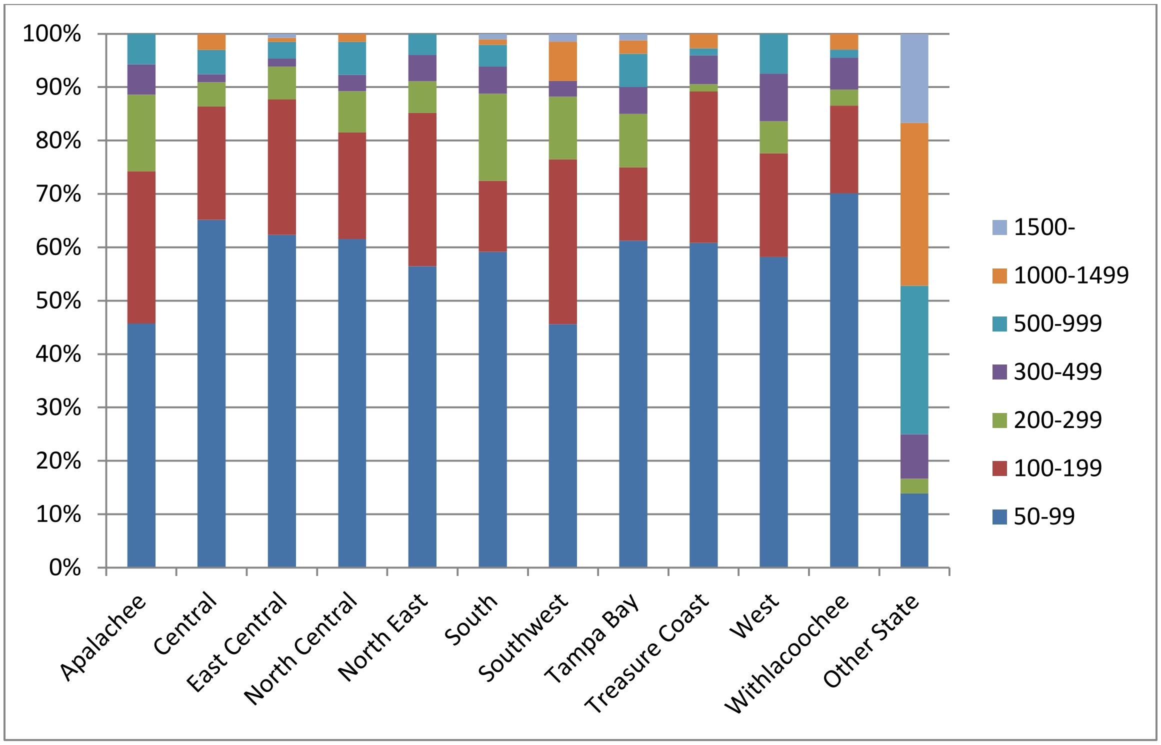


Figure 3-7 Percent of Outbound Long-Distance Trips by Region and by Distance

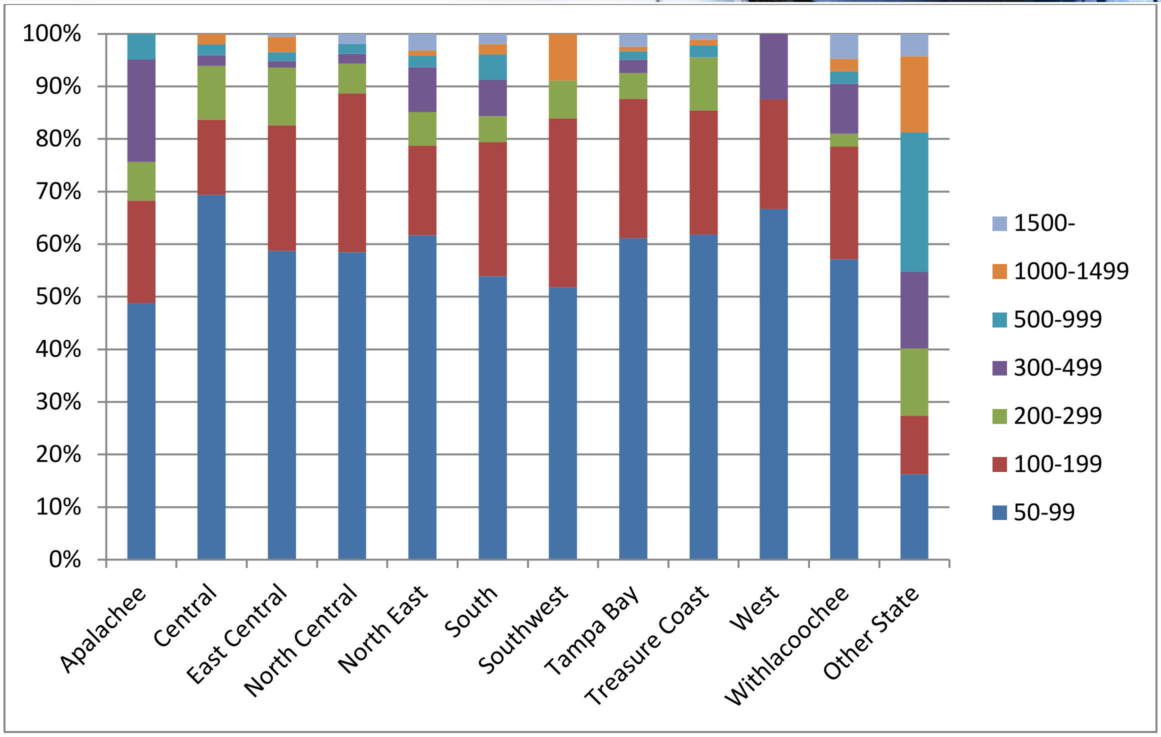


Figure 3-8 Percent of Inbound Long-Distance Trips by Region and by Distance

Overall, the personal car is the dominant mode of transportation for long-distance travel in Florida, accounting for about 88 percent of long-distance trips. In particular, the personal cars are commonly used for both outbound and inbound long-distance trips in the East Central, South, Tampa Bay, Treasure Coast, and West regions of Florida. It should be noted that the Withlacoochee region's shares of personal cars at about 79 percent for inbound long-distance trips are significantly lower than the East Central, Central, Tampa Bay, Treasure Coast, and West regions at 95 percent confidence interval. In addition, trips from other states also show low share of the personal cars at 70.1 percent for inbound trips.

Outbound trips to other states account for a significantly small portion of personal cars at 27.8 percent, but this can be adjusted if it is considered that long-distance trips to unknown destinations can be counted as outbound trips to other states. Still, the shares of personal cars for long-distance trips to/from other states are much lower than intrastate trips. Airplanes are commonly used for outbound long-distance trips to other states. They account for 19.7 percent of inbound trips and 63.9 percent of outbound trips. It is also worth noting that the personal cars' share is low in the southwest region at around 87 percent. Table 3-13 presents the distribution of mode choice by region.

Table 3-13 Percent of Travel Mode by Origin and Destination Region

	Region	Car	Air	Bus	Train	Other
Outbound	Apalachee	91.4	0.0	2.9	0.0	5.7
	Central	89.4	1.5	4.6	1.5	3.0
	East Central	90.8	3.9	1.5	0.0	3.9
	North Central	90.8	0.0	1.5	0.0	7.7
	North East	88.1	0.0	3.0	2.0	6.9
	South	93.9	2.0	3.1	0.0	1.0
	Southwest	86.8	1.5	4.4	0.0	7.4
	Tampa Bay	92.5	0.0	3.8	1.3	2.5
	Treasure Coast	93.2	0.0	4.1	0.0	2.7
	West	91.0	0.0	3.0	0.0	6.0
	Withlacoochee	91.0	4.5	3.0	0.0	1.5
	Other State	27.8	0.0	63.9	0.0	8.3
	Unknown	80.4	2.1	11.3	1.0	5.2
Inbound	Apalachee	87.8	0.0	9.8	0.0	2.4
	Central	95.9	0.0	2.0	2.0	0.0
	East Central	92.4	1.7	4.1	0.0	1.7
	North Central	88.7	0.0	3.8	0.0	7.6
	North East	90.4	1.1	3.2	2.1	3.2
	South	85.3	2.0	5.9	2.0	4.9
	Southwest	87.5	3.6	7.1	0.0	1.8
	Tampa Bay	91.7	2.5	2.5	0.0	3.3
	Treasure Coast	91.0	1.1	3.4	0.0	4.5
	West	91.7	0.0	0.0	0.0	8.3
	Withlacoochee	78.6	0.0	9.5	0.0	11.9
	Other State	70.1	1.7	19.7	0.0	8.6
FL Average		87.5	1.4	6.1	0.5	4.5

Among MSAs in Florida, the Tampa/St Petersburg/Clearwater MSA generates the largest share of long-distance trips at 9.1 percent, and this is followed by the Orlando MSA at 8.2 percent, the Jacksonville MSA at 5.0 percent, and the Miami and Daytona MSAs at 4.1 percent. The Ft. Myers/Cape Coral MSA records the longest average trip length at 357 miles with large standard deviation of 497.1 miles, while the Daytona Beach MSA has significantly short average trip length at 80.9 miles with the smallest standard deviation of 28.6 miles. The Sarasota/Bradenton MSA, one of two MSAs in the southwest region of Florida, also has relatively long average trip distance of 218.0 miles, and large standard deviation at 357.0 miles. The Daytona Beach MSA’s short average trip length is probably due to high concentrations of long-distance trips to the Orlando MSA, which is within 60 miles.

Other large MSAs such as the Miami, Orlando, Tampa/St. Petersburg/Clearwater, and Jacksonville MSAs show average trip length ranged between 146.8 and 193.8 miles. Among large MSAs in Florida, the Miami and Jacksonville MSAs show a relatively small standard deviation of 114.9 miles and 139.4 miles, respectively. It should be noted that non-MSA areas account for 23.5 percent of total long-distance trips, while interstate and other trips that have unknown origins account for 10.0 percent. These non-MSA areas have short average trip length of 150.7 miles with a standard deviation of 209.6 miles. Trips to other states have the longest average trip length of 983.6 miles, and the largest standard deviation of 734.6 miles. These travel patterns might present that unknown origins are likely part of interstate trips that cover geographically wide range of destinations. Table 3-14 and Figure 3-9 display the distribution of long-distance trips by MSA in Florida.

Table 3-14 Long-distance Trips by MSA in Florida

MSA	Number of Samples	Share (%)	Mean	Minimum	Maximum	Std Dev
Tampa/St. Petersburg /Clearwater	90	9.1	193.8	50	2652	343.6
Orlando	81	8.2	171.2	50	2239	288.7
Jacksonville	49	5.0	149.0	50	815	139.4
Miami	44	4.5	146.8	52	604	114.9
Daytona Beach	40	4.1	80.9	50	167	28.6
West Palm Beach /Boca Raton	40	4.1	162.3	50	1318	269.9
Fort Lauderdale	36	3.7	181.6	50	1512	264.3
Pensacola	36	3.7	209.5	50	964	230.9
Sarasota Bradenton	28	2.8	218.0	59	1486	357.0
Lake Land / Winter Haven	27	2.7	155.1	50	1151	240.8
Ft. Pierce/ Pt. Saint Lucie	25	2.5	131.9	52	524	114.3
Ft. Meyers/Cape Coral	20	2.0	357.0	50	1754	497.1
Gainesville	20	2.0	244.7	55	1065	308.2
Ocala	19	1.9	150.2	54	853	181.1
Melbourne/ Palm Bay	18	1.8	115.9	50	327	84.2
Tallahassee	18	1.8	188.1	53	907	202.8
Naples	15	1.5	147.4	52	327	79.2
Panama City	10	1.0	108.4	50	402	105.9
Punta Gorda	4	0.4	73.4	50	104	25.7
Other State	35	3.6	983.6	58	2761	734.6
Non MSA	231	23.5	150.7	50	1390	209.6
Unknown	98	10.0	477.3	50	3018	645.2
FL Total	984	100.0	226.1	50	3018	376.0

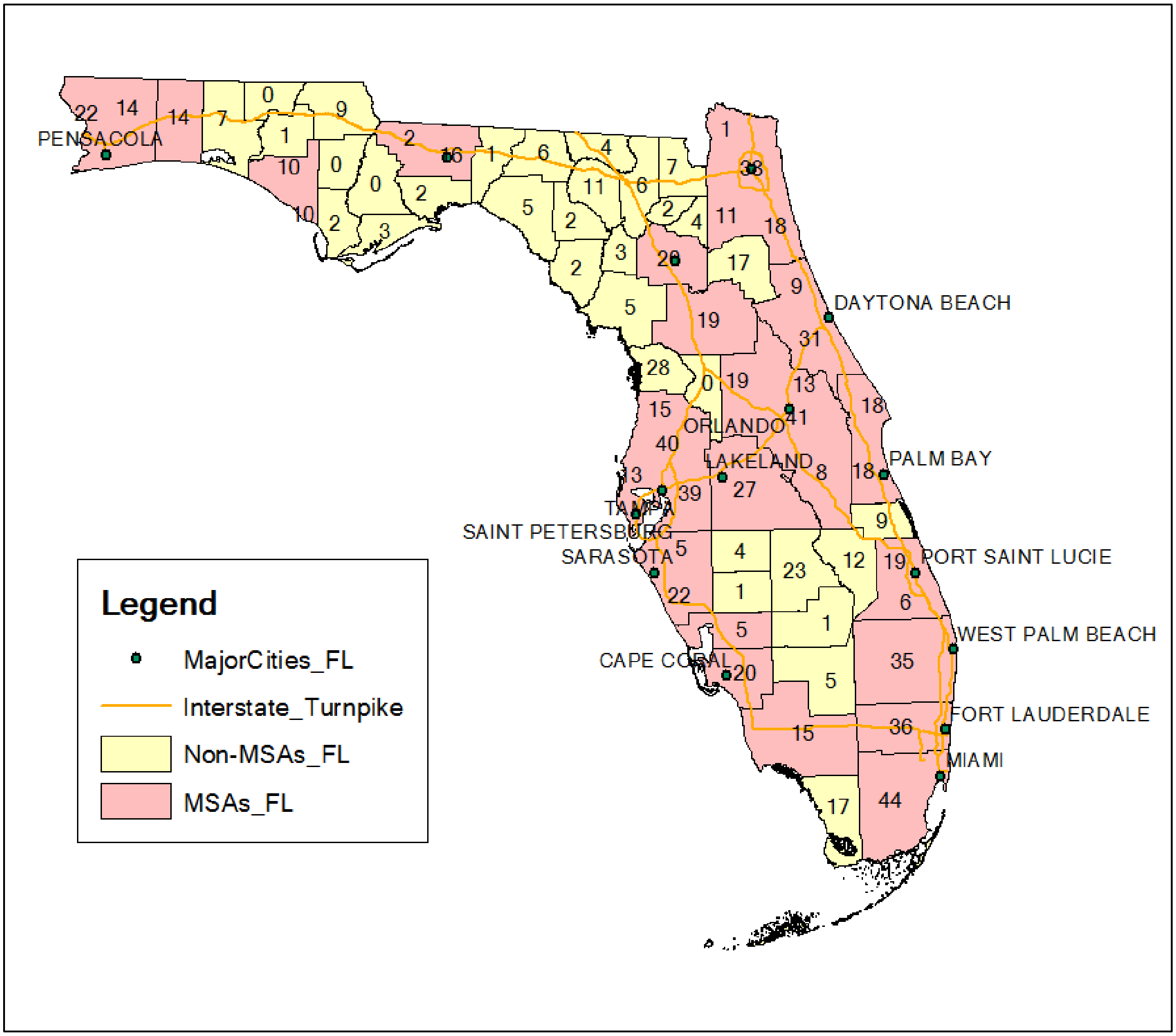


Figure 3-9 Numbers of Long-Distance Trips by County in the MSAs and Non-MSA Areas

3.1.3. TRAVEL PATTERNS BETWEEN ORIGINS AND DESTINATIONS

As presented in Table 3-15, intra-regional travel accounts for a large portion of long-distance trips generated in each region. For example, 34.3 percent, 30.0 percent, 38.8 percent, 40.8 percent and 44.8 percent of long-distance trips are intra-regional trips for the Apalachee, Tampa Bay, South, East Central and West regions, respectively. These large percentages of intra-regional trips may be resulted from the strong reliance of suburban or non-MSA areas on large MSA (such as Jacksonville, Tampa, Miami and Orlando) for socioeconomic activities. The low percentage of intra-regional trips of the Withlacoochee region at 13.4 percent and Central region at 21.2 percent can be understood in the same context. Since there is no large metropolitan area that can support people's economic needs, people in these regions may travel long-distance to MSAs in nearby regions.

In contrast, the West region provides an exception to this pattern by showing high percent of intra-regional trips even though there is no large MSA in the region. This may result from the distance to large MSAs. Since the region is approximately 300 to 400 miles away from either Jacksonville or Orlando, people in this region may have less need to travel to larger urban areas. The West region has especially large portion of intra-regional trips at 44.8 percent. It should be noted that the East Central region also shows relatively large share of intra-regional trips at 40.8 percent. However, this seems to present active interconnection with other regions rather than the effect of distance to large MSAs.

Table 3-15 Comparison of Intra-region and Inter-region Trips by Region

Region	Intra-region		Inter-region		Total
	Trips	%	Trips	%	Trips
Apalachee	12	34.3	23	65.7	35
Central	14	21.2	52	78.8	66
East Central	53	40.8	77	59.2	130
North Central	18	27.7	47	72.3	65
Northeast	35	34.7	66	65.3	101
South	38	38.8	60	61.2	98
Southwest	22	32.4	46	67.6	68
Tampa Bay	24	30.0	56	70.0	80
Treasure Coast	23	31.1	51	68.9	74
West	30	44.8	37	55.2	67
Withlacoochee	9	13.4	58	86.6	67
Average	-	31.7	-	68.3	-

The shares of intra-regional and inter-regional trips are presented in Table 3-16. The top 20 origin and destination region pairs account for about 49 percent of all long-distance trips reported in the 2009 NHTS data. Eight out of 20 origin and destination pairs are intra-regional trips within the East Central, South, Northeast, Tampa Bay, West, Treasure Coast, North Central and Southwest regions. Given the fact that more than 52 percent of trips are made in less than a 100-mile range, these results suggest that intra-regional travel explains these results.

It is worth noting that these regional origin-and-destination pairs present potential impacts of long-distance travel on existing highway corridors such as I-4, I-75, I-95, and the

Turnpike in Florida, and thus on congestion and delays on major road networks. For example, the Northeast, East Central, Tampa Bay, South, and Treasure Coast regions are strongly connected to each other, in addition to the high demand for intra-regional long-distance trips. Therefore, the I-4 corridor (between Daytona and Tampa), and Turnpike – I-95 corridor (connecting Orlando – Port Saint Lucie – Palm Beach – Fort Lauderdale – Miami) are considered important for Florida's long-distance transportation. The I-95 to I-4 corridor connecting Jacksonville, Daytona Beach and Orlando also seems to handle long-distance trips between the Northeast and East Central regions.

Interestingly, both the West and Tampa Bay regions have higher demand of long-distance trips to other states. These exceptional travel patterns can be explained by the higher share of long-distance trips over 300 miles of these regions. In particular, the West region is considered to have strong interrelationships with nearby states such as Alabama and Georgia. It should be noted that long-distance trips from these two regions would have impacts on different highways. For example, long-distance trips from the West region to other states may affect to I-10, I-65, and state highways, while long-distance trips from Tampa Bay regions are expected to use mainly the I-75 corridor.

Other origin-destination region pairs that show relatively large long-distance trips include intra Central region, East Central to Tampa Bay, North Central to Northeast, South to East Central, and Withlacoochee to East Central. These trips are also expected to have impacts on I-75, I-95, I-4, and Turnpikes in Florida.

Table 3-16 Top 20 Origin and Destination Region Pairs in Number of Trips

Rank	Origin Region	Destination Region	Trips	Share (%)
1	East Central	East Central	53	5.4
2	South	South	38	3.9
3	Northeast	Northeast	35	3.6
4	West	West	30	3.0
5	West	Other States	29	2.9
	Northeast	East Central	29	2.9
7	Treasure Coast	South	24	2.4
	Tampa Bay	Tampa Bay	24	2.4
9	Withlacoochee	Tampa Bay	23	2.3
	South	Treasure Coast	23	2.3
	Treasure Coast	Treasure Coast	23	2.3
12	Southwest	Southwest	22	2.2
13	Southwest	Tampa Bay	18	1.8
	North Central	North Central	18	1.8
15	Unknown	South	17	1.7
16	Tampa Bay	East Central	15	1.5
	East Central	Northeast	15	1.5
	Central	Tampa Bay	15	1.5
	Tampa Bay	Other States	15	1.5
	East Central	Treasure Coast	15	1.5
Top 20 Subtotal			481	48.9
Total Long-Distance Trips			984	100.0

Figure 3-10 graphically illustrates the shares of long-distance trips from each origin region to destinations. Among regions, three regions in northern Florida such as the West, Apalachee and North Central regions are interesting to note because they show highly biased travel patterns toward certain destinations including other states. In particular, the West region shows an extreme concentration of long-distance trips on both other states and intra-regional trips. Their travel patterns show that geographical locations may affect travel patterns including long-distance travel. For example, people in these northern regions of Florida seem to have strong relationships with adjacent states such as Alabama and Georgia. People who live close to other states tend to travel frequently for social and economic needs, such jobs, shopping, social and recreation. Interstate trips are also important component of long-distance trips for the Tampa Bay and the southwest regions. However, these regions are different from the northern regions because they have diverse destinations including the east central and north central regions.

In contrast, the Withlacoochee and the Central regions have the least interactions with other states, while they have large portion of long-distance travel demand to the East Central and Tampa Bay regions. Interestingly, the Central region has most diverse destinations for long-distance trips including the Tampa Bay, Treasure Coast, Southwest, and East Central regions. This may be possible because the Central region is geographically the center of all of these regions. The east central region is similar with the central region in long-distance travel destinations except it has more interactions with the northeast region. The South and Treasure Coast regions show high level geographical propensity toward the East Central and each other. However, long-distance trips from both the North Central and Northeast regions are concentrated on the northern regions even though the East Central region is one of popular destinations for long-distance trips in these regions.

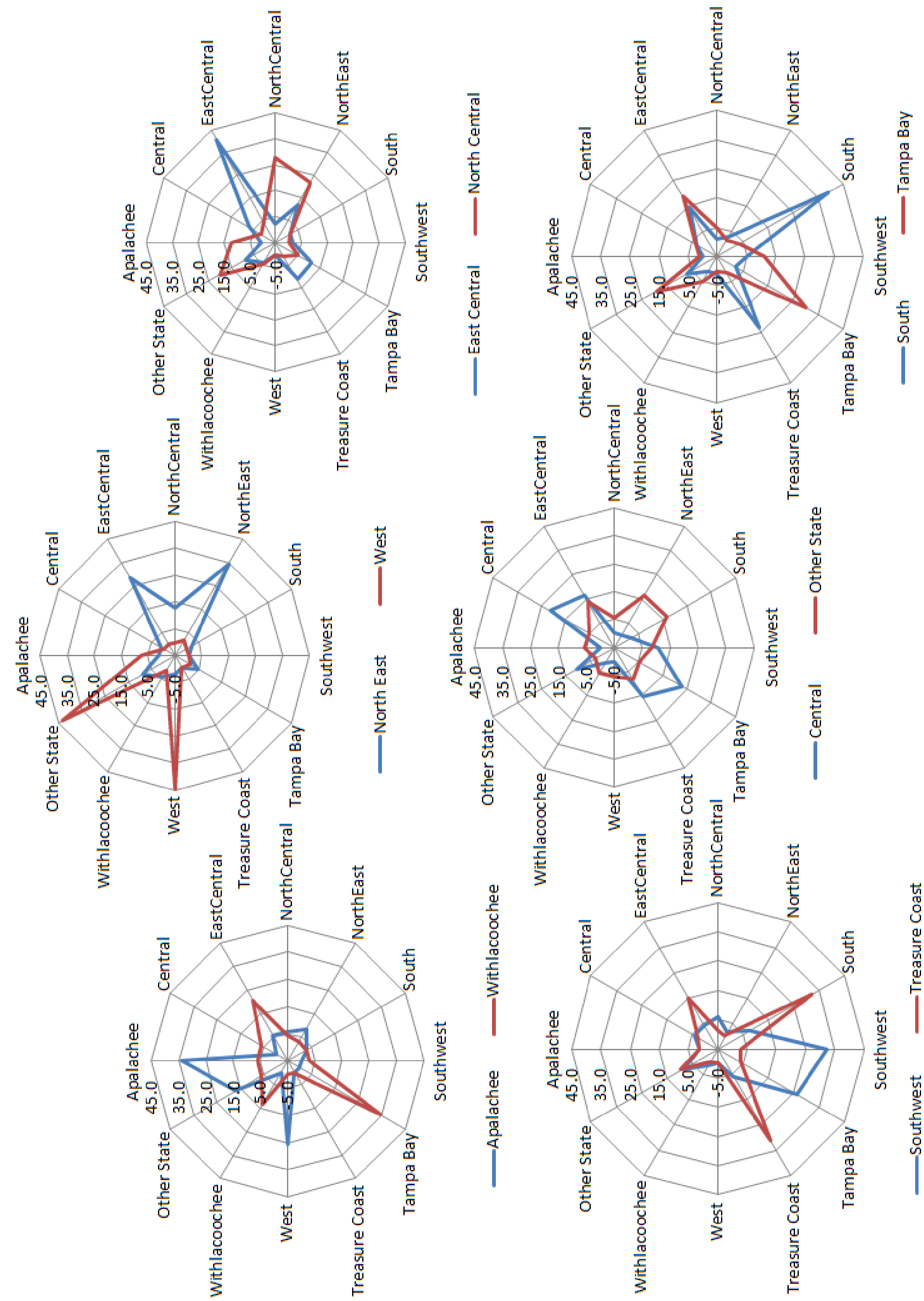


Figure 3-10 Shares of Long-Distance Trips between Origin and Destination

The geographical propensity can be clearly illustrated by removing relatively short trips for a new alternative intercity mode in the analysis. For that, this study removes trips that are less than 100 miles and trips that are longer than 500 miles. One hundred mile is a proximate distance from Orlando to Saint Petersburg, while 500 miles is the distance from Miami to Tallahassee, the distance at which high speed rail can compete with airplane and possibly automobile. This study has no specific intention to test feasibility of high speed rail, but 100 to 500 miles range will also be good for an alternative ground intercity mode.

As shown in Figure 3-11, intra-regional trips remain as an important part of long-distance trips in the West and South regions. However, the shares of intra-regional trips are decreased significantly at the East Central, Northeast, Tampa Bay, and Treasure Coast regions. In addition, some new origin and destination region pairs that are not highlighted in Figure 3-10 appear as important components of long-distance trips in Florida. For example, both the Withlacoochee and Apalachee regions become important destinations for the trips from other states, while other states become even more important destination for long-distance trips originated from the Tampa Bay, central, and Treasure Coast regions. Similarly, the Apalachee and northeast regions comprise major origin and destination region pairs with the Withlacoochee region. On the other hand, northern regions such as Apalachee, west, north central and northeast regions maintain strong relationships with each other.

These results increase the significance of both I-4 and Turnpike – I-95 corridors for long-distance travel in Florida because inter-regional trips among the northeast, east central, Tampa Bay, Treasure Coast, and South regions show robust relationships in long-distance travel demand. Therefore, I-95/Turnpike, I-4, and I-75 corridors need to be carefully managed and planned to address long-distance travel demands in the future. It should be noted that the I-10 corridor, connecting the west - Apalachee - northeast regions, increases its importance for long-distance trips in regard of 100 to 500 mile trips. In addition, origin and destination region pairs to/from the Withlacoochee and north central regions increase the importance of I-75 corridor.

Out of state destinations are still important for the long-distance trips ranged 100 to 500 miles, particularly in the central, east central, Tampa Bay, and northern regions. However, the south, southwest and Treasure Coast regions are less likely to interact with other states in this trip distance range. This might imply that the former region groups need to focus more on long-distance trips between 100 and 500 miles, while the latter may need to emphasize more on airplane trips that cover long-distance trips more than 500 miles.

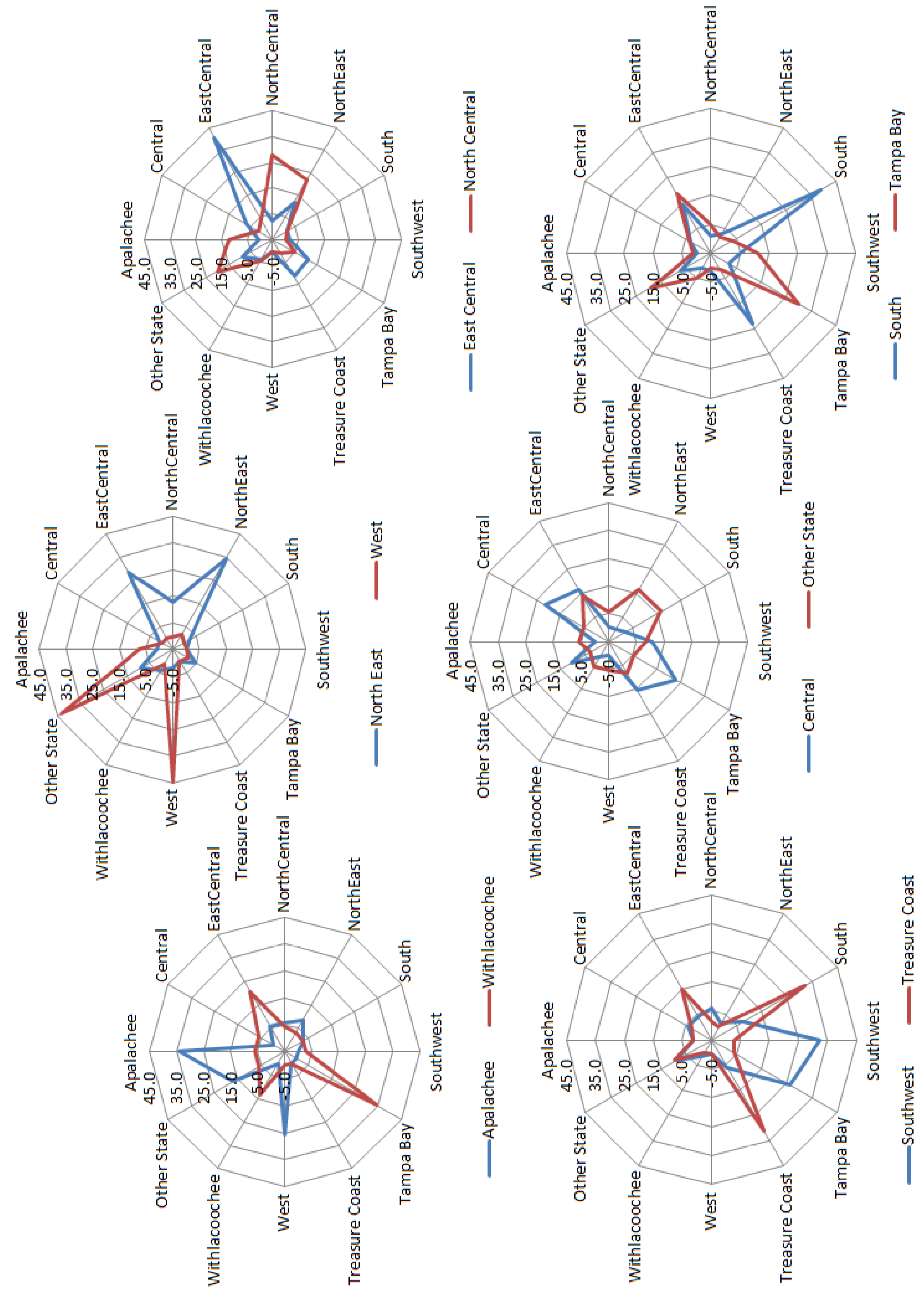


Figure 3-11 Patterns of Long-Distance Trips by Region at 100 to 500 Miles Distance

As shown Table 3-17, the Orlando MSA is the hub for long-distance travel network in Florida. It is frequent origin or destination for MSAs in the Tampa Bay, Northeast, Treasure Coast, and South regions such as Tampa/St. Petersburg/Clearwater, Jacksonville, West Palm Beach/Boca Raton, Melbourne/Titusville/Palm Bay, Lakeland, and Daytona Beach. In addition, there are connections between the Sarasota/Bradenton MSA and Tampa/St. Petersburg/ Clearwater MSA, and among West Palm Beach/Boca Raton, Ft. Lauderdale, and West Palm Beach MSAs.

The MSA level origin and destination analysis shows that Miami, West Palm Beach/Boca Raton, Jacksonville, Orlando, and Ft. Lauderdale retain wide interactions with multiple MSAs in Florida, and thus inter-MSA trips are important component of long-distance trips in these MSAs. In contrast, Daytona Beach, Tampa/St. Petersburg/Clearwater, and Pensacola MSAs have the least number of destinations for long-distance trips. In particular, Pensacola show extreme geographical propensity toward other states for long-distance trips (see Figure 3-12).

These origins and destinations pairs present the potential impacts of long-distance travel on the I-4, I-75, I-95, and Turnpike corridors in addressing long-distance travel needs in Florida. In particular, it is important for policy makers and planners to aware that Florida needs to address long-distance travel at 50 to 250 miles range. Since Orlando, the hub for long-distance travel is geographically in the center of Florida peninsular, top 20 origins and destinations pairs are located within 250 miles distance.

Non-MSA areas are also important in generating long-distance trips, and they have demand toward large MSAs such as Jacksonville, Tampa/St. Petersburg/Clearwater, Orlando, and Miami.

Table 3-17 Top 20 Origin and Destination MSA Pairs in Number of Trips

Rank	Origin	Destination	Trips	Percent
1	Tampa/St. Petersburg/ Clearwater	Tampa/St. Petersburg/ Clearwater	25	2.5
2	Daytona Beach	Orlando	19	1.9
3	Tampa/St. Petersburg/ Clearwater	Orlando	16	1.6
4	Tampa/St. Petersburg/ Clearwater	Sarasota/Bradenton	13	1.3
5	Sarasota/Bradenton	Tampa/St. Petersburg/ Clearwater	11	1.1
6	Fort Lauderdale	West Palm Beach/Boca Raton	10	1.0
7	Miami	West Palm Beach/Boca Raton	10	1.0
8	Orlando	Tampa/St. Petersburg/ Clearwater	10	1.0
9	Lakeland/Winter Haven	Tampa/St. Petersburg/ Clearwater	9	0.9
10	Orlando	Lakeland/Winter Haven	9	0.9
11	Orlando	Melbourne/Palm Bay	9	0.9
12	Orlando	Orlando	9	0.9
13	Jacksonville	Jacksonville	8	0.8
14	Orlando	Jacksonville	8	0.8
15	Orlando	West Palm Beach/Boca Raton	8	0.8
16	Ft. Pierce/Pt. St. Lucie	West Palm Beach/Boca Raton	7	0.7
17	Melbourne/Palm Bay	Orlando	7	0.7
18	Miami	Miami	7	0.7
19	West Palm Beach/Boca Raton	Fort Lauderdale	7	0.7
20	West Palm Beach/Boca Raton	Miami	7	0.7
Top 20 Subtotal			209	21.2
MSA Subtotal			620	23.5
Non-MSA Total			231	100.0

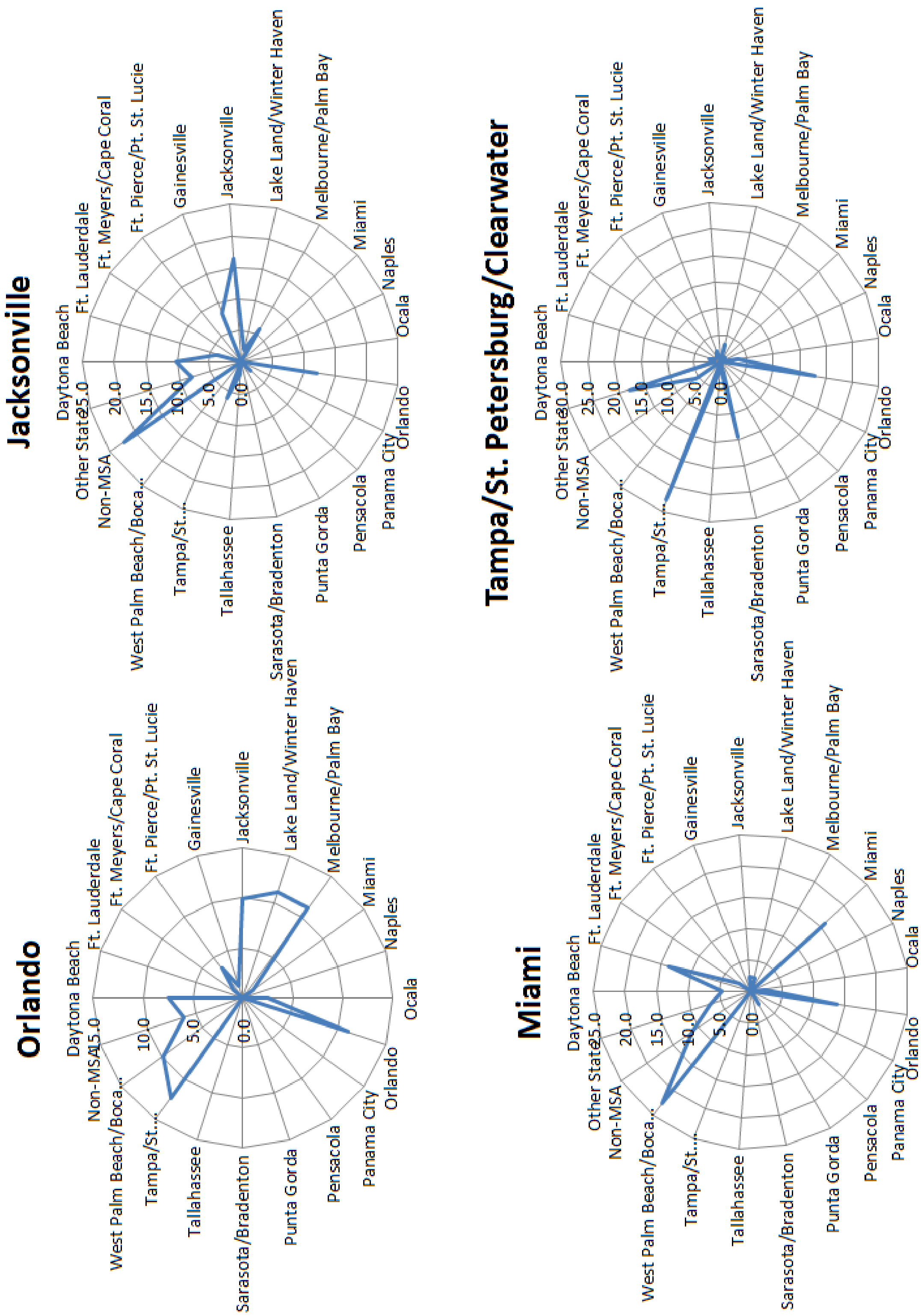


Figure 3-12 Patterns of Long-Distance Trips of Major MSAs in Florida

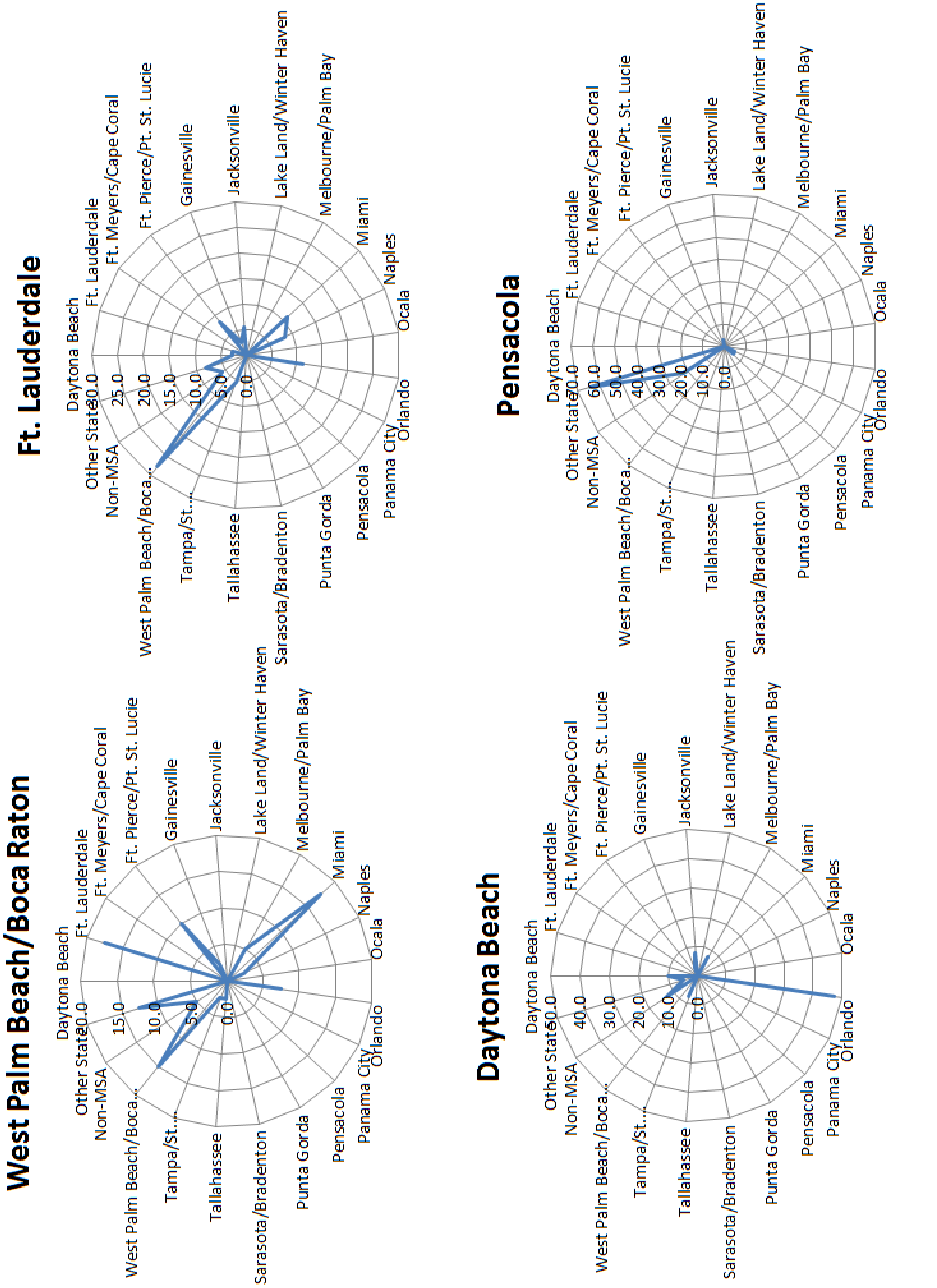


Figure 3-12 Continued

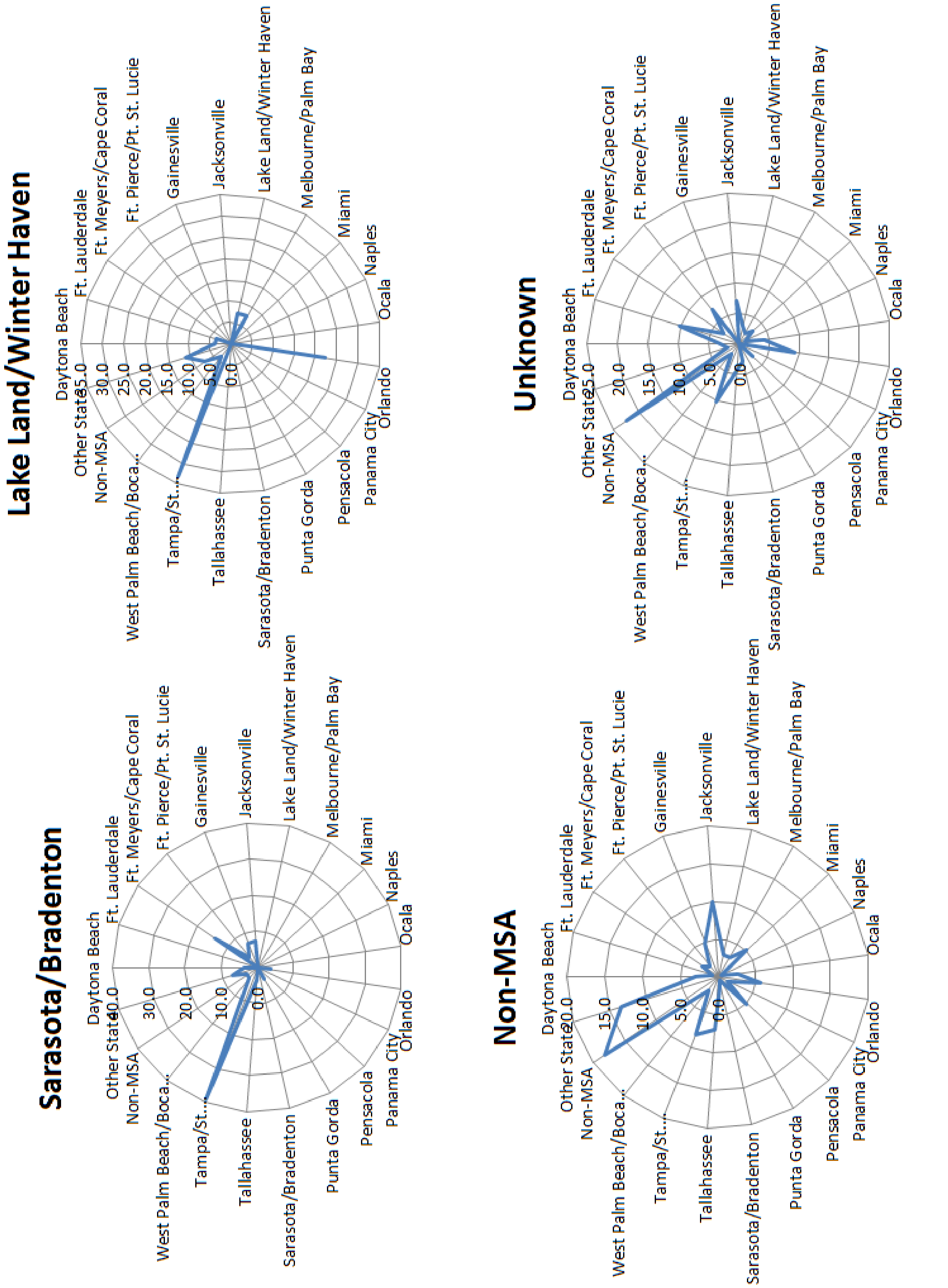


Figure 3-12 Continued

3.2. ESTIMATION OF MODE CHOICE MODELS

3.2.1 VARIABLES AND OPERATIONALIZATION

The factors that influence mode choice decision include alternative mode specific attributes such as travel time, travel cost, travel distance, and access/egress time (or/and cost), and traveler characteristics such as income group, age, number of vehicles, residence location, intrastate trip dummy, population density, number of travelers on the trip, and travel purpose. This study concentrates on the attributes that can be quantitatively measured to simplify the model development process. This study is, particularly, interested in the impact of travel mode characteristics on long-distance travel mode choice decision.

Table 3-18 Potential Independent Variables

Variables	Description	Measurement
Travel time	Travel time of each mode for that long-distance trip	Minute
Travel cost	Automobile: driving cost Bus/train/airplane: fare level	Dollar
Travel distance	Distance between origin and destination pairs	Mile
Access distance (or time/cost)	Network distance (or time) to nearest intercity terminals such as airport, bus terminal, train station	Miles (minutes)
Number of travelers	Total number of people on that trip	Person
Intrastate travel	Travel made within Florida	Yes, No, or Unknown
Trip purpose	Dummy variable that represents the purposes to make the trip: Three categories	Work, social/recreational, and others
Age related dummy	Age of the person surveyed (in case of household data, age of the main traveler	Year
Income group	Category of income	Low (less than 30000, medium (30000-60000), high (more than 60,000)
Urban area	Home address in urbanized area	Urban or Rural

These variables are calculated and presented as follows:

Actual **travel time** is available in the 2009 NHTS dataset since there is derived travel time (in minutes) of each trip. It can alternatively be calculated using start and end time of each trip reported in the survey.

The **travel costs** are calculated based on the distance traveled for each trip.

In order to calculate **driving cost** of the personal cars, this study uses the average driving costs per mile that has been issued by the American Automobile Association (AAA) in every year. The NHTS data does not present exact maker and model of personal cars used, but it provides information about modes such as car, van, SUV, and pickup truck and other truck car. By matching these classifications to the vehicle categories of the AAA such as small sedan, medium sedan, large sedan, SUV, and minivan, this study calculates an approximate driving cost of each long-distance trip.

Air fares are synthesized from the US DOT’s 10 percent sample ticket survey (DB1B data). This data present airport-to-airport fare, distance, number of scheduled service, available seats, and origin/destination airport pairs. Thus this study can find average fare at each airport based on distance groups such as less than 500 miles, 500 to 1000 miles, 1000 to 1500 miles, 1500 to 2000 miles, 2000 to 2500 miles, and more than 2500 miles.

The **intercity bus and train fares** are collected in reference to Amtrak and intercity bus companies.

The **travel distance** of main long-distance travel mode is actual distance between origin and destination reported by individual traveler for each trip.

For a trip that is made by bus, train, or airplane, this study calculates **access distance** from each household in the sample to intercity terminals. This study calculates network distance using X-Y coordinate of both household and intercity terminals, and road network in Florida. Since travelers who use these public intercity modes are subject to use secondary travel to/from intercity terminals, it is important to include the access travel time and cost in the regression model.

Access distance is measured as the network distance between individual and the intercity terminals (airport, bus terminal, and rail station) at the place of the home address.

Access time and cost is the travel time and cost to access intercity terminals calculated based on the calculated access distance.

The number of travelers on the trip is directly related to travel cost, and thus it is expected to affect strongly to the travelers' mode choice decision. Individuals who are traveling alone may have a greater tendency to choose common carriers while people who travel with family or colleagues may prefer in automobile because of the lower travel cost per person.

Intrastate travel means that the origin and destination of a trip is located in Florida. Meanwhile, interstate travels are trips that have either an origin or destination is in another state. This study includes this as a dummy variable.

Travel purpose of the trip includes home, work, school, shopping, medical, social, family or personal business, transporting someone, and meals. It has been argued that travelers on work trips have a higher probability to choose the airplane even though it is expensive.

This study uses **age** and **income** group variables that are collected in the 2009 NHTS and the Florida add-on, to see whether age and income influence traveler's mode choice decision.

Urban area indicator and **population density** are provided in the 2009 NHTS dataset. A dummy variable is introduced to the model to assess the potential difference in residence location.

3.2.2 HYPOTHETICAL RELATIONSHIPS OF VARIABLES TO MODE CHOICES

Among the range of variables that have been examined in the previous studies, both travel time and cost comprise the key variables that are expected to have negative signs. As travel time and cost increase, traveler's utility from a choice of the alternative decreases. Travel time is often split into in-vehicle time and out-of vehicle time of which the latter includes access/egress time, waiting time, terminal time, and transfer time. Meanwhile, travel cost commonly means the cost of driving automobiles or the fare level of public modes such as air, train and bus. In case of public long-distance travel mode, travel costs also can be divided into two subcategories such as fare and access/egress costs. All these subcategories of travel time and costs are also expected to have negative sign in the estimated models.

It should be noted that the ratio of the coefficient of travel cost over travel time implies the monetary value of travel time by which traveler makes trade-offs between various travel modes. In general, it is known that public intercity travel mode (bus or train) users are more sensitive to changes in travel cost of transit fares than to travel time, while air passengers are not very sensitive to cost and are highly sensitive to travel time having the highest value of time (Ashisbor, Baik and Trani, 2010; Bhat, 1997b; Carlsson, 2001). The conditional models are expected to provide the travel time and cost combinations to make a new alternative intercity mode attractive. In fact, most studies of HSR in Europe and Asia have evaluated the potential demand of a new HSR system by applying various scenarios of travel time and cost combinations to the estimated mode choice models (Beherens and Pels, 2009; Gonzalez-Savigant, 2004; Kim, Seo, and Kim, 2003; Lopez-Pita and Robuste, 2005; Ortuzar and Simonetti, 2008;

Park and Ha, 2003; Roman and Martin, 2007; Wardman and Whelan, 1997; Zhang and Xiao, 2007).

Travel distance can be used as an alternative indicator of travel time and cost because both time and cost are highly related to travel distance. Trip distance is expected to show a negative sign, and this implies that longer trip distances are associated with more time, more expense and less frequency. Therefore, this is also negatively related to individual's utility. In particular, distance variable is expected to interact negatively with automobile users' utility, while airplane user's utility is expected to increase as distance increases. Many previous studies have suggested that there exist thresholds at which travelers' mode choices change (Bel, 1997; Hensher, 2001; Jorgensen and Preston, 2007; Kitagawa, Terabe, and Sarachai, 2005; Wardman, 2001).

In addition to the attributes of the alternatives, travelers' characteristics are also frequently employed in many mode choice models. Thus, this study develops the ML models using these variables. This study includes both income and age variables in the model. Higher income travelers are generally assumed to choose an alternative mode that provides fast and convenient service even though it is more expensive. Hence, it is expected to have a positive sign for air travel, while a negative sign for public modes such as train and bus. The age variable is expected to have a positive sign for car because as people grow older, they substitute trips by car for train and airplane trips. For this age variable, this study applies a dummy variable that represents whether a long-distance trip includes people age 65 or more.

Notably, there are studies that emphasize the impacts of spatial attributes on travelers' mode choice decisions. In consideration of spatial characteristics this study includes dummy variables that represent the characteristics of residence locations, such as large MSA indicator and urban/rural area. MSA size, as a large city indicator, is expected to have a positive sign for train and bus because travelers in large metropolitan areas show a preference for the train and bus service providers. The existence of heavy rail service is also understood in the same context as MSA size. Higher demand for transport will facilitate public transportation network, and thus higher population density will associate with positive relation with larger share for train and bus.

In addition to those explanatory variables, a variety of other variables may affect travelers' mode choice decision including service frequency of public transportation modes, reliability and subjective factors such as comfort, perception of security check, privacy and convenience. However, this study does not include these variables because it is not possible or extremely difficult to collect data for the entire state. The NHTS 2009 and the Florida add-on data gathered daily travel data from current travelers, and thus it reflects current long-distance traveler's preference of mode choice under given travel and traveler characteristics. However, it does not provide information about travelers' subjective feeling of a travel mode or frequency of public transportation modes.

In the same context, the number of travelers on the trip is another variable that is expected to interact negatively with utility of certain modes including air. As the number of travelers increase total travel cost increases, and thus travelers may choose personal automobile instead of airplane because the larger party size the less a person is able to afford an expensive alternative (Capon et al., 2003). In addition, those traveling with family members may have preference to travel relatively short distance compared to those traveling alone. Trip purpose is a dummy variable that presents the reasons why people travel. This variable is expected to positively affect business travelers, particularly those who use airplane, since it is traditionally known that business passengers travel by air while non-business passengers travel by train or automobile for intercity travel. This is because most business passengers have no burden to pay for their trips. Figure 3-13 presents these relations in graphic.

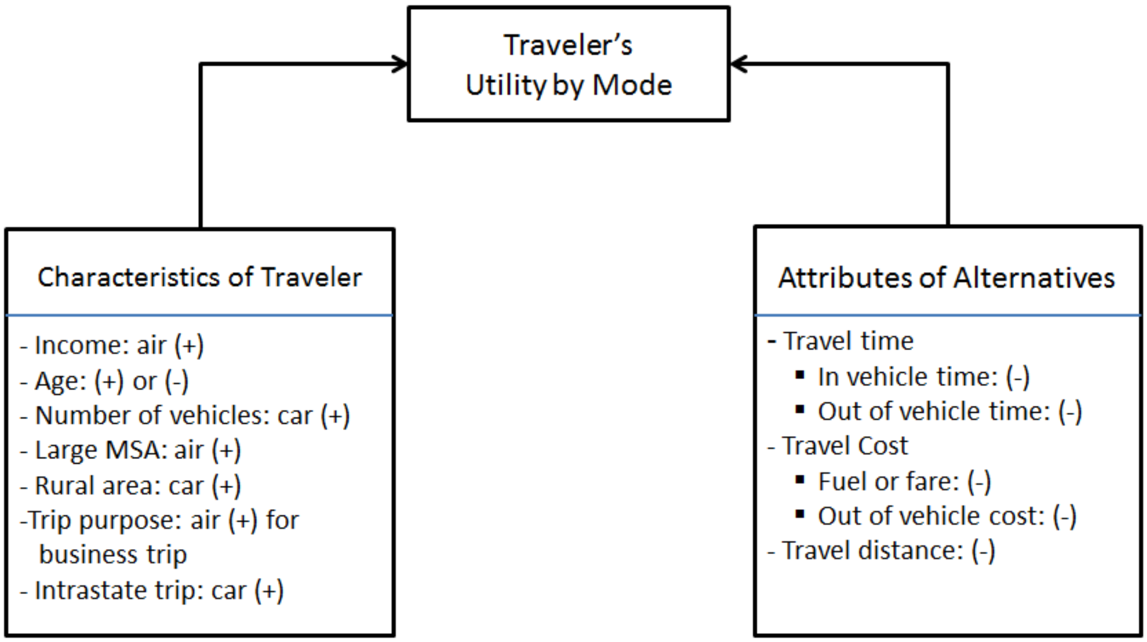


Figure 3-13 Hypothetical Relationship of Explanatory Variables to Travelers' Utility

3.2.3. RESULTS OF MODEL ESTIMATIONS

The key explanatory variables such as travel time and travel cost are statistically significant at 80 percent confidence interval in both the CL model and the ML model. The negative signs of parameters of travel time at -0.006 and travel cost at -0.006 for car indicate that travelers' utility decrease as these variables increase (See Table 3-19). In particular, car users are more responsive to increase in travel cost compared to travel time. Meanwhile, the estimated coefficients of travel time and cost have different signs in both airplane and bus. The negative parameters of travel time for bus of -0.095 and travel cost for airplane of -0.005 imply that additions of travel time and travel cost will reduce the utility of bus users and air travelers, respectively. In contrast, the positive parameters of travel time for airplane of 0.007 and travel cost for bus of 0.046 mean that addition of these variables affect positively to travelers' utilities. In other words, bus users and air travelers' utilities will increase as air travel time and bus fare increase, respectively.

The positive signs of parameters are not expected in the hypothetical interactions, but, they may happen because, unlike other modes, bus fares are not proportionally increased as travel time or travel distance increases. For example, bus fare is $61 for about 250 mile travel (or about 300 minutes travel) while it is $261 for about 3100 mile travel (or about 4800 minutes travel). Thus, bus users' unit fare by distance decreases from $0.24 to $0.08 as they travel longer distances. In the same context, air travelers' travel time is also not a proportional increment depending on the distance traveled because of inevitable time consumed on ground regardless of flight distance. For instance, it takes 65 minutes for about a 195 mile air trip from Orlando, FL to Miami, FL, while it is 145 minutes for about a 760 mile flight from Orlando, FL to Washington D.C. Thus, air travelers take advantage in travel time as they travel longer distance. These positive signs of these estimated parameters may imply that air travelers and bus users are willing to increase travel time and travel cost, respectively.

The estimated parameters of travel time and cost for personal car and bus are statistically significant at 80 percent confidence interval. The estimated coefficients of airplane are also statistically significant at 80 percent confidence interval at both models. Therefore, this study can discuss the effect of travel time and cost on mode choice decisions. Their signs, positive sign for travel time and negative sign for travel cost are considered as proper to explain the impacts of travel time and travel cost on the changes in utilities of airplane users.

In addition to alternative specific attributes, some traveler's individual characteristics appear to have impacts on mode choice decisions. The positive parameter of age-related variable indicates that people traveling with elderly are likely to choose personal cars. This may imply that people depends more on personal cars as they are getting older. However, travel by bus and airplane is similar irrespective of the age or the traveler. As expected, the high income group seems to travel more by airplane compared to medium and low-income travelers. However, its parameter is not statistically significant at 95% confidence interval, and thus it is not clear whether or not these positive impacts truly reflect the travel of the population.

The effects of geography measured through the location of the household shows that people in rural areas may have relatively higher probability to drive personal car to make long-distance trips compared to people living in urban areas. Since rural areas are expected to have less accessibility to airport and intercity bus services, the positive coefficient of car usage is reasonable. Considering that MSA size has no impacts on the utilities of travelers, and in turn on mode choice decisions, the effects of geography seem to need to be approached from a broad perspective.

In order to test the goodness-of-fit of the estimated CL and ML models statistically, this study conducted a chi-squared test (Log-Likelihood Ratio Test) using two log likelihood values from convergence models, -69.030 for the CL model and -65.253 for the ML model, and constant only models of-263.6 for both the CL and the ML models. The chi-squared value is expressed as follows:

$$\text{Chi} - \text{squared value} = -2\ (LL_R - LL_{UR})$$

Where, LL_R is the log likelihood of the restricted model (constant only model)

LL_{UR} is the log likelihood of the unrestricted model (convergence model)

The calculated chi-squared value of 389.14 and 396.70 are substantially larger than the critical chi-squared value of 31.41 at 95% confidence interval. This indicates that the independent variables used in this final model are statistically meaningful in predicting the probability of mode choice for long-distance trips. The adjusted r-squared value of 0.2619 for the CL model and 0.2475 for the ML model are high enough to say that these variables can explain the impacts on the probability of a specific mode choice.

Table 3-19 Estimation of Logistic Regression Models

Explanatory variables	Conditional Logit Model (CL)		Mixed Logit Model (ML)	
	Coefficient	t-value	Coefficient	t-value
Constant - Car - Bus	 6.790 9.648	 8.25 6.18	 6.816 10.138	 7.15 6.06
Travel time - Car - Airplane - Bus	 -0.006 0.007 -0.095	 -4.37 1.41 -6.13	 -0.006 0.007 -0.096	 -4.10 1.31** -6.08
Total travel cost - Car - Airplane - Bus	 -0.006 -0.005 0.045	 -2.03 -1.61 3.71	 -0.007 -0.005 0.046	 -2.22 -1.59** 3.79
Travel with Elderly - Car	-	-	 0.601	 1.00*
High Income ($70K or more) group - Airplane	-	-	 0.671	 1.08*
Rural area dummy - Car	-	-	 1.209	 1.92
Number of Cases	936		936	
Log Likelihood at Convergence	-69.030		-65.253	
Log likelihood at constant only model	-263.601		-263.601	
R-squared	0.2619		0.2475	

Note: *: estimated coefficient is statistically significant at 70% confidence interval. **: estimated coefficient is statistically significant at 80% confidence interval. Others are statistically significant at 90% confidence interval. Since the long-distance samples are limited, this study allowed large tolerance on estimated coefficients.

3.3. MARGINAL EFFECTS OF TRAVEL TIME AND COST

The marginal effects calculation measures the effect of a one unit change in explanatory variable on the dependent variable. Thus, they are different from the elasticity that measures the effect of a 1 percent change in explanatory variables on the dependent variable. The marginal effects are informative means to provide what is the change in the probability of choosing an alternative t for a decision maker i because of small change in the attribute *k* of alternative *t*. The direct marginal effects for continuous variables are expressed as:

$$\frac{\partial P_{i,t}}{\partial x_{i,t,k}} = P_{i,t}(1 - P_{i,t})\beta_k$$

Where, $P_{i,t}$ = the probability of individual *i* to choose mode *t*

β_k = estimated coefficient of variable *k*

Using the coefficient estimates of the CL model in Table 3-20 and individual traveler's travel time and travel cost data, this study calculate the average change in the probability of choosing an alternative mode by alternative specific attribute. As shown in Table 3-21, one hour increase in travel time is expected to decrease the probability of choosing personal car by 0.0059 percent. The probability of choosing bus is also expected to decrease by 0.0143 percent as travel time increases by one hour. In contrast, a one-hour increase in travel time is expected to increase the probability of choosing airplane by 0.0058 percent. Increases in travel costs also have the similar impacts on the probability of choosing personal car and airplane. A one hundred dollars increase in travel cost is expected to decrease the probabilities of choosing personal car and airplane by 0.0212 and 0.0069 percent, respectively. While, 0.0113 percent more travelers are expected to choose bus trip as travel cost increase by one hundred dollars.

Table 3-20 Average Marginal Effects of Travel Time and Cost by Mode

Alternative	Car		Airplane		Bus	
	Travel Time	Cost	Travel Time	Cost	Travel Time	Cost
Average Marginal Effect	-0.0059	-0.0212	0.0058	-0.0069	-0.0143	0.0113

It should be noted that airplane users are less likely affected by the changes in both travel time and cost, while bus users are much sensitive to the changes in travel time. The relatively higher average marginal effects of both travel time and cost show that bus users may have strong willingness to decrease travel time, but increase travel cost in order to increase their utilities. Car users are less sensitive to the changes in travel time, while they are highly responsive to the changes in travel cost.

3.4. SERVICE QUALITY OF A NEW ALTERNATIVE TRAVEL MODE

Using the coefficients of the travel time and cost from the CL model, this study attempts to identify the potential service quality of a new alternative mode. For that, this study applies access and egress time and cost to air, bus, and a new alternative mode. The access and egress time and cost are based on the average distances between households and intercity terminals, such as 29.1 miles for airport, 14.4 miles for bus terminals, and 21.2 miles for train stations. Including these distances to intercity terminals, air travelers have 60 minutes access and egress time, while bus users have 30 minutes of additional time. A new alternative mode is assumed to have 45 minutes of access and egress time since it could be either high speed rail or improved conventional train service. These average distances are applied to calculate the access cost based on driving costs of personal cars excluding other alternatives.

This study also presumes that a new alternative option replaces current bus service by improving its speed. For that, this study sets three levels of speeds for a new alternative mode such as 120, 150, and 200 miles per hour, and calculates travel times at a travel distance between 100 and 600 miles. These speeds resemble currently available speeds of train and high speed rail or improved train services in both the US and other countries. Meanwhile, the incremental travel distances from 100 miles to 600 miles represent the service range where a high speed ground transportation mode, including HSR system, is empirically expected to have competitiveness against air and personal cars. This study examines travel cost options to identify the potential probability of choosing a new alternative mode.

As shown in Table 3-21, the results show that a new alternative mode has 3.5 to 19.4 percent of probability at a 100 mile travel distance depending on the speed level. It provides the shortest travel time, while maintaining a lower fare level than airplane, regardless of the operation speed. Thus, a new alternative is expected to have a strong potential to attract passengers from personal cars and airplane at 100 mile distance. In a 200-mile distance, a new alternative would compete with personal cars and airplane when its speed is 150 or more miles per hour. A new alternative mode appears to draw nearly 21 percent of long distance travelers with a speed of 200 miles per hour. In addition, it accounts for about 13 percent of long-distance travelers by increasing its fare level up to $120 at a speed of 150 miles per hour. However, a new alternative mode may not be very attractive to long-distance travelers at a speed of 120 miles per hour. It can only have less than 7 percent of probability of usage, even at the same fare level with airplane. Thus it is insufficiently competitive in terms of the fare levels.

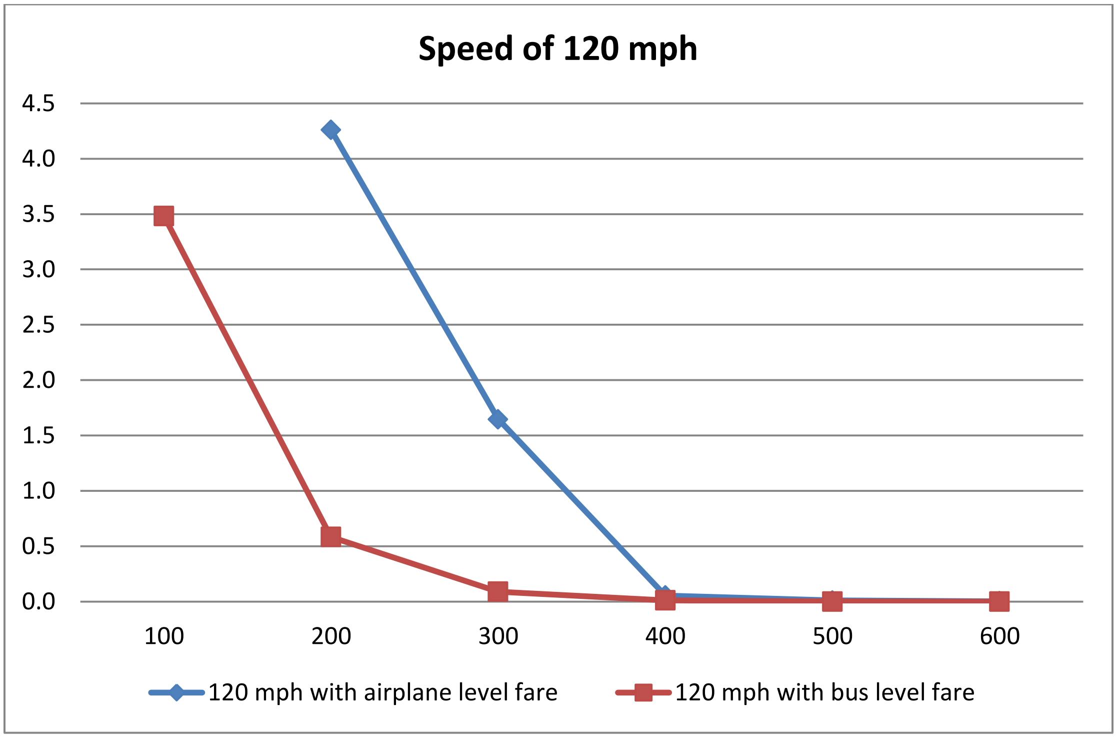
Both the 300 and 400 mile distances show similar patterns of the probability of choosing a new alternative. A new alternative is not sufficient to divert people from personal cars and airplane with a speed of 120 miles per hour, regardless of fare level. Meanwhile, it would have competitive power with a speed of 150 miles per hour, but it would raise the fare level up to (or even more than) that of airplane, which may, in turn, weaken its competitive position. In the same context, a new alternative has a very limited probability of less than 3 percent in a 400 mile service distance, even though its fare level reaches that of airplane (or more). Considering that its travel time is about 1.5 times longer than travel by airplane, the same fare as air travel may not be acceptable to passengers because the estimated mode choice model indicates that air travelers would be willing to reduce cost, while they are positive to travel time increases. Consequently, a new alternative mode is expected to strengthen the competitiveness when it is operated at a speed of 200 or more miles per hour. This speed would allow a new alternative mode to maintain a fare level less than that of airplane.

In both 500 mile and 600 mile service distances, a speed of 200 miles per hour is essential to draw about 5 percent and 4 percent of long-distance passengers from personal cars and airplane, respectively. However, it should be noted that a new mode may have weak competitiveness against both personal car and airplane, even with a speed of 200 miles per hour because its travel time is 1.3 times longer than that of airplane, and it has no flexibilities to adjust the fare level from the current bus fare of $190 and $230 at both distance ranges, respectively.

In summary, a new alternative is expected to have higher competitiveness against personal cars and airplane for the distance of 100 miles. Meanwhile, it would have a stronger competitiveness in the 200 mile distance when it provides with a speed of 150 or more miles per hour. In both 300 mile and 400 mile distances, a speed of 200 miles per hour is essential to strengthen competitiveness of a new alternative mode. Even a speed of 200 miles per hour is not sufficient to attract people from other modes in travel distances of 500 miles and 600 miles. A new ground travel mode is expected to account for less than 15 percent in these distances. Figure 3-14 displays the probabilities of a new ground mode by travel time and cost scenario.

Table 3-21 Potential Service Qualities of a New Alternative Mode

	Car		Air		Bus		New Alternative			Probability			
Distance	Time	Cost	Time	Cost	Time	Cost	Speed	Time	Cost	Car	Air	Bus	
100	105	30	115	70	165	45				0.9959	0.0040	0.0000	0.0348
							120	95	45	0.9613	0.0039		0.0854
							150	85	45	0.9110	0.0037		0.1944
							200	75	45	0.8024	0.0032		
200	220	65	115	135	300	90				0.9928	0.0072	0.0000	0.0058
							120	145	90	0.9870	0.0072		0.0426
									135	0.9505	0.0069		0.0378
							150	125	90	0.9553	0.0070		0.1316
									120	0.8621	0.0063		0.2080
							200	105	90	0.7863	0.0057		
300	330	95	120	200	430	135				0.9874	0.0126	0.0000	0.0009
							120	195	135	0.9865	0.0126		0.0165
									200	0.9711	0.0124		0.0153
							150	165	135	0.9723	0.0124		0.2245
									200	0.7657	0.0098		0.2117
							200	135	135	0.7783	0.0099		
400	445	125	135	210	560	175				0.9684	0.0316	0.0000	0.0001
							120	245	175	0.9683	0.0316		0.0005
									210	0.9679	0.0316		0.0050
							150	205	175	0.9636	0.0315		0.0235
									210	0.9456	0.0309		0.1823
							200	165	175	0.7918	0.0259		
500	550	155	150	260	745	190				0.9396	0.0316	0.0000	0.0000
							120	295	190	0.9396	0.0604		0.0001
									260	0.9395	0.0604		0.0005
							150	245	190	0.9391	0.0604		0.0112
									260	0.9291	0.0598		0.0530
							200	195	190	0.8898	0.0572		
600	670	185	170	310	890	230				0.8744	0.1256	0.0000	0.0000
							120	345	230	0.8744	0.1256		0.0000
									310	0.8744	0.1256		0.0002
							150	285	230	0.8743	0.1256		0.0055
									310	0.8696	0.1249		0.0434
							200	225	230	0.8364	0.1201		0.0433



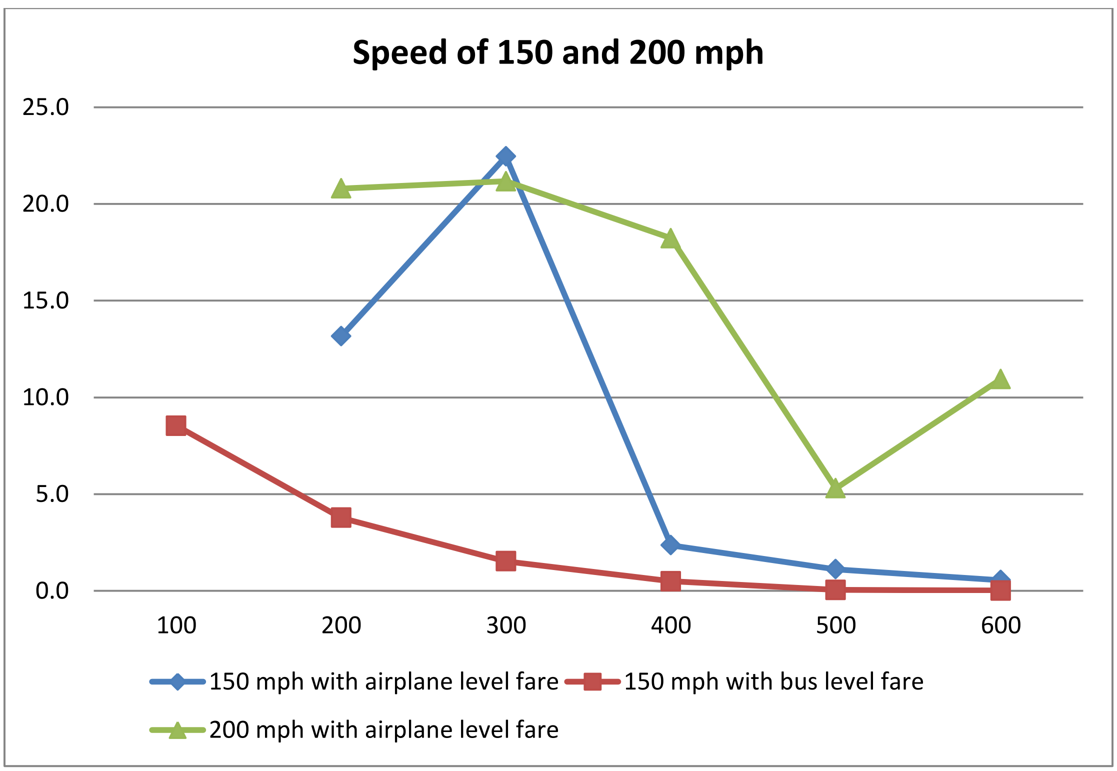


Figure 3-14 The Probabilities of Choosing Improved Ground Transportation Mode

CHAPTER 4 CONCLUSIONS, RECOMMENDATIONS, AND SUGGESTED RESEARCH

4.1. CONCLUSIONS

This study enhances fundamental understanding of long-distance travel patterns in Florida, and provides policy options for long-distance transportation planning in the future. For that, this study conducted descriptive analysis of the 2009 National Household Travel Survey (NHTS) and the Florida add-on data, developed logistic regression models that are sensitive to travel mode and travelers' characteristics, tested scenarios of travel time and cost where people may change their mode choice behavior, and suggested viable alternative options for long distance transportation planning in Florida. Among various trips by definition, this study focused on long-distance trips that are defined as trips of 50 miles or more from home to the farthest destination traveled (US DOT, 2011). In practice, this study, however, considers a trip as long-distance trip if at least one segment of the daily trips between origin and destination is 50 miles or more. This limited the long-distance trips mostly into intercity trips.

This study descriptively examined current patterns and characteristics of long-distance travel in Florida, focusing on the modes used, distance traveled, purpose of trips, and most importantly origin and destination pairs among eight regions in Florida. Long-distance travel has certain patterns, even though they are made as a part of daily activities. First, long-distance travel is likely to begin at home no matter how many trips are made by an individual in a given day, or prior to a long-distance trip. Consequently, home accounts for about 70 percent of total long-distance trip origins. Secondly, three quarters of long-distance trips are made in less than a 200-mile range from origins, possibly using personal cars. Eighty percent of car users travel less than 200 miles, and the airplane overtakes personal cars if the travel distance is over 1000 miles.

Third, people seem to locate themselves close to certain service facilities, such as medical/dental services and schools. Meanwhile, travelers with children make fewer trips by personal cars compared with other travelers without child. Bus showed relatively higher share for travelers with children, possibly because of higher share of charter bus in this traveler group. Fourth, the central region interacts the most actively with other regions, such as the central west, the central east and the southeast regions. In detail, the origin and destination pairs of MSAs show that Orlando plays a key role in long distance travel network up to 200 mile range. Thus I-4 corridor between Daytona and Tampa/Saint Petersburg MSAs, Turnpike – I-95 corridor that connects Orlando, Port Saint Lucie, Palm Beach, Fort Lauderdale, and Miami MSAs, and the northern section of I-95 between Jacksonville and Daytona Beach MSAs are important for Florida. Fifth, the northwest region has more active interactions with other states such as Georgia and Alabama, possibly because they are closely located to the northwest region. Therefore, a coordination system is essential to provide alternative options for intercity travel.

The estimated CL model showed that both travel time and travel cost decreased car users' utilities, indicating that people may shift to other modes as travel time and travel costs increase. The ratio of the coefficients of travel time and travel cost indicate that car users are willing to pay 46.15 cents to reduce 1 minute of travel time. This is equivalent to a $27.69 per hour value. The estimated coefficients of both travel time and travel cost for airplane are statistically significant at an 80 percent confidence interval. The positive sign of travel time is not expected, but it is considered to be acceptable because the positive sign of travel time shows that people will travel by airplane until they reach to certain threshold. In contrast, air travelers respond negatively to the travel cost, and thus people may choose other modes of transportation if air fare increases. In the same context, the negative sign of travel time and the positive sign of travel cost for bus are reasonable to explain the patterns of mode choice behavior. Bus users are willing to reduce travel time or spend more money to increase their utility of choosing bus. This is reasonable considering the fact that the bus has the longest travel time, while bus users pay the least fare among current modes in the market.

In addition to those alternative specific attributes, travelers' characteristics such as age, income, and location of residence appear to affect to the mode choice decisions. The results from the ML model showed that age has positive impacts on car users' mode choice decision. In addition, people in rural areas likely depend more on personal cars than people in urban areas. Income seems to be related positively to the choice of airplane, but it is not statistically significant at 90 percent confidence level. Other travelers' characteristics such as trip purpose, number of vehicles, number of people on that trip, and interstate trip dummy appear to have no significant impacts on mode choice decisions.

Overall, the independent variables used in this final model were statistically meaningful in predicting the probability of mode choice for long-distance trips. The adjusted r-squared value of 0.2619 showed that this mode can explain around 26.2 percent of the impacts of independent variables on the utility of each individual mode choice.

The measures of marginal effects show that potential changes in the probability of choosing an alternative depending on the changes in travel time and travel cost. The measures show that bus users are more sensitive to the changes in travel time and cost, while air travelers are less responsive to the changes of travel time and cost. The probability of choosing personal car decreases by 0.0059 percent and 0.0212 percent as travel time and cost increase 1 hour and $100, respectively.

Finally, this study identifies the potential service quality of a new alternative mode using the coefficients of the travel time and cost from the CL model. The results show that a new mode will be able to attract long-distance travelers if it has a speed of 120 or more miles per hour in the 100 mile range. However, a new alternative may have difficulties in the 200 mile distance range to attract travelers onto its system if its speed is less than 150 miles per hour. Between the 300 and 400 mile ranges, a speed of 200 miles per hour is likely necessary for a new alternative mode to be competitive against other modes in the market Even a speed of 200 miles per hour is not sufficient to attract people from other modes in travel distance ranges of 500 miles and 600 miles. A new alternative mode shares long-distance travel by about 5 percent and 4 percent in 500 miles and 600 miles transportation market, respectively. However, it may not be enough to support the operation of high-speed ground transportation system.

4.2. RECOMMENDATIONS

Based on finding on long-distance travel patterns, this study has several policy implications. First, since three-quarters of long-distance trips are made in less than a 200-mile range from origins, Florida needs to find an alternative travel mode or service or improve existing service that can cover up to a 200-mile travel distance. With 75 percent of long-distance trips averaging 109.2 miles in trip length that have both origins and destinations in Florida, such a service would be justified. In addition, origins and destinations pairs of long-distance trips show that Orlando MSA is the hub for long-distance trips connecting other MSAs in 50 to 250 miles distance. Secondly, considering the fact that the central region interacts the most actively with other regions, such as the central west, the central east and the southeast, comprehensive long-distance transportation plans are needed for I-4 corridor between Daytona and Tampa/Saint

Petersburg, and Turnpike – I-95 corridor that connects Orlando, Port Saint Lucie, Palm Beach, Fort Lauderdale, and Miami. In addition, I-95 north between Daytona Beach and Jacksonville should be prepared for the future because it is one of major corridors for the long-distance trips in a 100 to 500-mile range. Third, a coordination system with adjacent states like Georgia and Alabama will be critical for some regions including west, north central and Apalachee regions in Florida in order to address long-distance travel needs to/from those states.

In regards to these considerations, a new alternative needs to provide services to compete with personal cars up to 250 mile distance. For that, a speed of 150 miles per hour or more is required in the 200 mile distance based on the estimated models. However, it should be noted that it is more important for a new alternative to provide services with an appropriate fare level. For example, a new alternative can reduce travel time by 95 minutes at a speed of 150 miles per hour and 115 minutes at a speed of 200 miles per hour, which are equivalent to monetary savings of $43.84 and $53.07, respectively. Therefore, a new alternative mode would be able to charge less than driving cost plus monetary savings from travel time reduction. In other words, a new alternative mode may charge less than $108.84 at 150 miles per hour speed and $118.07 at 200 miles per hour speed assuming a driving cost of $65 for 200 mile distance.

4.3. LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

The descriptive analysis has several limitations. First of all, the 2009 NHTS and the Florida add-on data have limitations in representing complex long-distance traveler patterns and trends. For example, many trips provide no information about either the origin or the destination, so this study was not able to confirm their trips accurately. Secondly, a larger sample of trips would improve the accuracy of results. Since the dataset reflects daily travel behavior of ordinary

Americans, it can represent certain portions of long-distance travel. However, long-distance travel is not a common activity that happens on a daily, a weekly, or even a monthly, basis. So, any data collection effort should collect more travel information focusing on long-distance travel to enhance the current levels of analysis. For this, MSAs, such as Orlando, Tampa, Miami, and Fort Lauderdale, can be good places to collect additional data because now we know these areas are important for long-distance transportation plans in Florida. Third, descriptive analysis results are not sufficient to explain complex inter/multimodal systems of long-distance travel. Therefore, comprehensive studies (for example, a supportive connection system between stations and other local destinations) are of critical importance to produce the desired transportation plans and policy options. Cases studies for different states can advance the discussion of this study.

The mode choice model also has several limitations. First, this study reflected access distance to intercity terminals such as bus and airplane, and thus was able to improve the accuracy of travel time and cost. However, this study assumed that there is no difference in access mode. Therefore, the model could be improved by considering differences in access mode. Secondly, the estimated results are based on broad assumptions on missing information, such as fare levels of public intercity modes, in-terminal waiting time, and service frequency of public modes. These variables would be more accurately represented in future studies. Third, the structure of the equations should be tested to include nonlinear functions to determine if they are more suitable to explain complex mode choice behavior. Finally, analysis for demand forecasts can follow this study. The information on marginal effects and service quality of a new alternative mode will be able to enhance the study of demand forecast in Florida. For that, it is necessary to collect stated preference (SP) data from individuals who use intercity terminals. The SP data will reinforce the results of potential service quality for a new alternative mode.

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