THE FACTORS THAT AFFECT LONG-DISTANCE TRAVEL MODE CHOICE DECISIONS AND THEIR IMPLICATIONS FOR TRANSPORTATION POLICY

BY
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To my family

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LIST OF ABBREVIATIONS

AAA	American Automobile Association
ARTBA	American Road & Transportation Builders 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
ENC	East North Central division
FAA	Federal Aviation Administration
FDOT	Florida Department of Transportation
FRA	Federal Railroad Administration
HSR	High Speed Rail
MNL	Multinomial Logit
MT	Mountain division
NEC	North East Corridor
NHTS	National Household Travel Survey
PAC	Pacific division
RP	Revealed Preference
SA	South Atlantic division
SP	Stated Preference

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The overall goals of this study are to enhance the fundamental understanding of long-distance travel characteristics in the US, and to provide policy implications for long-distance transportation planning in the future. This study uses the 2009 National Household Travel Survey (NHTS) and state add-on data that provide a daily trip data base in both national and state perspectives. In particular, this study focuses on long-distance trips defining long-distance trip as a trip segment that is 50 or more miles from origin to destination.

In order to achieve the research goal, this study first summarizes current patterns and characteristics of long-distance travel in the United States. In addition, this study develops mode choice models for long-distance travel that can explain the relationship between travelers' choices of transportation mode and a set of explanatory variables such as alternative specific attributes (travel time, travel costs and access/egress time and costs), individual characteristics (income, age, and trip purpose), and geographical characteristics of household (MSA category, and existence of heavy rail service). This study estimates the Multinomial Logit models based on the mathematical function of the Conditional Logit (CL) model.

In order to develop logit models, this study estimates synthetic travel time and costs of all available transportation modes. In estimating synthetic travel time and costs, this study used all possible sources of published data including average driving costs per mile by passenger car type, air passengers fare and flight distance survey, bus and train fare and travel time tables. In addition, this study calculated shortest distance from each household to intercity terminals such as 422 commercial airports, 1482 bus terminals, and 533 train stations.

Finally, this study predicted the probability of choosing a new alternative by applying travel time and costs scenarios to the estimated model. For that, this study assumes a new alternative mode as an improved train system because no other ground modes are able to provide a speed of 200 or more miles. Based on the findings, this study suggests viable options for planners and decision makers to plan for long-distance transportation in the future.

CHAPTER 1
INTRODUCTION

Background

Extensive population growth and economic development have caused continuous increases in travel demand, average travel distance, and consequently congestion and delays. Average daily person miles traveled (PMT) in the US, for example, increased from 83.1 miles to 90.4 miles between 2001 and 2009. Meanwhile, average vehicle miles traveled (VMT) increased from 49.8 miles to 54.4 miles between 1990 and 2009 (Santos et al., 2011, p.10). It should be noted that highway delays near urban areas caused travelers to waste an average of 34 hours resulting in 3.9 billion gallons of fuel as of 2009. Overall, roadway congestions are known to cause a total of $115 billion congestion cost in 2009 (Schrank et al., 2010, p.7). In addition, 30 percent of the domestic flights in the US arrived late in 2007 which is up from 20 percent in 2003 (Whalen, Carlton, Heyer & Richard, 2008, p.31). The delays of air transportation are estimated to result in $32.9 billion of total costs in 2007 of which $16.7 billion is direct costs to passengers (Ball et al, 2010, p.3). These problems are expected to be worse in the future because the U.S. population is expected to grow to 439 million and the GDP is expected to increase to 43 trillion over the next 40 years (U.S. DOT, 2010, p.31) increasing travel demand on both highways and airports significantly.

In order to address growing congestion and delay problems, federal, state, and local governments have traditionally focused on the capacity expansion of existing transportation infrastructure through significant capital outlays. However, even these capacity additions will not be able to fully accommodate the predicted highways and airports demand at an adequate service level. Instead, highway congestion is rather expected to spread to medium-sized cities, small cities, and even suburban and rural fringe over the next 10 to 15 years (U.S. DOT, 2006, p.9). Meanwhile, providing additional capacity of highways near urban areas is increasingly difficult not only because highways are becoming increasingly expensive to build, but also because highway construction cost around urban areas, 8-10 million per mile of 4-lane highway, is nearly double compare to that of rural and suburban areas, 4-6 million per mile (ARTBA, 2010). It is also estimated that a greater number of large hub airports and their associated metropolitan areas are expected to face capacity constraints by 2013 and 2020. Besides, they will not be able to increase capacity beyond what is currently provided because some areas have limited geographical capability to increase runways (The MITRE Corporation, 2007, p.6)

These concerns have motivated both policymakers and researchers to acknowledge the needs of a new approach that can address current congestion problems as well as growing travel demand in the future. A variety of alternative options have been evaluated over the past decades, and considerable attention has been directed toward new ground transportation mode such as high speed rail (HSR), Maglev rail, and upgraded rail services. The US Department of Transportation (DOT) has attempted to provide a full array of affordable and practical mode choice options to reduce road travel (U.S. DOT, 2006; 2010). The Federal Aviation Administration (FAA) has emphasized the importance of exploring alternative means of transportation that can substitute short to medium distance air routes (U.S. DOT, FRA, 1997; U.S. DOT, FAA, 2001). In the same context, the FAA recommended the development of an efficient and effective intermodal system to mitigate capacity problems at airports (U.S. DOT, FRA, 1997).

In those provisions, the HSR option has been given top priority that is considered as a viable option to mitigate both highway and airport congestions by diverting long-distance travel demand to its system, and to reduce the need of massive capital spending to pay for capacity expansions in other existing modes (Peterman, Frittelli, & Mallett, 2009). The HSR system is also expected to improve attractiveness and the potential economic development of the regions by promoting accessibility and connectivity. These extensive interests and efforts resulted in the Obama administration's active leadership in a funding decision of $8 billion down payment on the HSR system in a 100-600 mile range intercity corridors that connect major metropolitan areas in the US (U.S. DOT, FRA, 2009).

However, it has been difficult to implement the high speed rail (HSR) proposals in the US because the success of the HSR option has been in question. Much of the criticism of HSR is based on the concerns about its cost effectiveness in the near to medium distance range. One of the major challenges results from the nation's geography with lower population density in urban areas compared to urban areas in Asia and Europe (Peterman et al., 2009). More importantly, HSR's competitiveness against personal automobiles puts the success of the system in question. Critics argue that HSR will not be able to compete with personal cars in the US because the 58 percent of the long distance trips are not that long, less than 250 miles (or 400 km) in round trip distance (U.S. DOT, FHWA, 2006), and personal cars account for more than 90 percent of trips that longer than 50 miles (U.S. DOT, BTS, 2006). These travel patterns may deteriorate HSR's competitiveness against automobile and air transportation because previous studies in Europe and Asia have suggested that HSR can have strong potential at a one-way service range between 250 mile and 500 mile.

Given these promises and concerns, it is needed to evaluate whether or not a new alternative high speed train system would be a viable option in the US. In the same context, it is necessary to understand whether there is such a desired service quality for a new alternative mode to become an effective and efficient option. However, there have not been sufficient efforts to evaluate the potentiality of HSR system in the US even though such supports are essential. In particular, academic studies have not been active in developing a broad spectrum of measures to propose a viable option for the US.

Statement of Problems

When a new alternative mode of transportation enters into an existing transportation market, it will inevitably compete with other modes of transportation in the market, and consequently a portion of other mode use will shift to a new mode. That portion of shift is critical to evaluate the adequacy and efficiency of a new transportation investment in a wide transportation system. In this respect, the focus has to be on the understanding of travelers' mode choice behavior because travel demand of certain mode of transportation depends largely on the individuals' choice decisions of modes. However, previous studies of HSR system have been faced criticisms with regarding to methodologies, data, and reliability of ridership estimations.

First of all, the method that was used to forecast the demand for HSR systems has raised several valid issues. Most ridership studies, for example: KPMG Peat Marwick LLP (1998) and SYSTRA (1998) for Florida corridor; Charles River Associates

(2000) and Cambridge Systematic (2006) for Bay Area / California High Speed Rail; and Chen (2011) for Richmond, VA - Washington, D.C. HSR line, have developed disaggregate demand models to forecast the travel demand of HSR systems in a specific corridor. However, majority of these studies formulated mode choice as separate binary diversion models in which percentage of automobile, air, and bus passengers are diverted to HSR. It is the simplest specification to evaluate the impact of a new alternative mode on the competing mode in the market, and to utilize the stated preference (SP) data that is collected for a HSR project in a given corridor. However, the binary diversion approach does not capture mode shift between the existing alternatives, and thus it can increase the difficulty of evaluating level of service changes to existing modes (Brownstone, Hansen, & Madanat, 2010).

Secondly, most demand forecasting efforts have used imperfect data because there is lack of public accessible data sources. Since HSR has unique attributes and does not exist in the market yet, well designed and collected stated preference (SP), revealed preference (RP), or combined dataset is essential to evaluate such an option (Roth, 1998). However, most survey datasets collected for HSR projects are considered to include a large portion of samples from wrongly defined populations. For example, SP data for California HSR surveyed largely from air transportation instead of personal car users that accounts for nearly 93 percent of total interregional travel. Hence, the estimated models can produce distorted mode choice decision of the average intercity travelers (Brownstone, et al., 2010). In addition, the SP data is susceptible to serious problems of survey respondent bias because respondents have the tendency to stick with their current mode choice regardless of the alternatives' attributes (Roth, 1998).

Thus, the estimated models are likely to contain unobserved serial correlation making the parameter estimates inconsistent.

Third, most of previous ridership studies are commercially confidential studies, and thus demand forecasts are often significantly optimistic and different ridership forecasting methods have yielded uncertain and inconsistent results (U.S. GAO, 2009). In addition, ridership studies have encountered criticism because parameters of the mathematical models were considerably adjusted from assigned values in the models, and thus the forecasts of demand have a strong likelihood of very large error bound from one level that can support the implementation of HSR investment to the other level that show significantly low demand (Brownstone et al., 2010). The reason is that most of ridership studies for HSR projects are, so far, conducted by private consultants who are working under a variety of pressures and for different types of clients that are directly related to the implementation of HSR projects. Florida High Speed Rail Authority (FHSRA), for example, estimated Florida HSR line between Tampa and Orlando would attract more than 10 percent of automobile users on the interstate highway (AECOM Consulting and Wilbur Smith Associates, 2002), but another study estimated that HSR would reduce traffic on the busiest sections of I-4 by less than 2 percent (Peterman et al, 2009). Similar results were produced in a study of HSR in the Northeast Corridor. The study noted that rail travel must be extremely competitive in factors such as speed or cost to attract automobile travelers because automobile travel is different from air and rail travel in that it involves door-to-door transportation, provides higher flexibility in time of departure and does not require individuals to share space with others (U.S. DOT FRA, 2008).

Therefore, it is needed to develop reasonable and applicable measures that can provide answers for policy makers and private industries to the questions: what are the existing patterns and trends of long distance travel in the US, and what are the factors that affect people to choose one transportation mode or another one? Furthermore, it is essential to lay the foundations of understanding: what are desired service qualities that may change long-distance travelers' mode choice behavior, and what are viable strategies for the future long-distance transportation plans?

Purpose of Study

The overall goal of this study is to enhance fundamental understanding of long-distance travel patterns and characteristics of the US. This study also aims to evaluate the potentiality of an alternative option for long-distance passenger service in the US and provide strategic policy options for transportation planning in the future. For that, this study analyzes current long-distance travel patterns and trends in the US using the 2009 National Household Travel Survey (NHTS) dataset, estimate mode choice models for long-distance travel, and predict the probability of choosing a new alternative option. In order to estimate mode choice models, this study develops methods to estimate synthetic travel time and costs for all alternative modes in the market. Since the NHTS provide information of travel time of mode used, this process is essential to develop mode choice models.

This study first conducts a descriptive analysis of long-distance travel using the 2009 NHTS which comprises all interviews from the national sample households, and the 20 add-on partners. The 2009 NHTS provides fully disaggregated information of personal and household characteristics of individual, actual travel behavior in long-distance trips, and main attributes of travel including trip purpose, number of people on that trip and travel time (Koppelman & Hirsh, 1986). Therefore, the 2009 NHTS is useful in examining the patterns and trends of long-distance travel. Previously conducted descriptive studies have focused on the fundamental questions: who is traveling, where are people traveling on long-distance trips, what are the modes used, and why are people traveling long-distances? (Bricka, 2001; Mallett, 2001; O'Nelill & Brown, 2001; U.S. DOT, BTS, 2003; U.S. DOT, BTS, 2006) In addition to these traditional questions, this study generate multi-dimensional table to structure, summarize, and display how those basic patterns are related with mode choice and travel distance. Moreover, this study presents origins and destinations of long-distance travel. The descriptive analysis is expected to enhance the understanding of current patterns and trends of long-distance travel from both national and regional perspectives.

Second, this study develops the multinomial logit (MNL) models adopting the mathematical function of the conditional logit (CL) model. The MNL model have relatively simple and closed form mathematical structures, and thus are straight forward to estimate and interpret the interactions of choice behaviors with the explanatory variables. In the mathematical function of the CL model, the probability of choosing a particular alternative mode is expressed as a function of the alternative-specific variables, and thus provides direct measures to evaluate the impacts of changes in a specific alternative mode on the probability of choosing that mode. This study uses the choices of individuals among four modes such as personal cars, bus, airplane, and train as dependent variable. Meanwhile, explanatory variables include both alternative specific variables (such as travel time, travel cost or/and travel distance), socio-demographic attributes of individuals (for example, income, age, gender, number of vehicles in the household, number of people on that trip, and trip purpose), and dummy variables that represent spatial characteristics of the household in the models.

Among those factors, this study is, especially, interested in the role of the travel time and travel costs on long-distance travel mode choice decisions. These factors are considered as the key variables that enable a particular mode to gain a comparative advantage over other alternative modes of transportation in the market. Therefore, it is needed to know travel time and costs of all available modes for each household. However, the 2009 NHTS dataset provides limited information of travel time of the mode used for that trip. Given these conditions, this study estimates synthetic travel time and costs for all alternative modes such as personal cars, bus, airplane, and train. Since this study can obtain census block group level spatial information on the households, it is possible to identify the intercity terminals that might be used by each household assuming people use the closest facilities, and in turn to calculate approximate distance and associated access time and costs to intercity terminals.

The empirical models are expected to provide useful information to explain travelers' mode choice behavior in the relationships with the unique characteristics of travel modes and travelers. In particular, the results are expected to provide useable variations among individuals and households, and present the potential variations among MSAs (or regions).

This study tests various scenarios of travel time and cost combinations to predict the changes in the probability of choosing a specific mode of transportation. For that, this study assumes an improved train system that can provide a speed of 150 or more miles per hour. The estimated probabilities of choosing an improved train system under scenarios are expected to provide valuable information to evaluate the possibility of an improved train system in the US. In addition, this study examines whether the probabilities of choosing an improved train system would vary across geographical locations. For that, this study uses regional dummy variables (such as northeast corridor (NEC), east north central (ENC), south atlantic (SA) division, and pacific (PAC) division) in addition to travel time and costs. The results are expected to help policymakers and researchers to predict the potential role of an alternative mode in the transportation market. It would also be possible to decide the level of service improvement to existing public long-distance travel modes to reduce the use of personal cars and airplanes.

Scope of Study

The first section of the Chapter 2 summarizes previous studies that developed mode choice models for long-distance or intercity travel. In Chapter 3, this study explains the theoretical frameworks of logistic regression models, and then presents the specific model that will be developed in this study. This will be followed by the section about data in which the 2009 NHTS data and states add-on data. This study focuses on long-distance trips among trips by definitions. The Chapter 4 describes the processes of choice model estimation comprising four sub-sections. The first section explains explanatory variables that might be included in this study, and this study presents hypothetical relationships of explanatory variables to the decisions on mode choices. The third section presents the methods to calculate synthetic travel time and costs, and access time and costs. Since, the 2009 NHTS presents travel time of the used mode for that trips, this study estimates the travel costs of mode used and both travel time and costs of alternative modes for the given travel distance. The last section of the Chapter

4 explains the results of estimated mode choice models. In the Chapter 5, this study expresses how travel time and costs of an improved train system affect to the choice decisions of households and individuals, and what appropriate policy options would utilize these findings. The Chapter 6 includes conclusions, recommendations, and suggested researches for the future.

CHAPTER 2
LITERATURE REVIEWS

Discrete mode choice models have been effectively employed to predict mode share either among existing alternative modes or the potential performance of a new alternative mode in a given transportation network. The former models are necessary where demand forecasts are required for all modes or those modes which are of interest to the studies. These models have predicted the market share for each alternative mode using the estimated mode choice models, and then apply the estimated mode share of each alternative mode to identify total demand for intercity travel.

Meanwhile the latter models are adopted where researchers are interested in how many travelers would shift from existing alternative mode to the new alternative mode. For example, many studies have actively measured the impacts of a new intercity mode on existing transportation market as many countries in both Europe and Asia have developed broad HSR networks. By estimating discrete choice models, those studies have presented the potential competitiveness of HSR against air, passenger car, bus and conventional rail service. Many of mode choice models have, more importantly, attempted to identify critical points of travel time, cost, or distance where travelers may change their mode choice decisions.

In estimating the potential changes in long distance travelers' mode choice decisions, mode choice models have adopted various factors that represent travel characteristic (such as travel time, cost, distance, trip purpose and frequency), travelers' characteristics (such as income, gender, age, and group size), 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). Among the range of variables that have been examined in the previous models, both travel time and cost consist of the key variables to all 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. Since public long-distance modes such as bus, train and airplane are inherently a part of inter/multimodal transportation system, they are associated with both access and egress time. It should be noted that travelers who use public transportation mode are considered to be sensitive to these out-of-vehicle times (Bhat, 1995; Koppelman and Wen, 2000). Travel cost commonly means cost of driving personal cars or/and fare of public transportation modes in those mode choice models. However, some exceptional cases include parking cost (Hensher, 1991), differences of fare level by service class (Koppelman, 1989), or access/egress expenses (Kitagawa, Terabe, and Saratchai, 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 order to characterize individual preferences in relation to travel alternatives, many of these studies have the most commonly used RP and/or SP survey data because they can show either actual or hypothetical travel behavior. The demand model estimates the mode choices of passengers assuming that once a person decides to make the journey, the available alternatives and their characteristics such as travel time and cost will condition traveler's choice. For example, many countries in both Europe and Asia have presented the impacts of a new intercity mode on existing transportation market and the potential competitiveness of HSR against air, passenger car, bus and conventional rail service as they developed broad HSR networks. 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, Innes and Stevens, 1992; Ashiavor, Baik and Trani, 2010, Wilson, Damodaran and Innes, 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 of potential threshold 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, Snell and Bhat, 2009). This variable assumes that travelers who travel alone likely prefer expensive but fast and comfort mode more than travelers in a group.

Moreover, purpose of trip is considered to have significant impacts on mode choice (Morrison and Winston, 1985; Wardman et al, 1997; Carlsson, 1999; Limtanakool, Dijst, and Schwanen, 2006). Since travelers' preferences vary with the purpose of their trip, the different trip purpose could be an important issue for mode choice decisions. Previous studies have shown that business travelers and leisure travelers are expected to be different in their sensitivity to travel time and cost because business travelers have subsidization of travel cost while leisure travelers pay for themselves. Service frequency, one of 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, Pidcock and Johnson, 1990; Wardman et al, 1997; Vrtic and Awhausen, 2002). The effects of service frequency or number of transfer on the mode choice are investigated when the model included air and/or rail. But, it is difficult to exactly measure service frequency because it varies depending on travel demand.

In addition to travel attributes, travelers' socioeconomic and demographic attributes such as income, education, car availability, age, gender, and education 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 focused more on the impacts of these socioeconomic and demographic variables than travel attributes in order to explain mode choice behavior. For example, Limtanakool, Dijst and Schwann (2006) examined the effects of age, gender, education, household type and car availability on mode choice decision in addition to income. Bhat (1997b) 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, there are researches that attempted to identify 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 have suggested that the 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; Timmermans et al., 2003; Schwanen and Mokhtarian, 2007; Dargay and Hanly 2004), while other studies presented that people in larger city are more like to have better public modes such as air and train as well as service quality (Baht, 1995, 1997a, 1998b; 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. In a similar vein, higher population densities are expected to associate 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. In this respect, it is important to measure impacts of spatial characteristics on travelers' mode choice decisions. It is also worthy of note that spatial characteristics and travel behavior can mutually affect each other. Travel behavior might be a critical factor for individuals or households to make location decisions, while urban form at the place of residence affect travel behavior (Scheiner and Holz-Rau, 2007).

Exceptionally, Sirinavasan, Bhat and Holguin-Veras (2006) and Winzar et al. (1990) concentrated on measuring impacts of perceptions on long distance travel mode choice decisions. The former study explained impacts of travelers' perception about security check system and stress level on air travelers' mode choice decisions, while the latter investigated whether comfort, food quality, reliability and convenience have links to long distance travel for pleasure. Comfort is expected to have impacts on whether or not travelers have higher probability to choose the luxury service class and to avoid bus, a less comfortable alternative. Reliability is presented as the share of departure/arrival within a certain time from the predetermined service time.

CHAPTER 3
ANALYSIS METHOD AND DATA

Theoretical Framework of Mode Choice Models

Probabilistic Choice Theory

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 & Koppelman, 1993; Koppelman & Bhat, 2006). Each utility that decision maker n obtains from alternatives allows researchers to rank a series of alternatives and identify the alternative that has the highest utility. Therefore, the individual, n, chooses an alternative if and only if:

$$U_{n,\mathrm{i}} > U_{nj} \ \ \forall\, i \neq j \qquad (3\text{-}1)$$

In probabilistic choice theory, the utility function for the individual n to choose mode t includes two components: the deterministic or observable portions that represent the portion of utility observed by the analyst ($V_{n,t}$), and the error or the portion of the unobserved utility to the analyst ($\varepsilon_{n,t}$).

$$\mathrm{U_{n,t} = V_{n,t} + \varepsilon_{n,t} \quad (t = i, j, ..)} \qquad (3\text{-}2)$$

The unobserved utility term ($\varepsilon_{n,t}$) makes the deterministic choice process as probabilistic, and thus leads to a random utility model (RUM) in which the highest observed utility has the highest probability of being chosen (Hess, 2005).

The Multinomial Logit Model

The error term (εn,t) has been considered as important to determine the mathematical form of choice model because traveler's mode choice decision are not completely and correctly measured or specified (Koppelman & Bhat, 2006). Thus, it has motivated researchers to develop numerous 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 (Forinash & Koppelman, 1993; Koppelman & Bhat, 2006). The MNL model gives the choice probabilities of alternative as a function of the deterministic portion of the utility of all the alternatives.

In the MNL model, the deterministic or observed portion ($V_{n,t}$) of the model is represented by a linear additive function that parameters, β_t, and explanatory variables, X. The parameters, β_t, may be interpreted as reflecting the effects of the covariates on the odds of making a given choice, while explanatory variables X are characteristics of individuals *n*. This observed portion can be presented as:

$$V_{nt} = \beta_t X_n \tag{3-3}$$

Therefore, the utility of an individual n to choose alternative t can be stated as:

$$U_{nt} = \beta_t X_n + \varepsilon_{nt} \tag{3-4}$$

In this utility function, the probability that individual *n* chooses an alternative mode is simply:

$$\begin{aligned} P_{ni} &= Prob\left(U_{ni} > U_{nj} \ \forall \ i \neq j\right) \\ &= Prob\left(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}\right) \\ &= \mathrm{Prob}\left(\varepsilon_{ni} - \varepsilon_{nj} > V_{ni} - V_{nj}\right) \end{aligned} \tag{3-5}$$

The choice probability for decision maker *n* to choose alternative *i* is given by:

$$P_n(i) = \frac{e^{V_{ni}}}{\sum_{t=1}^{T} e^{V_{nt}}} \tag{3-6}$$

Since the MNL model assumes that the error components are identically and independently distributed across alternatives, the choice probabilities do not involve the error term $\varepsilon_{n,t}$. Therefore the choice probability for decision maker n to choose alternative i can be expressed as:

$$P_n(i) = \frac{e^{\beta_i X_n}}{\sum_{t=1}^{T} e^{\beta_t X_n}} \tag{3-7}$$

This equation implies that the probability of choosing an alternative increases as the deterministic utility of that alternative increases, while decreases if the deterministic utility of each of the other alternatives increase. The MNL model has been widely used in many previous studies because it has a relatively simple and closed mathematical structure, and thus it is easy to estimate and explain the results.

In estimating the MNL models, this study employs mathematical function of the conditional logit (CL) model in which the probability of choosing a particular alternative mode is expressed as a function of the alternative-specific variables.

The Conditional Logit Model

According to Rodriguez (2012), McFadden (1974) proposed the CL model in which the expected utilities $U_{n,t}$ in terms of characteristics of the alternatives rather than attributes of the individuals. In the CL model, the observed portion of the utility of an individual n choosing alternative t is presented as:

$$V_{n,t} = \alpha_t Z_{n,t} + \varepsilon_{n,t} \tag{3-8}$$

Where, $Z_{n,t}$ is the attributes of the alternatives t, (t = i, j, …)

In the CL models, explanatory variables, Z, are assumed to have different values for each choice alternative in the model, and a single coefficient is estimated for each alternative-specific variable Z. In other words, the estimated model can present a separate coefficient on each independent variable for each possible outcome. Consequently, the impact of a unit change of explanatory variable is assumed to be constant across alternatives, and a variable Z is appeared to have no impact on choice probability if it has with no variation across alternatives (Hoffman and Duncan, 1988). In the CL model, the error terms follow independently and identically an extreme value distribution. Therefore, the difference of two error terms follows a logistic distribution as in the MNL model. Given these assumptions, the choice probability of the individual n to choose the alternative i can be expressed as equation (3-9):

$$P_n(i) = \frac{e^{\alpha_i Z_{n,i}}}{\sum_{t=1}^{J} e^{\alpha_t Z_{n,t}}} \tag{3-9}$$

Since the CL model assumes that the choice of mode depends only on the differences of variables in the utility function, it is appropriate to measure the impacts of a unit change in each explanatory variable on the probability of choosing a particular alternative. Therefore, the CL model is useful to evaluate how government policy affects to the attractiveness of an alternative mode (Hoffman and Duncan, 1988).

In theory, the CL model is assumed to estimate the probability of choosing an alternative mode using only the differences in the value of characteristics of the alternatives (for example, travel time and costs). Thus, it may be different from the MNL model which depends on individual characteristics to estimate the probability of choosing a specific mode. Yet in reality, many studies have developed the choice models to examine how both the characteristics of an alternative mode and the characteristics of individual affect the probability of choosing specific alternative mode (Abdekwahab, Innes and Stevens, 1992; Koppelman and Bhat, 2006; Koppelman and Sethi, 2000; LaMondia, Snell and Bhat, 2009; Swait, 2001; Wardman and Toner, 1997; Winzer, Pidock and Johnson, 1990). Moreover, there are studies that have developed the methods to use both alternative-specific attributes and the characteristics of individuals in the modeling framework of the CL model indicating that the CL model is just slightly different form of the exact same model as the MNL model (Hoffman and Duncan, 1988; Rodriguez, 2012; So and Kuhfeld, 2010).

Model Specification

This study estimates the utility of choosing an alternative mode as a function of the alternative-specific attributes and the characteristics of individuals. In estimating mode choice model, this study phases in these explanatory variables. This study, first, enters only travel time and travel costs of each travel mode into the mode choice model. These attributes are unique service attributes that are different among travel modes, and thus are expected to affect differently people's choice of travel mode. With these alternative-specific variables, the utility can be expressed as:

$$\begin{aligned} V_{n,t} &= \beta_0 + \alpha_1 Time_{n,1} + \alpha_2 Cost_{n,1} \\ &\quad + \beta_1 + \alpha_3 Time_{n,2} + \alpha_4 Cost_{n,2} \\ &\quad + \beta_2 + \alpha_5 Time_{n,3} + \alpha_6 Cost_{n,3} \\ &\qquad + \alpha_7 \mathrm{Time}_{\mathrm{n},4} + \alpha_8 \mathrm{Cost}_{\mathrm{n},4} \end{aligned} \tag{3-10}$$

Here, t = travel modes (1: personal cars, 2: bus, 3: airplane and 4: train)

β_0, β_1 and β_2 = constant for personal cars, bus, and airplane

$\alpha_{1\ldots6}$ = coefficients for each alternative-specific variable

In addition to these alternative-specific variables, this study incorporates characteristics of individuals such as age, income, purpose of travel, and attributes of residence location into the CL model. Since different characteristics of among individuals may have different effects on mode choice decisions, it is also valuable to understand the impact of individual characteristics on the probability of choosing travel mode. With these explanatory variables, the utility of an alternative is expressed as function of the attributes of the alternative modes and the characteristics of the traveler.

$$
\begin{aligned}
V_{n,t} = {} & \beta_0 + \alpha_1 Time_{n,1} + \alpha_2 Cost_{n,1} + \sum \gamma_i X_{i,1} \\
& + \beta_1 + \alpha_3 Time_{n,2} + \alpha_4 Cost_{n,2} + \sum \gamma_i X_{i,2} \\
& + \beta_2 + \alpha_5 Time_{n,3} + \alpha_6 Cost_{n,3} + \sum \gamma_i X_{i,3} \\
& + \alpha_7 \mathrm{Time}_{n,4} + \alpha_8 \mathrm{Cost}_{n,4} + \sum \gamma_i X_{i,4}
\end{aligned}
\tag{3-11}
$$

Where, t = travel modes (1: personal cars, 2: bus, 3: airplane and 4: train),

β_0, β_1 and β_2 = constant for car, bus and air,

X_i represents individual characteristics such as age, income, purpose of travel and attributes of residence location.

γ_i = coefficient associated with individual variable X_i

Since equation (10) is based on the mathematical function of the (CL) model, this study transforms individual characteristics into alternative-specific variables by attaching the individual characteristics to each mode of transportation. For example, this study constructs personal car users' age variable by applying the each age of an individual n to each personal car user if the person used car and zero otherwise.

Data

The 2009 National Household Travel Survey

In analyzing travel patterns of long-distance travel, this study uses the 2009 NHTS that includes all interviews from the national sample of 26,000 households and the 20 add-on partners. 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. The 2009 NHTS included more samples in both number of household and number of person terms than the 2001 NHTS. The 2009 NHTS is, therefore, expected to increase the availability of a data base with a national coverage of long distance travel. It is also expected to allow developing mode choice models that can test the potential variation among various geographic sectors.

The 2009 NHTS officially provides household, person, vehicle and daily trip level datasets for public use (US DOT FHWA, 2011), of which this study focuses on the daily trip level dataset. The daily trip dataset provides fully disaggregated information of daily trips for each person of sample household such as purpose of trip, mode of transportation, travel time, number of people in the vehicle, and the most importantly travel miles taken for a given trip. The dataset also provides information of traveler's socio-demographic characteristics such as age, income, gender, MSA category, and existence of heavy rail service. More importantly, it is possible to use the spatial information of sample households in a census block group scale. Thus, this study can calculate the shortest distance to each intercity terminal, and in turn estimate access time and costs.

In analyzing the daily trip datasets, this study focuses on the long distance travel among various travels by definition. Until 1995 American Travel Survey (ATS), US

Department of Transportation (DOT) defined long distance travel as trips that are taken away 100 miles or more from home, but 2001 National Household Travel Survey (NHTS) redefined it as “trips of 50 miles or more from home to the farthest destination traveled and include the return component of the trip as well as any overnight stops or stops made to change transportation modes” (US DOT BTS, 2003, p.1). Under this definition, any daily trips could be long-distance trip as long as total trip length is longer than 50 miles regardless of number of trip segments made in a daily survey. This seems to be too broad and vague to identify a true long-distance travel. Thus, this study narrows the standard of long-distance trip by counting a trip as long-distance trip only if a single trip segment is 50 or more miles. This confines the long-distance trips mostly to intercity trips.

Table 3-1. Household, Individuals and Daily Trips in the 2009 NHTS

Index	Measures
Number of Households	150,147
Number of Individuals	324,184
Number of Daily Trips	1,148,852
- Daily trips per household	7.7
- Daily trips per person	3.5
Number of Long-Distance Trips	28,420
(% in total daily trips)	2.5
- Long-distance trips per household	0.19
- Long-distance trips per person	0.09

Source: U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. URL: http://nhts.ornl.gov

As shown in Table 3-1, the daily trip dataset contains about 1,149 thousand trip segments that were made by 150,147 households or 324,184 individuals. Each household made an average of 7.7 trips in a given survey day, while each individual made an average of 3.5 trips. By the narrowed standard of long-distance trip in this study, the 2009 NHTS includes 28,420 segments that are 50 or more miles. These trips account for 2.5 percent in total daily trips of 1.2 million. Each household generated an average of 0.19 long-distance trips.

Operationalizing Daily Trips into Household Level Data

This study operationalizes the daily trips in the 2009 NHTS into household level data by applying four steps: 1) transform 1,148,852 daily trips into 324,184 individual level data, 2) sort out 17,316 individuals who have one or more trip segments that are 50 or more miles 3) identify trip segments that are involved in actual long-distance trips, and 4) transform 17,316 individual level data into 12,846 household level data.

For step 2, this study counts a trip as long distance trip if at least one segment in all trip segments is 50 or more miles. In step 3, this study identifies actual trip segments that comprise long-distance trips among daily trips segments. In other words, this study identifies true origin – destination or origin – intermediate stop (s) – destination from all trip segments made by an individual in a given survey date. For example, four trip segments out of ten daily trip segments could be involved in making a single long-distance trip. In most cases, intermediate destination (s) includes stop (s) for gas, rest or meal on the way to destination. In step 4, this study separately counts each individual in the same household if each (or any) household member made long-distance trip (s) with different transportation mode, trip purpose, and/or travel destination.

As results of the data conversions, this study obtains 12,846 long-distance travel samples for the whole US of which South Atlantic census division comprises the largest share of 4,702 samples and it was follows by West South Central (WSC), Pacific (PAC), and Middle Atlantic (MA) census divisions at 2,170, 1,853, and 1,502 samples, respectively. Table 3-2 shows the results from data operationalization processes, and table 3-3 presents number of samples by census division.

Table 3-2. Data Operationalization Processes Obtaining Household Level Dataset

Index	Samples
Number of Individuals in the 2009 NHTS	324,184
Individuals who have one or more of trip segment that is 50 or more miles (A)	17,316
Household level long-distance trip samples (B)	12,846
B / A (%)	74.2

Table 3-3. Household Level Long-Distance Trip Samples by Census Division

Census Division	Number of Samples	Share (%)
New England	296	2.3
Middle Atlantic	1,502	11.7
East North Central	638	5.0
West North Central	749	5.8
South Atlantic	4,702	36.6
East South Central	317	2.5
West South Central	2,170	16.9
Mountain	619	4.8
Pacific	1,853	14.4

Among states, Texas comprises the largest samples at 2,085, and it was followed by California, Virginia, New York, Florida, North Carolina, Georgia, and Arizona with 1,769, 1,473, 1,372, 1,072, 927, 709, 414 samples, respectively (see table A-1 in Appendix A for detailed information of samples by state). These states constitute major portion of datasets for census divisions such as WSC, PAC, SA, MA and Mountain (MT). These 12,846 household level long-distance samples are the basis of both descriptive analysis and developments of mode choice models.

Descriptive Analysis of Household Level Long-Distance Travel Data

As shown in Figure 3-1, nearly 90 percent of long-distance travelers used personal cars, while about 6.0 percent of travelers chose public intercity transportation modes such as bus, airplane, and train. Both East North Central (ENC) and East South Central (ESC) divisions show relatively higher share of personal cars at 90 percent, while Mountain division's share of personal cars was the least among divisions at 83.7 percent. It should be noted that airplane accounts relatively large shares in MT, WSC, and PAC, while New England (NE) and MA divisions were high in the share of bus. Train account for the largest share in MA, and it was followed by NE, ENC, PAC, and SA divisions.

It is also worthy to note that WNC, ESC, WSC, and MT divisions show nearly no record of train use, possibly because people in these areas live far away from train stations compared to other divisions. In detail, the average distances to train stations in these divisions of 79.7, 75.0, and 43.0 miles were much longer than the average distance of the whole US at 32.8 miles. Buses are appeared across the divisions even though there are variations among states. The average distance to bus terminals at 11.8 miles may explain these patterns (see table A-2 in Appendix A for more information).

Airplane shows the longest average travel distance about 1,262 miles with relatively large standard deviation among samples. This implies that air transportation covers various service distance ranges. In addition, there are large variations in average distances of air travel. For example, the average trip distances of both WNC (852.4 miles) and ESC (962.8 miles) divisions are much shorter than that of PAC, ENC, and MT divisions at 1,608.0, 1,308.0 and 1,212.0 miles, respectively. Interestingly, the two former divisions have no large scale airports, while the three latter divisions have one or more of airports that provide nationwide services. Table 3-4 presents descriptive statistics of long-distance travel by mode, and Table A-2 in Appendix A shows the same features comparatively among divisions.

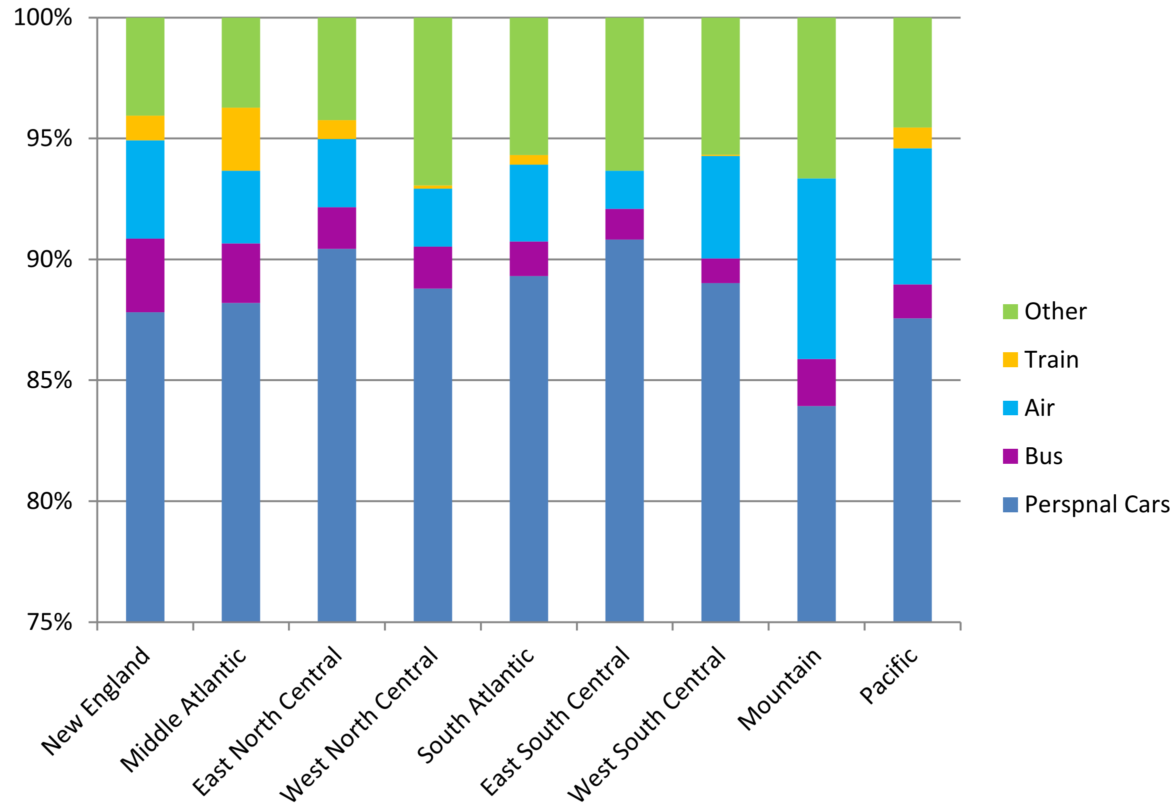


Figure 3-1. Share of Long-Distance Travel Mode by Census Division

Table 3-4. Descriptive Statistics of Long-distance Trips by Travel Mode

Mode	Number of Sample	Share (%)	Mean	Minimum	Maximum	Std Dev
Car	11,370	88.5	141.0	40.2	5,634.0	182.9
Bus	201	1.6	204.6	50.0	3,899.0	370.6
Airplane	489	3.8	1,261.5	58.1	9,113.0	1,062.0
Train	84	0.7	148.0	50.0	1,200.0	217.2
Other	682	5.3	204.6	50.0	3,000.0	247.6

About 55 percent of long-distance trips were made in a less than 100-mile range, and another 24 percent of destinations were within 200 mile range. In all, nearly 80 percent of long-distance trips were made within 200 miles range. MA and PAC divisions show relative large share of trip distance between 50 and 99 miles, while MT division records the smallest share at 45 percent in the same distance range. These patterns may be associated with the share of travel mode used. For example, MT division was the lowest for personal cars use, while airplane's share was the largest among census divisions. Table 3-5 and Figure 3-2 present these patterns of mode share by distance group.

Table 3-5. Share of Transportation Mode by Distance Group

Distance Range (miles)	50-99.9	100-199	200-299	300-499	500-749	750-999	1000-1499	1500-2499	2500-
Number of Trips	6,999	3,023	1,233	805	324	132	128	128	74
Share (%)	54.5	23.5	9.6	6.3	2.5	1.0	1.0	1.0	0.6

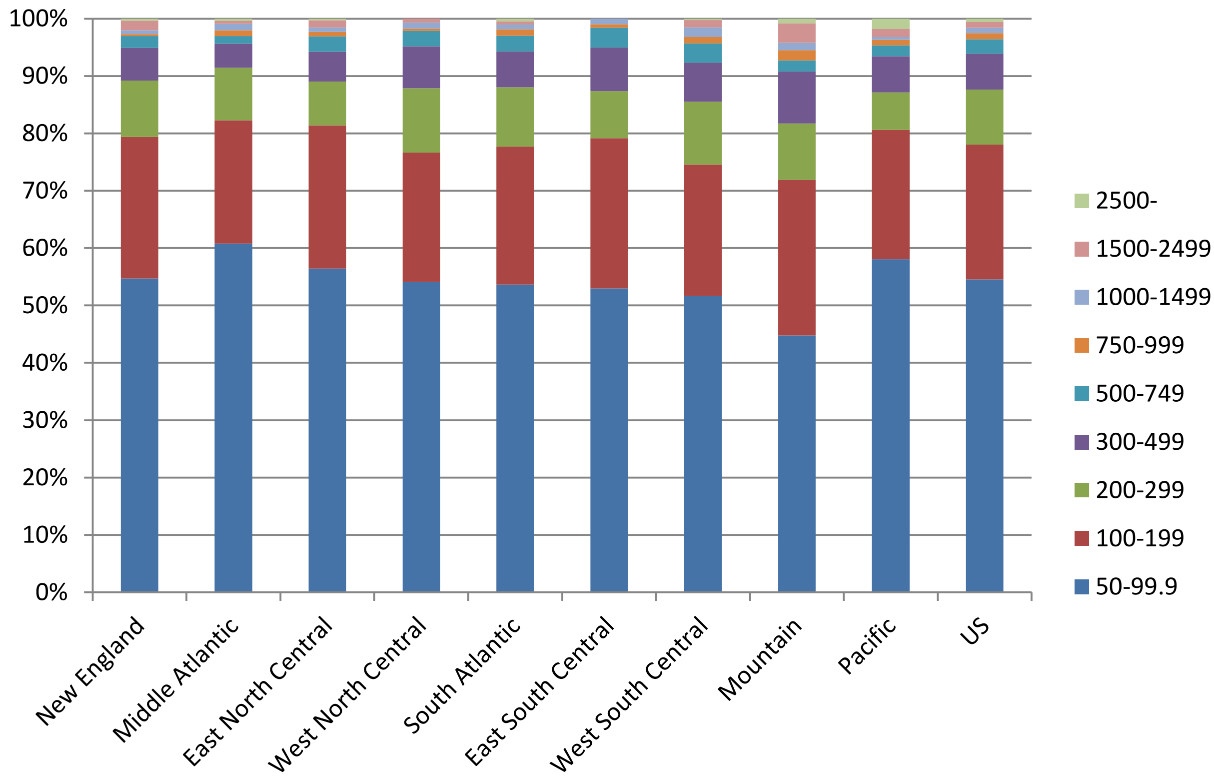


Figure 3-2.Distribution of Distance Group by Census Division

Over 93 percent of long-distance travelers use personal cars in less than 100 mile distance range, and personal cars' share decreases as travel distance increases. In contrast, airplane actively appeared over 300 miles travel distance range, and its share increases as travel distance increases. Airplane accounts for higher than personal cars from 750 miles travel distance. Both bus and train's shares are less than 3 percent in all distance ranges. These patterns are expected to appear across the census divisions even though there would be variations. Figure 4-1 illustrates the shares of modes used for long-distance travel by distance.

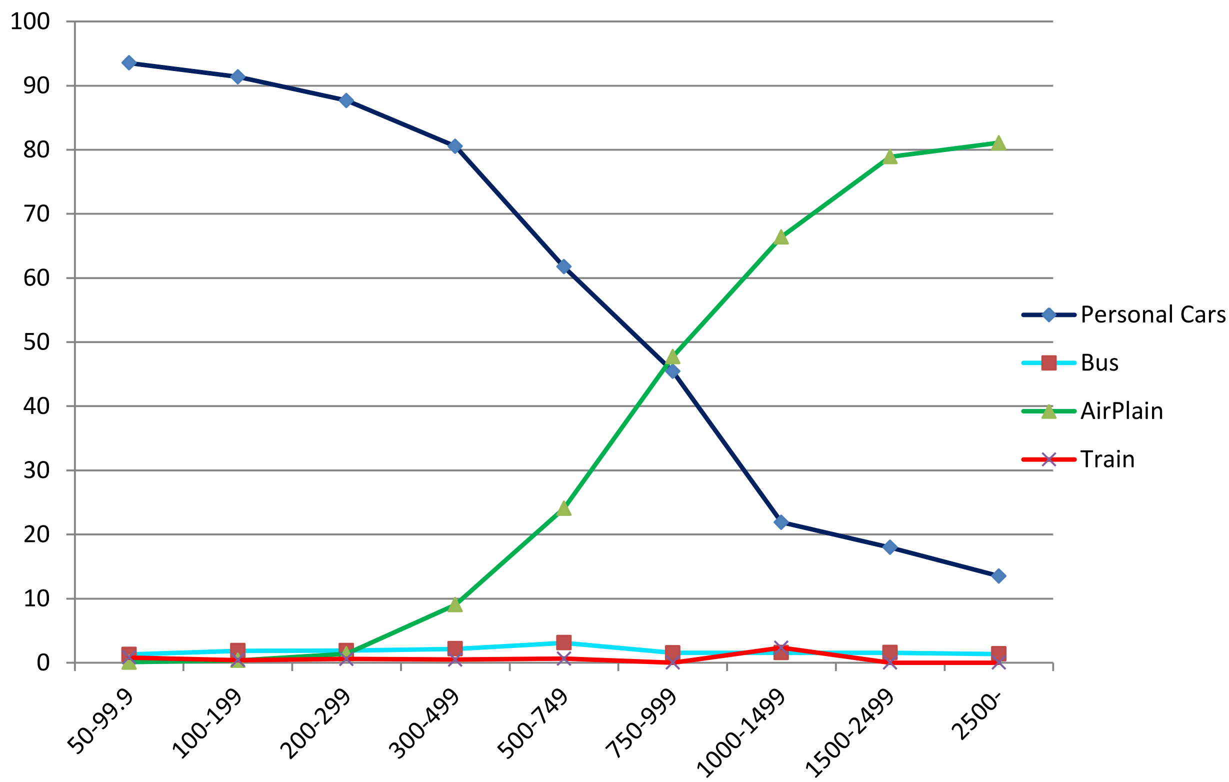


Figure 3-3. Share of Travel Mode by Distance Group

As shown in table 3-6, people make long-distance travel as they have social and recreational demand among purposes. It accounted for 32.5 percent of total long-distance trips, and business and returning to home trips followed by taking 24.6 percent and 12.9 percent. Interestingly, returning home and social/recreation trips have relatively large standard variations at 492.4 miles and 334.2 miles, respectively. Meanwhile, medical and dental trips show the shorted standard deviation of 54.7 miles, possibly implying that people tend to use hospitals near from their home.

Table 3-6. Descriptive Statistics of Long-Distance Travel by Trip Purpose

Purpose	Number of trips	Share (%)	Mean	Minimum	Maximum	Std. Dev.
Home	1,648	12.9	267.6	50	9113	492.4
Work	3,150	24.6	153.9	50	5634	328.1
School/Daycare	241	1.9	139.9	50	2904	242.1
Medical/Dental	448	3.5	90.93	50	429	54.7
Shopping	1,097	8.6	124.4	50	2533	176.7
Social/Recreation	4,153	32.5	207.6	50	5015	334.2
Family/Personal	796	6.2	182.2	50	3018	303.5
Transport Someone	530	4.1	120.4	50	1700	131.2
Meals	479	3.7	142.7	50	1576	153.5
Other	240	1.9	527.7	50	3612	659.9

As presented in table 3-7, more than 73 percent of long-distance trips are based on home, and another 42 percent and 31 percent are related to social/recreation places and workplaces, respectively. In detail, more than 60 percent of long-distance trips have home as their origins, while nearly 13 percent ended at home. Workplaces accounted for 6.7 percent of all origins and 24.6 percent of all destinations, while social and recreation trips took 9.5 percent of origins and 32.5 percent of destinations.

Table 3-7. Origins and Destinations of Long-Distance Travel

Places	Origin		Destination	
	Number of samples	Share (%)	Number of samples	Share (%)
Home	7751	60.4	1,648	12.9
Workplace	853	6.7	3,150	24.6
School/Religious activity places	117	0.9	241	1.9
Hospitals/ Dental service	69	0.5	448	3.5
Shopping centers	541	4.2	1,097	8.6
Social/Recreation places	1220	9.5	4,153	32.5
Family/Personal Business locations	216	1.7	796	6.2
Transport Someone	243	1.9	530	4.1
Restaurants/Cafes	150	1.2	479	3.7
Other places	146	1.1	240	1.9

Personal cars accounts for more than 95 percent for the trips to medical/dental service, shopping, and transport someone, possibly because those destinations are less accessible by public transportation modes. In contrast, both work and school/daycare trips show relatively low share of personal cars at around 81 and 83 percent, respectively. Instead, airplane accounts for nearly 4 percent of work trips, while bus accounts for over 8 percent of school/daycare trips. Assuming that business travelers are less sensitive to travel cost but more sensitive to travel time, these mode shares are acceptable. High share of bus for school/daycare trips also are reasonable if we counts that travelers aged between 16 and 25 are major travelers with this purpose, and they likely choose travel mode that is less cost but take longer time. Table 3-8 presents these shares of long-distance trips by travel purpose.

Table 3-8. Share of Long-Distance Travel by Trip Purpose

Purpose	Car	Bus	Air	Train	Other Modes
Home	87.8	0.6	7.7	0.5	3.5
Work	83.1	1.1	3.8	0.9	10.9
School/Daycare	81.3	8.3	0.8	0.4	9.1
Medical/Dental	95.1	0.7	-	0.5	3.6
Shopping	94.7	1.3	1.4	0.2	2.5
Social/Recreation	91.2	1.9	2.7	0.4	3.8
Family/Personal	91.8	1.5	3.3	0.4	2.6
Transport Someone	95.9	1.5	0.8	0.2	1.5
Meals	92.7	2.3	0.6	0.8	3.1
Other Purpose	51.7	2.9	32.9	7.5	5.0

As shown in Table 3-9, people in area with heavy rail system are likely to use public travel mode compared to the people in area with no heavy rain system. In particular, train's share of 2.7 percent in the area with heavy rail system appears much higher than that of 0.2 percent in the area of without heavy rail services. Both airplane and bus's shares are similar with train. These patterns result in the relatively low share of personal cars in locations with heavy rail services.

Table 3-9. Comparison of Travel Mode Share by Existence of Heavy Rail System

Index		Car	Bus	Air	Train	Other
With Heavy Rail system	Number of Trips	1,941	56	109	61	85
	Share (%)	86.0	2.5	4.8	2.7	3.8
No Heavy Rail System	Number of Trips	9,429	145	380	23	597
	Share (%)	89.1	1.4	3.6	0.2	5.6

Table 3-10 presents the effects of heavy rail system on the mode share for long-distance travel. Travelers in MSAs of 1 million or more with heavy rail service are favorable to train, while residents who live in MSAs of 1 million or more but have no heavy rail service are likely to be similar in choosing train. Instead, these MSAs show higher share of airplane in making long-distance trips. Personal cars account for more than 90 percent in non-MSA areas. These patterns would be interesting to examine in the mode choice model.

Table 3-10. Share of Travel Mode by MSA Category

MSA Category	Car	Bus	Air	Train	Other
MSA over 1million with Rail	1,941 86.0	56 2.5	109 4.8	61 2.7	85 3.8
MSA over 1million no Rail	2,928 87.3	45 1.3	224 6.7	13 0.4	139 4.1
MSA less than 1 Million	3,279 88.9	57 1.6	108 2.9	5 0.1	236 6.4
Not in MSA	3,222 90.9	43 1.2	48 1.4	5 0.1	222 6.3

As shown in Table 3-11, income seems to affect to the both frequency and average travel distance of travel because high income group comprises more shares of long-distance trips, and average trip distances increase as income increases. In addition, standard deviation of 399.1 miles is considerably higher than other income groups of 183.6 miles for low income group and 237.9 miles for medium income group. The large standard deviation of high income group may be associated with individual traveler's capability to make long-distance trips and to choose comfortable and convenient modes.

Table 3-11. Patterns of Long-Distance Travel by Income Group

Income Group	Number of Trips	Share (%)	Mean	Minimum	Maximum	Std Dev
Low Income	1,849	14.4	142.3	50	2,555	183.6
Mid-Income	3,078	24.0	158.0	50	4,325	237.9
High Income	7,185	55.9	210.5	50	9,113	399.1

Among income groups, high income group accounts for the largest share in airplane, while low income group rely relatively large portion of their long-distance trips on bus. Interestingly, train appears slightly higher at high income group. Therefore, it would be interesting to see whether these differences can be proved by the choice model.

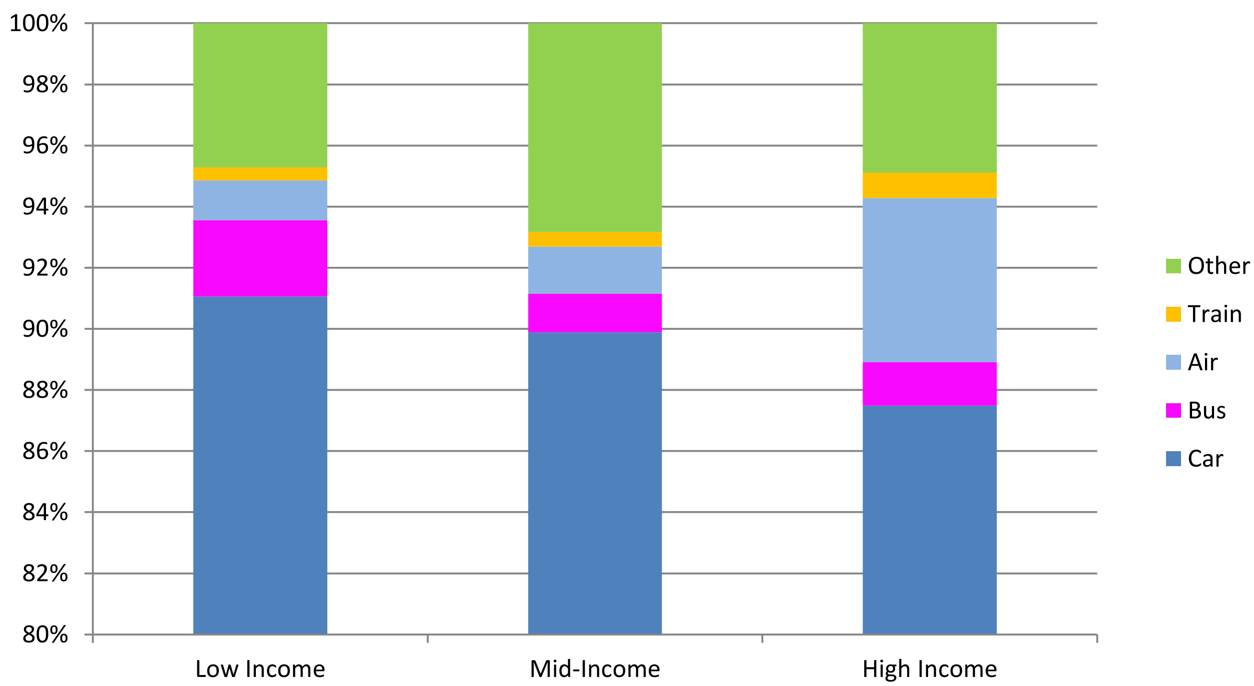


Figure 3-4. Share of Long-Distance Travel Mode by Income Group

Existence of child seems to have no effect on the average travel distance and the capability of traveling distance range. The average trip distances of traveling without child at 188.4 miles and traveling with child at 183.2 miles are similar each other. In addition, the standard deviations of 348.2 miles and 282.1 miles show no significant difference. However, relatively large portion, 4.0 percent, of people is expected to take airplanes when they travel without child. This is double of airplane's share for travelers traveling with child. The average number of people traveling together might be responsible for this gap. People traveling without child have an average of 1.1 persons on air travel, while the average number of people increases to 2.4 persons if people travel with child. It should be noted that this gap between groups is similar with the average number of travelers for personal cars at 1.3 and 2.7 for the group traveling without child and the group traveling with child, respectively. However, total travel costs are different because personal cars' costs are the same regardless of the number of travelers on that trip, while air travelers' costs are expected to increase as number of people increase. Table 3-12 and Figure 3-5 display descriptive statistics of long-distance travel depending on existence of child.

Similar with existence of child, traveling with the elderly (this includes travels made by the elderly) seems to have no effect on traveling patterns such as average travel distance and the range of traveling distance. As shown in table 3-13 and figure 3-6, the average distances of 189.0 and 183.3 miles for both groups of traveling with elderly and traveling without elderly are not significantly different. However, people show different mode choice behavior, if they are traveling in company with the elderly. Travelers are likely to choose more personal cars when they travel with the elderly in the group, while people traveling without the elderly show relatively higher share of airplane.

Table 3-12 Descriptive Statistics of Long-Distance Travel for Traveling with Child

Traveling With Child	Number of Trips	Share (%)	Mean	Minimum	Maximum	Std Dev
No	11,633	90.6	188.4	50	9,113	348.3
Yes	1213	9.4	183.2	50	3,612	282.1

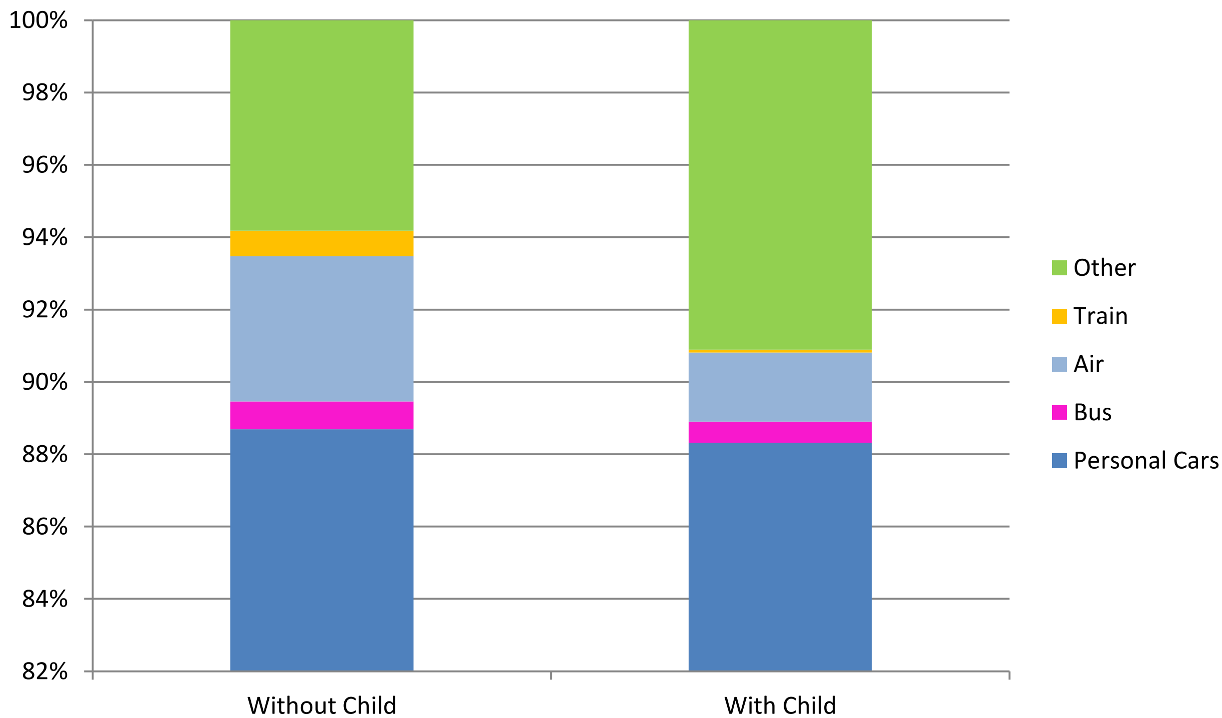


Figure 3-5. Share of Long-Distance Travel Mode by Existence of Child

Table 3-13. Descriptive Statistics of Long-Distance Travel by Existence of the Elderly

Traveling With the Elderly	Number of Trips	Share (%)	Mean	Minimum	Maximum	Std Dev
No	10,351	80.6	189.0	50	5,634	346.2
Yes	2,495	19.4	183.3	50	9,113	327.0

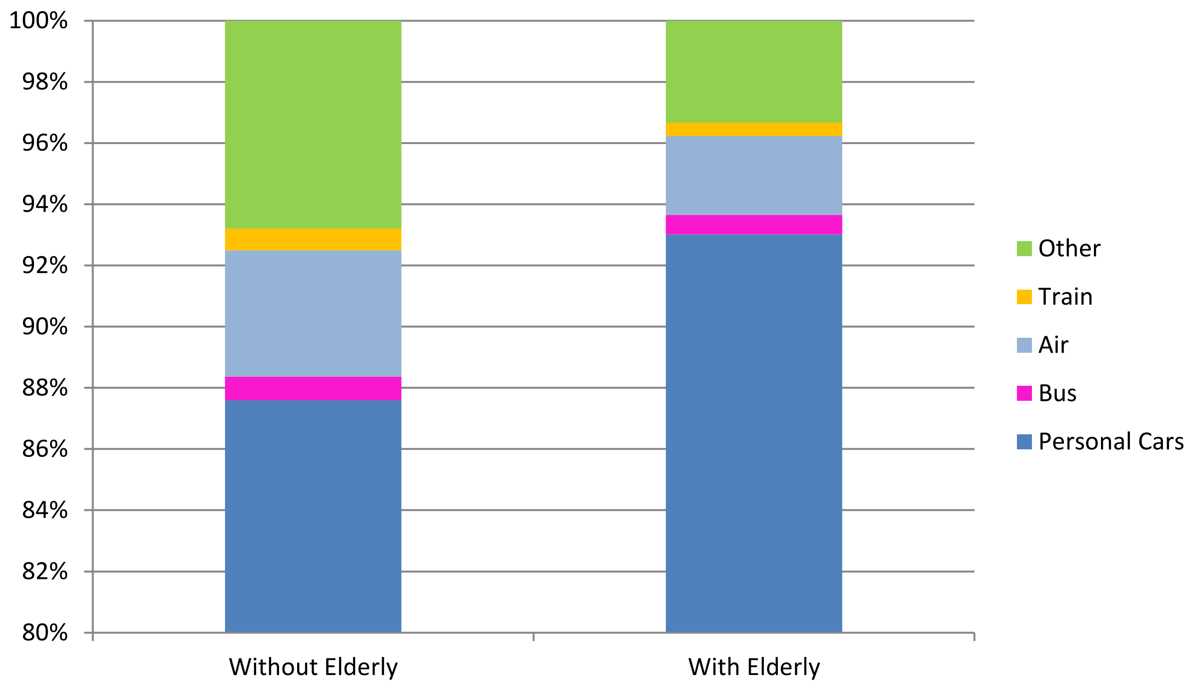


Figure 3-6. Share of Long-Distance Travel Mode by Existence of the Elderly

CHAPTER 4
ESTIMATION OF MODEL CHOICE MODELS

Explanatory Variables

As discussed in previous chapter, this study develops the MNL models adopting mathematical function from the conditional logit (CL) model. In order to simplify model development process, this study concentrates on the attributes that can be quantitatively measured among various set of potential explanatory variables.

In estimating the model, this study is, particularly, interested in the impact of travel time and cost on mode choice decisions for long-distance travel. In case of public transportation modes, both travel time and costs include access time and costs to the closest intercity terminal. Then, this study attempts to test the impacts of travelers' characteristics on mode choice decisions by adding individual characteristics such as age related attributes, purpose of trips and income group to explanatory variables. For that, this study transforms individual attributes into alternative-specific variables.

In addition, this study applies dummy variables that represent the geographical characteristics of residence location. These variables include MSA categories that classify MSA into four types such as MSA of 1 million or more with heavy rail service, MSA of 1 million or more without heavy rain service, MSA less than 1 million, and not in MSA. Furthermore, this study attempts to examine whether the impacts may vary across smaller geographical locations because these MSA categories are large. These sub-categories include state, combination of census division, MSA status and presence of a heavy rail system, and major transportation corridors. Table 4-1 presents potential explanatory variables that may be applied to the mode choice models.

Table 4-1. Potential Explanatory 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)	Shortest distance to intercity terminals such as airport, bus terminal, train station	Miles (minutes)
Number of travelers	Total number of people on that trip. This variable may be incorporated into total travel cost	Person
Trip purpose	Dummy variable that represents the purposes to make the trip: Three categories	Work, social/recreational, and others
Age indicator	Traveling with child Traveling with the elderly (age 66 or more)	Yes or no
Income group	Category of income	Low (less than 30000, medium (30000-60000), high (more than 60,000)
MSA Category	MSA category for the household home address	MSA of 1 million or more with rail MSA of 1 million or more but no rail MSA less than 1 million Non-MSA
Census Division and MSA status	Grouping of household by combination of census division, MSA status, and presence of rail system	32 groups depending on population size and existence of heavy rail service
Urban area	Home address in urbanized area or rural area	Urban or Rural

Hypothetical Relationships of Variables to Mode Choice Decisions

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 cost of driving automobiles or 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 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 mode (bus or train) users are more sensitive to changes in travel fares than travel time, while air passengers are not very sensitive to travel cost and are highly sensitive to travel time having the highest value of time (Ashiabor, 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 the 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; Wardsman 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 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 increase. Many previous studies have suggested that there exist threshold at which travelers' mode choices vary (Bel, 1997; Hensher, 2001; Jorensen 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 includes these variables into the model by transforming personal characteristics into alternative-specific variables. In specific, this study includes income, trip purpose, and age related attributes 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.

Trip purposes such as work related trips and social and recreational trips are employed in the models as dummy variables that present the reasons why people travel. Among trip purposes, work related variable is expected to positively affect to business travelers, particularly those who use airplane, since it is traditionally known that business passengers prefer air travel while non-business passengers tend to choose train or automobile for intercity travel. This is because most business passengers have no burden to pay for their trips. In addition, social and recreational trips are expected to have positive and significant effects on personal car and ground intercity mode users' utilities. Social and recreational trips are known to be less sensitive to travel time, and large in the average number of travelers.

In regard of age effects on mode choice decisions, this study uses dummy variables that reflect existence of child or the elderly in the travel group. Age is considered to affect to the mode choice decisions. However, this study cannot directly examine the impacts of age on mode choice decisions because household level samples can include many travelers, and thus it is not possible to apply a single age into the model. Given this condition, this study examines whether people traveling with child or the elderly are different in their mode choice decisions. Existence of child implies increase in number of travelers on that trip, and thus increases in travel costs except personal cars. Meanwhile, existence of the elderly may imply both increase in number of traveler and more demands on comfortable and convenient modes. With these variables, this study expects that traveling without child have positive effects on the probability of choosing airplane, while traveling with the elderly could increase the probability of choosing personal cars.

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 an indicator of large population and more public transportation service, is expected to have a positive sign for train and bus because a large metropolitan area. Existence of heavy rail service is also understood in the same context as MSA size. Higher demand of transportation will facilitate public transportation network, and thus large population will be positively related with the probability of choosing bus and train.

The number of travelers on the trip is another variable that is expected to interact negatively with utility of certain modes including air. As 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).

Figure 4-1 presents these relations in graphic.

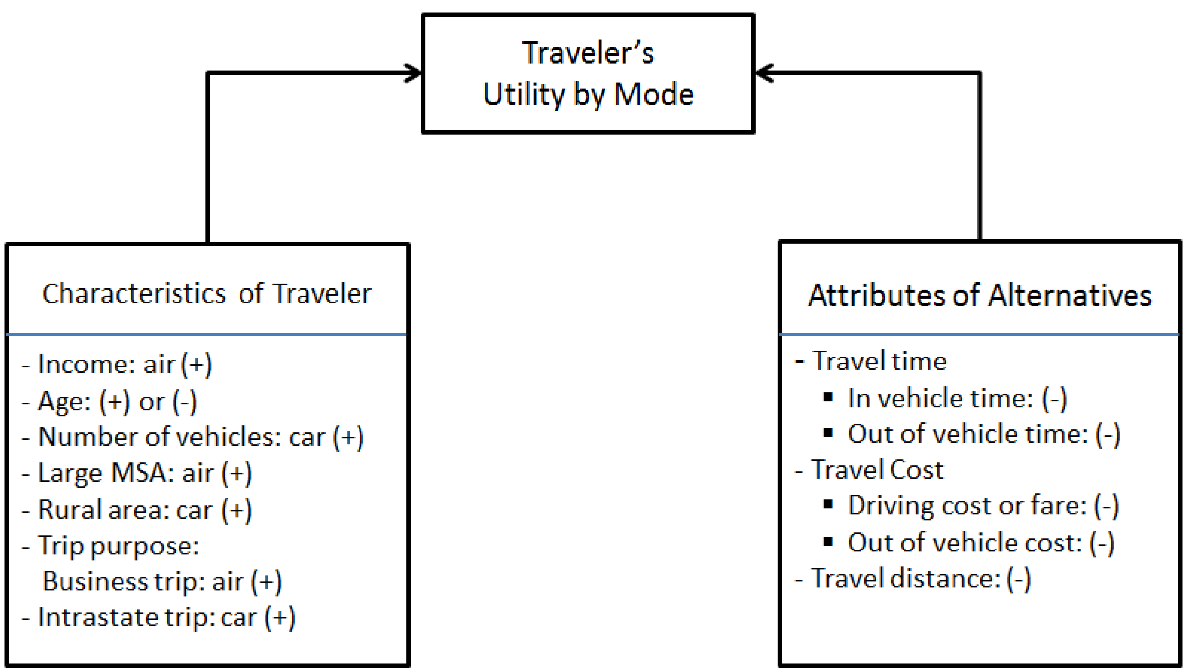


Figure 4-1. Hypothetical relationship of explanatory variables to travelers' utility

Estimating Synthetic Travel Times and Costs

In order to develop the mode choice models, travel time and costs for each alternative mode is essential. The 2009 NHTS data only provides actual travel time for each trip segment, and thus this study can calculate total travel time for a given long-distance travel made by the mode used. However, the 2009 NHTS does not provide travel costs of the mode used, and travel times and costs for other alternative modes that can be potentially used for each trip. In addition, the 2009 NHTS has no information about access time and costs to/from intercity terminals such as airport, bus terminal, and train station. Therefore, this study develops synthetic travel time and costs for all alternative modes using average driving costs per mile by passenger car type, air passengers fare and flight distance survey, bus and train fare and travel time tables. In estimating synthetic travel time and costs, this study takes into account one way trips assuming that people use the same mode of transportation for their returning trips.

Automobile Travel Times and Costs

Automobile travel time mainly includes driving time and rest time for night. In order to calculate driving times, this study applies average travel speed of 60 miles per hour to travel distance, and then inflates calculated travel time by distance ranges:

Travel distance less than 100 miles: 10 percent

Travel distance between 100 and 400 miles: 7 percent

Travel distance over 400 miles: 5 percent.

This method is simple, but effective to calculate driving time. In addition to driving time, this study applies time for intermediate overnight stay after every 10 hour driving. According to Ashiabor, Baik and Trani (2010), the Virginia Tech travel surveys reported that travelers make overnight stay after 8 hours and 10 hours trips for business and non-business trips, respectively. However, this study simple applies non-business standard because business trips accounted for less than 25 percent of total long-distance trips. The total travel times are sum of driving time and overnight time.

The driving costs are calculated similar to the procedure of driving time. The driving costs are calculated by multiplying an average driving cost per mile to travel distance reported in the 2009 NHTS. In calculating 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 (AAA, 2010). The 2009 NHTS data does not present exact model and maker of personal cars used, but it provides information about modes such as car, minivan, sports utility vehicle (SUV), and pickup truck and other truck. 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. The average driving costs are given as:

Average of Sedan: 16.74 cents per mile

Small sedan: 14.10 cents per mile

Medium sedan: 17.30 cents per mile

Large sedan: 18.82 cents per mile

Sport utility vehicle: 22.31 cents per mile

Minivan: 19.31 cents per mile

The lodging costs are calculated assuming a $100 lodging cost per overnight stay. It would be ideal to increase the lodging costs depending on number of people on that trip, but this is not considered in this study.

Airline Travel Time and Costs

Air fares and flight times are synthesized from the US DOT's 10 percent sample ticket survey data (DB1B data). This data presents commercial airlines' airport-to-airport fare, distance, flight time, number of scheduled service, available seats, and origin/destination airport pairs. From the dataset, this study can find average fare for 442 airports in regard of 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. In addition, these fare and flight time data can be separately obtained for origin and destination flights. So, it is possible to apply different fares depending on incoming or out-going travel.

In theory, air travelers prefer airports with low fares, high departure frequencies, and a large number of connections to other airports (Ashiabor, Baik and Trani, 2010). This may be true because air passengers, for example, pay 55 cents per mile at Orlando International Airport traveling to destination within 500 miles, while people pay 90 cents per mile to make the similar flight from Gainesville Regional Airport. Moreover, Orlando International Airport provides wide range of flight destinations with frequent schedule than Gainesville Regional Airport. However, this study simply assumes that air travelers choose nearest airport from home.

In order to identify the closest airport from each sample, this study uses the location information of census block group where each household is located. This study associates the average fare and flight time from the DB1B data with the nearest airport to each sample, and then calculates air fare and flight time for each sample at given travel distance.

In addition to air fare and flight time, this study adds access costs and time to airport using the distance from sample household to the nearest airport. As shown in table 4-2, the average distances to airport are relatively short at 14.8 miles in the census division of MT, and it was followed by PAC of 16.9 miles and Northeast Corridor (NEC) (that comprises New England and Middle Atlantic) of 18.3 miles. In contrast, ESC records the longest average distance of 28.3 miles. It should be noted that WSC, WNC, and MT show the largest standard deviations over 19 miles, and WSC includes the sample household which is located the farthest from airport at 157.4 miles. Interestingly, ENC is the second longest in average distance to airport at 26.5 miles, but it has the smallest maximum distance of 67.6 miles. In estimating access time and costs to airport, this study applies the same procedure with driving time and cost calculation. This study assumes that people uses personal cars to access airport.

Table 4-2. Average Distance to the Closest Airport by Census Division

Census Division	Number of samples	Mean	Minimum	Maximum	Std Dev
Northeast Corridor	1,798	18.3	0.2	82.6	14.9
East North Central	638	26.5	1.7	67.6	17.4
West North Central	749	21.8	1.2	97.4	19.6
South Atlantic	4,702	22.2	0.5	78.6	16.1
East South Central	317	28.3	0.7	81.5	18.6
West South Central	2,170	24.4	0.3	157.4	19.7
Mountain	619	14.8	0.3	104.9	19.1
Pacific	1,853	16.9	0.1	102.9	16.3
US	12,846	21.3	0.1	157.4	17.4

Final travel times for air travel are made up of the flight time and access time, while travel costs are computed as sum of air fare and access costs. It should be noted that total travel costs can be calculated by multiplying air fares with number of people on that trip. Unlike personal cars, air fares increase depending on number of travelers, and thus using total travel costs is reasonable. Individuals who are traveling alone may have greater tendency to choose common carriers while, people traveling with family members may prefer automobile to lower the travel cost per person.

Bus and Train Travel Time and Costs

Both travel time and costs for bus and train are obtained through similar procedure as that of air travel time and costs. In both modes, travel time consists of include in-vehicle time and access time, while travel costs comprises fares and access costs. Therefore, the total travel time and costs are sum of these two components.

First, this study builds up travel time and fares data for both modes in reference to Amtrak and Greyhound's real service operations. In order to identify patterns of travel time and fare for bus and train, this study collects actual fare and travel time from randomly selected origin destination pairs in regard of distances and location characteristics of terminals. Using these times and fares, this study estimates the travel distance per minute (mile per minute) and travel costs per mile (cents per mile) by distance group. In reality, both bus and train's fares do not monotonically increase as travel distance increases, but increase stepwise. Yet, this study allows them to increase proportionally within distance group.

Secondly, this study estimates the shortest distance from each household to bus terminal and train station like as this study did for airport. In calculating the shortest distances, this study uses 1,482 Greyhound terminals and 533 train stations. Table 4-3 presents the average distances by census division. NEC, WSC, and MT show relatively short average distance to bus terminals, while ESC records the longest average distance to bus terminal. In case of train station, people in both WNC and ESC divisions are the farthest in an average distances at 75 miles and 79.7 miles, while PAC and NEC show relatively short average distances of 11.4 miles, and 20.6 miles, respectively.

Table 4-3. Average Distances to Bus Terminal and Rail Station by Census Division

Terminal	Census Division	Number of samples	Mean	Minimum	Maximum	Std Dev
Bus	Northeast Corridor	1,798	7.9	0.1	113.2	8.6
	East North Central	638	11.7	0.3	48.9	10.5
	West North Central	749	13.6	0.0	89.8	14.2
	South Atlantic	4,702	13.9	0.0	66.5	12.7
	East South Central	317	16.5	0.6	54.8	13.1
	West South Central	2,170	9.8	0.1	78.0	11.7
	Mountain	619	10.3	0.3	120.3	16.0
	Pacific	1,853	11.4	0.5	86.3	8.0
	US	12,846	11.8	0.0	120.3	11.8
Train	New England	1,798	20.6	0.1	173.7	20.9
	East North Central	638	33.9	0.2	213.9	33.2
	West North Central	749	75.0	0.6	245.9	61.0
	South Atlantic	4,702	29.7	0.1	219.4	35.9
	East South Central	317	79.7	0.1	180.3	43.1
	West South Central	2,170	43.0	0.7	246.3	52.3
	Mountain	619	43.8	0.3	271.9	58.4
	Pacific	1,853	11.4	0.4	153.1	17.5
	US	12,846	32.8	0.1	271.9	42.3

It is true that there are other intercity bus services by region, but this study does not count them because many of them provide limited service within certain geographical locations. Like air fares, this study reflects number of travelers to the total fares of both bus and train.

Results of Model Estimations

As explained above, this study intends to test the impacts of alternative-specific characteristics on the probability of choosing a specific mode. At the same time, this study aims to examine the potential impacts of an individual attributes on the mode choice decisions for long-distance travel. In this regards, this study estimates multiple models that include alternative-specific characteristics, individual attributes, or both variables at the same model. For that this study develops a mode choice model that includes only travel time and costs of each alternative (the first column of Table 4-4).

Then, this study adds variables that represent travelers' characteristics such as income, travel purpose, and age related attributes (the second column of Table 4-4). Furthermore, this study expands the explanatory variables into geographical attributes of the household such as MSA categories, census divisions, and states. These models are expected to explain whether certain area has higher probability of choosing a specific alternative mode. These modes are presented from column 3 to column 6 in the Table 4-4.

Travel Time and Costs Variables

The estimated coefficients of both travel time and travel costs are negative in all models developed in this study. These negative signs indicate that travelers' utility decrease as travel time and costs increase as expected in hypothetical model. Thus, people may make less long-distance trips as travel time and costs increase. These estimated coefficients of personal cars are acceptable considering that personal cars account for large shares in shopping, social and recreation, and family or personal business trips, and people more likely travel with other family members for these trips.

It should be noted that the absolute values of the estimated coefficients for both travel times and costs are similar across predicted models even though they vary slightly depending on the explanatory variables added. For example, personal cars' coefficients of travel time at -0.0136 and travel costs at -0.0189 are similar with the coefficients of -0.0143 and -0.0193 in the model with individual characteristics. These coefficients imply that personal car users are less likely affected by exogenous factors in making mode choice decisions.

In contrast, the estimated coefficients of travel time and costs show that air travelers are more sensitive to travel time than travel costs. The absolute values of coefficients for air travel times are larger than the estimated coefficients for air travel costs meaning one unit change in travel time reduce more air travelers' utility. These results share the same view with many previous studies. These patterns are reasonable because people traveling with work related purposes are expected to use more airplane than travelers with other purpose. In addition, airplane users with work related purpose likely travel alone, and thus they are likely free from additional burden on travel costs.

Interestingly, airplane shows considerable differences among the estimated coefficients of travel time and costs as individual variables are included in the model. In other words, airplane's coefficients of travel time at -0.0118 and costs at -0.0014 in the time-cost only model are different from that of -0.0050 and -0.0006 in the model with individual characteristics. These changes imply that individual characteristics such as status of employment and income also affect to the probability of choosing airplane compared to other modes of transportation.

Ground intercity modes such as bus and train show similar patterns as personal cars in terms of the variations of coefficients on travel time and costs across the models. In other words, the estimated coefficients are relatively stable across the estimated models even though the estimated models show that individual characteristics affect more on the bus users' choice decisions than train. This may imply that both bus and train are not affected by individual characteristics compared to airplane. The higher absolute values of coefficients for travel costs show that both bus and train users are more sensitive to travel costs than travel time. These estimated coefficients support hypothetical assumptions on the impacts of travel time and costs on choice decisions for these modes.

Individual Socio-Demographic Variables

In addition to alternative specific attributes, some traveler's individual characteristics are appeared to have impacts on mode choice decisions. The estimated models with individual characteristics show that trip purpose, income, and age have significant and positive influences on the choice of transportation mode. First of all, the models show that people with social and recreational purpose are positive to choose personal cars or bus. In case of social and recreational purpose, personal car users travel in a group of 1.6 persons on average, which are relatively large than other mode. This implies that personal car users can benefit from total travel costs. In addition, bus users' low sensitivity on travel time justifies these results. Thus, these positive signs of social and recreational purpose on personal cars and bus are reasonable. It is worthy of note that long-distance travelers are likely to choose airplane when they have the needs for business trips. The positive signs of airplane for work related trips are as might be expected. Business travelers are expected to be paid for their trips, and thus they are less sensitive to travel costs than travel time.

As explained in previous section, this study indirectly examines the effects of age on the mode choice decisions by including dummy variables of people traveling with/without child and people traveling with/without the elderly. The results show that existence of child has no statistically significant impacts on mode choice decisions for all alternative modes. For example, people traveling with child and air travelers without child have positive sign on personal cars and airplane, respectively, but it was not statistically meaningful. In contrast, personal car users' utility is expected to increase if they travel with the elderly. Since existence of the elderly also includes the cases of traveling elderly without other age group, this may imply that people rely more on personal cars as they are aged. This is as expected. However, there are no other statistically significant impacts in regards of the elderly.

As expected, income is expected to be positively related to fast and convenient transportation service. The estimated coefficients show that the high income group is more favorable to use airplanes while people in low income group have higher utility as they choose buses. These results imply that higher income group is more sensitive to travel time, and this they will pay more if they can reduce travel time. In contrast, low income group is likely willing to reduce travel costs rather than travel time.

In summary, personal cars users have relatively higher utility if they are traveling with the elderly and have social and recreational purpose. Meanwhile, travelers are likely to increase the probability of choosing airplane as they are traveling for business purpose or earn more than $60,000 annually. The probabilities of choosing bus increase when travelers have social and recreational purpose or they earn less than $30,000 annually.

Geographical Characteristics of Household

This study uses dummy variables that represent geographical characteristics of household. In applying dummy variables, this study narrows geographical scale from MSA categories to state and major transportation corridor levels. The third column in Table 4-4 shows the results of how different MSA categories may increase or decrease the utility of an alternative mode. The estimated model shows that people in both MSA of less than 1 million and non-MSA may have relatively higher probability to drive personal car to make long-distance trips compared to people living in MSAs of 1 million or more. Since these areas are expected to have less accessibility to airport, intercity bus services and rail stations, the positive coefficients of personal cars are reasonable.

In fact, average distances to rail stations of 41.8 miles for MSA of less than 1 million and 54.6 miles for non-MSA are much longer than that of MSA of 1 million with heavy rail system at 11.0 miles and MSA of 1 million without heavy rail system at and 14.5 miles. The average distances to airports and bus terminals are similar with rail stations. Thus, people are not able to benefit from public transportation modes.

The MSAs of 1 million or more without heavy rail system is positive to the utility of people traveling with airplane. For example, the MSAs of 1 million or more with heavy rail system in both Middle Atlantic and South Atlantic divisions show much lower share of airplane compared to the MSAs of 1 million or more without heavy rail system in the same divisions. This result makes sense because airline companies can provide better services of frequent flight, more destinations, and low fares in large MSAs, and in turn these services attract more travelers as they have no competition with rail systems.

In contrast, both train and bus users are able to increase their utilities as they live in MSA of 1 million with heavy rail system. Among MSAs of 1 million with heavy rail system, the MSAs in NEC, ENC, SA, and PAC are positive to increase the probabilities of choosing train as shown in the fourth and fifth columns of the Table 4-4. These MSAs are known to have relatively developed rail service systems. Interestingly, these sub-MSA categories are matched with federal government's proposals of high speed rail development. Meanwhile, travelers have higher probabilities of choosing buses if they live in the MSAs of 1 million or more that are located in the NEC (which comprises New England or Middle Atlantic divisions). It should be noted that MSAs of 1 million or more in NEC are known to provide better intercity bus services than other areas in the US. Thus, this result is highly reasonable.

This study, finally, tests whether people's utility choosing an alternative mode may vary across the states in the US. The estimated model shows that airplane users' have higher utility as they live in Arizona, California and Florida, while bus users in New York can increase their utility of choosing bus. In similar context, travelers can increase their utility of choosing train by residing in California or New York. However, both coefficients of airplanes for California and Florida are statistically significant only at 70 percent significance interval, so it cannot be fully proved in this study.

Table 4-2. Estimations of Mode Choice Models

Variables	Time-cost effect		Socio-Demographic Attributes		Effects of MSA Categories	
	Estimate	t Value	Estimate	t Value	Estimate	t Value
Car	4.8998	32.29	4.9882	29.97	5.8974	26.18
Bus	0.7865	4.11	0.7466	3.54	1.6704	6.56
Car Time	-0.0136	-20.28	-0.0143	-20.69	-0.0136	-19.30
Air Time	-0.0118	-4.55	-0.0159	-5.72	-0.0050	-1.64
Bus Time	-0.0024	-3.59	-0.0028	-4.02	-0.0018	-2.65
Train Time	-0.0040	-5.52	-0.0042	-6.09	-0.0034	-4.68
Car Cost	-0.0189	-11.45	-0.0193	-11.41	-0.0219	-12.52
Air Cost	-0.0014	-3.57	-0.0009	-2.46	-0.0006	-1.67
Bus Cost	-0.0187	-5.70	-0.0193	-5.68	-0.0186	-5.62
Train Cost	-0.0097	-3.18	-0.0068	-2.48	-0.0072	-2.33
Car with Elderly			0.2920	2.27	0.2263	1.74
Car Social			0.8303	5.50	0.7795	5.13
Bus Social			1.0894	5.21	1.0123	4.83
Air Work			0.7485	4.79	0.8858	5.44
Air High Income			0.4522	3.26	0.5865	3.90
Bus Low Income			0.5779	3.32	0.6594	3.75
Car Non-MSA					0.5149	3.17
Car MSA of less than 1 million					0.2638	1.90
Air without Heavy Rail					0.2678	1.69
Train with Heavy Rail					2.4920	10.42
Bus with Heavy Rail					0.4833	2.73
Bus NEC MSA of 1Mil. or more						
Train NEC with Heavy Rail						
Train ENC with Heavy Rail						
Train SA with Heavy Rail						
Train PAC with Heavy Rail						
Air Arizona						
Air California						
Air Florida						
Bus New York						
Train New York						
Train California						
Log Likelihood at convergence		-2389		-2324		-2237
Log Likelihood at constant only		-3496		-3496		-3496
R2		0.3166		0.3352		0.3601

Table 4-2. Estimations of Mode Choice Models (Continued)

Parameter	Mixed Effects		Pure Corridor Effect		State Effects	
	Estimate	t Value	Estimate	t Value	Estimate	t Value
Car	5.8970	26.40	5.5948	31.88	5.5559	26.62
Bus	1.7105	6.81	1.3394	6.28	1.5231	6.19
Car Time	-0.0137	-19.38	-0.0134	-20.01	-0.0137	-19.57
Air Time	-0.0050	-1.65	-0.0040	-1.50	-0.0065	-2.15
Bus Time	-0.0018	-2.67	-0.0017	-2.68	-0.0019	-2.83
Train Time	-0.0032	-4.41	-0.0034	-4.36	-0.0032	-4.48
Car Cost	-0.0220	-12.59	-0.0213	-12.62	-0.0217	-12.45
Air Cost	-0.0006	-1.66	-0.0013	-3.20	-0.0006	-1.56
Bus Cost	-0.0186	-5.63	-0.0184	-5.67	-0.0186	-5.61
Train Cost	-0.0076	-2.44	-0.0122	-3.45	-0.0080	-2.59
Car with Elderly	0.2265	1.74			0.2481	1.90
Car Social	0.7859	5.17			0.7978	5.25
Bus Social	1.0041	4.78			1.0210	4.87
Air Work	0.8924	5.48			0.8506	5.26
Air High Income	0.5862	3.90			0.5045	3.42
Bus Low Income	0.6647	3.78			0.6792	3.87
Car Non-MSA	0.5436	3.46			0.8067	5.67
Car MSA of less than 1 million	0.2909	2.18			0.6154	5.36
Air without Heavy Rail	0.2586	1.66				
Train with Heavy Rail						
Bus with Heavy Rail						
Bus NEC MSA of 1Mil. or more	0.8230	3.81	0.9881	4.78		
Train NEC with Heavy Rail	3.0668	11.43	2.8195	11.90		
Train ENC with Heavy Rail	3.2503	5.87	3.0033	5.57		
Train SA with Heavy Rail	2.3014	6.82	2.1236	6.79		
Train PAC with Heavy Rail	1.6265	4.47	1.4099	4.14		
Air Arizona					0.5224	1.68
Air California					0.2208	1.18
Air Florida					0.2628	1.16
Bus New York					0.5127	2.59
Train New York					2.5615	10.62
Train California					1.1576	3.73
Log Likelihood at convergence		-2224		-2312		-2243
Log Likelihood at constant only		-3496		-3496		-3496
R2		0.3638		0.3387		0.3584

CHAPTER 5
POLICY IMPLICATIONS FOR FUTURE LONG-DISTANCE TRNSPORTATION PLAN

Average Marginal Effects of Travel Time and Costs

The marginal effects measure the effect of a one unit change in explanatory variable on the probability of choosing an alternative model. They are different from the elasticity that measures the effect of one 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:

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

By applying estimated coefficients to the individual traveler's travel time and travel costs by mode, this study calculates each individual's marginal effect of each average change in the probability of choosing an alternative mode by alternative specific attribute.

As shown in Table 5-1, one hour increase in travel time is expected to decrease the probability of choosing personal car by 0.035 percent, while the probabilities of choosing bus, air and train are also expected to decrease by 0.003 percent, 0.015 percent and 0.002 percent, respectively. Meanwhile, $100 dollar increases in travel costs are also expected to decrease the probability of choosing personal cars, bus, air and train by 0.079, 0.038, 0.004 and 0.008, respectively.

It should be noted that personal car users are the most sensitive to additional 1 unit of travel time and costs, while train users are less likely affected by the changes in both travel time and cost. Bus users are relatively sensitive to travel time compared to travel costs. In contrast, air travelers are likely willing to decrease travel time rather than decrease travel costs. This implies that service speed would be a key point to make a new alternative mode to compete with airplane.

Table 5-1. Average Marginal Effects of Travel Time and Costs by Mode

Index	Car		Bus		Airplane		Train	
	Travel Time	Travel Cost	Travel Time	Travel Cost	Travel Time	Travel Cost	Travel Time	Travel Cost
US Average	-0.035	0.079	-0.003	-0.038	-0.015	-0.004	-0.002	-0.008
NEC	-0.031	0.072	-0.002	-0.035	-0.012	-0.003	-0.002	-0.008
ENC	-0.033	0.075	-0.002	-0.033	-0.015	-0.004	-0.002	-0.007
SA	-0.034	0.077	-0.003	-0.037	-0.014	-0.004	-0.002	-0.009
PAC	-0.034	0.077	-0.002	-0.036	-0.014	-0.004	-0.002	-0.009

Major MSAs of 1 million or more with heavy rail system show similar measures of marginal effects for travel time and costs, although there are variations. For example, people in NEC are less responsive to the change of air travel time, while PAC region shows higher response in travel costs of train. Meanwhile, travelers in SA region are more sensitive to both bus travel time and train travel time compared to the average of the US. Interestingly, ENC is expected to experience less decrease in probabilities in every unit changes of travel time and cost for all modes. These variations may imply that policymakers and researchers are required to apply different strategies in different regions.

Estimations of the Probabilities Choosing a New Alternative Mode by Travel Time and Costs Scenario

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. This study presumes that an alternative mode replaces current train services by improving its speed. In specific, this study assumes a new high speed rail system as a new alternative mode because other ground transportation modes such as personal cars and bus cannot travel with such a speed. In order to calculate travel time of the alternative train system, this study assumes three speed levels such as 150, 200, and 300 miles per hour that are currently available for high speed rail around the world. By applying these speeds to the incremental travel distances from 100 miles to 600 miles, this study calculates in-vehicle times for the new alternative train system.

This study also estimates travel times for personal cars, bus, airplane and train in the same travel distances. These distances 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. In addition to in-vehicle time, this study applies access time and costs to public transportation modes including the new alternative mode. For that this study, first, assumes an average distances of 29.1 miles to airport, 14.4 miles to bus terminal, and 21.2 miles to train station. Second, this study assumes personal cars for all access travel.

This study, first, estimates the probability of choosing an improved train system for the whole of the US. Then, this study predicts the probabilities of major regions such as NEC, ENC, SA, and PAC. Since, these regions show relatively higher share of train, they might have different patterns in the probability estimations.

Estimations of the Probabilities of Choosing an Improved Train for the Whole of the US

As shown in Figure 5-1 and Table 5-1, an improved train service is expected to have less than 1 percent of probability in a 100 mile travel distance range regardless of speed levels and travel costs. In both 200 mile and 300 mile service ranges, the probabilities of choosing an improved train are expected to increase up to 2.5 percent. These shares are higher than current average share of train in the US, but the new train system is expected to suffer from insufficient demand. It should be noted that these estimated shares are still lower than current mode share of train at 2.6 percent in the NEC where Amtrak is experiencing serious revenue shortfall. In addition, it may be difficult for an improved train system to have price competitiveness against personal cars and airplane. For example, it is required to set a $100 fare with a speed of 300 miles per hour to retain 2.5 percent mode share, but, people already pay $149 for about 230 mile trip from Penn Station in New York to Union Station in Washington DC. It would be difficult for an improved train system to charge less than current fare level. Therefore, an improved train may not be an attractive policy option targeting 200 to 300 mile transportation market of the US.

A 400 mile seems to be a frontier for a new alternative rail system to draw long-distance travelers from other competing modes such as personal cars and airplane. A new alternative rail system has space to adjust its fare level by 1.5 times of driving costs, while it retains relative less constraint on service speed. For example, an improved train system can account for 1.8 percent at a speed of 200 miles per hour and a fare level of 1.5 times of driving costs. This is a significant rise of the probability, but the new train system is not free from constraints on travel time and costs. The new train system is required to maintain fare level as close to driving costs to maintain its competitive power. In general, construction costs increase as speed limit increases, thus a new rail system may suffer from revenue shortfall, and in turn this will escalate the concerns on cost effectiveness.

In both 500 mile and 600 mile service distance ranges, a new rail system is expected to draw more than 4 percent of long-distance travel demand if it could hold its fare level as close to driving costs. These probabilities are significantly higher than current average share of train in the US. However, it should be noted that the probabilities of choosing the new train system are expected to decrease to less than 3.6 percent with a fare level of 1.5 times of driving costs, and to less than 1.5 percent with a fare level of 2 times of driving costs. Therefore, an improved train system is likely to be restrained by travel time and costs constraints. Moreover, the shares of 5 to 8 percent may not sufficient to sustain massive construction and operation costs of high speed rail system.

In summary, an improved train is expected not to be competitive against personal cars in a distance range between 100 and 300 miles. In a 400 mile distance range, a combination of low fare level as close as to driving costs and a speed of 200 or more miles per hour is essential to assure the least probability of choosing a new alternative rail system. In contrast, it would have a relatively strong competitiveness in a distance range of 500 or more miles, but it is required to transport people with a speed of 200 or more miles per hour and a fare level of less than 1.5 times of driving costs.

Table 5-2. The Probabilities of Choosing an improved train System by Travel Time and Cost Scenario

Distance	Car		Air		Bus		Improved Train				
	Time	Cost	Time	Cost	Time	Cost	Speed	Time	Probability of Cost (%)		
100	**110**	**30**	**80**	**90**	**150**	**40**	**-**	**-**	**40**	**50**	**70**
							150	80	0.91	0.82	0.68
							200	70	0.94	0.86	0.71
							300	60	0.98	0.89	0.74
200	**220**	**65**	**115**	**135**	**300**	**90**	**-**	**-**	**70**	**100**	**130**
							150	120	1.43	1.08	0.81
							200	100	1.55	1.17	0.88
							300	80	1.68	1.26	0.95
300	**330**	**95**	**120**	**200**	**430**	**135**	**-**	**-**	**100**	**140**	**190**
							150	160	2.00	1.37	0.85
							200	130	2.25	1.54	0.95
							300	100	2.53	1.73	1.07
400	**445**	**125**	**135**	**210**	**560**	**175**	**-**	**-**	**130**	**190**	**250**
							150	200	2.75	1.56	0.88
							200	160	3.22	1.83	1.03
							300	120	3.75	2.14	1.21
500	**550**	**155**	**150**	**260**	**745**	**190**	**-**	**-**	**160**	**230**	**310**
							150	240	4.02	2.09	0.98
							200	190	4.86	2.54	1.19
							300	140	5.87	3.08	1.45
600	**670**	**185**	**170**	**310**	**890**	**230**	**-**	**-**	**190**	**280**	**370**
							150	280	5.18	2.24	0.95
							200	220	6.49	2.83	1.21
							300	160	8.11	3.57	1.53

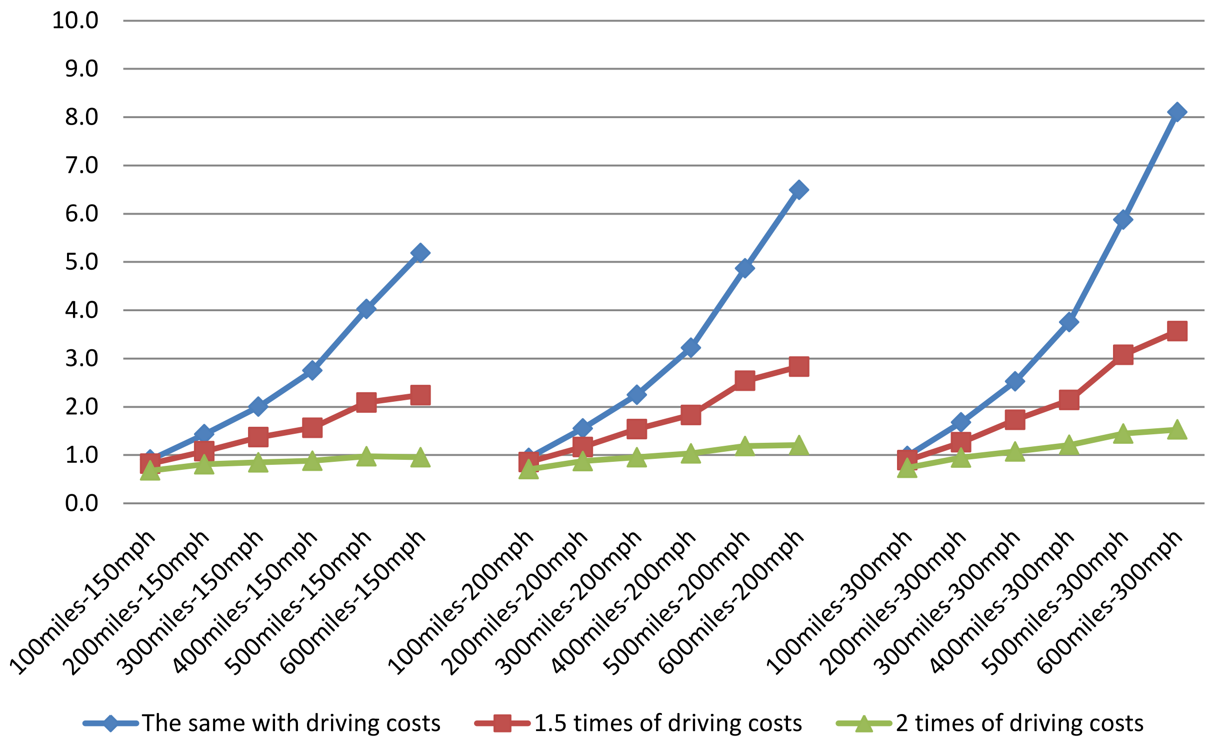


Figure 5-1. The Probabilities of Choosing an improved train Mode by Travel Time and Cost Scenario

Probability Estimations for the Major MSA Corridors

This study predicts the probabilities of MSAs of 1 million or more with heavy rail system in NEC, ENC, SA, and PAC regions where the probabilities of choosing train appeared positive and significant. By estimating the probabilities of choosing an improved train system in these regions, this study indirectly evaluates the potentiality of HSR systems in the US. The estimated probabilities are presented in Table 5-2 and Figure 5-2.

In the NEC, the new high speed train system is expected to share around 6 to 18 percent of long-distance travel assuming the same level of fare level as the driving costs. However, the probabilities are decreased to 5 to 6 percent if fare level goes up to 1.5 times of driving costs, and then decreased to 2 to 4 percent as fare level is set to 2 times of driving costs . More importantly, the shares of an improved train system at 600 mile distance are lower than that of 500 mile distance if fare levels are higher than 1.5 time of driving costs. These results seem to imply that an improved train is appropriate option for up to 500 mile distance ranges premising a fare level of less than 1.5 times of driving costs.

Overall, the predicted probabilities of ENC show similar patterns with that of NEC. An improved train system is likely to be competitive in ENC when it provides passenger services up to 500 mile range with a fare level of 1.5 times or more of driving costs. However, it should be noted that the probabilities of ENC are slightly higher than NEC by 400 mile distance range, while the probabilities of NEC are larger than ENC if travel distance is 400 or more miles, but less than 600 miles. This may imply that an improved train system would be more viable policy option for a relatively short distance range (up to 400 miles) in ENC.

The estimated probabilities of SA are higher than the average probabilities of the US in all distances and travel time scenarios as long as its fare level can be marked by 1.5 times of the driving costs. However, the probabilities are less than 4 percent as fare level increases to 1.5 times or 2 times of driving cost. In particular, the probabilities decrease continuously if fare level is set to 2 times of driving costs. These patterns may occur because train's marginal effect on travel cost is larger than NEC and ENC, and thus long-distance travelers in SA shift to other modes easily. Given these conditions, it is expected that a fare level of less than 1.5 times of driving costs is critical to SA for developing an improved train system. In addition, it is appropriate for SA to provide services as fast as possible because higher speed increases the probabilities of choosing the new alternative train system. This may imply that a new high speed rail system could be a viable policy option for SA in less than 500 mile range, but it may have much strict constraints in both travel time and costs compared to NEC and ENC.

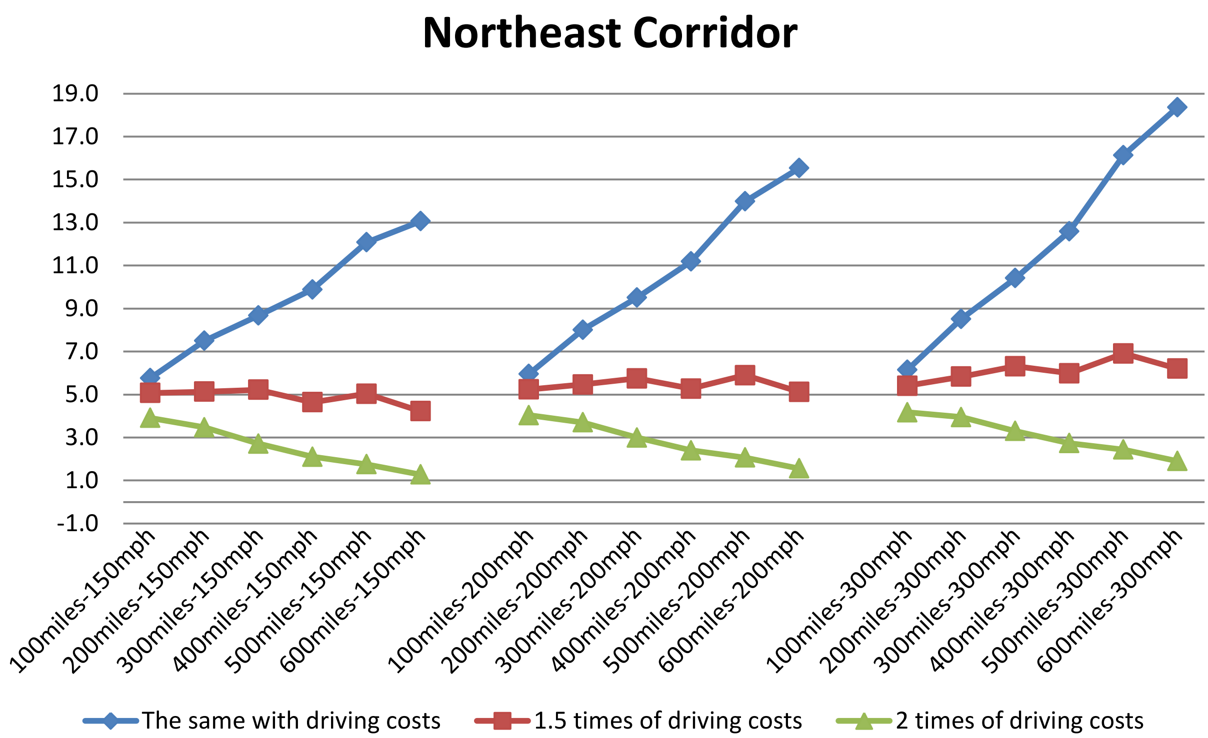
The estimated probabilities for PAC are interesting compared to other corridors. First of all, the probability of choosing an improved train system is higher than the US at all service speed levels if it can set the fare level as lower than driving costs. However, this may not be a possible option for an improved train system because this will be cause serious financial problems. Interestingly, the probabilities of choosing the new train system are higher than the average measure of the US if travel distance is 500 or more mils and the fare level is less than 1.5 times of driving costs. This simply implies that an improved train system might be a viable option in PAC for over 400 mile distance ranges.

The results present that an improved train system would be a policy option for PAC with higher limitations on both travel distance and fare level. The probabilities of choosing a new high speed rail system are higher than the average of the US if travel distance is less than 600 miles and fare level is similar as the driving costs. However, the probabilities are lower than national average if fare level is higher than 1.5 times of the driving costs and travel distance is 400 or more miles. Thus, the new train system is expected to have stronger restrictions on both travel distance and fare level. It should be noted that an improved train is relatively appropriate for short distance service in the PAC region. The results also show that the probabilities of choosing an improved train is much lower than the average measures of the US if fare level is 2 times or more of driving costs regardless of speed.

In summary, an improved train is expected to have advantage of serving long-distance travelers in less than 500 mile distance ranges. Among corridors, both NEC and ENC are expected to have the highest potential to develop an improved train system in this travel distance range, while SA and PAC are expected to face stronger travel time and costs constraints. In particular, PAC is expected to have less than 2 percent of probabilities if it provides passenger services less than 200 miles per hour. It should be noted that it is required to retain fare level of less than 1.5 times of the driving costs.

Table 5-3. Comparison of the Probabilities of Choosing an improved train System by Corridor

Distance	An improved train		Probability by Cost (%)														
	Time	Speed	US			NEC			ENC			SA			PAC		
	-	-	**40**	**50**	**70**	**40**	**50**	**70**	**40**	**50**	**70**	**40**	**50**	**70**	**40**	**50**	**70**
100	80	150	0.9	0.8	0.7	5.8	5.1	3.9	6.6	5.8	4.3	3.1	2.8	2.1	2.0	1.7	1.3
	70	200	0.9	0.9	0.7	6.0	5.2	4.0	6.9	6.0	4.5	3.2	2.8	2.2	2.1	1.8	1.4
	60	300	1.0	0.9	0.7	6.1	5.4	4.2	7.1	6.1	4.6	3.3	2.9	2.3	2.1	1.9	1.4
	-	-	**70**	**100**	**130**	**70**	**100**	**130**	**70**	**100**	**130**	**70**	**100**	**130**	**70**	**100**	**130**
200	120	150	1.4	1.1	0.8	7.5	5.1	3.5	8.3	5.4	3.5	4.2	2.9	2.0	2.7	1.8	1.2
	100	200	1.6	1.2	0.9	8.0	5.5	3.7	8.8	5.8	3.8	4.5	3.1	2.1	2.8	1.9	1.3
	80	300	1.7	1.3	0.9	8.5	5.8	4.0	9.4	6.2	4.0	4.8	3.3	2.3	3.0	2.1	1.4
	-	-	**100**	**140**	**190**	**100**	**140**	**190**	**100**	**140**	**190**	**100**	**140**	**190**	**100**	**140**	**190**
300	160	150	2.0	1.4	0.8	8.7	5.2	2.7	9.2	5.2	2.5	5.0	3.0	1.6	3.1	1.9	1.0
	130	200	2.2	1.5	1.0	9.5	5.7	3.0	10.1	5.8	2.8	5.5	3.3	1.8	3.5	2.1	1.1
	100	300	2.5	1.7	1.1	10.4	6.3	3.3	11.0	6.3	3.1	6.0	3.7	2.0	3.8	2.3	1.2
	-	-	**130**	**190**	**250**	**130**	**190**	**250**	**130**	**190**	**250**	**130**	**190**	**250**	**130**	**190**	**250**
400	200	150	2.7	1.6	0.9	9.9	4.6	2.1	10.1	4.3	1.8	5.8	2.8	1.3	3.6	1.7	0.8
	160	200	3.2	1.8	1.0	11.2	5.3	2.4	11.4	4.9	2.1	6.6	3.1	1.5	4.2	1.9	0.9
	100	300	3.8	2.1	1.2	12.6	6.0	2.7	12.8	5.6	2.3	7.5	3.6	1.7	4.7	2.2	1.0
	-	-	**160**	**230**	**310**	**160**	**230**	**310**	**160**	**230**	**310**	**160**	**230**	**310**	**160**	**230**	**310**
500	240	150	4.0	2.1	1.0	12.1	5.0	1.8	11.9	4.5	1.4	7.3	3.1	1.1	4.6	1.9	0.7
	190	200	4.9	2.5	1.2	14.0	5.9	2.1	13.8	5.3	1.6	8.5	3.6	1.3	5.4	2.2	0.8
	140	300	5.9	3.1	1.4	16.1	6.9	2.4	16.0	6.2	1.9	9.9	4.3	1.6	6.3	2.6	0.9
	-	-	**190**	**280**	**370**	**190**	**280**	**370**	**190**	**280**	**370**	**190**	**280**	**370**	**190**	**280**	**370**
600	280	150	5.2	2.2	1.0	13.1	4.2	1.3	12.6	3.6	0.9	8.1	2.7	0.8	5.1	1.6	0.5
	220	200	6.5	2.8	1.2	15.5	5.1	1.6	15.0	4.3	1.1	9.7	3.3	1.0	6.1	2.0	0.6
	160	300	8.1	3.6	1.5	18.4	6.2	1.9	17.7	5.2	1.4	11.7	4.0	1.3	7.4	2.4	0.7



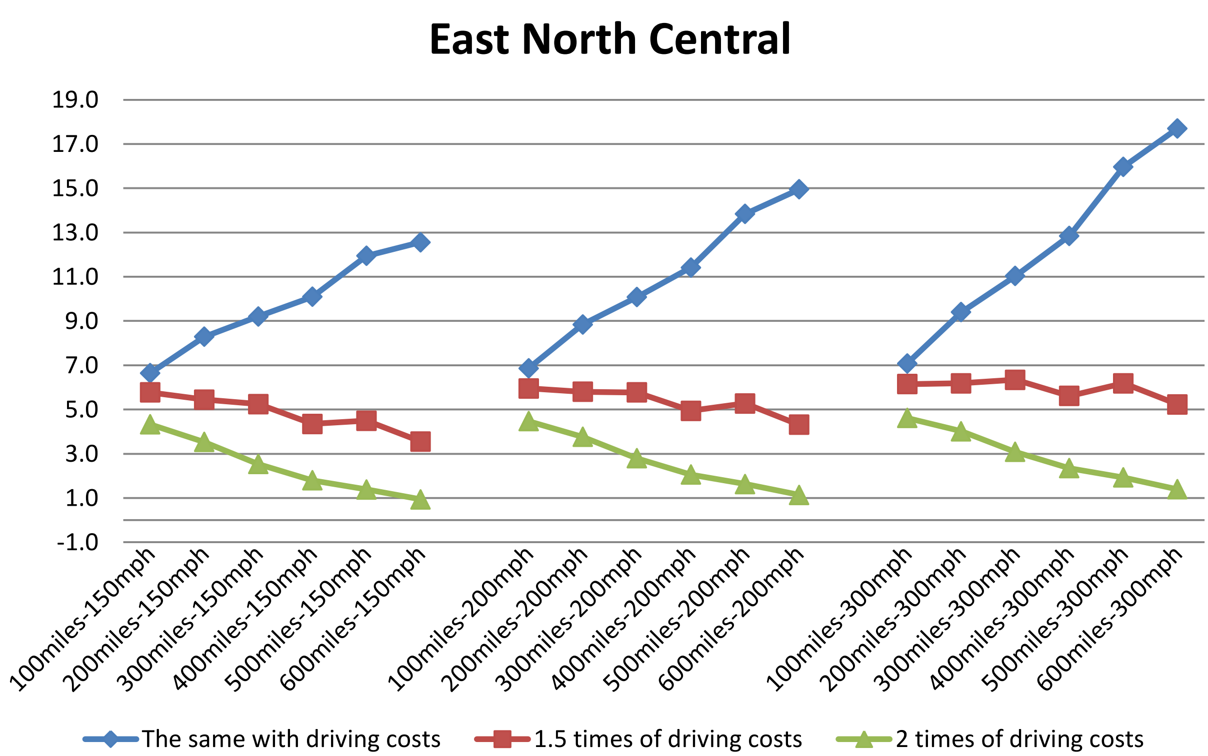
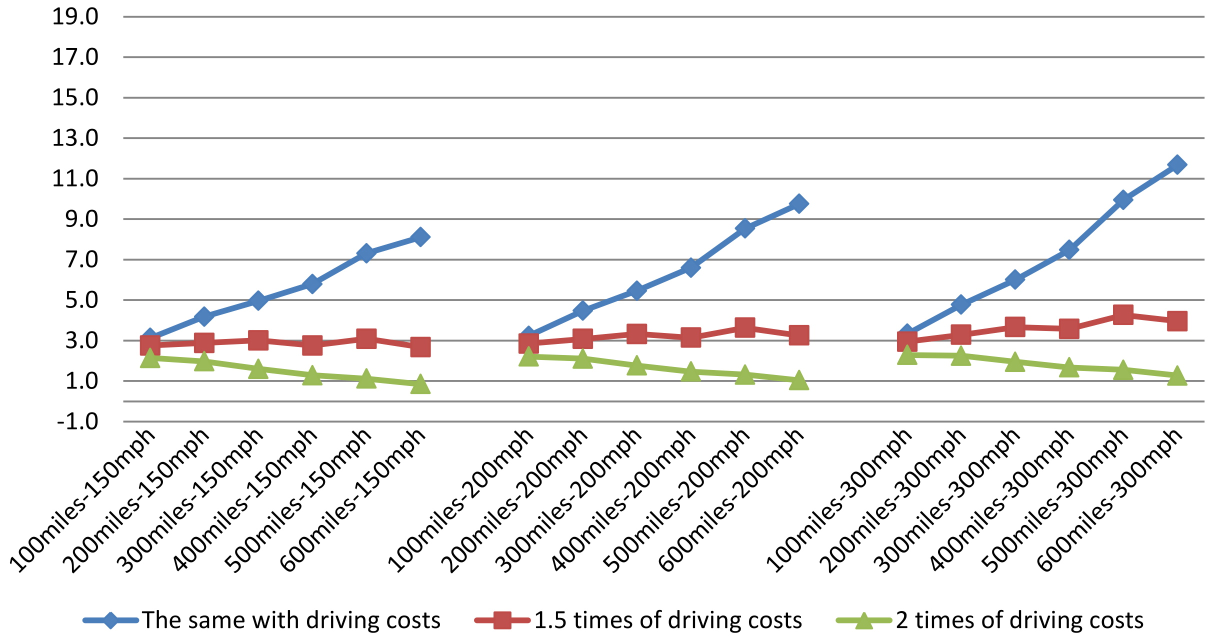


Figure 5-2. The Probabilities of Choosing an improved train Mode by Corridor and by Travel Time and Cost Scenario

South Atlantic



Pacific

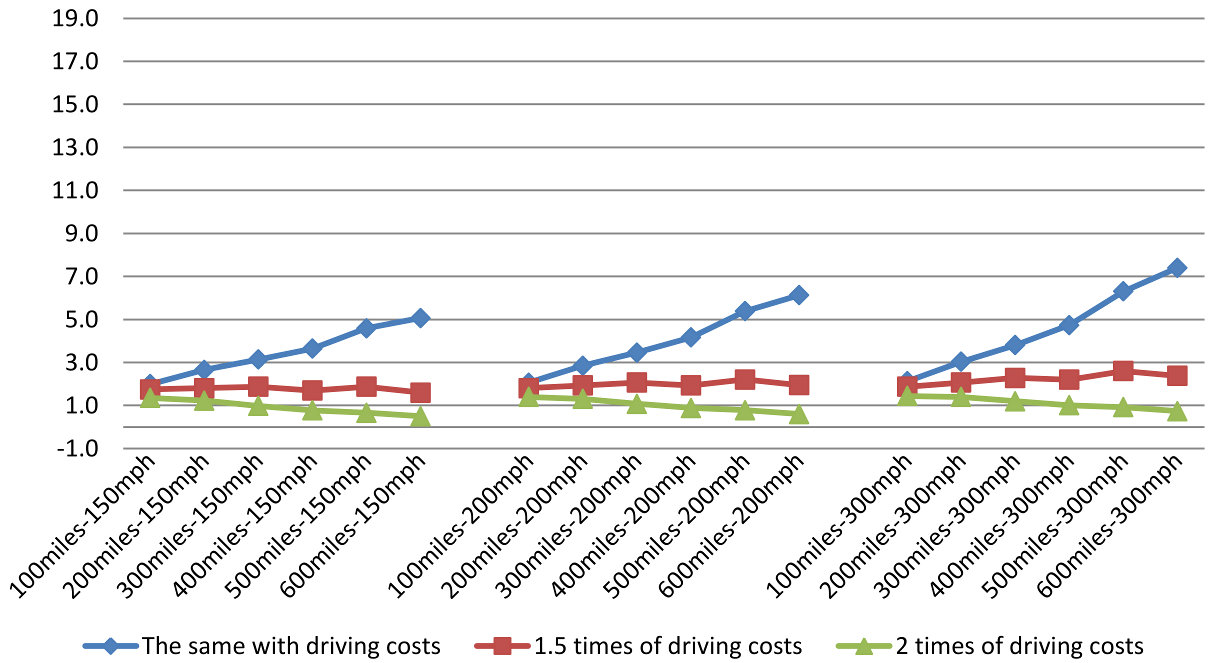


Figure 5-2. The Probabilities of Choosing an improved train Mode by Travel Time and Cost Scenario and by Corridor (Continues)

Policy Recommendations

Based on the findings of long-distance travel patterns, this study suggests several policy implications. First, nearly 80 percent of long-distance trips are made less than a 200-mile range with an average of 130 miles, and thus it is recommended to find a new alternative travel mode or improvement of current service that can cover up to a 200-mile travel distance. In addition, nearly 90 percent of long-distance trips are made by personal cars, and a new alternative mode is needed to have the capability to draw people from personal cars.

Secondly, it is known that public ground transportation modes such as bus and train are not popular alternative options to the people in the US. However, it may not true considering that both bus and train account for relatively large portion of total daily trips where these services are provided. For example, MSAs of 1 million or more show relatively large shares of bus at NEC (4 percent), MT (2.8 percent), SA (2.3 percent) and PAC (1.8 percent) divisions. Similarly, train accounts for about 4.9 percent, 5.1 percent, 2.5 percent, and 1.2 percent at NEC, ENC, SA, and PAC divisions where heavy rail services are provided. These patterns seem to imply that people may be willing to use a new alternative mode if they have such services with easy access and satisfaction of their service quality needs.

Based on the estimated empirical models, it is required for an improved train system to set its fare level less than 1.5 times of driving costs providing services at a speed of 200 or more miles per hour to retain its competitiveness power. In addition, an improved train system is expected to draw relatively higher share of passengers within 500 mile distance range of NEC, ENC, SA and PAC regions. Both NEC and ENC are especially considered as appropriate locations to construct an improved train system.

Assuming a fare level of 1.5 times of driving costs, ENC is expected to have higher probabilities in less than 300 miles distance compared to NEC, while NEC seems to be more favorable in the distance range of 300 to 500 miles. PAC is expected to draw the least probabilities of choosing an improved train system, while SA is expected to rely considerably on the scenario of travel time and costs. Figure 5-3 illustrates the probabilities of choosing an improved train system presuming a fare level at 1.5 times of driving costs.

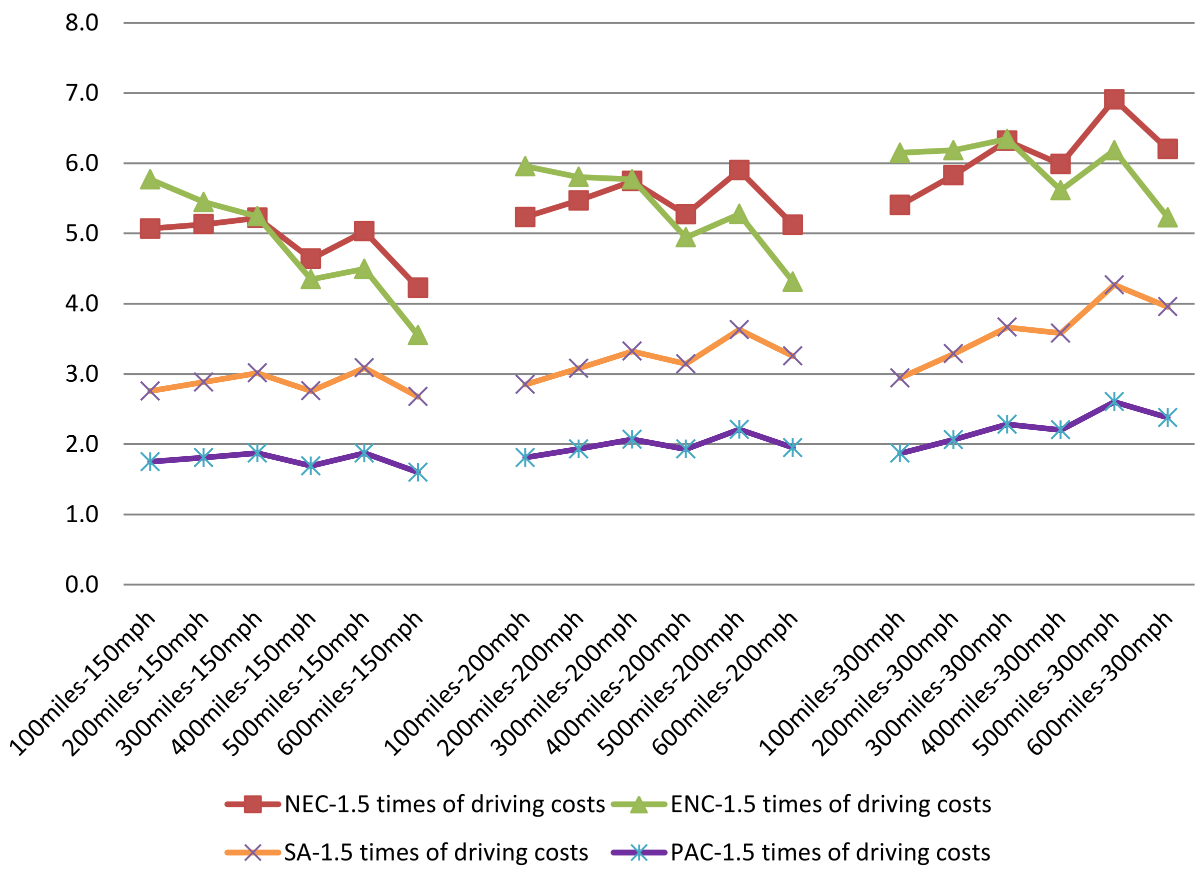


Figure 5-3. Comparison of the Probabilities of Choosing an improved train Mode with 1.5 times of Driving Costs

Depending on the estimated model and prediction of the probabilities of choosing an improved train system, PAC is expected to have relatively the lowest potentiality to implement high speed rail policy. However, these low shares of estimated probabilities may be complemented by air travel between major cities in the region. For example, there are nearly 14.8 million air passengers within 400 miles connecting major cities in California such as Los Angeles, San Francisco, San Jose, Oakland, San Diego, and Sacramento as of the end of 2012. Compared to the air passengers of NEC at 5.8 million and ENC at 4 million in the same distance range, these air travel demand is considered as large enough to form a strong ground to support an improved train system. It should be noted that the examples of the air-rail market in Europe have presented that high speed rail can account for more than 70 percent within 2 and a half hour journey. Therefore, an improved train system might draw more than 10 million of air passengers onto its system in PAC.

Similar patterns are witnessed in both northern and southern SA regions. For example, there are 11.5 million air passengers in northern corridor connecting major cities such as Atlanta, GA, Charlotte, NC, Raleigh-Durham, NC, Washington DC, and Baltimore, while airlines transported 13.5 million passengers among cities in southern SA such as Atlanta, GA, Orlando, FL, Miami, FL, Jacksonville, FL, and Fort Lauderdale, FL. In the same regards of air-rail market share experiences in Europe, 8 million and 9.5 million air passengers are expected to shift to an improved train system in northern and southern SA regions, respectively. These figures support current efforts of high speed rail system in the US, but they also recall the importance of target mode that can compete with high speed rail by distance range.

In summary, it is required for an improved rail system needs to provide fast and affordable service to compete with both airplanes and personal cars in a distance range of 500 or less miles. In specific, less than 1.5 times of driving costs and 200 or more miles per hour are considered as essential requirement for an improved train system to compete with personal cars and airline services. Among census divisions in the US, NEC, ENC, SA and PAC are considered to have higher potential to develop high speed rail system. In consideration of the estimated model, both NEC and ENC are higher in their probabilities of choosing an improved train system, while both PAC and SA are able to increase their possibilities of successful high speed rail implementations by providing services targeting on air passengers within 500 mile distance range. For that, it might be necessary to establish plans of high speed rail network from wide spatial perspective.

CHAPTER 6
CONCLUSIONS AND FURTHER STUDY

Conclusions

This study attempted to enhance fundamental understanding of long-distance travel patterns in the US, and provide policy options for long-distance transportation planning in the future. In achieving these research objectives, this study focused on four tasks as: 1) descriptive analysis of the 2009 NHTS and the state add-on datasets, 2) estimation of logistic regression models that are sensitive to both travel mode specific variables and travelers' characteristics, 3) prediction of the probabilities of choosing an improved rail system by applying scenarios of travel time and costs, and 4) implications for viable alternative options for long distance transportation planning in the US. Among various trips by definition, this study focused on long-distance trips that are defined as trips of 50 or more miles. This study counted a trip as long-distance trip if at least one segment of the daily trip is 50 or more miles. This narrowed the long-distance trips mostly into intercity trips.

It should be noted that this study explicitly attempted to develop a sound method to estimate synthetic travel time and costs of all alternative modes. Since the 2009 NHTS provides only information of mode used for a given long-distance trip and travel time, it is essential to estimate travel time and costs of all available modes. However, only couple of studies have presented the travel time and costs for the all available alternative modes. In estimating synthetic travel time and costs, this study used all possible sources of published data including average driving costs per mile by passenger car type, air passengers fare and flight distance survey, bus and train fare and travel time tables. In addition, this study calculated shortest distance from each household to intercity terminals such as airport, bus terminal, and train station. For that, this study used spatial information of census block group level household locations, 422 commercial airports, 1,482 greyhound terminals, and 533 train stations across the US. In estimating synthetic travel time and costs, this study takes into account one way trips assuming that people use the same mode of transportation for their returning trips

This study descriptively examined current patterns and characteristics of long-distance travel in the US, focusing on the modes used, travel distances, purpose of trips, and potential regional variations. Long-distance travel has certain patterns, even though they are made as a part of daily activities. First, long-distance travel is likely to be related with home how many trips are made by an individual in a given day, or prior to a long-distance trip. Consequently, home accounts for about 73 percent of total trips are made either from or to home. In detail, about 60 percent of trips were begun from home, while about 13 percent of long-distance trips were end at home. Secondly, about 80 percent f 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 airplane overtakes personal cars if the travel distance is over 800 miles. Third, people seem to locate themselves close to certain service facilities, such as medical/dental services and schools. Meanwhile, age seems to make no significant difference in generating long distance trips although travelers aged 40 to 49 and 50 to59 tend to travel slightly longer than other age cohorts. Fourth, the shares of buses and trains are relatively high where 1 million or more people reside or heavy rail system exists. This may show that people may change choice of mode if they have such a service within their boundary of life.

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 about 72 to reduce 1 minute of travel time. This is equivalent to a $43.17 per hour value for personal car users. The estimated coefficients of both travel time and travel cost for airplane are statistically significant at a 95 percent confidence interval. The negative signs of travel time and costs are as expected, thus the model is considered to be acceptable.

In addition to those alternative specific attributes, travelers' characteristics such as age, income, and location of residence appeared to affect to the mode choice decisions. The estimated models showed that age has positive impacts on car users' mode choice decision but it is not statistically significant at 80 percent confidence interval. However, certain age groups are positive and significant toward certain transportation mode. For example, people aged between 40 and 49 have higher probability of choosing airplane, while age group of 19 or less is likely to choose public modes such as buses and trains. Income seems to be related positively to the choice of airplane, while low income family is positive to bus among alternatives.

Interestingly, personal cars are likely used in MSA of less than 1 million or non-MSAs. In contrast, bus and train are positively and significantly related with population size and existence of heavy rail system. In addition, regional variations exist in the choice of public intercity modes. For example, MSAs of 1 million or more without heavy rail system are positive toward airplane, while both bus and train increase travelers' utilities in the MSAs of 1 million or more with heavy rail system. It should be noted that both air and train have regional variations, and thus they are positive and significant in certain regions. People have higher probability of choosing bus if they live in northeast corridor that comprises MSAs of 1 million or more with heavy rail in Middle Atlantic and New England divisions. Meanwhile, train increases its users' utilities as they reside northeast corridor, South Atlantic, East North Central, and Pacific divisions. Among states, Arizona, California, and Florida show positive signs of choosing airplane, but California and Florida's coefficients are not statistically significant at 80 percent confidence interval. Overall, the independent variables used in this final model were statistically meaningful in predicting the probability of mode choice for long-distance trips. The r-squared values of 0.3166 to 0.3638 are acceptable considering that the data is cross-sectional data.

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 0.035 percent and 0.079 percent as travel time and cost increase 1hour and $100, respectively. This shows that personal car users are more sensitive to costs than travel time. Among other variables, train users are relatively less sensitive to both travel time and costs, while bus users are cost sensitive and airplane users are travel time sensitive, relatively.

Finally, this study identified the potential service quality of a new alternative mode using the coefficients of the travel time and cost from the CL model. The results showed that a new mode will be able to attract long-distance travelers if it has a speed of 200 or more miles per hour in a service distance of less than 500 miles. In particular, NEC and ENC seem to have relatively higher potential among regions in the US, while SA and PAC are considered to have strong constraints on both travel time and costs. A speed of 200 or more miles per hour and a fare level of less than 1.5 times of driving costs are required for both SA and PAC.

Further study

The descriptive analysis has several limitations. First of all, the 2009 NHTS and the Florida add-on data have limitations to represent 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 in a day, a week, or even in a month. 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 required 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.

APPENDIX A
DISCRIPTIVE STATISTICS OF LONG-DISTANCE TRIP BY STATE

Table A-1. Long-Distance Trips and Average Trip Length by State

State	Number of Trips	Percent	Mean	Minimum	Maximum	Std Dev
AK	20	0.2	512.9	51	4520	1160.0
AL	31	0.2	156.6	50	1126	198.8
AR	21	0.2	89.9	50	255	47.2
AZ	414	3.2	272.6	50	3034	473.9
CA	1769	13.8	215.6	50	9113	507.3
CO	29	0.2	287.7	52	1500	345.6
CT	34	0.3	134.0	50	704	155.2
DC	6	0.1	345.9	50	1663	646.2
DE	26	0.2	162.0	52	1617	307.7
FL	1072	8.4	208.7	50	3216	363.6
GA	709	5.5	162.4	50	3022	195.8
HI	5	0.0	109.9	50	216	64.6
IA	350	2.7	150.6	50	2146	192.4
ID	23	0.2	118.6	50	402	92.2
IL	68	0.5	198.6	50	2150	368.7
IN	264	2.1	180.7	50	4500	385.8
KS	35	0.3	166.4	50	541	140.7
KY	22	0.2	166.9	50	627	145.1
LA	29	0.2	154.1	50	956	179.7
MA	33	0.3	121.8	50	407	82.4
MD	39	0.3	158.6	50	805	170.3
ME	35	0.3	108.3	50	332	76.8
MI	57	0.4	148.3	50	1082	185.7
MN	38	0.3	177.2	50	1470	234.0
MO	39	0.3	176.7	50	1537	265.9
MS	37	0.3	152.7	50	1296	227.1

Table A-1 (Cont.)

State	Number of Trips	Percent	Mean	Minimum	Maximum	Std Dev
MT	30	0.2	194.6	50	689	181.0
NC	927	7.2	168.9	50	3612	249.0
ND	43	0.3	106.0	50	437	76.0
NE	95	0.7	227.4	50	1595	289.0
NH	23	0.2	119.5	50	551	114.5
NJ	61	0.5	145.8	50	945	178.7
NM	30	0.2	263.5	50	1650	359.9
NV	24	0.2	200.7	50	1207	242.8
NY	1372	10.7	157.6	50	3899	276.0
OH	54	0.4	322.1	50	5634	803.2
OK	35	0.3	159.0	50	1200	196.7
OR	26	0.2	218.7	50	2517	478.0
PA	69	0.5	195.8	50	2302	320.2
RI	17	0.1	209.9	50	1825	424.0
SC	415	3.2	160.5	50	2042	173.7
SD	149	1.2	178.8	50	1381	203.2
TN	227	1.8	154.5	50	1216	154.3
TX	2085	16.2	201.4	50	4325	309.8
UT	23	0.2	262.4	50	2054	496.1
VA	1473	11.5	172.3	50	4091	308.0
VT	154	1.2	219.2	50	3000	393.3
WA	33	0.3	404.0	50	5004	1044.0
WI	195	1.5	150.0	50	2000	192.9
WV	35	0.3	160.0	50	735	148.5
WY	46	0.4	142.0	50	585	118.0
US Total	12846	100.0	187.9	50	9113	342.6

Table A-2. Descriptive Statistics of Long-Distance Travel by Mode and by Division

Mode	Census Division	Mean	Minimum	Maximum	Std Dev
Cars	New England	121.8	50.3	704.2	96.9
	Middle Atlantic	123.3	50.2	1811.0	132.3
	East North Central	148.0	50.3	5634.0	290.7
	West North Central	143.3	50.2	2146.0	149.3
	South Atlantic	140.6	50.2	3018.0	153.8
	East South Central	140.5	50.2	1296.0	136.6
	West South Central	150.2	50.2	2557.0	170.6
	Mountain	165.2	50.2	2113.0	217.2
	Pacific	137.7	50.2	4240.0	245.7
Bus	New England	161.7	54.0	550.5	152.0
	Middle Atlantic	236.8	50.0	3899.0	631.5
	East North Central	177.7	55.0	660.0	168.7
	West North Central	215.1	51.0	556.0	165.0
	South Atlantic	206.6	50.0	2017.0	302.9
	East South Central	193.0	52.0	430.0	168.0
	West South Central	265.7	50.0	987.5	254.5
	Mountain	248.7	50.0	1508.0	403.5
	Pacific	104.3	50.0	408.6	85.9
Airplane	New England	1084.0	58.0	2119.0	675.1
	Middle Atlantic	1194.0	250.0	3000.0	740.2
	East North Central	1308.0	70.0	4500.0	1075.0
	West North Central	962.8	170.1	1595.0	517.5
	South Atlantic	1199.0	75.0	4091.0	860.6
	East South Central	852.4	539.1	1216.0	302.9
	West South Central	1124.0	112.0	4325.0	720.2
	Mountain	1212.0	90.0	3034.0	800.9
	Pacific	1608.0	106.7	9113.0	1429.0
Train	New England	179.5	60.0	415.5	204.4
	Middle Atlantic	111.1	50.0	1028.0	160.8
	East North Central	74.4	50.0	101.8	23.0
	West North Central	65.0	65.0	65.0	.
	South Atlantic	155.0	50.0	561.3	142.6
	West South Central	300.0	300.0	300.0	.
	Pacific	129.9	50.0	1053.0	246.7

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BIOGRAPHICAL SKETCH

The author received Bachelor of Science majoring architectural engineering at Yonsei University in Seoul, South Korea. Then, he earned his Master of Engineering degree concentrating on urban planning. His thesis, titled as “An Effect of Transportation Investment on Economic Productivity,” analyzed how transportation investments are related with total factor productivity of manufacturing industry in Korea. He began his professional carrier at Transportation and Logistics Institute of Keumho Engineering Corporation in October, 1994, and worked for about two and 8 months focusing on analysis of the impacts of urban development on transportation congestions and delays. In June, 1997, he moved to the Korea Transport Institute, the transportation policy and planning oriented government research division. For about five and a half year, he served as researcher of Aviation Research Division and Transportation Economics Division, and manager of Division of Research Planning and Budget. He conducted various research projects dealing with financing strategies for transportation infrastructure investment, cost-benefit analysis for transportation projects, the impacts of transportation on regional economies, and the role of the private sector in transportation and their cost recovery.

In spring, 2003, he entered to Indiana University Bloomington, and he transferred to University of Texas at Austin in fall, 2005. He earned Master of Public Affairs After from both programs. He began his doctoral study at University of Florida in fall, 2009, and he earned Doctor of Philosophy in May, 2013 with dissertation, titled as “The Factors that Affect Long-Distance Travel Mode Choice Decisions and Their Implications for Transportation Policy.”