3-30-2004

An Analysis of Characteristics of Long and Short Commuters in the United States

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by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Civil Engineering
Department of Civil and Environmental Engineering
College of Engineering
University of South Florida

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Date of Approval:
March 30, 2004

Key Words: Commuter behavior, socio-demographic characteristics, job access, residence and workplace location, transportation equity, social isolation.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to Dr. Ram Pendyala, my major professor, for his continued support and able guidance in my research efforts. I would like to thank Dr. Steven E. Polzin, Dr. Jian John Lu, and Juan Pernia for serving on my committee and providing their valuable suggestions. I also thank the Department of Civil and Environmental Engineering for providing with such excellent facilities and research environment. I would also like to thank the faculty of Center for Urban Transportation Research for the excellent coursework they provided during the Master's program. Finally, I would like to thank my friends and colleagues Siva, Abdul, Ravi, Sashi, Uttam, Sharath, Buggana, Vipan, Ashish, Ram Nehra, Amlan, Xin Ye, Constantinos, Isidro and Challa for their support and encouragement throughout my research.

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AN ANALYSIS OF CHARACTERISTICS OF LONG AND SHORT COMMUTERS IN THE UNITED STATES

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ABSTRACT

An in-depth-analysis was carried out on short, medium and long commuters using the National Household Travel Survey (NHTS) of 2001 and American Community Survey (ACS) of 2000 to determine the role of individual, household, trip and area related characteristics on commute length. The individuals with commute time less than or equal to 15 min were considered as short commuters and individuals with commute time greater than 15 min but less than 60 min were considered as medium commuters and the individuals with commute time 60 min or more were considered as long commuters. The commute time is considered as a link joining the residence and workplace locations. The availability of the desired mode used is considered as flexibility in moving the location of these points in the area. As the jobs get dispersed the lower income people face more and more transportation problems in linking the residence and workplace. There is a potential threat in their social, physical and economic isolation in the society. The individual, household, and area related characteristics are assumed to influence both the commute time and location of these points. The descriptive analysis using NHTS 2001 and ACS 2000 revealed that the characteristics of short and long commuters are different in nature. A commuter type choice model and commute length measurement models were used to estimate the influence of socio-demographic characteristics on the residential and workplace separation. Multinomial Logit Model (MNL) methodology was adopted to develop the commuter type choice model and Structural Equations Model methodology (SEM) was adopted with commute time and commute distance as endogenous variables to estimate the commute length on a continuous scale. The models confirmed the importance of demographic variables in explaining commuter length.

CHAPTER 1

INTRODUCTION

1.1 Background

Over 60% of the U.S population lives in the metropolitan areas-ten of these areas have five million or more people and many other areas have experienced a rapid growth of about 25% or more in a decade (Census 2000). The growth of these metropolitan areas in both population and area resulted in continued dispersion of jobs and population to the outer fringes. The lower income people who are mostly city residents have greater difficulty in accessing job opportunities in suburban areas. The significant challenge of lower income people is overcoming transportation problems to reach their jobs. There is a potential threat to their social, physical and economic isolation in the society. The policies that are meant to suppress the use of automobile could have unintentional influence on lower income people who are just on the verge of obtaining mobility. Some of the factors mentioned above explain the reason why 56 percent of the lower income people are short commuters. Women who play a major role in taking care of young children and household maintenance are also restricted to the job opportunities and prefer to work very close to home. On the other hand, higher income people like to live in lower density areas, generally suburban areas and are capable of traveling great distances to reach the jobs they satisfy. Commute time reflects an individual's preference for residential and workplace location. The preferences are influenced by many other factors that explain an individual's choice for being a long or short distance commuter.

An in-depth analysis is necessary to evaluate the above hypothesis about short and long commuters. Analyzing the restrictions and preferences that lead an individual to be a particular type of commuter would help for making better policies to provide mobility options and job accessibility for those in real need. This research work is an attempt to provide thorough analysis to the policy makers for clear understanding of the commuter choice (short, medium or long) from the available databases. This study uses commute time, a measurement of accessibility and mobility to define commuter choice. The main purpose of the study is to analyze different characteristics and find their effect on the commuter length choice. Hence, the market segmentation would be based on commuter choice rather than on income, gender, race or other individual characteristics. This study is critical in identifying the role of transportation in offering different opportunities through commuting choices to people for reducing the socio-economic disparities.

1.2 Problem Definition

Commute time reflects the work and home separation. The individual, household, and area related characteristics are assumed to influence both the commute time and location of work and home. The mode choice is assumed to be the next immediate or the simultaneous step in this decision making process (commuting to work). The disutility in the length of commute would result in a change of either the residence or the workplace location. This freedom to change the location according to the utility differs for different sections of the people. This freedom is less for lower income people because, of the budget constraints. This will affect their choice of short, medium or long commute, which is considered as a measure of accessibility and mobility.

As the jobs get dispersed the lower income people face more and more transportation problems in linking the residence and workplace. In this attempt they move their residence location closer to transit-serviced areas and get engaged in the jobs closer to these transit serviced areas. This is resulting in their social, physical and economic isolation in the society.

The following section gives an overview of the changing commute time and commute mode over the decade. This will give an idea about the aggravating problem. The remaining sections of this chapter describe the subjects “commuter behavior” and “market segments” in the direction of study and finally the objective, approach and outline of the thesis are presented.

1.3 Commute Time and Commute Mode

According to the United States Census Bureau (U.S Census 2000 Journey to Work) and United States Department of Transportation (U.S DOT, FHWA Journey to Work) the average commute time has increased from 21.7 minutes in 1980 to 25.5 minutes in 2000. The increase in the commute time from 1990 to 2000 is more than four times the increase from 1980 to 1990. There are nearly ten million workers in the United States who spend 60 or more minutes to reach their jobs. These facts have important implications for the congestion, urban sprawl, growth, deteriorating transportation infrastructure, aging population, auto ownership, vehicle utilization and transit rider ship. There is also a change in the commute mode over the years as seen from the US Census Journey to Work report. It shows the percentage of commuters who carpool has decreased from 19.7 in 1980 to 11.3 in 2000. The mode share of public transportation and non-motorized travel also follow a downward trend leaving the drive alone mode as the dominant choice of the commuters.

Commute time and commute mode indicates an individuals access to job opportunities defined by urban structure, individual’s life style and transportation system. Commute time is an essential part and an alternative measurement of total travel time expenditure (Mokhtarian and Chen, 2002) inherent to an individual in order to engage in activities and satisfy their needs. More importantly, it is compulsory and regular time expenditure because of the mandatory type of activity at the destination.

All the individual decisions and inherent qualities about commute time and commute mode result in aggregate behavior called as *"Commuter Behavior"*. Hence, to understand the commuter behavior, a disaggregate study of commuters with different commute times would help in implementing policies and adopting strategies specifically focused on certain groups to control urban sprawl, congestion, pollution, excessive energy consumption and other adverse impacts on the society.

1.4 Commuter Behavior

Commuter behavior is about the awareness, attitudes, perceptions and options of the people who travel regularly on a daily basis to perform a desired or necessary activity. The study of commuter behavior is essential in understanding how people prefer to commute under certain circumstances in order to maximize the perceived utility of a commute alternative to perform a particular or sequence of activities.

Commuter behavior interests researchers in both public and private agencies in transportation and related fields in implementing policies and adopting strategies. In public agencies, policy makers study the commuter behavior to get feedback about the existing policies and make future decisions to minimize transportation costs on the society. Policy makers and planners are interested in knowing the behavior and analyzing the reason for such behavior.

1.5 Market Segments

Commute time, a regular travel time-expenditure to work gives inference of an individual's value for time and is a measurement of total travel time-expenditure. Hence, in this study the market segmentation is based on the commute time to study their individual, household and commute characteristics. The market is segmented into three categories-short commuters, medium commuters and long commuters.

Short commuters are defined as those individuals who commute 15 minutes or less to work. Medium commuters are defined as those individuals who commute more than 15 minutes but less than 60 to work. Finally long commuters are defined as those who commute 60 minutes or more to work. These three market segments are considered for this study but the main focus will be on the short and long commuters. The terms-'market segments' and 'groups' are used interchangeably hereafter.

1.6 Objectives of the Study

The objectives of the study are

- To analyze the socio-economic characteristics of different commute lengths
- To verify if there is any significant influence of socio-economic characteristics on the commute time
- To compare the work trip characteristics like departure time, distance and commuting mode (drive alone or carpool) of different groups
- To analyze and compare the variation of mode share by purpose within each group and between the groups
- To study the other trip characteristics of different commute lengths
- To construct models that estimate the effect of socio-economic and area characteristics on the commute time
- To construct a model that predicts the probability of an individual to be a short, medium or long commuter

1.7 Approach of the Study

The American Community Survey (ACS) of 2000 and National Household Travel Survey (NHTS) of 2001 were used for this study. Both the NHTS and ACS have detailed information about the person and household characteristics. However, information about trip characteristics is only available in NHTS 2001 data and not in ACS 2000 data. Hence, they were studied using only the NHTS 2001 data. However, as anyone could expect, the analysis of the data was done separately without merging the two datasets. The analysis of person, household and area related characteristics were carried out at the person level by adding the household characteristics to the person file. The trip characteristics were analyzed by aggregating the trip file to the person level. Only those individuals who reported non-zero travel time to work were considered for the study. The sample used for the study did not include all the workers but only those workers who commute to work. Hence the workers who work at home daily are not included in the study.

The commuters are classified into three market segments based on their reported travel time to work as short, medium and long commuters. The commuter type definitions are defined in the previous section 1.5. The main focus of the study is on short and long commuters.

In this study a commuter type choice model was developed to estimate the influence of socio-demographic characteristics in making a commuter type choice. Multinomial Logit Model (MNL) methodology was adopted to develop the commuter type choice model. A Structural Equations Methodology (SEM) was also developed to estimate the influence of socio-demographic characteristics on the commute length on a continuous scale. Commute time and commute distance were used as endogenous variables.

1.8 Outline of the Thesis

The thesis is composed of seven chapters. This chapter has provided an introduction about the background, problem definition, commute time, commute mode, commuter behavior, market segments, objective and approach of the study. Chapter 2 presents a review of literature related to this study. Chapter 3 provides a description of the data from National Household Survey of 2001 and American Community Survey of 2000. Chapter 4 provides descriptive analysis of the three market segments. Chapter 5 explains the methodology for the Multinomial Logit Modeling (MNL) and Structural Equations Modeling (SEM). Chapter 6 explains the model estimation and results. Chapter 7 concludes the analysis of short and long commuters and provides scope for further study.

CHAPTER 2

LITERATURE REVIEW

Commuter behavior is of central interest to many researchers in transportation and other related fields to measure the performance of transportation system and its interrelationships with area characteristics that define urban spatial structure. Lot of research has been done on the commuter behavior and is difficult to cover the whole body of literature. This chapter provides literature review on commuter behavior related to this study.

2.1 Commute Time and Mode Choice

Commute time and mode choice are central in explaining the commuter behavior and other travel behavioral characteristics. The study of mode choice modeling to work has long been central to the evaluation of the efforts to mitigate traffic congestion (Palma and Rochat, 2000). Recent studies have examined the role of non-work travel mode on commute mode as well as other residential location and land use (Bhat, 1997; Anas et. al, 1996; Ben-Akiva and Bowman, 1998; Boarnet and Sarmiento, 1998). Cevero et. al, 1998 has found that decentralization has reduced traffic congestion and travel distances and has contributed to a weakening of transit systems. Mannering et al, (1985) found that the number of autos in the household influences the commute mode and suggested that it should be considered as an endogenous variable in models. Some researchers claim that basic commute mode choice encountered by an individual is between automobile and public transit and explain that modal split should be based in this binary choice (Train, 1980; Hensher and Johnson, 1982). However a wide variety of structured mode choice models have been developed over the years (Train, 1980; Mannering and Winston, 1985; Thobani, 1984; Berkovec and Rust, 1985; Hensher et al., 1991; Ben-Akiva et al., 1994).

The changing commute pattern has strong influence on commute time and other travel time both in space and time. Research on cross sectional data across the world suggested that the commute time mostly range between 25 to 35 minutes (Kenworthy and Laube, 1999). On the other hand, some researchers have found that it varies with space and time (Gordon et. al, 1989; Cevero et.al, 1988). Levinson (1998) found that the variation in commute time in space and time is less when compared to other characteristics like distance traveled and mode choice. Variations are caused by individual and household characteristics, the spatial context of the commute, access to transportation and factors related to the activity and travel patterns of workers (Turner and Niemeier, 1997).

Many studies have analyzed the influence of work duration on the commute time and found different commute times for same work duration (Golob and McNally, 1997; Golob et.al, 1995; Golob, 2000; Lu and Pas 1999; Dijst and Vidakovic, 2000). Schwanen and Martin (2001) developed a theoretical framework to address the relationship between commuting time and duration of the workplace visit. Number of researchers have suggested or proven that commute time and work activity duration are positively correlated (Hamed and Mannering, 1993; Kitamura, 1990 and Kitamura, 1998; Levinson, 1999). The following section discusses the literature on the effect of commute time on residential and workplace location.

2.2 Residential and Workplace Location

The connection between the residential location and work place location is a central part of the theory for defining the urban spatial structure. Many economic models have emphasized the trade-off between commuting costs and housing costs and placed this trade-off at the core of models of residential location (Wingo, 1961; Kain, 1962; Alonso, 1964; Muth, 1969). The dispersal of job opportunities has created a much more complicated behavioral response to the linkage between work and residence (William et. al, 2002). Researchers have found that there is an “indifference zone” that exists for workers within which the changes to employment opportunities do not have much influence on residential location. Beyond this zone the commuting distance has influence on an individual’s relocation of household (Getis, 1969; Brown, 1975).

A study by Cevero and Wu (1997) in San Francisco Bay area, a polycentric city found evidence that suburban employment tends to generate shorter commutes than central city employment. Many studies have examined the impact of commuting times on the relocation to suburbs (Doom et. al, 1990; Bell, 1991; Cevero et. al, 1992; Wachs et. al, 1993) and found that commuting patterns are adjusting to metropolitan dispersal to avoid congestion and long commutes. Levinson (1998) attempted to study the dynamic behavior by including residential duration and job duration and found the newly relocated individuals have shorter than average commutes. He feels that that long residential durations and long employment durations will have short commutes, as they are spatial stable for a long time.

A number of studies have examined the interrelations between the job changes and residential changes. Van et. al, (1997) and Rouwendal (1999) have found that increasing commute time increases the probability to accept a change and the job change is sensitive to residential location than the reverse, due to high costs of residential change. Some researchers have examined a sequential residential and workplace choice and found strong correlation between them (Waddell, 1993; Gordon et. al, 1982; Linneman et. al, 1983). Crane (1996) explained that connection between home and workplace is not static and is dependent on the future opportunities and aspirations.

Some researchers have studied the residence and job location changes for dual worker households. Abraham et, al, (1997) found that the probability of moving is more strongly related to commuting distance for women than men. Sermons et al (1999) found that the work place location of women is not an exogenous variable in explaining the location of household. Some researchers have studied the gender differences in journey to work and found that women's commute times are shorter because of low wages and dual role or mother and worker they play. This section has reviewed the literature that explains the relationships between the commute times and residential and job locations. The following section will present the literature on the relationship of commute time with total travel time expenditure.

2.3 Transportation Equity

The deficiencies present in urban growth and transportation systems lead to the patterns of social and urban segregation. The main obstacles to the people, notably the poor in daily travel weigh heavily on schedules, complicate access to services ever further, limit the use of urban space, and place considerable pressure on household budgets. Consequently, the low income people tend to retreat into their neighborhood where the low-quality urban facilities are unable to assist in the development of human and social capital and economic opportunities, the alleviation of poverty or the prevention of social exclusion (Olvera et al, 2003). The concept of social exclusion highlights the deterioration of the employment market and more generally the crisis that affects social links in the various spheres (economic, political, social, and spatial) of community life (Baker, 2001).

High-density neighborhoods of low-income households lack local facilities, and poor and/or expensive transport considerably increases social exclusion. This issue was given very little attention in developing countries (Vasconcellos, 2001) and most research in this area deals with poverty and transport (Godard and Diaz Olvera, 2000, Grieco et al., 1996 and Turner and Kwakye, 1996). However, in the largest cities of these countries, several factors like explosive population growth, increasing poverty, rapid and disorderly expansion of the urbanized zone, reinforcement of the spatial split between residential, employment and service areas, poor supply of urban services and infrastructures, and the deregulation process combine to make social exclusion problems even more severe. The spatial dispersion of residential areas is a source of particular problems as jobs and the main urban facilities are highly concentrated in the CBD and here transportation becomes a key issue (Olvera et al, 2003). Transportation difficulties reduce the number of accessible jobs even further, and also, for trips to and from work, longer commutes in transit or the difficulty in walking long commutes can reduce the productivity of workers, notably the poor. This population is physically more vulnerable and more affected by greater fatigue caused by difficult daily travel than people with better living standards.
"Low productivity, low income and low capital formation are some of the economic factors in the vicious circle of poverty" (Adjibolosoo, 2000).To ensure equity as a whole, "Two interdependent aspects of public policy must then be addressed to alleviate poverty and prevent social exclusion: the improvement of accessibility throughout the city and the availability of basic services locally" (Werlin, 1999).

2.4 Access to Job Opportunities

Research has provided evidence that the process of suburbanization creates new job opportunities that are not equally exploited by all workers (Pinto, 2001). The most important explanation is the spatial mismatch hypothesis, first developed by John Kain (1968). According to the hypothesis, the important job growth in the suburbs combined with serious constraints on African-Americans' residential choices have created a surplus of workers relative to the number of available jobs in inner-city neighborhoods, where African-Americans are concentrated. The main assumption is that discrimination in the suburban housing market generates this hostility, preventing a natural relocation of work. So as a result African-Americans will have relatively poor access to job opportunities, and they may also have a longer commute to work when compared to whites in a city. As a consequence, poor labor-market outcomes should be expected for African-American households.

Many researchers have done studies concerning the spatial mismatch hypothesis (Kain, 1992; Ihlanfeldt et. al, 1998). They investigated the relationship between employment, wages, or labor force participation and measures of job accessibility. The results suggest that poor job access worsens labor-market outcomes, confirming the argument. Some researchers have tested the spatial mismatch hypothesis by examining commuting times of African-Americans and whites (Gabriel et. al, 1996). Their study showed that African-Americans have significantly longer commuting times than whites. There are also some investigations that and that job decentralization leaves low-wage jobs in the central business district (CBD) (Straszheim, 1980; Vrooman et. al, 1980; Reid, 1985; Ihlanfeldt, 1988; Ihlanfeldt et. al, 1991).

2.5 Travel Time Expenditure

Commute time is an essential part and an alternative measurement of total travel time. "In particular, because of the regularity, frequency and importance of the commute trip, responses to a question about the ideal commute time can be considered reasonably informative" (Mokhtarian et al, 2002).

Lot of research has been done on travel time over the forty years and has been a variable of central importance to many researchers to understand its demand for travel (Pas, 1998). The behavioral theory assumes that people have a certain amount of time that they are willing to spend on travel; this concept is called "travel time budget". Several studies on TTB reveal that on average, taken over the regional or national scale is constant over space and time: a universal constant of 1.1-1.3 hours (per traveler) per day (Bieber, et al., 1994; Zahavi and Ryan, 1980; Zahavi and Talvitie, 1980; Hupkes, 1982; Schafer and Victor, 2000; Vilhelmson, 1999).

A common observation in this theory is that as the transportation system is improved due to the advances in technology or additions of capacity to the system- travel distance tends to increase so as to keep travel times constant (Zahavi and Ryan, 1980; Hupkes, 1982; Marchetti, 1994). Recent research showed that the African villages, while almost entirely pedestrian based, did not generate different daily travel times than cities in developing Asia, which were not on average different from Japan or Europe or the U.S. (Barnes, 2001). The TTB is also linked to induced travel debate, people taking advantage of improvement to travel (Mokhtarian et al., 2002)

Many researchers have also incorporated TTB into the travel behavioral models (Zahavi, 1979; Golob, et al., 1981; Goodwin, 1981; Gunn, 1981). Recently researchers used the concept of TTB to study the mobility as incomes rise and slower modes are replaced by faster modes (Schafer, 1998, 2000; Schafer and Victor, 2000). The following section discusses the research on commute time considered as a central part of total travel time expenditure.

Researchers who argued for the stability of travel time expenditures at the aggregate level found that there was considerable variation at the disaggregate level (Zahavi and Talvitie, 1980). Analysts have attempted to relate these variations to a number of potential explanatory characteristics as explained below.

Research on travel time expenditure reveals that an individual's travel time expenditure is strongly related to person and household characteristics, attributes and activities at the destination, and characteristics of the residential areas (Mokhtarian and Chen, 2002).

The above literature suggests that the study of commuter behavior at the disaggregate level is vital in understanding the strong interrelationship that exists between the commute time and the set of characteristics explained above. Most of the studies discussed above are done with market segmentation based on individual, household or area related characteristics like income, age, gender, race, household size, auto-ownership, area-population etc., For example, low income vs. high income groups, male vs. female, single worker household vs. multi-worker households and soon. The present study is based on the market segmentation based on commute time an indicator of transportation system performance and urban growth. The present study focuses on identifying whom the short and long commuters and exploring the reasons behind their behavior rather than on how different sections of people behave in transportation system. This type of study would help in identifying the sections of the people who are affected by or affect the transportation system more directly and gives a broader look at the transportation system in forming policies.

CHAPTER 3

DATA DESCRIPTION

The National Household Travel Survey (NHTS) data of 2001 and American Community Survey (ACS) data of 2000 were considered for this study. This chapter provides detailed discussion of the survey and description of the datasets. The datasets are discussed in two main separate sections as follows.

3.1 National Household Travel Survey Data of 2001

The National Household Travel Survey (NHTS) provides detailed information on demographic characteristics of households, people, vehicles, and detailed information on daily and longer-distance travel for all purposes. The NHTS is the combination of Nationwide Personal Transportation Survey (NPTS) and American Travel Survey. It assists transportation planners and others who need comprehensive data on travel and transportation patterns in the United States. The NHTS survey data are collected from a sample of U.S. households and expanded to provide national estimates of trips and miles by travel mode, trip purpose, and a host of household attributes. Previously the daily travel surveys were conducted in 1969, 1977, 1983, 1990 and 1995. The series of daily travel surveys conducted over the years can provide detailed information about the person travel patterns in the United States. The information about both daily travel and longer distance travel is collected in single survey.

The NHTS collected travel data from a national sample of the civilian, non-institutionalized population of the United States. People living in college dormitories, nursing homes, other medical institutions, prisons, and military bases were excluded from the sample. The survey was conducted using Computer-Assisted Telephone Interviewing (CATI) technology. Each household in the sample was assigned a specific 24-hour "Travel Day" and kept diaries to record all travel by all household members for the assigned day. A 28-day "Travel Period" was assigned to collect longer-distance travel (over 50 miles from home) for each household member, and includes information on long commutes, airport access, and overnight stays. The assigned travel day was the last day of the assigned travel period. The NHTS 2001 interviews were conducted from April 2001 through May 2002

The 2001 NHTS data can be used to investigate topics in transportation safety, congestion, mobility of various population groups, the relationship of personal travel to economic productivity, the impact of travel on the human and natural environment, and other important subjects. These data provide planners and decision makers with up-to-date information to assist them with effectively improving the mobility, safety, and security of our Nation's transportation systems.

The 2001 NHTS data set includes household data on the relationship of household members, education level, income, housing characteristics, and other demographic information. It provides Information on each household vehicle, including year, make, model, and estimates of annual miles traveled. The driver information is also collected for every trip. Detailed information about the trips made during the 24 hr assigned day is collected. For example, the time the trip began and ended, length of the trip, composition of the travel party, mode of transportation, purpose of the trip, and the specific vehicle used. Information on long distance travel during an assigned four-week period was also collected in the same survey. if no long-distance trips were made during the four-week travel period, data on the most recent long-distance trip by any mode and the most recent long-distance train trip. Respondents were asked to mention round-trips taken during a four-week period (the household's travel period) where the farthest point of the trip was at least 50 miles from home, including the farthest destination, access and egress stops and overnight stays on the way to and from the farthest destination, mode, purpose, and travel party information. The NHTS also provides geographic area specific characteristics of the household and workplace. Information about telecommuting, public perceptions of the transportation system, data on Internet usage and the typical number of transit, walk and bike trips made over a period longer than the 24-hour travel day was also collected. The survey data is made available in the form of four separate files, which are household file, person file, vehicle file and daily trip file.

- Household file contains information about household characteristics of people in the sample. A household identification number identifies each household. Each record in household file is a household. There are 26,038 household records in the household file.
- Person file contains information about the person characteristics of people in the sample. Household identification and person identification number together identifies a person. Each record in the person file is a person. There are 60,282 person records in the person file.
- Vehicle file contains information about each vehicle owned by households in the sample. Household identification and vehicle identification number together identify a vehicle. Each record in the vehicle file is a vehicle. There are 53,278 vehicle records in the vehicle file.
- Trip file contains information about the trip characteristics of people in the sample. Each record in the trip file is a trip. There are nearly 248,517 records in the trip file.

The household, person, and vehicle identification numbers are used to connect information in file to another. Weights given in the data files are used to get the national estimates. In this study only the household, person and trip files were used for analyzing the different commuter types. All the household characteristics were merged to the person file using household and person identification number. The trip characteristics in the trip file were aggregated, restructured to the person level. There are 60,282 records present in the person file each record represents an individual identified by both the household and person identification number. Now, all the individual, household, area specific and trip characteristics are available at the person level. From this master data file the commuters are selected using commute time.

3.2 American Community Survey Data of 2000

The American Community Survey is a nationwide survey and a critical element in the Census Bureau's reengineered 2010 census. The American Community Survey is a way to provide the data communities need every year instead of once in ten years. It is an on-going survey that the Census Bureau plans will replace the long form in the 2010 Census. Information from the long form is used for the administration of federal programs and the distribution of billions of federal dollars. The American Community Survey is conducted under the authority of Title 13, United States Code, Sections 141 and 193. The Census Bureau may use this information only for statistical purposes. Full implementation of the American Community Survey is planned in every county of the United States, pending Congressional funding. The survey would include three million households. Data are collected by mail and Census Bureau staff follows up with those who do not respond. The ACS provides information about demographic, housing, social, and economic characteristics every year for all states. ACS has information about journey to work and can be used to study the commuter behavior. American community survey in the present form gives area specific characteristics up to the state level. For smaller areas, it will take three to five years to accumulate sufficient sample to produce data for areas as small as census tracts. The ACS 2000 data set consists two files-household and person file

- Household file contains information about the household characteristics of people in the sample. A household identification number identifies each household. Each record in household file is a household. There are 514,779 household records in the household file.

- Person file contains information about the person characteristics of people in the sample. Household identification and person identification number together identifies person. Each record in the person file is a person. There are 1,192,206 person records in the person file.

The data is present for all states together and also separately. The information about the area specific characteristics is limited to the state level. The availability of information at the county and city level is expected in the future. In this study all the household characteristics were merged to the person file using household and person identification number. There are 1,192,206 records present in the person file each record represents an individual identified by both the household and person identification number. Now, all the individual, household characteristics are available at the person level. From this master data file the commuters are selected using commute time.

CHAPTER 4

DESCRIPTIVE ANALYSIS OF COMMUTERS

4.1 Background

This chapter provides detailed data description about the person, household, trip and area characteristics of short, medium and long commuters using NHTS data of 2001 and ACS data of 2000 discussed in the previous chapter. All the data analysis was carried out at the person level by merging the household characteristics to the person file and aggregating and restructuring the trip file to person level. As our study is about the commuters, only those individuals who reported non-zero travel time to work were considered. Hence, the workers who work at home were not included in the study. The person and household characteristics of the commuters are discussed in detail for both the data sets. The commute characteristics are discussed mostly using NHTS 2001 dataset, as information about commute characteristics is not elaborately present in ACS 2000 dataset. The area characteristics of the commuters are discussed more using the NHTS 2001 data than ACS 2000 data, as geographic information and area-specific information is limited in ACS 2000 data. The characteristics are studied for three types of commuters-short, medium and long commuters. Short commuters are defined as those individuals who commute 15 minutes or less to work. Medium commuters are defined as those individuals who commute more than 15 but less than 60 minutes to work. Finally long commuters are defined as those who commute 60 minutes or more to work. The study is mainly focused on the short and long commuters. The following table below shows the sample size and weighted population of the commuters for the two data sets.

Table 4.1 Sample Size and Weighted Population of Commuters

Data Set	Year	Short Commuters	Medium Commuters	Long Commuters	All Commuters
NHTS	2001				
Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
PUMS ACS (USA)	2000				
Sample Size		249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population		56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)

The NHTS 2001 data shows that there are 46.3% of short commuters and 6.1% of long commuters. The ACS 2000 data shows that there are 45.2% of short commuters and 7.2% of the long commuters. The difference may be attributed to the missing data. Both the data sets were used to study all possible characteristics and were compared wherever it was possible.

4.2 Person Characteristics

Person characteristics like gender, age, race, education, income and driver status of the individual are analyzed for short, medium and long commuters for the two data sets. The Table 4.2 and Table 4.3 show the above mentioned person characteristics for the NHTS and ACS data sets respectively.

The NHTS 2001 data shows that 50.5% of the short commuters are males and 49.5% of the short commuters are females, which implies almost equal share of males and females. Whereas in long commuters, 63.6% are males and 36.4% of them are females. ACS 2000 data also shows exactly the same shares for males and females in short commuters and almost same for long commuters-64.5% of the long commuters are males and 35.5%.

The share of males in long commuters is 27-29 % more than females. This means that men are traveling longer distances than females to reach their jobs. This may be because, men relatively have more ability or freedom to make long commutes to access job opportunities than females. This could also be attributed to the lead role females' play in household maintenance and childcare, which restrict them to work close to work. In married couple households, when the males are household heads and main source of income, the females try to access jobs in the near vicinity (Hjorthol, 2000).

The NHTS 2001 data shows that 11.2 % of the short commuters are 16 to 20 years of age, while only 4.0% of the long commuters belong to this age group. The share of individuals aged between 21 to 24 years is almost same in both short and long commuters (7.8% in short and 7.7% in long commuters). The share of individuals with age between 25 to 44 years is more in long commuters than in short commuters-47.5 % of this age group in short commuters and 51.9% in long commuters. This difference in share between short and long commuters is also observed in age group of 45 to 65 years. Some difference is observed in ACS 2000 data but the same trend is present. The trend shows that an individuals' share in long commuters is increasing with age up to 65 years and finally dropping thereafter. This indicates that when individuals are young (16-20years) and just enter the work force they work very close to home and as they gain experience and achieve financial freedom, their preferences for life style tend to increase and this influences their ability to commute long distances to satisfy their needs. Individuals after reaching 65 years, (retirement age) because of low wages or because of older age, restrict their commute to shorter distances.

Two major groups show interesting behavior in commuting to work as seen from the NHTS and ACS data sets. NHTS 2001 data shows that individuals who are white make

81.1 % of the short commuters and 73.6% of the long commuters. Black or African American individuals are 9.2 in short commuters and 13.4% in long commuters. This might be because of the Black or African American people use transit for traveling to work, which is usually slower than automobiles. The same trend is observed in ACS but there is a difference in the magnitude of the shares between the datasets, which is attributed to the different classification adopted.

The educational attainment is the next important indicator of job choice of an individual. Highly educated people have more preferences in job choice and residential location. Highly educated people try to achieve the jobs that meet their qualifications and that satisfy their requirements. Long commuting can be considered as a tradeoff for their preferences. Individual incomes are generally proportional to educational attainment and so highly educated people have more freedom for household location in low-density and suburban lifestyle, which are generally far away from the main city. This is clearly observed in both NHTS 2001 and ACS 2000 data sets. The share of moderately and highly educated people is more in long commuters than in short commuters. The NHTS data shows that the share of individuals with bachelors' degree is 22.8% in long commuters and 16.3% in short commutes.

The ACS data shows that 20.0% of long commuters hold bachelors' degree where as only 16.0% of them hold in short commuters. The share of masters' degree holders in long commuters is 6.9% and 5.6% in short commuters. The share of professional and doctorate degree holders show the same trend but the difference is not so significant (In both NHTS and ACS).

Both the data sets show that most of the lower income people are making short commutes. The share of moderate to higher-income people is more in long commuters than in short commuters. The NHTS data shows that people with annual income less than $15,000 make 41% of the short commuters and only 12% of the long commuters. ACS data of 2000 shows that lower income people make 28% of the short commuters and only 15.6% of long commuters. The huge difference in the two data sets is because of the large amount of missing data (95%) about person's income in NHTS. The ACS shows that as income increase there share in long commuters is increasing.

The information about driver status is present only in the NHTS dataset and not in ACS dataset. The data shows that share of the drivers in long commuters are less (91.1%) when compared to short commuters (95.2%). This may be because regular transit users who are long commuters fall into this "not a driver" category.

Table 4.4 and Table 4.5 present the distribution and percentage of commuters by Standard Occupational Category (SOC). The percentage of long commuters is more for individuals working in Computer and Mathematical occupations, Legal occupations, and Construction and Extraction occupations. This variable needs further investigation before making any conclusions.

Table 4.2 Person Characteristics of Commuters (NHTS)

Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Gender					
	Male	50.5	55.1	63.6	53.5
	Female	49.5	44.9	36.4	46.5
Age					
	Under 16 years	0.0	0.0	0.0	0
	16 to 20 years	11.2	5.0	4.0	7.9
	21 to 24 years	7.8	7.4	7.7	7.6
	25 to 44 years	47.5	53.1	51.9	50.5
	45 to 64 years	30.0	31.9	34.0	31.1
	65 years and over	3.4	2.5	2.5	2.9
Race					
	White	73.0	70.5	64.0	71.3
	African American, Black	10.5	12.3	13.6	11.6
	Asian Only	2.3	2.7	3.5	2.6
	American Indian, Alaskan	0.4	0.4	0.6	0.4
	Native Hawaiian, Pacific Isld	0.3	0.3	0.5	0.3
	Hispanic/Mexican Only	5.9	5.4	6.7	5.7
	White & African American	0.1	0.1	0.0	0.1
	White & Asian	0.1	0.2	0.1	0.1
	White & American Indian	0.9	1.0	1.0	0.9
	White & Hispanic	4.3	4.9	6.1	4.7
	African American & Hispanic	0.2	0.2	0.7	0.2
	American Indian & Hispanic	0.2	0.1	0.2	0.1
	Other Combination 2 Races	0.6	0.6	1.8	0.7
	Other Combination 3 Races	0.2	0.2	0.2	0.2
	Other multiracial	0.1	0.1	0.3	0.1
	Other specify	0.8	1.0	0.8	0.9
Education					
	Less then high school graduate	11.3	7.3	9.2	9.3
	High school graduate, inc GED	30.7	27.9	27.5	29.2
	Vocational/technical training	3.5	4.0	3.8	3.8
	Some college, but no degree	19.3	18.0	14.5	18.4
	Associate's degree	7.1	8.9	6.7	7.9
	Bachelor's degree	16.3	19.8	22.8	18.4
	Graduate/professional school	1.9	2.0	2.1	2.0
	Graduate/professional degree	9.7	12.2	13.3	11.1

Table 4.2 (Continued)

Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Income					
	less than $ 15,000	41	28	12	33.2
	$15,000 - $19,999	11.0	10.0	15.9	10.8
	$20,000 - $24,999	12.3	10.7	14.7	11.6
	$25,000 - $49,999	24.3	30.7	33.6	27.8
	$50,000 - $74,999	5.5	12.7	7.5	9.0
	$75,000 - $99,999	3.7	4.6	4.1	4.2
	$100,000 and above	2.4	3.7	12.3	3.5
Driver status					
	driver	95.2	95.2	91.1	95.0
	not a driver’	4.8	4.8	8.9	5.0

Table 4.3 Person Characteristics of Commuters (ACS)

Sample Size		249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population		56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Gender	Male	50.5	56.1	64.5	54.2
	Female	49.5	43.9	35.5	45.8
Age	Under 16 years	0.0	0.0	0.0	0.0
	16 to 20 years	8.9	4.5	3.4	6.4
	21 to 24 years	8.8	7.5	6.6	8.0
	25 to 44 years	46.4	52.0	53.6	49.6
	45 to 64 years	32.4	33.6	34.2	33.1
	65 years and over	3.5	2.5	2.2	2.9
Race	White alone	81.1	77.1	73.6	78.7
	Black or African American alone	9.2	11.7	13.4	10.7
	American Indian alone	0.5	0.4	0.5	0.5
	Alaska Native alone	0.0	0.0	0.0	0.0
	American Indian & Alaska Native	0.1	0.1	0.2	0.1
	Asian alone	3.3	4.3	5.1	3.9
	Native Hawaiian/Pacific Islander	0.1	0.1	0.1	0.1
	Some other race alone	3.9	4.5	5.1	4.3
	Two or more major race groups	1.7	1.7	2.0	1.7
Education	Less than High school graduate	15.50	13.1	14.3	14.1
	High school graduate	29.6	27.3	26.2	28.3
	Some college but no degree	7.3	7.2	6.9	7.3
	Vo/Tech/Bus school degree	15.7	15.4	15	15.5
	Associate degree in college	7.2	7.8	7.3	7.5
	Bachelor's degree	16	19.1	20	17.7
	Master's degree	5.6	6.9	6.9	6.4
	Professional school degree	2	2.2	2.2	2.1
	Doctorate degree	1.1	1.1	1.2	1.1
Income	less than $ 15,000	28	18.1	15.6	22.4
	$15,000 - $19,999	10.5	8.9	7.2	9.5
	$20,000 - $24,999	10.6	10.1	8.3	10.2
	$25,000 - $49,999	33.1	37.8	36.5	35.6
	$50,000 - $74,999	10.6	14.8	17.8	13.1
	$75,000 - $99,999	3.1	4.9	6.6	4.2
	$100,000 and above	4.2	5.4	7.9	5

Table 4.4 Distribution of Commuters by Standard Occupational Category (ACS)

Sample Size	249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population	56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Occupational Category	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Management Occupations	8.8	9.5	11.0	9.3
Business and Financial Operations Occupations	3.3	4.7	5.3	4.1
Computer and Mathematical Occupations	1.7	3.1	4.2	2.6
Architecture and Engineering Occupations	1.5	2.6	2.6	2.1
Life, Physical, and Social Science Occupations	0.8	1.1	1.1	1.0
Community and Social Services Occupations	1.7	1.4	1.2	1.5
Legal Occupations	0.9	1.2	1.5	1.1
Education, Training, and Library Occupations	6.3	4.6	2.8	5.2
Arts, Design, Entertainment, Sports, and Media Occupations	1.5	1.7	1.9	1.6
Healthcare Practitioners and Technical Occupations	4.6	5.0	3.6	4.7
Healthcare Support Occupations	2.2	2.0	1.7	2.1
Protective Service Occupations	2.0	2.1	2.4	2.1
Food Preparation and Serving Related Occupations	6.9	3.6	2.5	5.0
Building and Grounds Cleaning and Maintenance Occupations	3.7	3.3	3.4	3.5
Personal Care and Service Occupations	3.0	2.0	1.8	2.4
Sales and Related Occupations	12.8	9.9	9.3	11.1
Office and Administrative Support Occupations	15.6	15.8	13.7	15.5
Farming, Fishing, and Forestry Occupations	0.8	0.5	0.6	0.6
Construction and Extraction Occupations	4.1	6.4	11.5	5.7
Installation, Maintenance, and Repair Occupations	3.7	4.2	4.6	4.0
Production Occupations	7.6	8.8	6.4	8.1
Transportation and Material Moving Occupations	6.4	6.3	6.8	6.4
Military Specific Occupations	0.2	0.2	0.1	0.2

Table 4.5 Percentage of Commuter Type within each Standard Occupational Category (ACS)

Sample Size	249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population	56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Occupational Category	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Management Occupations	42.7	48.7	8.6	100
Business and Financial Operations Occupations	36.1	54.6	9.3	100
Computer and Mathematical Occupations	31.0	57.3	11.8	100
Architecture and Engineering Occupations	32.7	58.4	8.9	100
Life, Physical, and Social Science Occupations	37.6	54.4	8.0	100
Community and Social Services Occupations	49.9	44.5	5.7	100
Legal Occupations	38.0	52.1	10.0	100
Education, Training, and Library Occupations	54.3	41.8	3.8	100
Arts, Design, Entertainment, Sports, and Media Occupations	42.5	49.1	8.4	100
Healthcare Practitioners and Technical Occupations	43.9	50.5	5.5	100
Healthcare Support Occupations	47.6	46.4	6.0	100
Protective Service Occupations	43.2	48.6	8.2	100
Food Preparation and Serving Related Occupations	62.1	34.3	3.6	100
Building and Grounds Cleaning and Maintenance Occupations	48.1	45.0	6.9	100
Personal Care and Service Occupations	55.1	39.5	5.4	100
Sales and Related Occupations	51.9	42.1	6.0	100
Office and Administrative Support Occupations	45.4	48.3	6.3	100
Farming, Fishing, and Forestry Occupations	54.9	37.9	7.2	100
Construction and Extraction Occupations	32.5	53.0	14.6	100
Installation, Maintenance, and Repair Occupations	41.5	50.2	8.3	100
Production Occupations	42.7	51.6	5.7	100
Transportation and Material Moving Occupations	45.4	46.9	7.7	100
Military Specific Occupations	50.5	45.0	4.5	100

4.3 Household Characteristics

Household characteristics like household size, family structure, income, number of workers, number of vehicles and number of children are analyzed for short, medium and long commuters for the two datasets and are presented in the Table 4.6 and Table 4.7. The share of 3 or more person households is more in long commuters when compared to short commuters. The NHTS data shows that the share of individuals in long commuters increases with the household size. But, when we observe the number of children and the age of the children in the household the share of individuals is increasing in long commuters with the number of children and decreasing with the increase in children's age. The ACS data also shows the same trend but the family structure variable is classified in different way. The ACS data shows that the share of individuals in long commuters increases with number of children. The existence of a family in the household increases an individuals' share in long commuters.

Both the NHTS and ACS data show that individuals belonging to higher income households have larger share in long commuters than in short commuters. The NHTS data shows that higher income households ($100,000 and above) have a share of 22.7% in long commuters and only 14.5% in short commuters. The similar difference was observed in ACS data with higher income household individuals share of 24.5% in long commuters and 16.9% in short commuters.

The NHTS data shows that the share of individuals with zero vehicle households is high in long commuters. The ACS data shows the same trend and individuals with 5 or more vehicles also have bigger share in long commuters. This could be because the long commuters are generally lower income households who do not afford a vehicle and travel in transit (slow modes) and very higher income household who live in suburbs and travel great distances to access jobs in the other areas.

Table 4.6 Household Characteristics of Commuters (NHTS)

Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Number of people					
	1 person	9.0	8.2	6.7	8.5
	2 person	28.5	29.7	26.5	28.9
	3 person	22.8	23.5	23.9	23.2
	4 person	23.0	23.3	25.7	23.3
	5 or more	16.8	15.4	17.3	16.1
Family structure					
	one adult, no children	8.7	7.9	6.2	8.1
	2+ adults, no children	29.0	31.4	30.2	30.2
	one adult, youngest child 0-5	1.2	0.9	1.5	1.1
	2+ adults, youngest child 0-5	18.7	20.7	22.5	19.9
	one adult, youngest child 6-15	1.9	1.9	2.0	1.9
	2+ adults, youngest child 6-15	21.6	21.3	21.9	21.5
	one adult, youngest child 16-21	1.5	1.2	1.2	1.3
	2+ adults, youngest child 16-21	11.6	8.9	9.7	10.2
	one adult, retired, no children	0.2	0.1	0.0	0.2
	2+ adults, retired, no children	5.6	5.6	4.9	5.6
Total Income					
	less than $ 15,000	6.2	4.7	6.5	5.5
	$15,000 - $19,999	4.5	3.9	4.2	4.2
	$20,000 - $24,999	4.8	3.6	2.6	4.1
	$25,000 - $49,999	33.4	29.3	25.9	31.0
	$50,000 - $74,999	22.2	23.8	21.6	22.9
	$75,000 - $99,999	14.4	16.8	16.5	15.7
	$100,000 and above	14.5	17.9	22.7	16.6

Table 4.6 (Continued)

Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Number of workers					
	no worker	0.0	0.0	0.0	0.0
	1 worker	23.5	24.8	27.5	24.4
	2 workers	51.7	54.7	51.3	53.1
	3 workers	17.2	14.1	15.5	15.6
	4 workers	5.8	5.1	4.7	5.4
	5 workers	1.7	1.3	1.0	1.5
Vehicle availability					
	0	2.5	3.5	7.7	3.3
	1	17.9	16.7	17.8	17.3
	2	41.5	43.0	40.2	42.1
	3	22.5	22.0	22.2	22.2
	4	10.0	9.9	7.7	9.8
	5 or more	5.6	5.1	4.5	5.3
Number of children					
	0	50.8	51.2	46.6	50.7
	1	21.3	20.9	22.3	21.2
	2	18.7	18.6	19.3	18.7
	3	6.5	6.5	8.8	6.6
	4 or more	2.8	2.8	3.0	2.8

Table 4.7 Household Characteristics of Commuters (ACS)

Sample Size		249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population		56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Characteristic		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Number of People	1 person	12.3	11.3	10.4	11.7
	2 person	30.4	30.5	29.0	30.3
	3 person	21.4	21.9	21.8	21.6
	4 person	20.3	20.6	21.3	20.5
	5 or more	15.6	15.7	17.5	15.8
Family structure	married couple (f)	62.3	63.6	64.4	63.1
	male hholder, no wife (f)	5.1	5.4	6.0	5.3
	female hholder, no husband (f)	12.0	11.9	12.4	12.0
	male hholder, living alone (nf)	6.4	5.9	6.0	6.2
	male hholder, not living alone (nf)	4.7	4.6	4.0	4.6
	female hholder, living alone (nf)	5.9	5.4	4.4	5.6
	female hholder not living alone (nf)	3.6	3.2	2.9	3.4
Income	less than $ 15,000	5.5	3.8	4.3	4.6
	$15,000 - $19,999	4.0	3.0	2.8	3.5
	$20,000 - $24,999	4.9	4.0	3.8	4.4
	$25,000 - $49,999	29.2	26.5	24.1	27.6
	$50,000 - $74,999	25.2	25.7	24.7	25.4
	$75,000 - $99,999	14.2	16.2	15.8	15.3
	$100,000 and above	16.9	20.7	24.5	19.3
Number of workers	No workers	0.2	0.2	0.3	0.2
	1 worker	19.1	20.7	24.1	20.2
	2 workers	55.2	56.5	55.0	55.8
	3 or more workers	25.4	22.6	20.6	23.7

Table 4.8 Distribution of Long Commuters by Household Property Values (ACS)

Property Value	Percentage
Less than $ 10000	1.1
$ 10000 - $ 14999	0.7
$ 15000 - $ 19999	0.7
$ 20000 - $ 24999	1.0
$ 25000 - $ 29999	0.9
$ 30000 - $ 34999	1.0
$ 35000 - $ 39999	1.2
$ 40000 - $ 49999	2.6
$ 50000 - $ 59999	2.7
$ 60000 - $ 69999	3.6
$ 70000 - $ 79999	3.9
$ 80000 - $ 89999	4.7
$ 90000 - $ 99999	4.6
$100000 - $124999	10.1
$125000 - $149999	10.2
$150000 - $174999	9.4
$175000 - $199999	7.0
$200000 - $249999	11.5
$250000 - $299999	5.9
$300000 - $399999	8.3
$400000 - $499999	3.9
$500000 - $749999	3.2
$750000 - $999999	0.9
$1000000+	0.8

Table 4.9 Distribution of Long Commuters by Duration of Status by Household Ownership Type (ACS)

Duration of Status	Owned	Rental
12 months or less	8.8	31.8
13 to 23 months	3.2	6.6
2 to 4 years	25.0	33.4
5 to 9 years	23.8	15.6
10 to 19 years	23.2	8.6
20 to 29 years	10.6	3.0
30 years or more	5.3	1.0
Total	100	100

4.4 Trip Characteristics

Commute time distribution of commuters are presented in Table 4.10 and Table 4.11 for NHTS 2001 and ACS 2000 data respectively. The tables also give information about the average travel times by purpose. The NHTS 2001 data shows that average commute time for all commuters in United States is 23.5 minutes. The ACS 2000 data shows the average commute time as 24.3 minutes. The Table 4.12 shows commute distance distribution of short, medium and long commuters by trip purpose for NHTS 2001 data. This table shows that there are some commuters who travel 20 to 39.99 miles to work in less than or equal to 15 minutes and on the other side there are some commuters who spend 60 or more minutes traveling to work to cover a distance of 1 mile. This behavior is strongly attributed to area specific attributes and modal level of service variables. The average commute distance traveled for all commuters in United States is 13.2 miles.

Table 4.13 shows the average trip rates for different commuter types. The average trip rate for short commuters is more than long commuters because, long commuters spend most of the travel time in commuting to work and so this decreases their average trip frequency for other activities. The short commuters on the other hand have time for other activities on the way to work and return home like dropping off kids, shopping trips etc., The interesting trend is that even if the average trip rates vary with commute length, the proportions of work/work related/return to work/return home and other travel in total trips do not vary significantly with commute length. This indicates that commute length affects the participations rate for work/work related/return to work/return home and other travel but not the percentage of participation (in terms of number of trips). The short commuters do more social recreational, serve passenger and return home trips when compared to long commuters. Table 4.14 and Table 4.15 provide average trip length and total trip lengths by purpose for different type of commuters. The trends in these tables are similar to that of commute times and trip rates. This trend is highly reflected in the average and total travel time expenditures provided in Table 4.16 and Table 4.17. The table 4.15 shows the travel time expenditure by purpose by commuter type. It can be seen that travel time expenditure of long commuters is more for both work/work related/return to work/return home and other travel. Long commuters spend more time on daily total travel than short and medium commuters. Within each commuter type the proportions of work/work related/return to work/return home travel time and other travel time in "total travel time" also vary significantly with commute length. This could have significant influence on out of home and in home activity durations. The travel time expenditures and activity durations by commute length needs further research. The VMT is another important variable that explains the commuter behavior. The average and total VMT traveled are shown in Table 4.18 and Table 4.19 respectively. The commute time influences other trip characteristics of commute trip and other non-work travel and this is shown in Table 4.20, which shows the mean departure time by purpose for different commuters. The departure time for work trip for long commuters is 1 hr 17 minutes earlier than short commuters. Other trips like work related, religious, shopping, eat meat and serve passenger are also starting early for long commuters than short commuters. The trips like school, medical, family and personal, social recreational and return home trips are starting later for long commuters than short commuters. Figures 1 to 3 show the departure time distributions for different trips purposes. Figure 4.1 and Figure 4.2 shows that long commuters start early to work and work related trips when compared to short and medium commuters. Figure 4.3 shows that the peak of the departure time distributions of short and long commuters for school trip are separated significantly in the time of day. Carpooling is another important aspect related to commuter behavior. Table 4.21 and Table 4.22 show the drive alone vs. carpooling behavior among different type of commuters using NHTS 2001 data and ACS 2000 data respectively. NHTS 2000 data shows that the share of carpooling and transit is more in long commuters than in short commuters. This could be attributed to the commute mode itself. Travel time is "alternative attribute" of mode. So, the people who are carpooling or traveling by transit might be spending more time in reaching their work than it usually takes by drive alone or personal vehicle and could be the main reason for their commute being long. The directional relationship between the commuter choice and mode choice needs further research. The NHTS 2001 data shows that 84.7% of short commuters drive alone, which only 57.5% of the long commuters do. The share of transit users is 26.3% in long commuters whereas it is only 0.94% in short commuters. The ACS 2000 data shows that 82.25% of short commuters drive alone, which only 58.58% of the long commuters do. The share of transit users is 23.82% in long commuters where as it is only 1.07% in short commuters. The Table 4.23 shows mode-share by trip purpose for different commuters. It shows that 14.3% of long commuters travel to work by rail transit. Nearly 47% of the long commuters travel to work related trips using pickup and other truck. It is interesting to note that 29.3 % of the long commuters ride on rail to school whereas only 0.7% of the short commuters do. The same is the case with religious trips, 28.4 % of the long commuters walk to religious trips whereas only 0.6% of the short commuters do. Nearly 33% of the long commuters walk to eat/meal trips while only 9.8% of short commuters do.

Table 4.10 Commute Time Distribution by Commuter Type (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Trip length (min)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
1min-4 min	10.7	0.0	0.0	5.0
5min-9min	26.8	0.0	0.0	12.4
10min-15min	62.5	0.0	0.0	14.4
16min-29min	0.0	48.3	0.0	37.5
30min-44min	0.0	36.6	0.0	17.4
45min-59min	0.0	15.1	0.0	7.2
60min-74min	0.0	0.0	58.3	3.6
75min-89min	0.0	0.0	14.4	0.9
90min-104min	0.0	0.0	16.4	1.0
105min-119min	0.0	0.0	1.3	0.1
120min or 149min	0.0	0.0	5.0	0.3
150min or more	0.0	0.0	4.5	0.3
Average Commute Time	9.8	29.7	78.3	23.5

Table 4.11 Commute Time Distribution by Commuter Type (ACS)

Weighted Population	56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Trip length (min)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
1min-4 min	8.4	0.0	0.0	3.8
5min-9min	25.6	0.0	0.0	11.6
10min-15min	66.0	0.0	0.0	29.8
16min-29min	0.0	44.3	0.0	21.0
30min-44min	0.0	40.4	0.0	19.2
45min-59min	0.0	15.4	0.0	7.3
60min-74min	0.0	0.0	61.0	4.4
75min-89min	0.0	0.0	9.6	0.7
90min-104min	0.0	0.0	15.2	1.1
105min-119min	0.0	0.0	1.2	0.1
120min or 149min	0.0	0.0	6.4	0.5
150min or more	0.0	0.0	6.5	0.5
Average Travel Time	9.9	29.7	79.3	24.3

Table 4.12 Commute Distance Distribution by Commuter Type (NHTS)

Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Trip Length (miles)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Less than 1 mile	11.0	0.4	0.6	5.3
1 to 1.99 miles	9.8	0.7	0.4	5.0
2 to 2.99 miles	13.7	1.1	0.4	7.0
3 to 4.99 miles	21.2	3.4	2.1	11.7
5 to 9.99 miles	33.1	15.2	2.6	22.8
10 to 14.99 miles	9.3	23.6	5.7	15.8
15 to 19.99 miles	1.4	19.5	4.5	10.1
20 to 39.99 miles	0.4	32.2	31.5	17.3
40 to 99.99 miles	0.0	3.9	47.3	4.6
100 to 199.99 miles	0.0	0.0	3.9	0.2
200 or more miles	0.0	0.0	1.1	0.1
Average Commute Distance	4.8	17.3	46.4	13.2

Table 4.13 Average Trip Rate by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	1.04	1.04	1.07	1.04
Work-related	0.17	0.17	0.16	0.17
School	0.06	0.04	0.02	0.05
Religious	0.02	0.02	0.01	0.02
Medical/dental	0.04	0.04	0.02	0.04
Shopping	0.38	0.36	0.34	0.37
Other family & personal	0.34	0.29	0.19	0.30
Social Recreation	0.30	0.26	0.18	0.27
Eat meal	0.28	0.31	0.27	0.30
Serve passenger	0.35	0.32	0.30	0.33
Return to work	0.33	0.26	0.21	0.29
Return home	1.69	1.45	1.29	1.55
Other trip purpose	0.01	0.02	0.04	0.02
Total	5.03 (100%)	4.59 (100%)	4.10 (100%)	4.8 (100%)
Work/work related/return to work/return home	3.23 (64.3%)	2.94 (64.0%)	2.73 (66.5%)	3.06 (64.3%)
Other travel	1.80 (35.7%)	1.65 (36.0%)	1.37 (33.5%)	1.70 (35.7%)

Table 4.14 Average Trip Length Traveled by Purpose by Commuter (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	4.99	16.17	34.69	12.29
Work-related	1.48	1.94	1.85	1.73
School	0.42	0.31	0.33	0.36
Religious	0.13	0.15	0.06	0.13
Medical/dental	0.36	0.39	0.30	0.37
Shopping	1.26	1.64	2.90	1.55
Other family & personal	1.25	1.46	1.69	1.38
Social Recreation	2.12	2.38	1.95	2.24
Eat meal	1.03	1.19	0.87	1.10
Serve passenger	1.20	1.53	3.00	1.47
Return to work	1.69	1.52	0.96	1.56
Return home	5.44	12.64	25.72	10.21
Other trip purpose	0.09	0.12	0.23	0.11

Table 4.15 Total Trip Length Traveled by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	5.27	17.32	36.37	13.08
Work-related	2.71	3.05	3.20	2.91
School	0.45	0.33	0.33	0.38
Religious	0.13	0.16	0.08	0.14
Medical/dental	0.37	0.43	0.34	0.40
Shopping	1.65	2.12	3.83	2.01
Other family & personal	1.70	2.00	2.01	1.87
Social Recreation	2.68	2.75	2.08	2.68
Eat meal	1.24	1.44	0.99	1.33
Serve passenger	1.95	2.48	4.86	2.39
Return to work	1.94	1.79	0.99	1.81
Return home	9.06	17.20	31.81	14.44
Other trip purpose	0.10	0.13	0.24	0.12
Total	29.25 (100%)	51.21 (100%)	87.11 (100%)	43.6 (100%)
Work/work related/return to work/return home	18.98 (64.9%)	39.37 (76.9%)	72.37 (83.1%)	32.24 (74.0%)
Other travel	10.28 (35.1%)	11.84 (23.1%)	14.74 (16.9%)	11.32 (26.0%)

Table 4.16 Average Trip Duration by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	11.90	29.72	65.84	23.92
Work-related	2.67	3.13	2.75	2.90
School	0.96	0.75	1.05	0.86
Religious	0.29	0.30	0.22	0.29
Medical/dental	0.66	0.80	0.62	0.73
Shopping	3.18	3.77	6.87	3.69
Other family & personal	3.11	3.47	3.53	3.32
Social Recreation	4.97	4.99	4.68	4.96
Eat meal	2.56	3.14	2.82	2.87
Serve passenger	2.60	3.20	5.05	3.04
Return to work	3.69	3.32	2.53	3.44
Return home	13.06	25.74	51.58	21.62
Other trip purpose	0.17	0.28	0.73	0.26

Table 4.17 Total Travel Time Expenditure by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	12.47	30.93	68.06	24.90
Work-related	4.53	5.06	4.85	4.81
School	1.05	0.78	1.05	0.92
Religious	0.31	0.32	0.25	0.31
Medical/dental	0.70	0.88	0.72	0.79
Shopping	4.16	4.86	8.50	4.77
Other family & personal	4.29	4.68	4.21	4.48
Social Recreation	6.18	5.87	5.13	5.96
Eat meal	3.07	3.71	3.34	3.41
Serve passenger	4.31	5.17	8.56	4.99
Return to work	4.22	3.87	2.63	3.95
Return home	21.81	35.45	61.64	30.92
Other trip purpose	0.19	0.34	0.91	0.30
Total	67.27 (100%)	101.94 (100%)	169.83 (100%)	90.5 (100%)
Work/work related/return to work/return home	43.02 (64.0%)	75.31 (73.9%)	137.18 (80.8%)	64.59 (71.4%)
Other travel	24.25 (36.0%)	26.63 (26.1%)	32.66 (19.2%)	25.93 (28.6%)

Table 4.18 Average VMT by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	4.60	14.57	27.52	10.90
Work-related	1.22	1.62	1.57	1.44
School	0.34	0.28	0.15	0.30
Religious	0.09	0.12	0.06	0.10
Medical/dental	0.32	0.34	0.25	0.33
Shopping	1.08	1.43	2.55	1.34
Other family & personal	0.98	1.25	1.13	1.12
Social Recreation	1.41	1.62	1.21	1.50
Eat meal	0.75	1.00	0.71	0.87
Serve passenger	1.05	1.31	2.42	1.26
Return to work	1.48	1.25	0.88	1.33
Return home	4.77	11.31	19.78	8.90
Other trip purpose	0.06	0.09	0.14	0.08

Table 4.19Total VMT by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	4.85	15.11	28.22	11.32
Work-related	2.40	2.57	2.49	2.49
School	0.36	0.29	0.15	0.32
Religious	0.09	0.12	0.07	0.11
Medical/dental	0.34	0.37	0.28	0.35
Shopping	1.43	1.86	3.40	1.76
Other family & personal	1.35	1.73	1.40	1.54
Social Recreation	1.75	1.90	1.36	1.81
Eat meal	0.88	1.21	0.80	1.04
Serve passenger	1.71	2.14	3.97	2.06
Return to work	1.71	1.48	0.91	1.55
Return home	7.89	15.28	23.73	12.49
Other trip purpose	0.06	0.10	0.16	0.09
Total	24.83 (100%)	44.15 (100%)	66.95 (100%)	36.9 (100%)
Work/work related/return to work/return home	16.84 (67.8%)	34.43 (78.0%)	55.34 (82.7%)	27.84 (75.5%)
Other travel	7.98 (32.2%)	9.72 (22.0%)	11.61 (17.3%)	9.06 (24.5%)

Table 4.20 Mean Departure Time by Purpose by Commuter Type (NHTS)

Sample Size	6,386 (45.7%)	6,826 (48.8%)	764 (5.5%)	13,976 (100%)
Weighted Population	28,192,662 (44.5%)	31,412,074 (49.6%)	3,738,126 (5.9%)	63,342,863 (100%)
Purpose	Short Commuters	Medium Commuters	Long Commuters	All Commuters
To work	8.45 AM	8.12 AM	7.35 AM	8.30 AM
Work-related	11.55 AM	11.52 AM	11.20 AM	11.46 AM
School	10.33 AM	12.11 PM	2.21 PM	11.08 AM
Religious	5.14 PM	5.36 PM	4.29 PM	5.18 PM
Medical/dental	12.56 PM	12.31 PM	1.34 PM	12.44 PM
Shopping	3.17 PM	3.16 PM	2.31 PM	3.13 PM
Other family & personal	2.14 PM	2.27 PM	2.28 PM	2.23 PM
Social Recreation	4.03 PM	4.1 PM	4.44 PM	4.20 PM
Eat meal	2.16 PM	2.01 PM	1.45 PM	2.09 PM
Serve passenger	1.01 PM	12.35 PM	12.57 PM	12.45 PM
Return to work	1.22 PM	1.11 PM	1.22 PM	1.17 PM
Return home	4.39 PM	5.02 PM	5.20 PM	4.50 PM
Other trip purpose	4.11 PM	2.29 PM	3.07 PM	2.55 PM

Table 4.21 Drive Alone vs. Carpooling (NHTS)

Sample Size		11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population		54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Commute Pattern		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Drive alone		84.69	82.18	57.27	81.81
	Car	57.16	55.69	37.31	55.25
	Van	5.83	4.96	3.22	5.26
	SUV	7.21	7.40	5.19	7.18
	Pickup truck	13.76	13.54	10.38	13.45
	Other truck	0.42	0.24	1.05	0.37
	RV	0.01	0.01	0.00	0.01
	Motorcycle	0.30	0.34	0.13	0.31
Carpool		8.29	9.75	14.52	9.37
	Car	5.92	6.77	7.86	6.44
	Van	0.73	0.92	2.20	0.91
	SUV	0.50	0.62	0.65	0.57
	Pickup truck	1.11	1.43	3.61	1.42
	Other truck	0.03	0.02	0.19	0.03
Transit		0.94	6.65	26.56	5.22
	Local public transit bus	0.73	3.22	9.12	2.43
	Commuter bus	0.03	0.14	1.24	0.16
	Charter/tour bus	0.00	0.04	0.41	0.05
	City to city bus	0.00	0.05	0.50	0.05
	Amtrack/inter city train	0.00	0.18	1.20	0.16
	Commuter train	0.00	0.70	6.31	0.72
	Subway/elevated rail	0.14	2.25	7.24	1.57
	Street car/trolley	0.03	0.05	0.28	0.06
	Passenger line/ferry	0.00	0.01	0.27	0.02
	Sailboat/motorboat/yacht	0.00	0.00	0.00	0.00
Other		6.08	1.42	1.65	3.59
	Commercial/charter plane	0.00	0.00	0.49	0.03
	Private/corporate airplane	0.00	0.00	0.00	0.00
	School bus	0.11	0.07	0.47	0.12
	Taxicab	0.10	0.05	0.00	0.07
	Hotel/airport shuttle	0.00	0.00	0.07	0.00
	Bicycle	0.71	0.36	0.20	0.51
	Walk	5.03	0.90	0.37	2.78
	Other	0.12	0.03	0.05	0.07
Total		100	100	100	100

Table 4.22 Drive Alone vs. Carpooling (ACS)

Sample Size		249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population		56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
Commute Pattern		Short Commuters	Medium Commuters	Long Commuters	All Commuters
Drive alone	Car, Van, or Truck	82.25	80.07	58.80	79.52
Carpool	Car, Van, or Truck	9.83	11.84	14.57	11.13
Transit		1.07	6.12	23.82	5.11
	Bus or trolley bus	0.90	3.55	11.00	2.89
	Streetcar or trolley car	0.01	0.10	0.19	0.07
	Subway or elevated	0.13	2.08	7.02	1.56
	Railroad	0.02	0.36	5.21	0.56
	Ferryboat	0.00	0.03	0.40	0.04
Other		6.85	1.97	2.82	4.24
	Taxicab	0.20	0.09	0.03	0.13
	Motorcycle	0.14	0.12	0.08	0.13
	Bicycle	0.61	0.31	0.19	0.44
	Walked	4.92	0.84	0.30	2.65
	Worked at home	0.00	0.00	0.00	0.00
	Other method	0.99	0.60	2.23	0.89

Table 4.23 Mode Share by Trip Purpose by Commuter Type (NHTS)

Trip Purpose	Type	Auto	Truck	Walk/ Bike	Airplane	Bus	Rail	Ship	Taxi	Other
To work	Short	77.5	17.6	4.1	0.0	0.5	0.1	0.0	0.1	0.13
	Medium	74.7	17.6	2.2	0.1	2.7	2.5	0.0	0.1	0.15
	Long	56.0	16.4	3.6	0.0	9.2	14.3	0.3	0.0	0.19
Work-related	Short	61.1	33.5	3.7	0.1	0.7	0.2	0.0	0.3	0.94
	Medium	62.1	30.7	5.0	0.2	0.9	0.7	0.0	0.2	0.31
	Long	44.6	47.6	4.1	0.0	0.0	3.6	0.0	0.0	0.00
School	Short	77.2	11.1	5.4	0.0	5.5	0.7	0.0	0.0	4.51
	Medium	71.2	9.0	11.9	0.0	6.5	1.3	0.0	0.0	5.88
	Long	51.9	8.7	10.1	0.0	0.0	29.3	0.0	0.0	0.00
Religious	Short	87.8	10.6	0.6	0.0	0.6	0.4	0.0	0.0	0.00
	Medium	93.1	6.2	0.0	0.0	0.7	0.0	0.0	0.0	0.00
	Long	50.5	0.0	28.4	0.0	7.0	14.1	0.0	0.0	0.00
Medical/ dental	Short	88.6	8.4	3.0	0.0	0.0	0.0	0.0	0.0	0.00
	Medium	81.7	11.9	1.4	0.0	0.3	1.2	0.0	1.2	2.30
	Long	70.1	7.0	6.4	0.0	0.0	9.7	0.0	6.8	0.00
Shopping	Short	81.7	13.8	4.3	0.0	0.1	0.1	0.0	0.0	0.00
	Medium	79.9	14.3	5.0	0.0	0.3	0.5	0.0	0.0	0.00
	Long	62.7	18.8	11.9	0.0	5.1	1.6	0.0	0.0	0.00
Family & personal	Short	77.2	14.0	8.3	0.0	0.1	0.1	0.0	0.0	0.05
	Medium	75.5	11.9	11.2	0.1	0.6	0.6	0.0	0.1	0.05
	Long	62.9	14.6	16.6	0.0	3.9	1.3	0.7	0.0	0.00
Social	Short	64.6	12.8	21.3	0.1	0.3	0.0	0.0	0.0	1.11
	Medium	60.9	11.4	23.1	0.4	0.5	1.0	0.0	0.5	2.19
	Long	49.9	11.7	28.2	0.4	2.5	2.9	0.0	0.0	5.32
Eat meal	Short	74.4	15.2	9.8	0.0	0.4	0.0	0.0	0.2	0.18
	Medium	71.8	13.3	13.7	0.0	0.3	0.7	0.0	0.3	0.00
	Long	55.3	9.4	33.3	0.0	0.0	1.5	0.0	0.0	0.51
Serve passenger	Short	87.2	10.7	1.6	0.1	0.2	0.0	0.0	0.0	0.33
	Medium	87.3	9.9	1.9	0.0	0.5	0.5	0.0	0.0	0.18
	Long	81.6	11.1	3.3	0.0	3.6	0.4	0.0	0.0	0.00
Return to work	Short	68.1	20.4	10.6	0.0	0.4	0.1	0.0	0.1	0.55
	Medium	63.9	18.4	16.1	0.0	0.5	0.5	0.0	0.4	0.37
	Long	49.0	8.9	39.3	0.0	0.0	2.0	0.0	0.8	0.00

Table 4.23 (Continued)

Trip Purpose	Type	Auto	Truck	Walk/ Bike	Airplane	Bus	Rail	Ship	Taxi	Other
Return home	Short	77.8	15.7	5.9	0.0	0.3	0.1	0.0	0.0	0.15
	Medium	75.5	15.4	5.6	0.0	1.8	1.4	0.0	0.2	0.16
	Long	61.9	14.6	6.3	0.2	7.7	8.5	0.1	0.6	0.27
Other trip purpose	Short	78.8	12.8	4.6	0.0	0.8	1.6	0.0	0.0	2.53
	Medium	80.7	7.3	9.4	0.0	0.4	0.9	0.0	0.0	1.87
	Long	52.8	8.6	29.5	2.0	0.8	6.4	0.0	0.0	0.00
All Trips	Short	76.6	16.1	6.6	0.0	0.4	0.1	0.0	0.0	0.31
	Medium	74.4	15.4	7.0	0.1	1.4	1.3	0.0	0.2	0.32
	Long	59.5	15.5	11.0	0.1	5.8	7.4	0.1	0.3	0.37
All Trips	All	74.6	15.7	7.0	0.0	1.2	1.0	0.0	0.1	0.32

Table 4.24 Trip Length of Long Commuters by Job Specialization

Occupation Type	Commute Time (min)	Commute Distance (mile)
Sales or Service	78.94	43.91
Clerical or administrative support	70.43	31.90
Manufacturing, construction, maintenance, or farming	80.45	53.11
Professional, managerial or technical	78.85	47.21

Figure 4.1 Work Trip Departure Time Distribution by Commuter Type

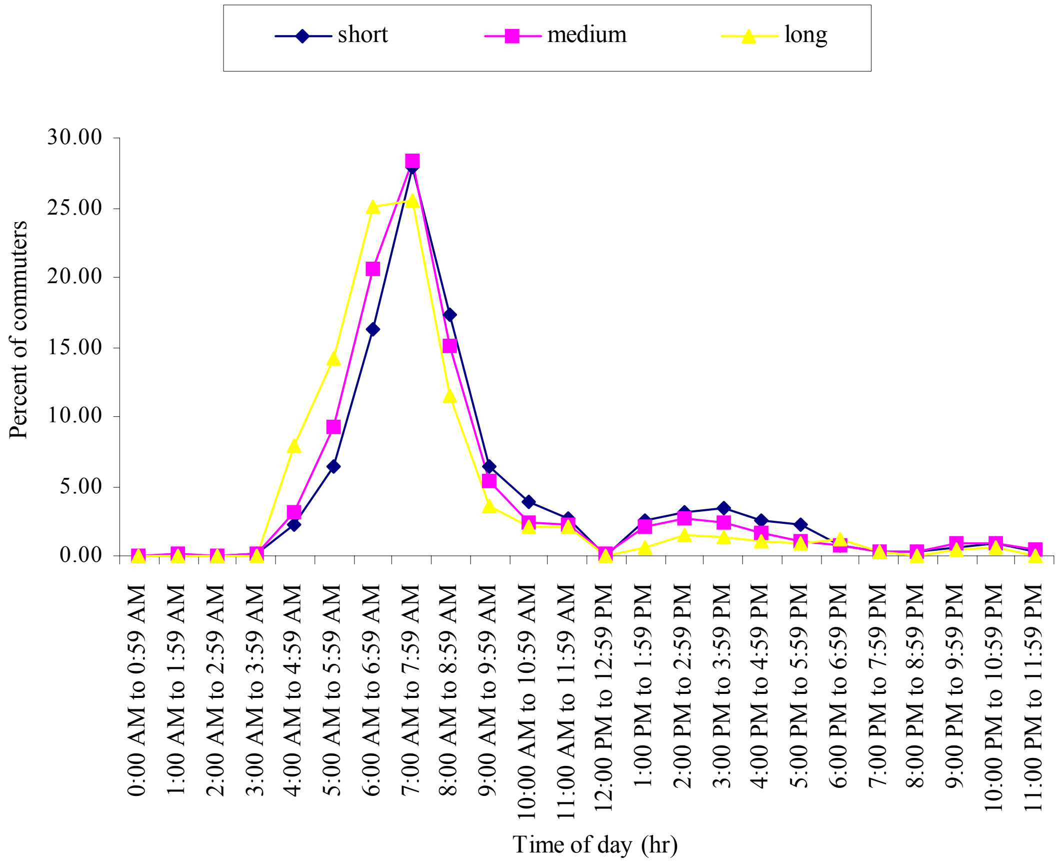


Figure 4.2 Work Related Trip Departure Time Distribution by Commuter Type

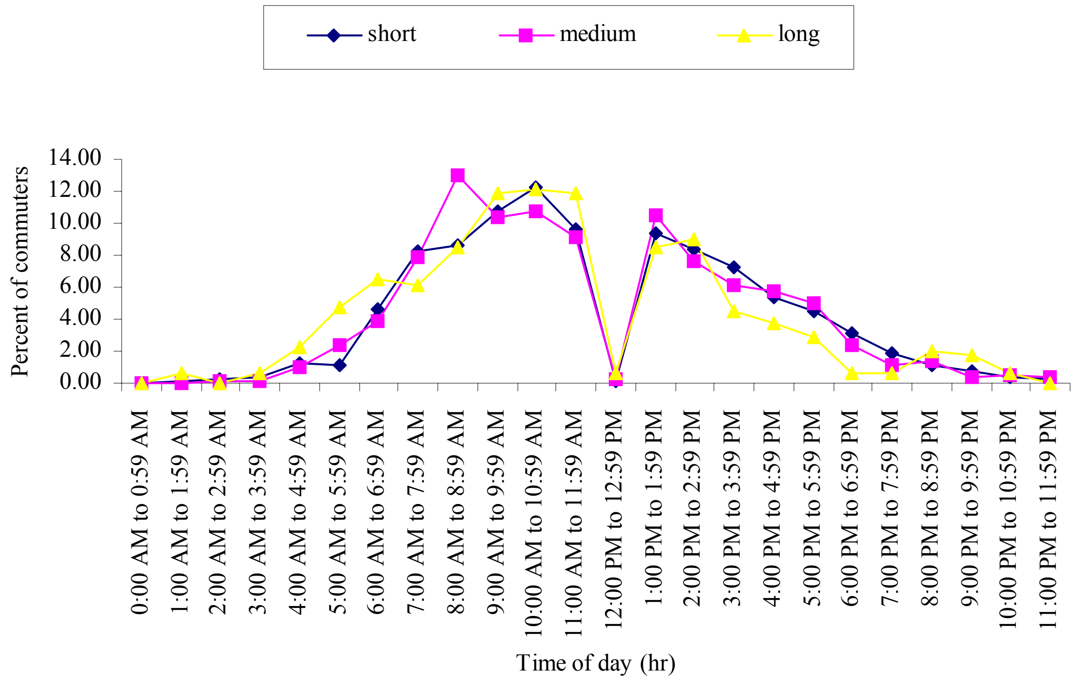
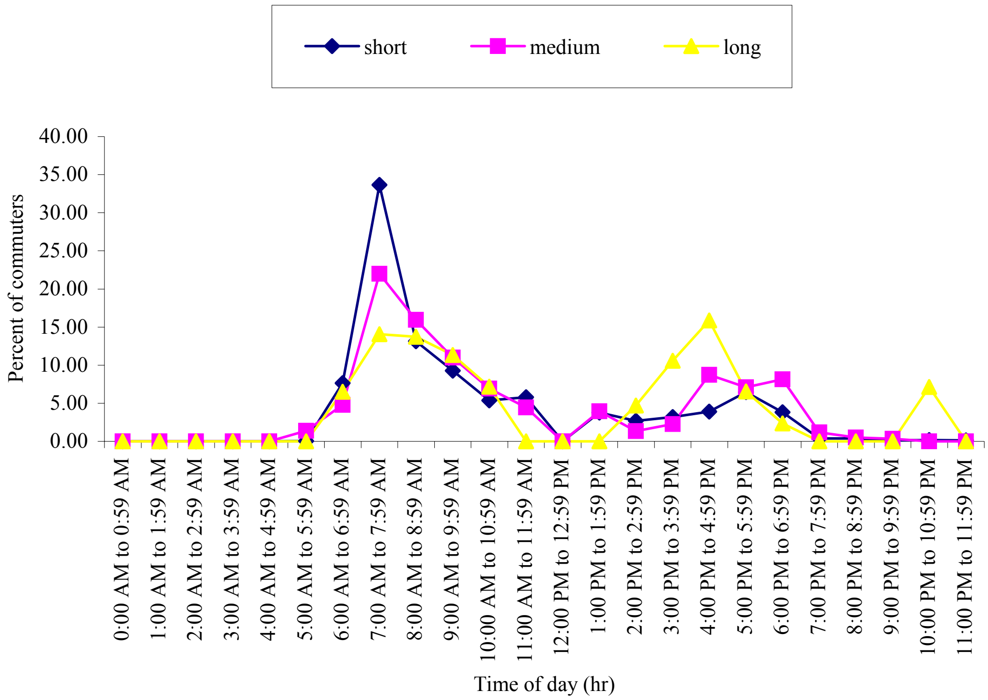


Figure 4.3 School Trip Departure Time Distribution by Commuter Type



4.5 Area Related Characteristics

The percentage of long commuters in Metropolitan Statistical Area (MSA) increases with the population. This is because, the population influences the congestion and urban sprawl and in turn they together increase the commute time. The Table 4.25and Table 4.26 shows the distribution and percentage of commuters by population of the MSA. The Table 4.27 and Table 4.28 show the same aspect of commuters with respect to type of urban area commuter belongs. The tables show that nearly 70 % of the commuters belong to an urban area. The share of the individuals in long commuters increases as we move from urban cluster to lower density areas. The proportion of long commuters is more in an area surrounded by urban areas.

The average commute time of all commuters is increasing with the MSA population as shown in Table 4.29. But within long commuters the commute time is very high, 107.26 min for MSAs of population less than 250,000. This is because of their long distance travel shown in Table 4.30. The average travel distance is 73 miles for long commuters in MSA with population less than 250,000 whereas only 37.4 miles in MSA with population equal to or more than 3 million.

The average commute time of all commuters is more in areas surrounded by urban areas as shown in Table 4.31. The average commute distance also shows the same trend, it is 16.53% in areas surrounded by urban areas and it is 17.11% in non-urban areas from Table 4.32. For non-urban areas the commute distances are more and commute times are less when compared to areas surrounded by urban areas because of the low congestion and due to wide sprawl present in the non-urban areas. Table 4.33 and Table 4.34 show the distribution and percent of commuters by each state.

The tables show that Alaska, Iowa, Montana, Nebraska, North Dakota, South Dakota and Wyoming have the high percentage of short commuters. The North Dakota has the highest percentage, 75.5% of short commuters followed by Wyoming at 73.5%. Illinois, Maryland, New Jersey, New York and West Virginia show high percentage of long commuters. New York has the highest percentage, 15.2% of long commuters followed by New Jersey at 13.3%.

Table 4.35 shows the average commute time of commuters for each state. The important identification is that, the states that have low percentage of long commuters have the longest commutes for them and at the same time this behavior is not observed for the whole set of commuters. The average commute time is high for Illinois, Maryland, New Jersey and New York. New York State has the highest commute time of 30.6 min and is followed by Maryland State at 29.1 min.

The Table 4.36 and Table 4.37 show the average commute time and average commute distance of different commuters by CMSA. The average commute time for the short commuters is low for Chicago, Cleveland, New York and Seattle. The average commute time for long commuters is high for Denver, Milwaukee, New York, and San Francisco.

The average commute time is highest for New York at 31.7 min followed by Miami at 30 min. The average commute distance is highest for Dallas at 16.32 miles and followed by Philadelphia at 16.31 miles. The longest commute distance for long commuters is in Milwaukee, a distance of 70 miles. The shortest commute distance for short commuters is for New York at 3.47 miles.

Table 4.25 Distribution of Commuter Type by MSA Size (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
MSA Size by Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an MSA (CMSA) of Less than 250,000	9.3	4.7	2.7	6.7
In an MSA (CMSA) of 250,000 – 499,999	9.1	7.2	4.0	7.9
In an MSA (CMSA) of 500,000 – 999,999	8.7	8.2	4.0	8.2
In an MSA (CMSA) of 1,000,000 - 2,999,999	21.5	24.2	11.9	22.2
In an MSA (CMSA) of 3 million or more	29.9	40.1	61.0	36.7
Not in MSA or CMSA	21.4	15.5	16.3	18.3

Table 4.26 Percentage of Commuter Type by MSA Size (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
MSA Size by Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an MSA (CMSA) of Less than 250,000	64.1	33.4	2.5	100
In an MSA (CMSA) of 250,000 - 499,999	53.8	43.1	3.1	100
In an MSA (CMSA) of 500,000 - 999,999	49.4	47.6	3.0	100
In an MSA (CMSA) of 1,000,000 - 2,999,999	44.9	51.8	3.3	100
In an MSA (CMSA) of 3 million or more	37.9	51.9	10.2	100
Not in MSA or CMSA	54.2	40.3	5.5	100

Table 4.27 Distribution of Commuter Type by Urban Area Type (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Urban Area Type	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an Urban Cluster	13.3	7.0	8.7	10.0
In an Urban Area	68.3	70.3	71.0	69.4
In an Area Surrounded by Urban Areas	0.0	0.1	0.1	0.1
Not in Urban Area	18.4	22.6	20.2	20.5

Table 4.28 Percentage of Commuter Type by Urban Area Type (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Urban Area Type	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an Urban Cluster	61.4	33.3	5.3	100
In an Urban Area	45.6	48.1	6.3	100
In an Area Surrounded by Urban Areas	24.8	62.2	13.0	100
Not in Urban Area	41.7	52.3	6.0	100

Table 4.29 Average Commute Time by Commuter Type by MSA Size (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
MSA Size by Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an MSA (CMSA) of Less than 250,000	9.57	26.45	107.26	17.6
In an MSA (CMSA) of 250,000 – 499,999	9.55	27.09	86.00	19.4
In an MSA (CMSA) of 500,000 – 999,999	10.19	27.46	89.38	20.6
In an MSA (CMSA) of 1,000,000 – 2,999,999	10.15	28.18	78.04	21.5
In an MSA (CMSA) of 3 million or more	10.11	31.43	74.39	27.6
Not in MSA or CMSA	8.40	29.54	82.38	21.2
Average Commute Time for all Areas	9.8	29.7	78.3	23.5

Table 4.30 Average Commute Distance by Commuter Type by MSA Size (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
MSA Size by Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an MSA (CMSA) of Less than 250,000	4.58	16.90	73.40	10.29
In an MSA (CMSA) of 250,000 - 499,999	4.88	16.95	61.98	11.88
In an MSA (CMSA) of 500,000 - 999,999	4.87	16.82	61.06	12.26
In an MSA (CMSA) of 1,000,000 - 2,999,999	4.79	16.36	48.05	12.12
In an MSA (CMSA) of 3 million or more	5.12	16.56	37.40	14.20
Not in MSA or CMSA	4.54	21.33	65.07	14.55
Average Commute Distance for all Areas	4.8	17.3	46.4	13.2

Table 4.31 Average Commute Time by Commuter Type by Urban Area (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Urban Area Type	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an Urban Cluster	8.13	30.43	85.35	19.50
In an Urban Area	10.14	29.34	76.48	23.43
In an Area Surrounded by Urban Areas	7.39	31.34	93.53	33.43
Not in Urban Area	9.35	29.52	80.25	24.28
Average Commute Time for all Areas	9.8	29.7	78.3	23.5

Table 4.32 Average Commute Distance by Commuter Type by Urban Area (NHTS)

Sample Size	11,876 (47.6%)	11,641 (46.7%)	1,431 (5.7%)	24,948 (100%)
Weighted Population	54,462,391 (46.3%)	55,736,358 (47.5%)	7,207,110 (6.1%)	117,405,859 (100%)
Urban Area Type	Short Commuters	Medium Commuters	Long Commuters	All Commuters
In an Urban Cluster	3.77	21.89	60.39	12.67
In an Urban Area	4.80	15.67	39.61	12.08
In an Area Surrounded by Urban Areas	4.54	14.78	47.84	16.53
Not in Urban Area	5.69	20.97	62.94	17.11
Average Commute Distance for all Areas	4.8	17.3	46.4	13.2

Figure 4.4 Commute Length by MSA Size

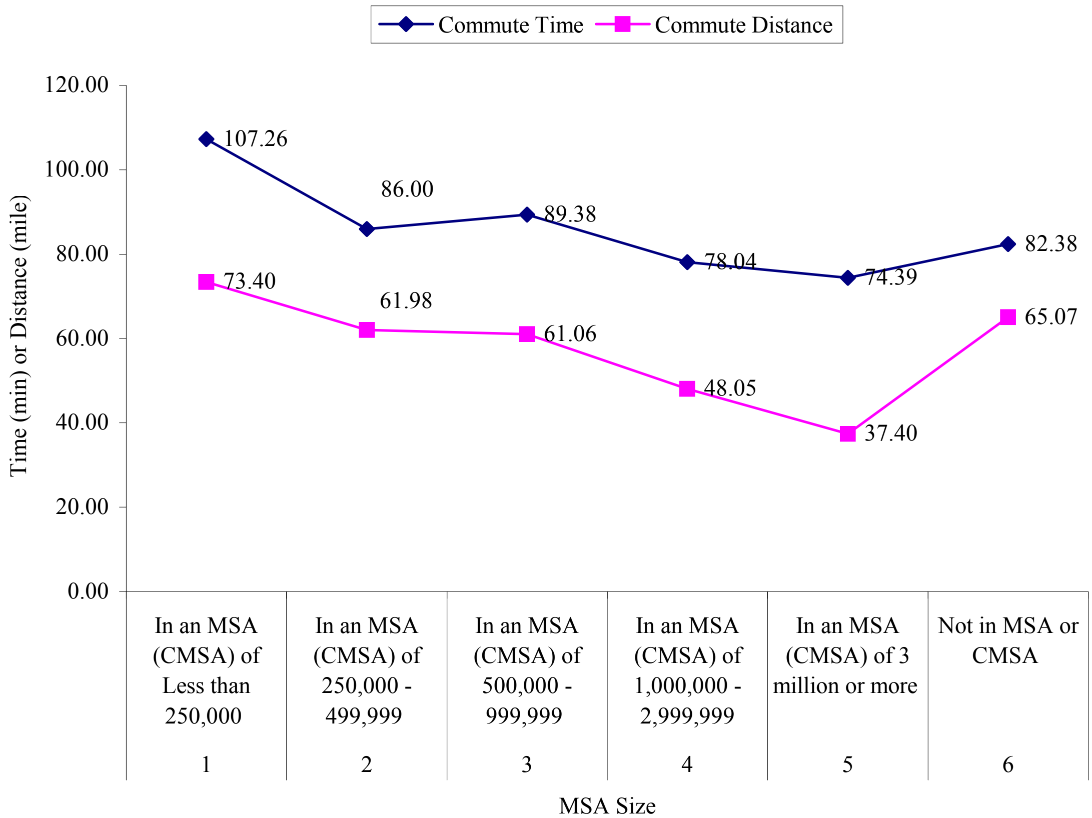


Figure 4.5 Commute Length by Area Type

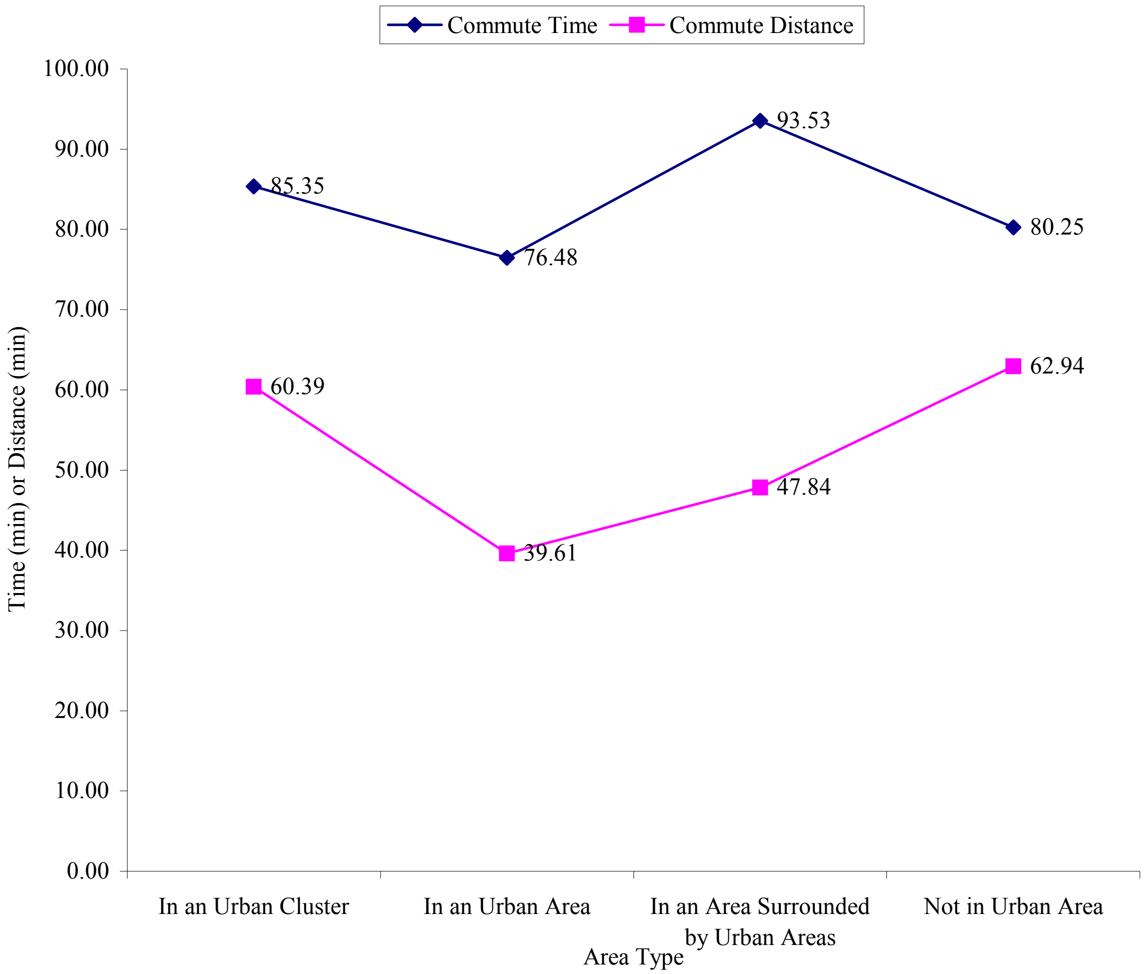


Table 4.33 Distribution of Commuter Type by State (ACS)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Alabama	6,657	1,811,511	1.6	1.4	1.0	1.5
Alaska	4,335	273,359	0.3	0.1	0.2	0.2
Arizona	7,576	2,130,871	1.7	1.8	1.3	1.7
Arkansas	4,058	1,116,363	1.2	0.7	0.5	0.9
California	47,338	14,293,902	10.4	12.1	14.9	11.5
Colorado	7,871	2,059,058	1.7	1.7	1.2	1.7
Connecticut	6,202	1,569,885	1.3	1.3	1.2	1.3
Delaware	4,612	361,564	0.3	0.3	0.3	0.3
District of Columbia	3,458	258,527	0.1	0.3	0.3	0.2
Florida	23,975	6,778,674	5.1	6.0	4.6	5.5
Georgia	13,033	3,661,077	2.7	3.2	3.4	3.0
Hawaii	5,049	526,881	0.4	0.5	0.4	0.4
Idaho	4,028	554,924	0.6	0.3	0.3	0.4
Illinois	20,807	5,597,098	4.0	4.7	6.5	4.5
Indiana	11,007	2,794,209	2.5	2.2	1.3	2.3
Iowa	9,591	1,348,296	1.5	0.8	0.5	1.1
Kansas	7,708	1,272,298	1.4	0.7	0.5	1.0
Kentucky	10,094	1,670,616	1.5	1.3	1.0	1.3
Louisiana	8,856	1,778,972	1.6	1.3	1.3	1.4
Maine	3,912	593,782	0.6	0.4	0.4	0.5
Maryland	10,871	2,472,095	1.4	2.4	3.2	2.0
Massachusetts	11,858	3,023,476	2.2	2.6	3.0	2.4
Michigan	17,670	4,377,200	3.6	3.6	2.5	3.5
Minnesota	10,514	2,466,115	2.2	2.0	1.1	2.0
Mississippi	8,781	1,144,638	1.1	0.8	0.6	0.9
Missouri	9,995	2,481,971	2.1	2.0	1.5	2.0
Montana	4,151	383,352	0.5	0.2	0.1	0.3
Nebraska	7,414	810,569	1.0	0.4	0.2	0.7

Table 4.33 (Continued)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Nevada	4,265	945,361	0.7	0.9	0.3	0.8
New Hampshire	5,138	627,842	0.5	0.5	0.5	0.5
New Jersey	14,341	3,920,068	2.7	3.2	5.8	3.2
New Mexico	3,587	750,450	0.8	0.5	0.3	0.6
New York	27,879	8,003,123	5.1	6.6	13.6	6.5
North Carolina	13,210	3,534,703	3.0	2.9	2.0	2.9
North Dakota	4,720	302,715	0.4	0.1	0.1	0.2
Ohio	20,478	5,079,864	4.3	4.1	2.3	4.1
Oklahoma	5,281	1,460,340	1.5	1.0	0.6	1.2
Oregon	5,831	1,496,406	1.4	1.1	0.8	1.2
Pennsylvania	21,539	5,342,327	4.5	4.2	3.9	4.3
Rhode Island	4,772	470,137	0.4	0.4	0.3	0.4
South Carolina	6,446	1,767,891	1.5	1.4	1.0	1.4
South Dakota	7,114	349,254	0.4	0.2	0.1	0.3
Tennessee	9,570	2,508,523	2.1	2.1	1.4	2.0
Texas	27,958	9,070,833	7.2	7.6	6.2	7.3
Utah	4,990	999,329	1.0	0.7	0.5	0.8
Vermont	4,239	292,138	0.3	0.2	0.1	0.2
Virginia	13,159	3,304,550	2.4	2.9	2.7	2.7
Washington	10,379	2,631,623	2.0	2.2	2.3	2.1
West Virginia	6,300	685,156	0.6	0.5	0.8	0.6
Wisconsin	10,948	2,557,671	2.4	1.9	1.0	2.1
Wyoming	4,181	227,959	0.3	0.1	0.2	0.2

Table 4.34 Percentage of Commuter Type within each State (ACS)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Alabama	6,657	1,811,511	48.6	46.3	5.1	1.5
Alaska	4,335	273,359	63.9	31.1	4.9	0.2
Arizona	7,576	2,130,871	45.3	49.4	5.2	1.7
Arkansas	4,058	1,116,363	57.8	37.9	4.2	0.9
California	47,338	14,293,902	40.8	49.9	9.3	11.5
Colorado	7,871	2,059,058	45.9	49.1	5.0	1.7
Connecticut	6,202	1,569,885	45.2	48.2	6.6	1.3
Delaware	4,612	361,564	47.6	46.2	6.2	0.3
District of Columbia	3,458	258,527	28.5	62.7	8.9	0.2
Florida	23,975	6,778,674	42.2	51.7	6.0	5.5
Georgia	13,033	3,661,077	40.7	51.0	8.2	3.0
Hawaii	5,049	526,881	41.7	50.6	7.6	0.4
Idaho	4,028	554,924	59.6	36.0	4.3	0.4
Illinois	20,807	5,597,098	39.8	49.9	10.3	4.5
Indiana	11,007	2,794,209	50.0	45.8	4.1	2.3
Iowa	9,591	1,348,296	63.9	32.8	3.3	1.1
Kansas	7,708	1,272,298	62.2	34.6	3.2	1.0
Kentucky	10,094	1,670,616	50.2	44.5	5.3	1.3
Louisiana	8,856	1,778,972	50.7	42.8	6.5	1.4
Maine	3,912	593,782	52.4	41.9	5.7	0.5
Maryland	10,871	2,472,095	31.9	56.4	11.7	2.0
Massachusetts	11,858	3,023,476	41.2	50.1	8.7	2.4
Michigan	17,670	4,377,200	46.6	48.3	5.1	3.5
Minnesota	10,514	2,466,115	49.0	46.9	4.1	2.0
Mississippi	8,781	1,144,638	51.9	43.0	5.0	0.9
Missouri	9,995	2,481,971	46.4	48.1	5.6	2.0
Montana	4,151	383,352	71.8	25.7	2.5	0.3
Nebraska	7,414	810,569	66.1	31.3	2.6	0.7

Table 4.34 (Continued)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Nevada	4,265	945,361	43.3	53.6	3.2	0.8
New Hampshire	5,138	627,842	46.9	45.3	7.8	0.5
New Jersey	14,341	3,920,068	38.6	48.1	13.3	3.2
New Mexico	3,587	750,450	57.0	38.9	4.0	0.6
New York	27,879	8,003,123	35.9	48.8	15.2	6.5
North Carolina	13,210	3,534,703	47.0	48.1	5.0	2.9
North Dakota	4,720	302,715	75.5	21.7	2.8	0.2
Ohio	20,478	5,079,864	47.9	48.1	4.0	4.1
Oklahoma	5,281	1,460,340	57.9	38.4	3.7	1.2
Oregon	5,831	1,496,406	52.5	43.0	4.6	1.2
Pennsylvania	21,539	5,342,327	47.3	46.2	6.5	4.3
Rhode Island	4,772	470,137	50.2	44.5	5.3	0.4
South Carolina	6,446	1,767,891	48.8	46.3	4.9	1.4
South Dakota	7,114	349,254	71.9	25.9	2.2	0.3
Tennessee	9,570	2,508,523	46.2	48.6	5.2	2.0
Texas	27,958	9,070,833	44.3	49.6	6.1	7.3
Utah	4,990	999,329	55.3	40.3	4.3	0.8
Vermont	4,239	292,138	53.6	42.1	4.3	0.2
Virginia	13,159	3,304,550	41.1	51.5	7.4	2.7
Washington	10,379	2,631,623	43.6	48.6	7.8	2.1
West Virginia	6,300	685,156	46.6	43.4	10.0	0.6
Wisconsin	10,948	2,557,671	53.7	42.9	3.4	2.1
Wyoming	4,181	227,959	73.5	19.8	6.7	0.2

Table 4.35 Average Commute Time by State by Commuter Type (ACS)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Alabama	6,657	1,811,511	10.0	29.1	87.1	22.8
Alaska	4,335	273,359	9.0	26.6	94.2	18.7
Arizona	7,576	2,130,871	10.1	29.1	80.7	23.2
Arkansas	4,058	1,116,363	9.7	28.0	85.5	19.8
California	47,338	14,293,902	10.4	30.0	77.5	26.4
Colorado	7,871	2,059,058	10.1	29.3	80.9	23.1
Connecticut	6,202	1,569,885	10.3	28.7	83.3	24.0
Delaware	4,612	361,564	10.5	28.2	83.2	23.1
District of Columbia	3,458	258,527	11.4	30.1	72.1	28.5
Florida	23,975	6,778,674	10.3	29.5	79.5	24.5
Georgia	13,033	3,661,077	10.1	30.9	77.9	26.3
Hawaii	5,049	526,881	10.2	30.6	72.1	25.2
Idaho	4,028	554,924	9.4	28.0	87.0	19.5
Illinois	20,807	5,597,098	9.7	31.4	74.8	27.2
Indiana	11,007	2,794,209	9.8	28.4	83.2	21.3
Iowa	9,591	1,348,296	9.0	28.0	83.9	17.7
Kansas	7,708	1,272,298	8.8	28.1	80.6	17.8
Kentucky	10,094	1,670,616	10.0	28.9	86.4	22.5
Louisiana	8,856	1,778,972	9.9	28.6	85.9	22.9
Maine	3,912	593,782	9.2	29.4	91.7	22.4
Maryland	10,871	2,472,095	10.6	31.1	75.2	29.7
Massachusetts	11,858	3,023,476	9.9	30.8	74.6	26.0
Michigan	17,670	4,377,200	10.0	29.6	81.7	23.1
Minnesota	10,514	2,466,115	9.4	29.3	79.3	21.6
Mississippi	8,781	1,144,638	9.7	28.7	90.3	22.0
Missouri	9,995	2,481,971	9.7	29.7	79.8	23.2
Montana	4,151	383,352	8.7	28.1	88.2	15.7
Nebraska	7,414	810,569	8.9	26.3	93.4	16.6

Table 4.35 (Continued)

Sample Size			249,880 (47.4%)	242,264 (45.9%)	35,602 (6.7%)	527,746 (100%)
Weighted Population			56,067,997 (45.2%)	58,929,736 (47.5%)	8,941,813 (7.2%)	123,939,546 (100%)
State Name	N (Sample)	N (Population)	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Nevada	4,265	945,361	10.8	26.8	82.1	21.6
New Hampshire	5,138	627,842	9.6	29.8	76.9	24.0
New Jersey	14,341	3,920,068	9.9	30.8	79.0	29.1
New Mexico	3,587	750,450	9.4	28.1	81.8	19.6
New York	27,879	8,003,123	10.0	31.7	75.7	30.6
North Carolina	13,210	3,534,703	10.2	29.2	82.8	22.9
North Dakota	4,720	302,715	8.6	27.9	93.7	15.2
Ohio	20,478	5,079,864	9.9	28.6	82.3	21.8
Oklahoma	5,281	1,460,340	9.7	27.8	86.4	19.5
Oregon	5,831	1,496,406	9.7	28.7	82.6	21.2
Pennsylvania	21,539	5,342,327	9.7	30.1	82.2	23.8
Rhode Island	4,772	470,137	10.0	28.6	78.7	21.9
South Carolina	6,446	1,767,891	10.3	28.7	86.0	22.5
South Dakota	7,114	349,254	8.6	26.4	94.9	15.1
Tennessee	9,570	2,508,523	10.3	29.2	82.0	23.2
Texas	27,958	9,070,833	10.1	29.6	77.9	23.9
Utah	4,990	999,329	9.8	28.0	81.9	20.3
Vermont	4,239	292,138	9.1	29.1	85.4	20.8
Virginia	13,159	3,304,550	10.4	29.8	80.5	25.6
Washington	10,379	2,631,623	10.0	29.5	81.8	25.1
West Virginia	6,300	685,156	9.4	30.0	88.5	26.2
Wisconsin	10,948	2,557,671	9.5	28.2	93.4	20.4
Wyoming	4,181	227,959	8.4	28.6	92.1	18.0
Average Time			9.9	29.7	79.3	24.3

Table 4.36 Average Commute Time by CMSA (NHTS)

Sample Size			3,401 (39.0 %)	4,484 (51.6)	813 (9.4%)	8,698 (100%)
Weighted Population			17,706,776 (39.0%)	23,751,852 (38.6%)	4,374,181 (9.4%)	45,832,809 (100%)
CMSA Name	N Sample	N Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Boston--Worcester--Lawrence, MA--NH--ME--CT CMSA	607	3,091,566	10.55	32.30	69.68	26.28
Chicago--Gary--Kenosha, IL--IN--WI CMSA	726	3,713,079	9.15	32.50	72.69	28.76
Cincinnati--Hamilton, OH--KY--IN CMSA	180	879,371	10.41	26.54	68.43	19.98
Cleveland--Akron, OH CMSA	319	1,439,342	9.51	29.30	60.00	22.47
Dallas--Fort Worth, TX CMSA	324	1,654,824	10.42	31.81	73.60	27.43
Denver--Boulder--Greeley, CO CMSA	287	1,256,429	10.20	28.34	81.71	22.48
Detroit--Ann Arbor--Flint, MI CMSA	433	1,910,668	10.13	31.11	68.84	23.43
Houston--Galveston--Brazoria, TX CMSA	300	1,737,975	10.44	31.73	71.70	27.06
Los Angeles--Riverside--Orange County, CA CMSA	1,037	6,297,337	10.68	30.17	73.14	27.88
Miami--Fort Lauderdale, FL CMSA	225	1,664,172	10.49	32.95	75.35	30.07
Milwaukee--Waukesha, WI PMSA	184	713,697	10.21	27.39	90.00	19.08
New York--Nr.New Jersey--Long Island, NY--NJ--CT--PA CMSA	1,477	8,161,875	9.85	32.66	78.50	31.72
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD CMSA	500	2,499,760	10.01	30.51	71.69	24.60
Portland--Salem, OR--WA CMSA	223	853,460	9.89	28.61	74.37	23.81
Sacramento--Yolo, CA CMSA	188	896,578	9.98	28.08	66.64	21.12
San Francisco--Oakland--San Jose, CA CMSA	612	3,370,225	9.87	31.87	79.04	25.90
Seattle--Tacoma--Bremerton, WA CMSA	382	1,720,666	10.35	29.35	70.50	26.21
Washington--Baltimore, DC--MD--VA--WV CMSA	694	3,971,786	10.48	32.76	73.74	28.87
Average Commute Time			10.14	31.27	74.77	27.26

Table 4.37 Average Commute Distance by CMSA (NHTS)

Sample Size			3,401 (39.0 %)	4,484 (51.6)	813 (9.4%)	8,698 (100%)
Weighted Population			17,706,776 (39.0%)	23,751,852 (38.6%)	4,374,181 (9.4%)	45,832,809 (100%)
CMSA Name	N Sample	N Population	Short Commuters	Medium Commuters	Long Commuters	All Commuters
Boston--Worcester--Lawrence, MA--NH--ME--CT CMSA	607	3,091,566	4.47	16.15	39.65	13.24
Chicago--Gary--Kenosha, IL--IN--WI CMSA	726	3,713,079	3.86	15.17	33.64	13.19
Cincinnati--Hamilton, OH--KY--IN CMSA	180	879,371	4.90	14.97	47.37	11.05
Cleveland--Akron, OH CMSA	319	1,439,342	4.92	17.66	26.54	12.85
Dallas--Fort Worth, TX CMSA	324	1,654,824	5.18	21.08	32.88	16.32
Denver--Boulder--Greeley, CO CMSA	287	1,256,429	4.11	15.47	37.01	10.88
Detroit--Ann Arbor--Flint, MI CMSA	433	1,910,668	4.52	18.71	41.07	13.26
Houston--Galveston--Brazoria, TX CMSA	300	1,737,975	5.24	20.58	32.36	15.92
Los Angeles--Riverside--Orange County, CA CMSA	1,037	6,297,337	4.81	16.71	42.43	15.09
Miami--Fort Lauderdale, FL CMSA	225	1,664,172	4.52	17.22	41.98	15.22
Milwaukee--Waukesha, WI PMSA	184	713,697	4.85	15.89	70.00	10.66
New York--Nr.New Jersey--Long Island, NY--NJ--CT--PA CMSA	1,477	8,161,875	3.47	14.58	35.40	13.55
Philadelphia--Wilmington--Atlantic City, PA--NJ--DE--MD CMSA	500	2,499,760	16.49	13.62	39.04	16.31
Portland--Salem, OR--WA CMSA	223	853,460	4.23	15.49	42.62	12.60
Sacramento--Yolo, CA CMSA	188	896,578	4.51	18.84	28.00	12.71
San Francisco--Oakland--San Jose, CA CMSA	612	3,370,225	4.18	16.41	44.59	12.99
Seattle--Tacoma--Bremerton, WA CMSA	382	1,720,666	4.49	15.87	34.31	13.51
Washington--Baltimore, DC--MD--VA--WV CMSA	694	3,971,786	4.55	17.01	34.79	14.13
Average Commute Distance			5.05	16.42	37.57	13.88

4.6 Summary of Person, Household and Area Characteristics

The descriptive analysis of the data provided us with an idea of characteristics of the short and long commuters. The following Table 4.38 shows some important person, household and area characteristics of an individual that are significant in short and long commuters in NHTS 2001 and ACS 2000

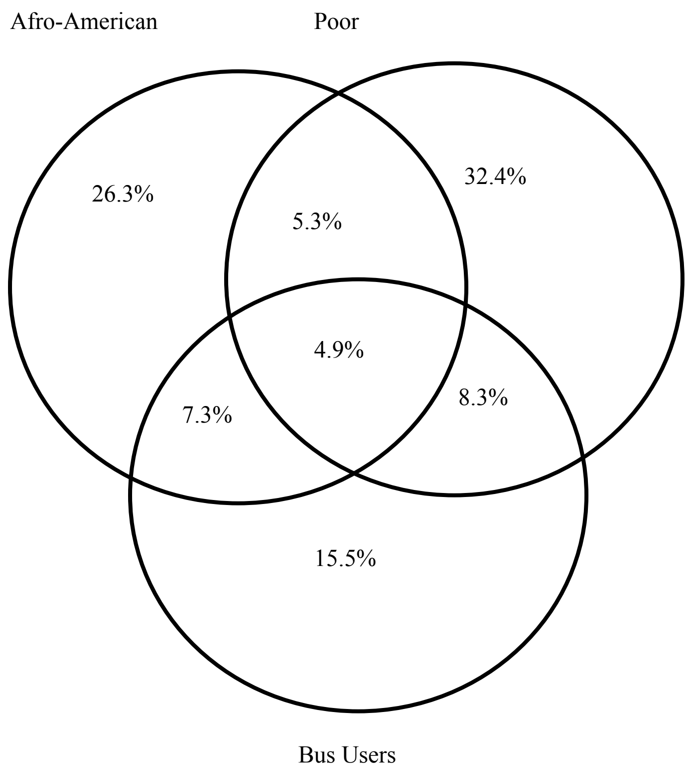
Table 4.38 Summary of the Person and Household Characteristics

Characteristic	NHTS 2001		ACS 2000	
	Short Commuters	Long Commuters	Short Commuters	Long Commuters
Gender	-	Male	-	Male
Age	16 to 20 years	25 to 64 years	16 to 20 years	25 to 64 years
Race	White	Black or Afro-American	White	Black or Afro-American
Education	-	Bachelors, Graduate and Professional		Bachelors, Graduate and Professional
Income	less than $15,000	$100,000 and above	less than $19,999	greater than $ 25,000
Driver Status	-	not a driver	NA	NA
Household Size	single person household	-	single person household	5 or more household
Family Structure	One adult, no children	-	-	-
Household Income	$25,000-$49,999	$100,000 and above	$25,000-$49,999	$100,000 and above
Number of Workers	-	single worker	3 or more workers	single worker
Number of Vehicles	-	zero vehicle	-	zero vehicle
Number of Children	no children	3 or more children	no children	1 or more children
MSA Population	less than 250,000, not in MSA/CMSA	3 million or more	NA	NA
Urban Area Type	urban cluster	Inside urban area, not in urban area	NA	NA

4.7 Afro-American, Poor and Bus Users

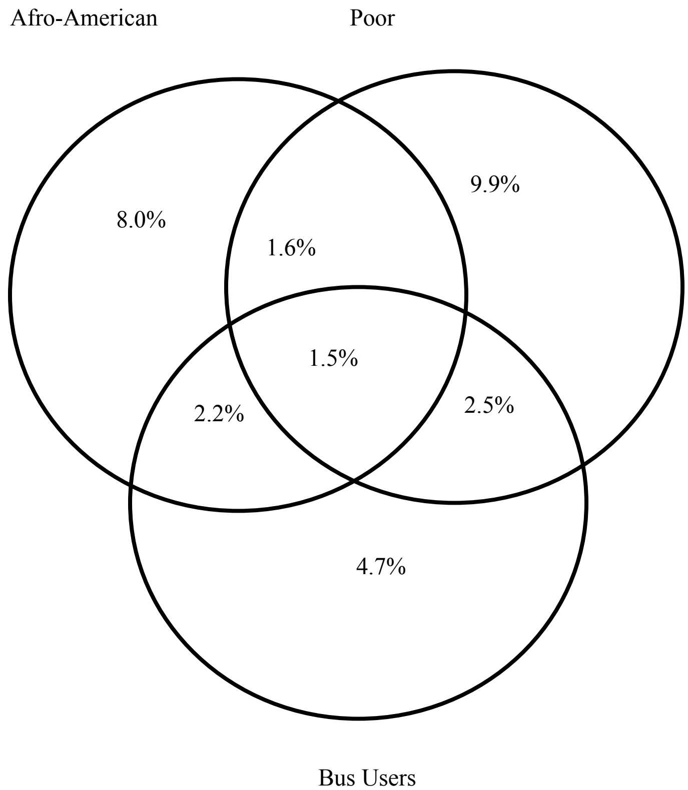
Analysis was done to know if the percentage of Afro-Americans (11.7), poor people (18.1) with personal annual income less than $15,000 and bus transit users (11.00) of long commuters are same. The Figure 4.6 and Figure 4.7 reveal that Afro-American, Poor and Bus users do not belong to the same group in long commuters.

Figure 4.6 Proportions of Combination of Afro-American, Poor and Bus user groups



Total Population (N) = 2,734,364

Figure 4.7 Percentage of Combination of Afro-American, Poor and Bus user groups in Long Commuters



Total Population (Long Commuters) (N) =8,941,813

4.8 Range of Short and Long Commuters

The Figure 4.8 shows the distribution of commuters by time. The Figure 4.9 and Figure 4.10 shows how the percentage of short and long commuters changes with upper and lower limits of short and long commuters.

Figure 4.8 Distribution of Commuters by Time

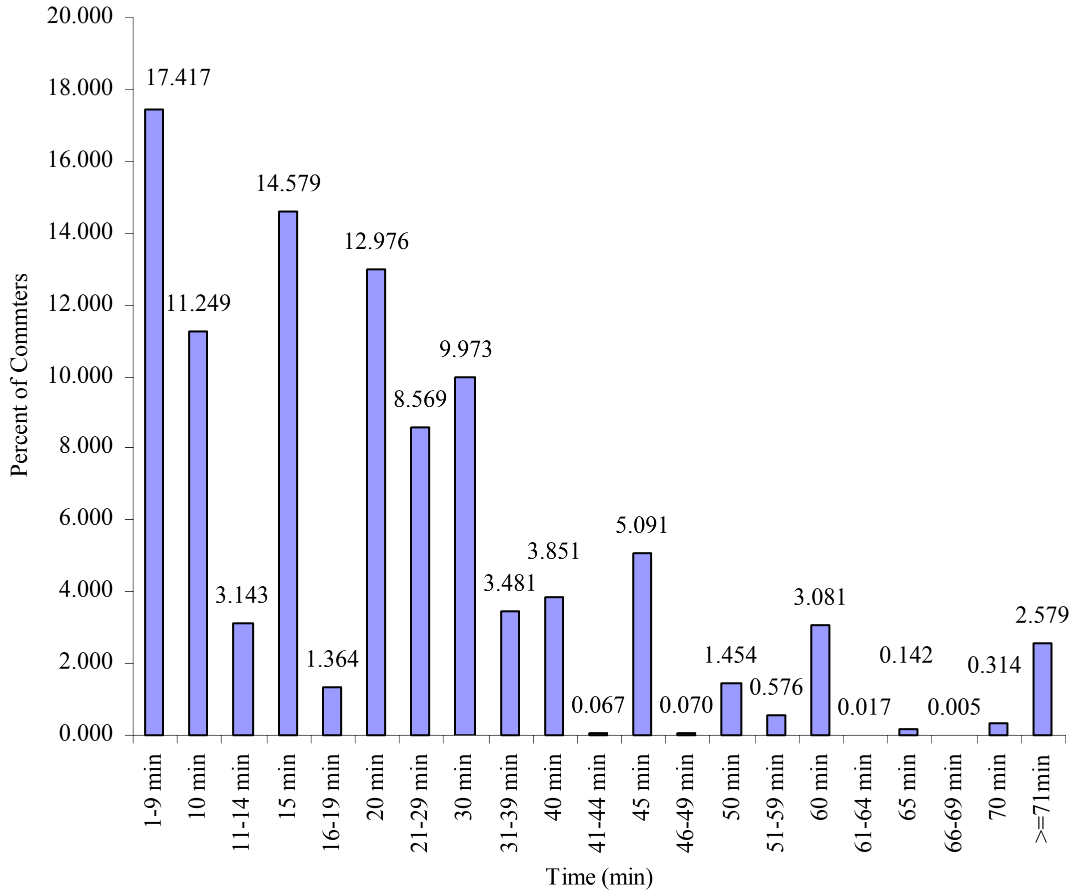


Figure 4.9 Share of Short Commuters by Upper

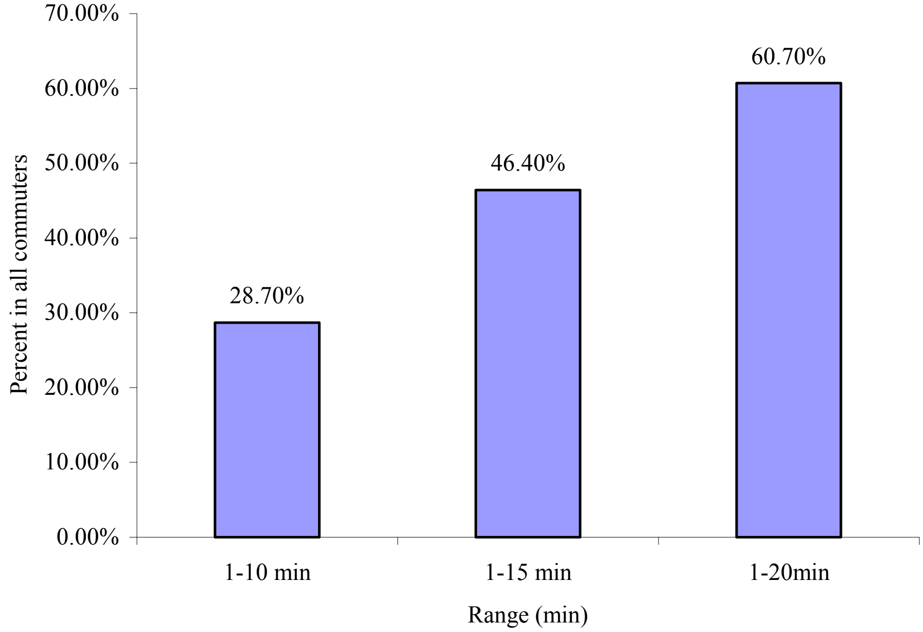
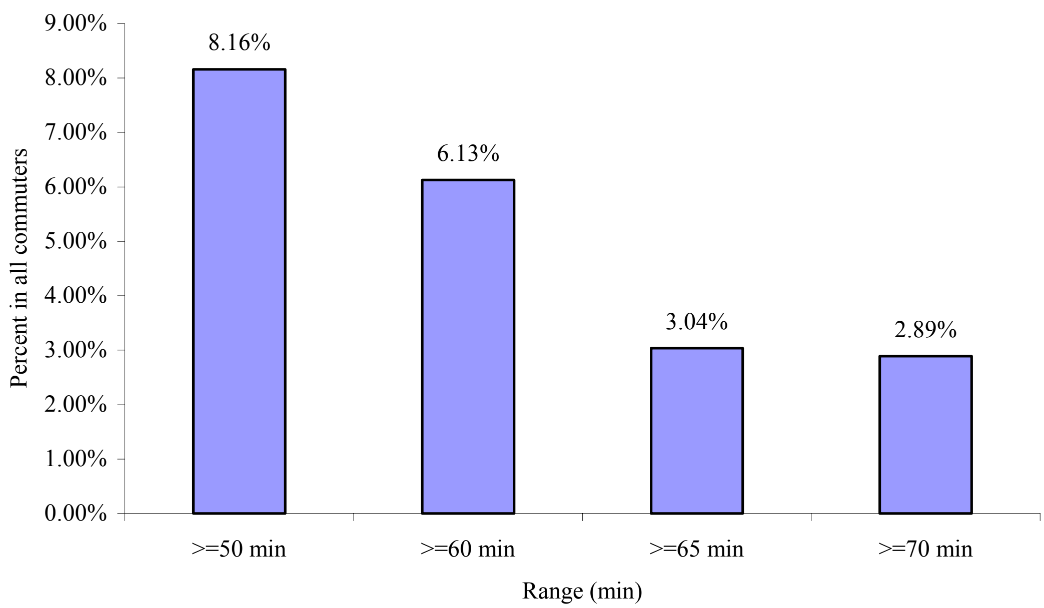


Figure 4.10 Share of Long Commuters by Lower Limit



CHAPTER 5

METHODOLOGY

The descriptive analysis explained in the previous chapter highlighted the distributions of the individual, household and area related characteristics of short, medium and long commuters and it helped in comparing the characteristics between short and long commuters. But the descriptive analysis alone is not very effective in forming policies, as it does not reveal the sensitivity of the commute length to characteristics. More rigorous data analysis is necessary to explain the sensitivity of the commute length and in knowing the characteristics involved in the process of commuter type choice. Modeling the commuter behavior in this context would help in identifying the magnitude and type of effects of the aforementioned characteristics on the commute length and commuter type choice. The models developed in this study are centered on the commuter type choice and commute length.

A Multinomial Logit Model (MNL) and a Structural Equations Model (SEM) was developed. MNL model was constructed to study the influence of the different characteristics on the choice of commuter type. The SEM was constructed to measure the commute characteristics like commute time, commute distance and departure time. This chapter explains the theory related to the models developed in this study and the test-statistics used in evaluating the models. The following sections explain the theory and test-statistics related to Multinomial Logit Models and Structural Equations Models.

5.1 Theory of Multinomial Logit Models

Modeling individual decision-making behavior is fundamental to predicting aggregate (population) behavior. Classical economic consumer choice theories offer convenient paradigms for modeling such individual choice behavior. These choice theories also consider the psychological processes underlying decision-making behavior. A choice may be viewed as the result of a sequential decision-making process that includes the following steps:

- Definition of the choice
- Generation of the alternatives
- Evaluation of the attributes
- Choice
- Implementation

A decision maker would collect information on the available alternatives, and then apply a decision rule to choose an alternative for the desired activity. So, any theory is a collection of procedures that define/describes the decision maker, choice set, attributes of the alternatives and decision rule. The multinomial logit models are based on the probabilistic choice theory with random utility functions. A basic assumption in discrete choice analysis is that each alternative in the choice set of a decision maker is associated with a utility and that the decision maker chooses the alternative with the highest utility. Thus, the probability of choice i is equal to the probability that the utility of alternative i is greater than or equal to the utilities of all other alternatives in the choice set.

$P(i|C_n) = Pr\ [U_{in} \geq U_{jn}\ ,\ \text{all}\ j \ni C_n]$

Where,

i = the choice alternative,
j = other alternatives in the choice set not equal to i,
U_{in} = Utility of an individual 'n' choosing the alternative i,
U_{jn} = Utility of an individual 'n' choosing the alternative j,
C_n = choice set, consists of all the alternatives feasible to the individual. It is a subset of Universal set of alternatives represented as C, ($C_n \subseteq C$)

Utilities are not known to analyst with certainty and therefore treated as random variables. Choice probabilities are derived by assuming a joint probability distribution for the set of random utilities $\{U_{in},\ i \ni C_n\}$. The utility is assumed to consist one part observable and one part not observable by the analyst. The observable part is called the systematic part of the utility function and the unobservable part as the random or stochastic part of the utility function. The utility function is represented as:

$U_i = V_i + \varepsilon_i$

Where,

U_i = total utility of the alternative i.,

V_i = observable part, and

ε_i = unobservable part

Thus the probability of choice i is equal to,

$$P_n(i) = \Pr(U_{in} \geq U_{jn}, \forall j \in C_n, j \neq i)$$

$$= \Pr(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \forall j \in C_n, j \neq i)$$

$$= \Pr(\varepsilon_{jn} \leq V_{in} - V_{jn} + \varepsilon_{in}, \forall j \in C_n, j \neq i)$$

The unobservable part is assumed to be stochastic. This means that the alternative a decision-maker would actually choose cannot be predicted with certainty, but an assumption on the distribution of the random or stochastic part will allow one to predict the probability that it could be chosen. Thus for a population of decision-makers, the share of the population choosing each alternative may be predicted. Since there are more than two choices or alternatives, derivation of multinomial choice models get more complicated. The most convenient way to express $P_n(i)$ is to reduce the multinomial choice problem to a binary one. To do this, we note that:

$U_{in} \geq U_{jn}$, $\forall j \ni C_n$, $j \neq i$ is equivalent to

$$U_{in} \geq \max_{\substack{j \in C_n \\ j \neq i}} U_{jn}$$

In effect, we create a composite alternative out of all the elements of C_n other than i, and we use the utility of best alternative to represent the entire composite. If U_{in} exceeds the utility of the composite alternative, then i is chosen; otherwise it is not. Thus

$$P_n(i) = \Pr[V_{in} + \varepsilon_{in} \geq \max_{\substack{j \in C_n \\ j \neq i}} (V_{jn} + \varepsilon_{jn})]$$

Since U_{in} is a random variable, max U_{jn} is also a random variable. The stochastic or random part of the utility function is assumed to be independent and identically Gumbel distributed. The properties of the Gumbel distribution the yields the following form for the probability of choice i.

$$P_n(i) = \frac{e^{U_{in}}}{\sum_{j=1}^{J_n} e^{U_{jn}}}$$

Where,

$P_n(i)$ = Probability of individual n choosing alternative i,
U_{jn} = Utility derived by individual n from alternative j,
J_n = Number of available alternative choices,

The utility derived by the individual n from alternative j, may be modeled as a linear function of explanatory variables as follows:

$U_{jn} = \beta_{0j} + \beta_{1j}X_{1nj} + \beta_{2j}X_{2nj} + \ldots\ldots\ldots\ldots + \beta_{kj}X_{knj} + \varepsilon_{jn}$

Where,

β_{0j} = alternative specific constant for alternative j

$\beta_{1j}, \beta_{1j}, \beta_{2j\ldots}\beta_{kj}$ = coefficients associated with explanatory variables

$X_{1nj,}\ X_{2nj\ldots\ldots}X_{knj}$ = explanatory variables for individual n
ε_{jn} = disturbance term

k = number of explanatory variables included in the model

The β values reflect the sensitivity of the variables included in the model. The log of the denominator of the multinomial logit model equation also has useful property in that it can be interpreted as the expected maximum utility of the alternatives in the choice set.

5.2 Test Statistics for Multinomial Logit Models

Multinomial logit models may be subjected to a series of statistical tests, which are briefly described here. The first test is the log-likelihood ratio test (LLR), which is similar in purpose to the F-test used with the linear regression models, and is used to test the overall significance of the model. The LLR test is used to test the null hypothesis that the coefficients of the demographic variables in the model are collectively zero. Under the null hypothesis that all the coefficients are zero, that is, $\beta_1 = \beta_2 = \ldots = \beta_k = 0$, the statistic $-2[L(0) - L(\beta)]$ is χ^2 distributed with k degrees of freedom. More informative is to test the null hypothesis that all coefficients except for the alternative specific constants are zero. Test statistic is $-2[L(c) - L(\beta)]$with K-J df, where J is the number of alternatives in the choice set and L(**c**) is the log likelihood of a model with only constants. L(**c**) can be obtained by estimating a model with J-1 alternative specific constants or

$$L(c) = \sum_{i=1}^{J} N_i \ln\left(\frac{N_i}{N}\right)$$

Where, N_i is the number of observations selecting alternative i and N is the total sample size.
The ρ^2 is an informal goodness of fit statistic that measures the fraction of an initial log-likelihood value explained by the model.

It is defined as

$$\rho^2 = 1 - \frac{L(\hat{\beta})}{L(0)}$$

This statistic is similar to R^2 in Linear regression models. There are no general guidelines for when a ρ^2 value is sufficiently high. For the same estimation data set, the ρ^2 of a model will always increase or at least stay the same whenever new variables are added (similar to R^2 in regression). For this reason, we also use the adjusted ρ^2,

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\beta}) - K}{L(0)}$$

It should be noted that if ρ^2 increases but $\bar{\rho}^2$ decreases, then it means that the added variables do not provide sufficient explanatory power to the model to compensate for the degrees of freedom utilized by the "larger" model specification.

Another measure of goodness of fit is "percent predicted correctly" defined as

$$(100/N) \cdot \sum_n \hat{y}_n$$

Where,

$\hat{y}_n$ is 1 if the highest predicted probability corresponds to the chosen alternative and 0 otherwise. This should be used with considerable caution.

The test statistics discussed above may be applied for overall model. The conventional t-statistic is used to test the significance of the coefficient of any given variable (as in linear regression model). The t-statistic is used to test whether β_i is equal to a certain value, say c (c = 0 in this case). That is, we are interested in testing whether the population value of the coefficient, β_i, equals c

H_0: $\beta_i = c$

Then, the statistic is:

$$t = \frac{\hat{\beta}_i - c}{s\sqrt{c_{ii}}}$$

has a t-distribution with degrees of freedom [n-(p+1)] where n is the sample size and p is the number of explanatory variables included in the model. If the t-statistic has an extreme value, which will occur with only a small probability (say, 0.05), then we reject the null hypothesis and conclude that the population value of β_i does not equal c. If this is true, it implies that variable X_i does not influence the utility function. In this case, the test statistic becomes:

$$t = \frac{\hat{\beta}_i}{s\sqrt{c_{ii}}}$$

5.3 Theory of Structural Equations Models

A typical structural equations model (with 'G' number of endogenous variables) is defined by a matrix equation system as shown in Equation 5.1.

$$\begin{bmatrix} Y_1 \\ . \\ . \\ . \\ Y_G \end{bmatrix} = \begin{bmatrix} Y & X \end{bmatrix} \begin{bmatrix} B \\ \Gamma \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ . \\ . \\ . \\ \varepsilon_G \end{bmatrix} \tag{5.1}$$

This equation can be rewritten as

$$Y = BY + \Gamma X + \varepsilon \tag{5.2}$$

(or) $$Y = (I - B)^{-1}(\Gamma X + \varepsilon) \tag{5.3}$$

where Y is a column vector of endogenous variables,
B is a matrix of parameters associated with right-hand-side endogenous variables,
X is a column vector of exogenous variables,
Γ is a matrix of parameters associated with exogenous variables, and
ε is a column vector of error terms associated with the endogenous variables.

Structural equations systems are estimated by covariances-based structural analysis, also called method of moments. In this approach of estimation, instead of minimizing sum of squared differences of observed and predicted individual values, the difference between the sample covariances and the covariances predicted by the model is minimized. The observed covariances minus the predicted covariances form the residuals. The fundamental hypothesis for the covariances-based estimation procedures is that the covariance matrix of the observed variables is a function of a set of parameters as shown in Equation 4:

$$\Sigma = \Sigma(\theta) \tag{5.4}$$

where Σ is the population covariance matrix of observed variables,
θ is a vector that contains the model parameters, and
$\Sigma(\theta)$ is the covariance matrix written as a function of θ.

Equation 5.4 implies that each element of the covariance matrix is a function of one or more model parameters. The relation of Σ to $\Sigma(\theta)$ is basic to an understanding of identification, estimation, and assessments of model fit. The matrix $\Sigma(\theta)$ has three components:

(a) the covariance matrix of Y,
(b) the covariance matrix of X with Y, and
(c) the covariance matrix of X.

Considering first $\Sigma_{YY}(\theta)$, the implied covariance matrix of Y can be derived as:

$$
\begin{aligned}
\Sigma_{YY}(\theta) &= E(YY') \\
&= E[(I-B)^{-1}(\Gamma X+\varepsilon)((I-B)^{-1}(\Gamma X+\varepsilon))'] \\
&= (I-B)^{-1}(E(\Gamma XX'\Gamma')+E(\Gamma X\varepsilon')+E(\varepsilon X'\Gamma')+E(\varepsilon\varepsilon'))(I-B)^{-1'} \\
&= (I-B)^{-1}(\Gamma\Phi\Gamma'+\Psi)(I-B)^{-1'} \qquad (5.5)
\end{aligned}
$$

where Φ = covariance matrix of X, and
Ψ = covariance matrix of ε.

The implied covariance matrix of X, $\Sigma_{XX}(\theta)$, is equal to Φ, or

$$
\begin{aligned}
\Sigma_{XX}(\theta) &= E(XX') \\
&= \Phi \qquad (5.6)
\end{aligned}
$$

The final part of the implied covariance matrix is $\Sigma_{XY}(\theta)$, the implied covariance of X with Y:

$$
\begin{aligned}
\Sigma_{XY}(\theta) &= E(XY') \\
&= E[X((I-B)^{-1}(\Gamma X+\varepsilon))'] \\
&= \Phi\Gamma'(I-B)^{-1'} \qquad (5.7)
\end{aligned}
$$

Now, assembling Equations 5.5 through 5.7, the implied covariance matrix of Y and X is

$$
\Sigma(\theta)=\begin{bmatrix} (I-B)^{-1}(\Gamma\Phi\Gamma'+\Psi)(I-B)^{-1'} & (I-B)^{-1}\Gamma\Phi \\ \Phi\Gamma'(I-B)^{-1'} & \Phi \end{bmatrix} \qquad (5.8)
$$

Before estimating model parameters, it is first necessary to ensure that the model is identified. Model identification in simultaneous structural equations systems is concerned with the ability to obtain unique estimates of the structural parameters. The identification problem can be resolved if travel behavior theory can be used to place restrictions on the set of simultaneous structural equations. These restrictions may take a variety of forms such as the use of extraneous estimates of parameters, knowledge of exact relationships among parameters, knowledge of the relative variances of

disturbances, and knowledge of zero correlation between disturbances in different equations. The restrictions usually employed are zero restrictions that take the form of specifying certain structural parameters to zero, i.e., certain endogenous variables and certain exogenous variables do not appear in certain equations. It has been shown that in the case of zero restrictions on structural parameters, each equation can be checked for identification by using either the rank condition or the order condition. If an equation is identified, it may be either 'exactly-identified' or 'over-identified'. An equation is 'exactly-identified' if the number of identifying restrictions placed on the model is the minimum needed to identify the equation, and an equation is over-identified if there are some additional restrictions beyond the minimum necessary to identify the equation.
In order to check for identification of a structural model, the commonly used identification rules are t-Rule, Null B Rule, and Recursive Rule. The t-Rule, the Null B Rule, and Recursive Rule are conditions for the identification of the model as a whole. The first is only a necessary condition, but the second and third are sufficient conditions. The t-Rule is the most general rule and applies to all of the models, whereas the Null B Rule is appropriate only when B=0, regardless of the form of Ψ. The recursive rule is appropriate for models with triangular B matrices and diagonal Ψ matrices. Finally, the rank and order conditions establish the identification status of equations. If each equation meets the rank rule, then the model as a whole is identified. Both, rank and order conditions allow any nonsingular (I-B) matrix and assume no restrictions for the Ψ matrix. A detailed discussion on checks for identification for structural equations models may be found in Bollen *(1989)*. A summary is shown in the table below.

Table 5.1 Identification Rules for Structural Equations with Observed Variables Assuming No Measurement Error ($\mathbf{y = By + \Gamma x + \zeta}$)

Identification Rule	Evaluates	Requirements	Necessary Condition	Sufficient Condition
t-Rule	Model	$t \leq (½)\ (p+q)(p+q+1)$	Yes	No
Null B Rule	Model	B=0	No	Yes
Recursive Rule	Model	B triangular Ψ diagonal	No	Yes
Order Condition	Equation	Restrictions $\geq (p - 1)$ Ψ free	Yes	No
Rank Condition	Equation	Rank $(C_i) = p - 1$ Ψ free	Yes	Yes

p = number of endogenous variables; q = number of exogenous variables
t = number of unknown parameters in θ
For definition of C_i, see notes on identification in simultaneous equation systems (under rank condition)

The unknown parameters in B, Γ, Φ, and Ψ are estimated so that the implied covariance matrix, $\hat{\Sigma}$, is as close as possible to the sample covariance matrix S. In order to achieve this, a fitting function $F(S, \Sigma(\theta))$ which is to be minimized is defined. The fitting function will have the following properties:

- $F(S, \Sigma(\theta))$ is a scalar;
- $F(S, \Sigma(\theta)) \geq 0$;
- $F(S, \Sigma(\theta)) = 0$ if and only if $\Sigma(\theta) = S$, and
- $F(S, \Sigma(\theta))$ is continuous in S and $\Sigma(\theta)$.

Available methods for parameter estimation include maximum likelihood (ML), unweighted least squares (ULS), generalized least squares (GLS), scale free least squares (SLS), and asymptotically distribution-free (ADF). Each of these methods minimizes the fitting function and leads to consistent estimators of θ. Among these methods, the two most widely used estimation techniques are maximum likelihood (ML) and asymptotically distribution-free (ADF).

The ML method of estimation is most appropriate when all of the endogenous variables included in the model system are continuous variables. The fitting function that is minimized in the ML method of estimation of structural parameters is shown in Equation 5.9

$$F_{ML} = \log | \Sigma(\theta) | + \mathrm{tr}\,(S\, \Sigma^{-1} (\theta)) - \log | S | - (G + K) \tag{5.9}$$

where G = Number of excluded endogenous variables on RHS of the model, and
K = Number of included exogenous variables on RHS of the model.

The asymptotic covariance matrix for the ML estimator $\hat{\theta}$ is given by,

$$\left(\frac{2}{N-1}\right)\left\{E\left[\frac{\partial^2 F_{ML}}{\partial\theta\partial\theta'}\right]\right\}^{-1} \tag{5.10}$$

When $\hat{\theta}$ is substituted for θ, we have an estimated asymptotic covariance matrix that allows tests of statistical significance on parameters of $\hat{\theta}$.

The ML estimator provides a test of overall model fit for overidentified models. The asymptotic distribution of (N-1) F_{ML} is a χ^2 distribution with $(½)(p+q)(p+q+1) - t$ degrees of freedom, where t is the number of free parameters and F_{ML} is the value of the fitting function evaluated at the final estimates. The null hypothesis of the chi-square test is H_0: $\Sigma = \Sigma(\theta)$. This implies that the overidentifying restrictions for the model are correct. Rejection of H_0 suggests that at least one restriction is in error so that $\Sigma \neq \Sigma(\theta)$. In general, the suitability of the chi-square test depends on having a sufficiently large sample, on the multinormality of the observed variables, and on the validity of $\Sigma = \Sigma(\theta)$.

5.4 Test Statistics for Structural Equations Models

The chi-square test of overall model fit is called the discrepancy in the model. The null hypothesis under test is that the model fits the data, so one hopes to find a small, non-significant chi-square value for this test. This chi-square value is verified along with the degrees of freedom. 'Degrees of freedom' is the difference between the number of distinct sample moments and number of distinct parameters to be estimated. The probability value tells us that the chi-square value obtained would be that large or larger with that chance if the null hypothesis that the model fits the data were true. If the probability value of the chi-square test is smaller than 0.05 level used by convention, one has to reject the null hypothesis that the model fits the data.

Some descriptive statistics are RMR, GFI and AGFI, PGFI and RMSEA. The RMR is the root mean square residual. RMR is the square root of the mean squared amount by which the sample variances and covariances differ from the corresponding estimated variances and covariances, estimated on the assumption that your model is correct. The smaller the RMR, the better the fit.

GFI is the Goodness of Fit Index. GFI varies from 0 to 1, but theoretically can yield meaningless negative values. By convention, GFI should by equal to or greater than .90 to accept the model. By this criterion the present model is accepted.

AGFI is the Adjusted Goodness of Fit Index. AGFI is a variant of GFI, which uses mean squares instead of total sums of squares in the numerator and denominator of 1 - GFI. It, too, varies from 0 to 1, but theoretically can yield meaningless negative values. AGFI should also be at least .90. By this criterion the present model is accepted.

PGFI is the Parsimony Goodness of Fit Index. It is a variant of GFI, which penalizes GFI by multiplying it times the ratio formed by the degrees of freedom in your model and degrees of freedom in the independence model.

RMSEA is the root mean square error of approximation, which incorporates the discrepancy function criterion (comparing observed and predicted covariance matrices) and the parsimony criterion. By convention, there is good model fit if RMSEA less than or equal to .05. There is adequate fit if RMSEA is less than or equal to .08.

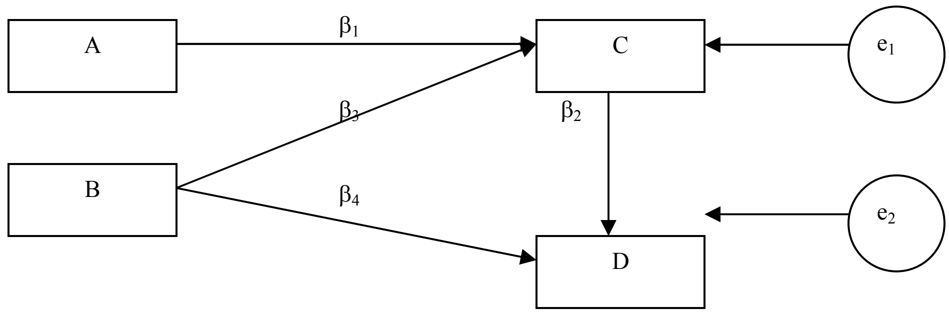
Other descriptive fit statistic to assess the overall fit a model to the data is comparative fit index (CFI). CFI compares the absolute fit of the specified model to the absolute fit of the Independence model. The "independence model" is the model in which variables are assumed to be uncorrelated with the dependent(s), so if the fit for "your model" is no better than for the "independence model," then the specified model should certainly be rejected. The greater the discrepancy between the overall fit of the two models, the larger the values of the descriptive statistic. CFI varies from 0 to 1. CFI close to 1 indicates a very good fit, and values above .90 an acceptable fit. There are many other fit measures.

Each researcher has his or her favorite collection of fit statistics to report. The important fit measures considered are chi-square for a certain degrees of freedom and probability value, CFI and RMSEA.

After the model has been evaluated for its goodness-of-fit, one would be interested in knowing the effect of explanatory variables on endogenous variables and more importantly the effects of endogenous variables on other endogenous variables. There are two types of effects, direct and indirect effects. A direct effect is one where a variable directly affects another variable as depicted by a direct arrow linking the two variables in the path diagram. On the other hand, an indirect effect is one where a variable influences another variable through a mediating variable. The sum of direct and indirect effect is called the total effect. From the figure 5.1, A and B are the exogenous variables and C and D are endogenous variables. The e_1 and e_2 are the disturbances associated with C and D respectively. $\beta_{1,}$ β_2, β_3 and β_4 are coefficients associated with the relation A and C, C and D, B and C, and B and D.

The direct effect is the effect of A on C, C on D, B on C, B on D. Indirect effect is the effect of A on D through D. It is important to note that A does not affect D directly but A influences D through C.

Figure 5.1 Direct and Indirect Effects



The direct effect of A on C is β_1

The indirect effect of A on D is given by $\beta_1 * \beta_2$

Similarly,
The direct effect of B on D is β_4

The indirect effect of B on D is $\beta_3 * \beta_2$

The total effect of B on D is the sum of direct and indirect effects = $\beta_4 + \beta_3 * \beta_2$

CHAPTER 6

MODEL ESTIMATION RESULTS

6.1 Commuter Type Choice Model

A Multinomial Logit Model was developed to analyze the influence of individual, household and area related characteristics on the commuter type choice. Multinomial Logit Model was developed using both the NHTS 2001 data set and ACS 2000 data set. In both the models, the utility function of medium commuter type has been set to zero as the base alternative. The utility functions for short and long commuters were first defined by including all possible best combination of characteristics available in the corresponding datasets were included. The variables were tested for their significance at 95% level of confidence by running the models in LIMDEP 3.0 (An Econometric Modeling Software Tool). All the significant variables were retained and the model was tested for good-of-fit using standard test-statistics. The Table 6.1 and Table 6.2 show the results of MNL using the NHTS 2001 and ACS 2000 datasets respectively.

These models are estimated to determine potentially the maximum extent to which the demographic variables can explain the commuter type choice. In these models, typical individual characteristics like gender, age, race, income, education, driver and the household characteristics like household size, driver count, household income, number of children, property value and finally the area related characteristics like size of the area and urban area type are found to be significant at 95% level of confidence. All the coefficients in the model have the expected signs.

The constants in the MNL model shown in Table 6.1 shows that there is general tendency for a commuter to be a short commuter. The gender variable (dummy =1 for male, 0 or else) shows a negative coefficient for short commuter utility function (SCUF) and positive for long commuter utility function (LCUF) indicating that females generally prefer to be short commuters or males have more tendency to be long commuters. The age variable shows a positive coefficient in SCUF indicating that as age increases the commuters tend to be short commuters. The dummy variable for middle age shows a negative coefficient in SCUF indicating that middle-aged commuters have more likely to be long commuters. The dummy variable for White American race group shows coefficient that is positively associated with short commuting and negatively associated with long commuting. The coefficient of education variable in SCUF is negatively associated and shows that highly educated people have tendency to be long commuters. The coefficient of the dummy variable for driver status (driver = 1,0 or else) is negatively associated with both the SCUF and LCUF and shows that drivers are more likely to be short commuters than long commuters. The coefficient of the dummy variable representing the managerial or professional type of occupation in LCUF is positively associated with long commuting.

The first of household characteristic, the household size variable shows that its coefficient is negatively associated with SCUF indicating that as the household size increases the chances of being a short commuter decreases. The coefficient of driver count variable is positively associated with SCUF indicating that as the number of drivers in the household increases their chances of being a short commuter increases. The low household income coefficient is positively associated with SCUF and the high household income coefficient is negatively associated with SCUF. Indicating that low household income increases the tendency of an individual to be a long commuter. Also the high household income coefficient in LCUF is positively associated. The coefficient for number of children in the household is positively associated with SCUF indicating that presence of children restricts the individual to be a short commuter.

The area related characteristic, dummy for size of population of an area greater or equal to 3 million has a coefficient that is positively associated with LCUF. The dummy variable urban cluster and urban center has a coefficient that is negatively associated with LCUF.

The MNL model using ACS 2000 data also revealed the similar kind of results. There are some interesting variables in this model. The coefficient of personal income variable is negatively associated with SCUF. The coefficient for the dummy variable for low personal income also reveals the same meaning. The coefficient for dummy for the duration of residence at a place for 10 years or more is positively associated with SCUF indirectly indicating that, as the commuting falls short the duration of status is as high as 10 years.

The log-likelihood value at convergence for the MNL model using NHTS 2001 dataset is $[L(\beta)] = -19938.7$. Therefore, the test statistics is $-2[L(c) - L(\beta)]$ = 1503.41 with 21 degrees of freedom. The critical (0.05 level) value of χ^2 with 21 degrees of freedom is 32.67. The log-likelihood value at convergence for the MNL model using ACS 2000 dataset is $[L(\beta)] = -21299.9$. Therefore, the test statistics is $-2[L(c) - L(\beta)]$ = 1208.2 with 21 degrees of freedom. The critical (0.05 level) value of χ^2 with 21 degrees of freedom is 32.67. Thus, the hypothesis that the coefficients of the individual, household and area related characteristics considered are zero is rejected. This confirms the importance of demographic variables in explaining the commuter type choice behavior.

The adjusted likelihood ratio index $\bar{\rho}^2$ is 0.03586 for NHTS 2001 and 0.027 for ACS 2000. The values are low but this goodness-of-fit measure does not have the real statistical interpretation (R^2 in regression does have a statistical interpretation). The low value could be because of hidden effects of area related characteristics like urban growth, structure, congestion and the transportation facilities. The hidden effects could also be due to the interrelationships that exist between mode-choice and commute type choice. This study merits particular attention. This is included in the further study in the research.

Table 6.1 Commuter Type Choice Model (NHTS)

Variable	Variable Type	Short Commuters		Long Commuters	
		β-Coeff	t-stat	β-Coeff	t-stat
Constant		0.3708	3.214	-1.905	-12.277
Male	(= 1 if male, 0 else)	-0.1501	-5.335	0.4375	7.084
Age	Continuous	0.0019	1.695	-	-
Middle Age	(=1 if age 25-64, 0 else)	-0.4387	-10.526	-	-
White	(=1 if race is white, 0 else)	0.1244	3.352	-0.1373	-1.918
Well educated	(=1 if more than bachelors, 0 else)	-0.1182	-3.781	-	-
Driver status	(=1 if driver, 0 else)	-0.2089	-2.333	-0.774	-5.749
Personal income	Continuous	-	-	-	-
Low personal income	(=1 if income < 20,000; 0 else)	-	-	-	-
High personal income	(=1 if income >= 75,000, 0 else)	-	-	-	-
Managerial/Professional Occupation	(=1 if such occupation, 0 else)	-0.2398	-7.998	0.2891	4.374
Household size	Continuous	-0.1038	-3.261	-	-
Household income	Continuous	-	-	-	-
Low household income	(=1 if income <15,000, 0 else)	0.2077	3.241	-	-
High household income	(=1 if income >=75,000, 0 else)	-0.1491	-3.725	0.1293	1.781
Number of children	Continuous	0.1392	4.343	-	-
Number of workers	Continuous				
Number of drivers	Continuous	0.1399	4.517	-	-
High Property value	(=1 if value >= 150,000, 0 else)	-	-	-	-
Duration of stay for 10 years or more	(=1 if stay >=10 years, 0 else)	-	-	-	-
Area type	(=1 if urban area/cluster, 0 else)	0.4672	13.984	-0.3311	-4.607
Area population greater than or equal to 3 million	(=1 if size is >= 3 million, 0 else)	-0.5198	-16.471	0.9112	14.221

Note: Medium Commuter is the base alternative

$[L(0)] = -26070.0$

$[L(\beta)] = -19938.7$

$[L(c)] = -20690.0$

$\chi^2 = 1503.4$; $\bar{\rho}^2 = 0.036$

Note: Medium Commuter is the base alternative
$\left[L(0)\right] = -26732.5$
$\left[L(\beta)\right] = -21299.9$
$\left[L(c)\right] = -21904.0$
χ^2 = -1208.2; $\overline{\rho}^2$ = 0.027

The $\overline{\rho}^2$ is low because of unobserved effects due to the missing variables related to network level of service variables, urban structure and job opportunities.

Table 6.2 Commuter Type Choice Model (ACS)

Variable	Variable Type	Short Commuters		Long Commuters	
		β-Coeff	t-stat	β-Coeff	t-stat
Constant		-0.274	-2.768	-1.70	-9.808
Male	(= 1 if male, 0 else)	-0.143	-4.869	0.39	6.776
Age	Continuous	0.006	4.539	-0.01	-2.12
Middle Age	(=1 if age 25-64, 0 else)	-0.259	-6.002	-	-
White	(=1 if race is white, 0 else)	0.297	7.3	-0.21	-2.963
Well educated	(=1 if more than bachelors, 0 else)	-	-	-	-
Driver status	(=1 if driver, 0 else)	-	-	-	-
Personal income	Continuous	0.000	-4.61	-	-
Low personal income	(=1 if income <= 20,000, 0 else)	0.466	12.747	-0.18	-2.403
High personal income	(=1 if income >= 75,000, 0 else)	-	-	0.51	7.505
Managerial/Professional Occupation	(=1 if such occupation, 0 else)	-	-	-	-
Household size	Continuous	-0.130	-6.54	0.11	3.291
Household income	Continuous	0.000	4.627	-	-
Low household income	(=1 if income <15,000, 0 else)	-	-	-	-
High household income	(=1 if income >=75,000, 0 else)	-0.134	-3.767	-	-
Number of children	Continuous	0.163	7.167	-0.08	-2.037
Number of workers	Continuous	0.117	4.409	-0.18	-4.047
Number of drivers	Continuous	-	-	-	-
High Property value	(=1 if value >= 150,000, 0 else)	-0.240	-8.029	-	-
Duration of stay for 10 years or more	(=1 if stay >=10 years, 0 else)	0.171	5.992	-	-
Area type	(=1 if urban area/cluster, 0 else)	-	-	-	-
Area population greater than or equal to 3 million	(=1 if size is >= 3 million, 0 else)	-	-	-	-

Note: Medium Commuter is the base alternative

$[L(0)] = -26732.5$

$[L(\beta)] = -21299.9$

$[L(c)] = -21904.0$

$\chi^2 = -1208.2; \bar{\rho}^2 = 0.027$

6.2 Model of Commute Length

The results of the SEM model of commute length are shown in Table 6.3. The discrepancy is 26.075 and the probability is 0.053 with 16 degrees of freedom. The Path diagram for the constructed model is shown in Figure 6.1. The model shows that the individual characteristics like gender, middle age, driver status, managerial or professional occupation and household characteristics like number of children, high household income and area related characteristics like MSA population of over 3 million and urban area or urban cluster are significant. All the signs of the variables in the model are as expected.

The variables gender, middle age, managerial and professional occupation, and high household income, MSA with population of over 3 million and urban area or urban cluster are dummy variables and number of children is continuous variable. The gender has positive influence on distance this indicates that males have tendency to travel long distances for jobs than females. The model shows that middle-aged people generally travel long distances than other age groups. The people working in managerial and professional occupational are also travel long commutes. The model shows that individuals living inside the urban area type or urban cluster have shorter commutes when all other characteristics are equal.

The model shows that middle age, MSAs with population 3 million or more and urban areas or urban clusters have positive influence on individual’s commute time. The commute distance has positive influence on commute time, which is expected. The model shows that number of children tends to decrease an individual’s commute time.

Table 6.3 Structural Equations Model for Commute Length

	Intercept	Effects	Male	Middle Aged	Driver Status	Managerial/ Professional Occupation	Number of Children	Household Income >= 75k	Urban Area/Cluster	MSA Size 3 million	Commute distance
Commute Distance	2.924	Total	0.189	0.393	0.000	0.351	0.000	0.311	-0.749	0.483	0.000
		Direct	0.189	0.393	0.000	0.351	0.000	0.311	-0.749	0.483	0.000
		Indirect	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Commute Time	2.050	Total	0.167	0.503	-0.869	0.310	-0.049	0.274	-0.398	0.741	0.000
		Direct	0.000	0.156	-0.869	0.000	-0.049	0.000	0.263	0.315	0.881
		Indirect	0.167	0.347	0.000	0.310	0.000	0.274	-0.661	0.426	0.000

Chi-square: (χ^2) = 26.075

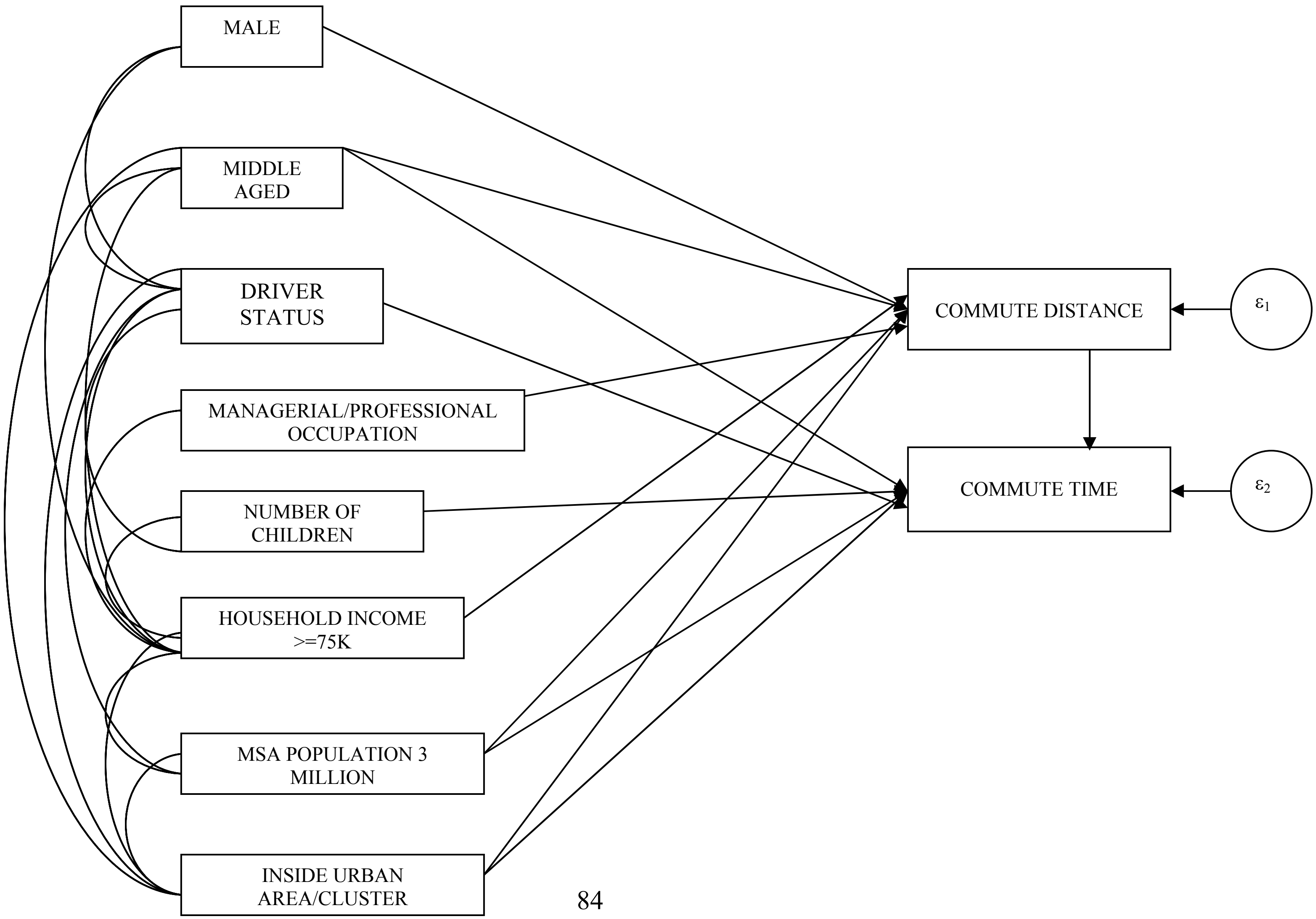
Degrees of Freedom: (df) = 16

Probability Value: (P) = 0.053

Comparative Fit Index: (CFI) = 1.000

Root Mean Square Error of Approximation: RMSEA = 0.0016

Figure 6.1 Structural Equations Model of Commute Length



CHAPTER 7

CONCLUSIONS AND FURTHER RESEARCH

7.1 Conclusions

The individual, household, trip and area related characteristics of short, medium and long commuters are discussed and models were developed to measure the commute time and propensity for a commuter type. The descriptive analysis using NHTS 2001 and ACS 2000 revealed that the characteristics of short and long commuters are different in nature. The descriptive analysis of data provides better understanding about the variation in the aforementioned characteristics influencing the commuting pattern. The influences of these characteristics are examined in detail for each of the commuter types. The analysis provides better understanding about the behavioral nature of the commuters in making short and long trips to work. This information can be used to formulate adequate commuter type choice models.

The commuter type choice models developed based on probabilistic theory with random utility function provides a way in order to develop choice models for commute type. The commuter type choice models developed using the NHTS 2001 and ACS 2000 have expected signs for all the coefficients. The models confirmed the importance of demographic variables in explaining the commuter type choice behavior. The commute length measurement model developed using the structural equations framework captures the simultaneous effect of the demographic characteristics on commute distance and time.

The models reveal that demographic characteristics should be included in explaining the commuter type choice behavior and commute length that in way reflects the choice for residential and workplace location. There are some deficiencies in the models that can be attributed to the limitation of the datasets.

This study provides analysis for policy makers who are concerned about the job accessibility and mobility options of the poor. Alan E. Pisarski had done a lot of research in this direction. In his studies on commuting to work, he focused on transportation's role in providing mobility options, policy impacts on poor, impacts of urban sprawl on inter city travel, and impacts of congestion on commute time. His studies include public policy planning, travel behavior planning and statistical analysis. Our study provided in-depth analysis of different commuter types. This study can be used for policy planning in the direction of providing mobility options for the poor as it provides insights into whether an individual of particular type is because of his own preference or other external constraints.

7.2 Further Research

The analysis of trip characteristics of short, medium and long commuters revealed interesting trends about trip rates and travel time expenditures. Study of trip chaining behavior, travel time expenditure, activity durations and vehicle utilization patterns of short and long commuters would be an interesting area to explore. More research is needed to find the direction of the relationship between commuter type choice and mode choice of an individual. Models that consider combined choice of commuter type and mode choice would capture:

- The effects of demographic characteristics on commuter type choice and mode choice simultaneously.
- The influence of mode on the residential location choice, which is reflected in commuter type choice or the commute time.

For this type of research to be done the data has to be available regarding the availability of public transit (NHTS 2001 provides information of availability of only rail transit to a household). However, even if the data is available the mode choice modeling considers only those who have access to both auto and transit and this will exclude the zero-vehicle households as a result the low-income people may not be considered for the study. In this the case the research would not be useful for policy planning in the direction of transportation equity.

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