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An Analysis of Household Vehicle Ownership and Utilization Patterns in the United States Using the 2001 National Household Travel Survey

Abdul Rawoof Pinjari
University of South Florida

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by

Abdul Rawoof Pinjari

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Major Professor: Ram M. Pendyala, Ph.D.
Steven E. Polzin, Ph.D., P.E.
Jian J. Lu, Ph.D., P.E.

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AN ANALYSIS OF HOUSEHOLD VEHICLE OWNERSHIP AND UTILIZATION PATTERNS IN THE UNITED STATES USING THE 2001 NATIONAL HOUSEHOLD TRAVEL SURVEY

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ABSTRACT

Vehicle ownership and utilization have a profound influence on activity-travel patterns of individuals, vehicle emissions, fuel consumption, highway capacity, congestion and traffic safety. The influence could be further skewed by the diversity of the vehicle fleet. This thesis presents a detailed analysis of the 2001 National Household Travel Survey data to understand the vehicle ownership patterns, fleet mix, allocation and utilization in the context of household and person socio-demographic characteristics. Along with a rich descriptive analysis, models of vehicle ownership and utilization are estimated to distinguish four vehicle types; cars, SUVs (sport utility vehicles), vans and pickup trucks based on their ownership by households and utilization patterns by household members. The primary driver level vehicle utilization analysis provides insights into the extent of allocation of a vehicle to a single person. In addition to confirming many perceptions about the ownership, acquisition and utilization patterns of different types of vehicles, this analysis brings out some subtle differences and similarities among the vehicle types. The analysis results indicate a greater propensity to acquire and use larger vehicles such as minivans, sports utility vehicles and pickup trucks among certain socio-demographic segments of population. Increased ownership and use of vans and SUVs, and their usage as personal vehicles rather than just work vehicles warrants a need to revise vehicle type specific policies, transportation planning and control measures.

CHAPTER 1
INTRODUCTION

1.1 Background

Household vehicle ownership and utilization is an important facet of revealed travel behavior. Over the past few decades, vehicle ownership levels and vehicle utilization levels have consistently grown both on a macroscopic (population) and a microscopic (individual) level. Increasing levels of complexity in people's activity and trip chaining patterns have also contributed to changes in vehicle ownership and utilization patterns. In addition, new vehicle technology and design has made it possible for people to own and use different types of vehicles including cars, vans, sport utility vehicles (SUV), trucks, and so on.

However, cars have continued to lose their market share of private vehicles; the share of cars has gone down from 80 percent in 1977 to 65 percent in 1995. In the meantime, minivans and sport utility vehicles (SUVs) claimed a larger market share. (Hu, et. al. 1999). The percentage of cars present in today's fleet is about 60 while minivans, SUVs and pickup trucks have grown in the market share to about 39 percent. The NHTS data indicates that out of all the household vehicles that were acquired in the past one-year (with respect to the NHTS survey time of April 2001 through May 2002) 55.5 percent were cars, 9 percent vans, 14.8 percent SUVs and 16.6 percent were pickup trucks. Percentage of cars of the remaining vehicles in the fleet is 58.2 indicating that cars are losing their market share to light duty vehicles.

Industry sales data also shows an increase in the light duty vehicles (vans, SUVs, pickup trucks). 1999 data of Polk Company indicates that Light Duty Trucks capture 51 percent of new passenger vehicle sales (kockelman, et. al. 2000). Between 1975 and 2003, market share for new passenger cars decreased from 81 to 52 percent. Growth in the light truck market has been led recently by the increase in the market share of SUVs. The SUV market share increased by more than a factor of ten, from less than two percent of the overall new light vehicle market in 1975 to 24 percent of the market in 2003. Over the same period, the market share for vans increased by 80 percent, while that for pickups remained relatively constant. (Hellman, et. al. 2000). These trends, showing an increasing share of vans, SUVs and pickup trucks may have several implications to transportation planning, policy and perhaps regulatory action from the perspective of fuel economy, emission standards and transportation safety.

1.2 Motivation

Increasing vehicle ownership and utilization can influence the transportation system in terms of its performance and the externalities it could cause to environment and community. The diversity in the vehicle fleet can skew this influence. In addition, the differences in ownership and utilization of different vehicles can further influence these effects. The increased ownership and use of different types of vehicles like vans, SUVs and pickup trucks can have several implications to energy consumption, fuel economy, emission levels, highway capacity and safety. These vehicles consume more fuel per mile than ordinary automobiles. They are huge and occupy more roadway and parking space, but are still measured equivalent to cars in capacity considerations. Accident frequencies and injury severity could substantially differ across different types of vehicles (Chang, et. al. 1999, Ulfarsson, et. al. 2004, Kockelman, et. al. 2002). Most of these differences across different types of vehicles have several important implications to transportation planning and policy in the context of fuel economy and energy use, vehicle emissions, traffic congestion, and safety. Light Duty Truck classification protects SUVs, pickup trucks and vans from various stringent regulations. Pickup trucks were owned and used primarily for work purposes and blue collared jobs. The perceived difficulty of these vehicles in meeting the stringent emission standards was the reason behind their classification as LDTs (Light Duty Trucks). Minivans and SUVs were also classified as LDTs, based on structural similarities, along with pickup trucks. These vehicles enjoy a variety of regulatory protections like higher emission caps and do not endure luxury-goods or gas-guzzler taxes. (Kockelman, et. al. 2000). All of these factors entail a closer look at the ownership and utilization patterns of these vehicle types. An in-depth analysis is required to assess the differences in ownership and utilization patterns of different types of vehicles. It is also important to understand the demography of current vehicle fleet. In other words, we have to take stock of the current diversity of vehicle fleet.

Households own different types of vehicles to utilize them for daily travel. The travel needs of a household depend upon its socio-demographic characteristics. Hence it is the socio-demographics of a household that shape its vehicle ownership type and level. So it is important to understand the isolated effect of each of the socio-demographic factor on household vehicle ownership and utilization patterns. To state succinctly, it is necessary to understand 'who owns, what types of vehicles, why, and who drives, what types of vehicles, for going where, and for what purposes. Essentially, it is important to analyze and distinguish different types of vehicles (cars, vans, SUVs and pickup trucks) based on their ownership utilization patterns in the context of socio-demographic attributes of households that own them and persons that drive them.

1.3 Objectives of the Thesis

As vehicle ownership and utilization by vehicle type is of much interest to transportation planners and policy makers, this thesis aims to provide a rather detailed analysis of vehicle ownership, fleet mix and utilization patterns of different vehicle types in the United States, using the data recently available from the 2001 National Household Travel Survey (NHTS). An extensive analysis is provided in the context of socio-demographic attributes to distinguish the four vehicle types; cars, vans, SUVs and pickup trucks, based on their ownership patterns, trends in recent acquisitions, allocation and utilization patterns. While it would certainly be interesting to study vehicle ownership and utilization patterns over time using a series of nationwide personal transportation survey (NPTS) data sets, it was considered beyond the scope of this thesis which is aimed at taking stock of the current situation. A longitudinal analysis of vehicle ownership and utilization should undoubtedly be undertaken and that remains as a subsequent research effort. This study considers cars, SUVs, vans and pickup trucks as the major vehicle types.

The objectives of the study are briefly listed below:

- To carry out a detailed descriptive analysis of the 2001 NHTS data in order to distinguish cars, vans, SUVs and pickup trucks based on their ownership patterns in terms of market share, age and length of ownership and recent vehicle acquisitions.
- To perform a detailed descriptive analysis of the 2001 NHTS data in order to distinguish cars, vans, SUVs and pickup trucks based on their utilization patterns in terms of annual mileage, daily travel, weekday-weekend differences, trip characteristics (trip purpose, occupancy, trip length etc.) and allocation to primary drivers.
- To understand the structural relationships between socio-demographic factors and vehicle ownership and utilization patterns in a unified framework. (A joint structural equations model of household vehicle ownership and utilization is developed in this context, which can enable the isolation of each socio-demographic factor in a simultaneous and multivariate framework.)
- To understand the vehicle type choice behavior in recent vehicle acquisitions. (A multinomial logit model for the recently owned vehicle type is developed to understand the differences in choice making and preferences across vehicle types in the recent vehicle acquisitions.)
- To analyze the vehicle type choice behavior in trip making. (A multinomial logit model for the vehicle type chosen by a driver for his/her trip is developed in order to understand the vehicle utilization patterns.)

1.4 Organization of the Thesis

The rest of this thesis is organized as follows. Next chapter provides an extensive review of the literature available, highlighting the importance of the topic. Various research efforts in the direction of distinguishing different vehicle types and several important modeling efforts of vehicle ownership and utilization are reviewed. The third chapter describes the 2001 NHTS data and provides a detailed description of the data preparation process for further analysis. The fourth chapter presents the results of an extensive descriptive analysis of vehicle ownership, utilization and allocation patterns. The fifth chapter furnishes details of the methodology of the modeling frameworks used in the study. Sixth chapter focuses on the models of vehicle ownership, utilization, and choice behavior. It includes a structural equations model for vehicle ownership and utilization in a unified framework, a multinomial logit model of a household's choice of the type of recently acquired vehicle and a multinomial logit model of driver's vehicle type choice for his/her trip. Finally, conclusions and implications of the findings for policy measures and planning practice are discussed in final chapter (7) of the thesis along with further extensions of the topic for future research.

CHAPTER 2
LITERATURE REVIEW

2.1 Importance of Vehicle Ownership and Utilization

Vehicle ownership and utilization has been the subject of substantial amount of research in the past. As these concepts are central to transportation planning and decision-making, researchers and data analysts have spent considerable time and attention to these issues. Vehicle ownership and availability are the key determinants of mode choice. Pucher, et. al. (2003) showed how even a single car owned would affect the travel behavior of a household. Considering the share of transit, Polzin, et. al. (2003) found a drop from 19.1 percentage of total trips by households with no car to only 2.75 percentage of trips by households with one car. Vehicle ownership and utilization patterns can have profound impact on the disaggregate travel characteristics and thus on the over all travel demand. Liss, et. al. (2003) analyzed the 2001 NPTS/NHTS data and found that the annual miles for each individual vehicle declined slightly as the vehicle travel by household members is spread over more vehicles but after controlling for income, households having more vehicles than drivers accounted for more trips and mileage than households with fewer vehicles than drivers, also shown by McGuckin, et. al. (2003). Increased ownership and use of different types of vehicles certainly has implications in the context of fuel consumption, vehicle emissions and air quality, crash injury severity, accident rates, highway safety and general health issues. Matthew (2003) presented a possibility of relationship between the extent of vehicle ownership, availability and use to the extent of active walking and general health issues.

2.2 Trends in Vehicle Ownership and Utilization

Researchers have also concentrated on the longitudinal aspects of vehicle ownership and utilization. Polzin, et. al. (2003) showed the increased availability of vehicles through changes in the ratios of vehicles to adults, drivers and workers since 1969. They also made an important observation that the number of zero vehicle households has only declined from 11.4 million in 1969 to 10.9 in 2001, even though the share of zero car households has declined. This reveals the importance of vehicle ownership at different levels, especially zero vehicles. Murakami, et. al. (1999) analyzed the vehicle availability of persons with low income and pointed out that despite having fewer vehicles, people in low income households make most of their trips in private vehicles owned by someone else. Hu. (2003) presented the trends in increasing vehicle ownership, increasing share of SUVs, vans and pickup (P/U) trucks, and the increased use of older vehicles in U.S. Pickrell, et. al. (1999) used 1969-95 NPTS data to offer insights into the changing patterns of household vehicle ownership by analyzing the growth in personal motor vehicle travel; changes in the number, type, and age distribution of household motor vehicles; and the determinants of households' vehicle utilization patterns. Hu, et. al.

(1999) presented the changes in the availability and utilization of household vehicles in their 'Summary of Travel Trends' report utilizing the 1969-1995 NPTS data. They showed the continued loss of market share of automobiles (out of all private vehicles) from 80 percent in 1977 to 65 percent in 1995, while mini vans and SUVs gained the market share. They also presented the significant increase in the length of time vehicles were held and operated by households in 1995 when compared to that of 1969. Pisarski (1994) presented the trends and emphasized the implications of ageing of the vehicle fleet and increased travel on older vehicles based on an analysis of 1969-90 NPTS data.

2.3 Factors Affecting Vehicle Ownership and Utilization

A wide variety of factors affect the vehicle ownership and utilization patterns of a household. Pisarski (1996) emphasized the skewing of auto ownership and usage by race, ethnicity and immigrant population. Pisarski (2003) pointed out the increased vehicle ownership by minorities could have profound impact on national transportation patterns and growth. He also pointed out the possible growth in travel as a result of increased access to and use of personal vehicles by young people, older population, women and racial and ethnic minorities. Gardenhire, et. al. (2001) found behavioral differences in the factors affecting auto ownership of low income households compared to medium and high income households. Their analysis revealed that poor households convert income into automobiles at a higher rate and convert larger adult household size into automobiles at a lower rate than non-poor households. Hess. et. al., (2002) tested a model, for Portland, Oregon, that explained automobile ownership on the basis of household, neighborhood, and urban design characteristics. They found a strong evidence of the effect of mixed land use on automobile ownership; as land use mix changed from homogeneous to diverse, the probability of owning an automobile decreased, *ceteris paribus*. Karlaftis, et. al. (2002) investigated the effect of traffic and network efficiency parameters on automobile ownership. They pointed out that traffic network and efficiency parameters did not, on the one hand, affect autolessness (zero vehicle ownership), but they did, on the other hand, affect the number of automobiles owned by a household. Purvis (1994) estimated auto ownership models using the 1990 Census Public Use Microdata Sample (PUMS) and discussed the strengths and weaknesses of using PUMS versus household travel survey data for aggregate auto ownership forecasting purposes. Choo, et. al. (2002) analyzed the dependence of vehicle type choice on person's attitudes, personality, lifestyle and mobility choices.

2.4 Differences Among Vehicle Types

Research in the recent past has also concentrated on distinguishing various types of vehicles based on their ownership and utilization. Hu (2003) emphasized the need to understand how various types of vehicles are being owned and used; specifically the need to address the question "Who owns what type of vehicle, going where, when, and for what purpose?" Hu, et. al. (1999), in their 'Summary of Travel Trends' report provided the changes in the distribution of vehicles by type utilizing the NPTS data from 1977 to 1995. They found that "Automobiles continued to lose their market share of private vehicles, from 80 percent in 1977 to 65 percent in 1995. In the meantime, minivans and sport utility vehicles (SUVs) claimed a larger market share. Regardless of vehicle type, all vehicles were in operation longer in 1995 than in the past.” Pickrell, et. al. (1999) utilized NPTS data from 1969 to 1995 to analyze the growth in personal vehicle travel, changes in the number, types, and age distribution of household motor vehicles, and the determinants of household vehicle use patterns. Kockelman, et. al. (2000) characterized and distinguished the ownership patterns and use of light duty trucks from that of passenger cars using the 1995 NPTS data. They used the NPTS 1995 data to estimate WLS (weighted least squares) models of VMT on each vehicle, negative binomial regression models of the number of person trips carried by the vehicle on a travel day, ordered probit models for vehicle occupancy for a trip, multinomial logit models for the vehicle type chosen for trip by driver, and multinomial logit models for the newest vehicle type owned by the household. They found the socio-economic attributes and vehicle prizes to be the key determinants of vehicle type choice, ownership and utilization. They found that “the average LDT (Light Duty Truck) is used over long distances with more people aboard and is purchased by wealthier households living in less dense neighborhoods.” Anderson, et. al. (2001) distinguished the ownership and use characteristics of pickup trucks in the 1995 NPTS. They observed that households with more vehicles, rural households, single-family dwelling unit and mobile home households, and middle-income households typically owned pickup trucks. Men, drivers with less education and full-time workers were more likely to drive a pickup truck on a travel day than their counterparts. They observed that a “higher portion of trips to work, work-related trips, long trips, and trips with fewer people were by pickup truck.” Anderson, et. al. (1999) also characterized pickup truck drivers with respect to demographic factors, and their behavior from safety point of view. Niemer, et. al. (2001) used 1995 NPTS data to analyze the vehicle fleet with respect to who were driving the vehicles, what types of trips were the vehicles being used for, and where the primary accumulation of vehicle miles of travel (VMT) was occurring. Kockelman. (2000) characterized light duty trucks and passenger cars based on emissions, safety, and fuel economy and examined household usage differences among the vehicle types. The paper pointed out that LDTs are used in ways very similar to passenger cars but enjoy lenient regulation.

2.5 Modeling Vehicle Ownership and Utilization Patterns

This section presents an extensive review of previous work that involves modeling various aspects of vehicle ownership, vehicle type choice, and vehicle utilization.

2.5.1 Previous Research Reviews

A research review paper by Tardiff (1980) classified the models in the research by the kind of vehicle choice under the study (Vehicle ownership levels, purchased new vehicle type choice, joint ownership level and mode choice etc) discussed the models on the basis of function forms, explanatory variables and results. The author highlighted the advantages of joint models of vehicle ownership and combination and vehicle type choice over individual conditional choice models. He also emphasized the need to use the previous vehicle ownership as important factor in deciding the recent ownership decisions. This thesis incorporates some of these improvements by presenting a joint model system of household vehicle ownership and utilization and by considering previous vehicle ownership level and combination in the choice making behavior of recent vehicle purchases. Mannering, et. al. (1985) presented a research review with respect to relationship of number and type of autos owned, usage, VMT (Vehicle Miles traveled) on each vehicle, market equilibrium and dynamic components of vehicle demand. The above two reviews also suggested some directions for automobile ownership, utilization and demand models. Given that the above reviews are relatively former in time, Choo, et. al. (2002) discussed the above two research reviews in detail and also provided an excellent literature review of vehicle type choice models and vehicle use models estimated in current research. They reviewed and assessed various analyses present in the research in context of various aspects; modeling, explanatory variables included, and significant results of the efforts. They also provide different vehicle type classifications present in the academic literature and various statistical reports. Though many extensive literature reviews exist in the context of our topic, this section also reviews of some of the important modeling efforts in the past in the context of the current topic.

2.5.2 Important Modeling Efforts in the Past

Lave, et. al. (1979) estimated a multinomial logit model of vehicle type choice for households buying a new car for a stratified random sample of 541 new car buyers in 1976. The estimates indicated that larger households were more likely to buy subcompact cars while households with more miles driven were more likely to choose larger cars. Manski, et. al. (1980) presented multinomial logit models of vehicle type choice conditional on the number of vehicles owned (joint choice model foe two-vehicle households) for a nationwide sample of 1,200 households. Their models had 25 randomly selected alternative vehicle types, out of 600 different types by make, model and vintage in the universal set, along with the chosen alternative. They found that seating and luggage space positively affected vehicle choice in larger single-vehicle households. Scrappage rate showed a negative effect for the vehicle type choice. Transaction cost variable showed a negative affect on the choice probability due to the inertia or propensity to retain existing vehicle. Hocherman, et. al. (1983) estimated two-stage nested logit model of vehicle type purchased, conditional on a purchase being made. The upper level was for a choice between buying a first car or replacing an existing car and the lower level choice making was for the chosen alternative plus 19 randomly selected alternatives from the universal set of 950 vehicle types. They found that the attributes engine size of previous car, brand loyalty, number of same type of cars present along with income showed a positive effect on the vehicle type choice.

Berkovec, et. al. (1985) developed a nested logit model of vehicle type held households for a U.S nation wide sample of 237 single-vehicle households with the upper level having three vehicle age group categories and the lower level having 5 vehicle classes based on size. Their analysis suggested that number of seats had a positive effect and the vehicle size attributes like turning radius in urban areas had a negative effect perhaps due to parking issues. Berkovec (1985) presented a simulation model to forecast automobile demand under various gas price policies. He estimated log linear model of scrappage rate and then developed a nested logit model of vehicle type choice conditional on household vehicle ownership. The simulation model results indicated that households were less likely to change vehicle types owned, as gas price increases. Thus the total sales of new vehicles would decrease and scrappage rates of older vehicles would increase due to fuel inefficiency as the gas price increased.

Mannering et. al. (1985) developed a dynamic model of household vehicle ownership and utilization behavior in which they estimated models of vehicle type choice, utilization, and quantity choice for single-vehicle households and two-vehicle households. They used lagged utilization variables of a vehicle type were taken as brand loyalty variables which showed positive effect on the vehicle type choice. The estimates of the choice probability with respect to income and capital cost were less elastic for two vehicle households than for single vehicle households. Mannering, et, al. (2002) present a nested logit model of vehicle type choice conditional on different vehicle acquisition methods such as leasing financing etc. The results indicate that regardless of the acquisition type, households are more likely to choose a vehicle with higher brand loyalty and residual values. Households leasing a vehicle tend to place high value on attributes such as passenger side air bag and horsepower and are more likely to choose larger vehicles and SUVs. Kitamura, et. al. (2000) estimated ordinary least squares models of annual vehicle mileage for the vehicle last acquired by a household as a function of primary driver and secondary driver attributes, vehicle attributes, household attributes, and residential attributes such as accessibility indices and residential density. The selectivity bias correction terms they incorporated to deal with the potential correlation between error terms of vehicle type choice and vehicle use were found to be not significantly contributing to the model improvement.

Mannering (1983) estimated a simultaneous equation system for a sample of two vehicle households to study vehicle use in multi-vehicle households. The results highlighted that income and vehicle fuel efficiency are crucial in the allocation of household travel among vehicles. Mannering (1986) further extended this work and showed the potential bias in results due to the use of vehicle attributes (endogenous variables) as exogenous variables in the household vehicle utilization models. Golob, et. al. (8) estimated structural equation models of household annual VMT (vehicle miles traveled) by vehicle type for single-vehicle households and two-vehicle households separately for a sample of 4,747 California households. The results indicate that women tend to drive less, while workers tend to drive more. Households that own mini or small cars drive less and households with older heads tend to drive less, while those with more children or high income drive more. Golob (1990) formulated a structural equations model linking car ownership, travel time by car, public transit and non-motorized modes at two points of time for Netherlands data. The model specification included car ownership as ordered-response probit variables and all travel times as censored (tobit) continuous variables. Golob, et. al. (1996) formulated and estimated a structural driver allocation and usage model for two vehicle households to study household vehicle usage behavior.

Hensher (1985) developed six simultaneous equation models for one-, two-, and three-vehicle households for household vehicle use in short and long run using three stage least squares method for a sample of 1,436 households from the first wave of a household panel survey in Sydney, Australia. These simultaneous equations model systems generally found household and person attributes, vehicle attributes, and residential attributes to be significant determinants of vehicle ownership and utilization. Hensher, et. al. (1985) developed a series of discrete-choice models to explain household automobile fleet: its composition and changes over time for a panel of 354 Sydney households. This dynamic model system allowed for prior decisions, brand loyalty, and costs of transacting, which were found to be important. Bhat, et. al. (1998) compared a series of discrete choice modeling specifications and found that the unordered response model structure is the most appropriate for household auto ownership modeling. Zhao, et. al. (2002) estimated a multivariate negative binomial model of household vehicle ownership by vehicle type for the 1995 NPTS data. The estimates suggest that household size, income, population density, and vehicle price affect the vehicle ownership decisions of a household. SUVs are preferred most, and pickup trucks the least, by high income, large size households.

In summary, household vehicle ownership and fleet combination models are all generally estimated in a simultaneous equations framework. Least squares, structural equations models or discrete choice models were used for the vehicle ownership and fleet combination and utilization patterns. Discrete choice models were also formulated for vehicle ownership combination. Various disaggregate vehicle type choice models are generally used for the vehicle type choice, in which vehicle and household characteristics are generally used as explanatory variables. Two types of vehicle type choice models; vehicle holdings and vehicle purchase models are generally formulated.

The above is by no means a comprehensive review of the literature as it is truly quite vast. However, this section amply illustrates the importance that the profession has given to the study of vehicle ownership, utilization, allocation, and vehicle type choice. While this thesis does not provide new methodologies for analyzing vehicle ownership and utilization, it provides a detailed descriptive analysis of vehicle type distribution, allocation and usage and carefully formulated models of vehicle ownership and usage using the most recent 2001 NHTS data. From that standpoint, it is useful in that it takes stock of the current situation and offers comparisons across demographic groups and vehicle types that may be useful in a policy context. Next section provides a brief description of the National Household Travel Survey data sets used for this study.

CHAPTER 3
DATA DESCRIPTION

3.1 The National Household Travel Survey

The 2001 National Household Travel Survey (NHTS) data is used for the analysis of vehicle ownership and utilization patterns in this study. The NHTS, sponsored by the Federal Highway Administration (FHWA), the Bureau of Transportation Statistics (BTS) and the National Highway Traffic Safety Administration (NHTSA), is an integration of the two national travel surveys. They were previously called as the Nationwide Personal Transportation Survey (NPTS) and the American Travel Survey (ATS). The data sets, corresponding documentation and relevant information can be accessed from the website developed by Oak Ridge National Laboratory (ORNL). One can also make use of the web-based analysis tools that are designed for preliminary analysis.

The purpose of the NHTS interviews, conducted from April 2001 through May 2002, is to take an inventory of the daily and long-distance travel (over 50 miles from home) in the United States. There are approximately a total of 66,000 households in the final 2001 NHTS dataset. This analysis uses the sample of 26,000 households that are in the national sample, while the remaining 40,000 households from nine add-on areas are not used for this study. The study also excludes the long-distance travel data. Essentially, this study makes use of the daily travel data of the nationally representative sample of 26,000 households that was released in January 2003. The daily travel 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. The basic sampling method used for this survey is the stratified random sampling technique with each stratum of random sample from each state in the United States. The data is collected from a sample of the civilian, non-institutionalized population of the United States. Hence, People living in college dormitories, nursing homes, other medical institutions, prisons, and military bases were excluded from the sample.

This is the only data available at the national level, which includes the demographics of households, household members, the vehicles owned by the households and detailed trip based information on the daily and long-distance travel for all purposes by all modes. Hence, NHTS 2001 provides the opportunity to study the current vehicle ownership, fleet combination, allocation and utilization patterns through linking and combining the vehicle travel with the demographics of the travelers, the household and the vehicles owned by them. This analysis provides a better understanding of activity and travel patterns on personal vehicles, which can assist the planners and decision makers to effectively plan and formulate policies in the context of transportation safety, energy consumption, and environmental impact and general health. The next section provides a detailed description of the data preparation process for the proposed analysis.

3.2 Data Preparation

This section describes the process of building the data sets required for the analysis from the available 2001 NHTS data sets.

3.2.1 Original Data Sets

The 2001 NHTS data contains four different data files; household file, person file, trip file and vehicle file. The household file, prepared based on the household interview contains variables describing the household characteristics and household member characteristics that include the socio-demographics, and geographic characteristics of the household and the demographic, and working status of all household members. The household file contains information on all members of the household (such as age, gender, and employment and driver's license status) regardless of whether all of the members responded to the Person Interview. The person file prepared based on the Person Interview, contains the demographic, driving, travel to work, travel evaluation and Internet use information of 60,282 members from the 26,038 households. The trip file contains the purpose, mode, distance and duration, temporal, occupancy, origin and destination characteristics of all the daily trips (248,517) made by all the persons in the trip file. All the four files are linked through common variables called identification (ID) variables, which enable the data combining and preparation for further analysis.

3.2.2 Vehicle File Preparation

Each record in the vehicle file provides information about a particular vehicle. The original vehicle file from the 2001 NHTS has variables describing the vehicle attributes (make, model, type and year), ownership length, mileage, household attributes, and the person IDs of primary driver. Additional variables describing the primary driver characteristics (Age, Gender, Employment status etc) are added to this file from the 2001 NHTS person file based on the common household ID and person ID of primary driver. Now the vehicle file contains the attributes of primary drivers as well.

A set of variables for the total household trips carried by the vehicle on the travel day is created for all trip purposes. These variables were created for both the person trips and vehicle trips (or driver trips). Similarly, additional variables were appended for daily mileage (VMT or Vehicle Miles of Travel) and duration the vehicle was driven. These variables describe the total household utilization of the vehicle on the travel day. Another set of variables is created for the primary driver's utilization of the vehicle. This set has variables for trip frequencies, total travel duration, and travel distance (VMT) of the primary driver on his/her vehicle for all the purposes.

3.2.3 Primary Driver File Preparation

Each person in the person file is appended with his/her trip frequencies, travel durations and the VMTs on the travel day for all purposes. Each person (record) in the person file is flagged, if he/she is a primary driver. For every primary driver's record, variables are appended for the household vehicle number and the type of the vehicle he/she is a primary driver of. A separate primary drive file is also created in which each record is a primary driver. This has the information about his demographic characteristics like age, sex, working status etc and the vehicle(s) number of the household and the type of the vehicle (s) that he is the primary driver of. This file also has all his/her travel information as a set of variables for his/her trip frequency, total travel duration and the VMT on travel day.

3.2.4 Household File Preparation

The household file is appended with the household vehicle fleet ownership and utilization variables. The variables for the vehicle fleet combination are essentially the number vehicles of each type owned. The vehicle utilization variables include the daily VMT on vehicles of each type and also the total daily household VMT. Household vehicle number and the characteristics of the most recent type of vehicle owned by the household are also appended. This includes the vehicle type its age, and the time when the vehicle was bought. Thus, the NHTS data is appended with required variable sets and ready for an extensive analysis. The next section presents a detailed descriptive analysis of the 2001 NHTS and the findings in the context of vehicle ownership and utilization.

CHAPTER 4
DESCRIPTIVE ANALYSIS

4.1 Background

This section presents a detailed descriptive analysis of the vehicle ownership and utilization patterns in the 2001 NHTS. First subsection provides general findings from NHTS of the current vehicle ownership and demographics of the households and the population in United States. The next two subsections provide the descriptive analysis for vehicle ownership and vehicle utilization patterns respectively.

4.2 General Findings from the 2001 National Household Travel Survey

Tables 4.1 and 4.2 give an overview of the population characteristics in terms of the socio-demographics of households and household members respectively. Table 4.1 provides weighted analysis for an overview of household socio-demographic characteristics. There are a total of 107,368,651 (about 107 million) households of which 92.1 percent households own at least one vehicle. The average household size is 2.56 persons per household. About a quarter of them are single person households and another quarter of the households have more than three persons. On an average there are 0.67 children (<18yrs) and 1.31 employed persons per household. About two-thirds of the households have no children while one-fifth of the households reported having no worker. The average vehicle ownership is 1.9 vehicles per household. Only 7.9 percent of households have no vehicle.

When the household attributes of zero-vehicle households are compared to those of other households, they are of smaller size (on average 1.7 members per household). In fact, a huge 61 percent of them are single person households. Most of zero vehicle households fall in the lower income category (<$25,000 per year), no children category and no workers category. A huge 90.6 percent of them are from urban areas and 61 percent live in apartment or condominium types of houses.

About 37 percent of households own two vehicles and 23.5 percent of the households own three or more vehicles. Interestingly, only about 13 percent of households have three or more licensed drivers even though 23.6 percent of households report having three or more vehicles. This suggests that the number of vehicles exceeds the number of drivers in many households. In fact, Only 13.5 percent of households have less number of vehicles than drivers and the remaining 86.4 percent of households have either equal number (65.1 percent households) or more (21.3 percent households) vehicles than the count of drivers they have. At an aggregate level, the average vehicle ownership of 1.9 vehicles per household is more than the average number of licensed drivers per household (1.7). These trends indicate a high vehicle ownership even at the micro level of a person (driver).

Table 4.1 Household Characteristics of the 2001 NHTS Data

Characteristic	All Households	Households With Vehicles	Households Without Vehicles
Sample Size	26,038	24,615	1,423
Weighted Population	107,368,651	98,878,005	8,490,646
Household Size	2.56	2.63	1.80
1 person	25.82%	22.79%	61%
2 persons	32.63%	33.76%	19.5%
3 persons	16.53%	17.40%	6.4%
≥ 4 persons	25.02%	26.06%	13%
No. of Children (under 18)	0.67	0.69	0.39
0 children	64.4%	63%	80.7%
1 child	14.6%	15.1%	7.9%
2 children	13.8%	14.5%	5.7%
3+ children	7.3%	7.4%	5.7%
No. of Workers	1.31	1.37	0.6
0 workers	22.9%	20.1%	55.3%
1 worker	34.5%	34.6%	33.7%
2 workers	33.7%	35.8%	8.6%
3+ workers	8.9%	9.4%	2.4%
No. of Licensed Drivers	1.75	1.86	0.45
0 licensed drivers	5.38%	0.34%	64.1%
1 licensed driver	31.85%	32.11%	28.9%
2 licensed drivers	49.25%	52.99%	5.7%
3 or more drivers	13.52%	14.56%	1.3%
Annual Income			
$25 K or less	29.1%	25.2%	78%
$25 K - $50 K	33.3%	34.7%	15.5%
$50 K - $75 K	17.3%	18.4%	3.4%
Greater than $75 K	20.3%	21.6%	3.1%
Vehicle Ownership	1.90	2.06	NA
0 auto	7.9%	0%	NA
1 auto	31.4%	34.1%	NA
2 autos	37.1%	40.3%	NA
≥ 3 autos	23.6%	25.6%	NA
Dwelling Unit Type			
Detached single house	63.7%	67%	26.2%
Duplex	4.7%	4.7%	4.7%
Row House/Town House	3.6%	3.6%	3.6%
Apartment/Condo	22%	18.7%	61%
Mobile Home/Trailer	5.7%	5.8%	4.1%
Residential area type			
Urban	79.5%	78.6%	90.6%
Non-Urban	20.5%	21.4%	9.4%

Table 4.2 Person Characteristics of the 2001 NHTS Data

Characteristic	All Persons		All drivers		Primary Drivers	
	Workers	Non-Workers	Workers	Non-workers	Workers	Non-Workers
Sample Size	29,729	30,433	28,701	14,601	25,674	11,247
Population	138,291,467	138,164,039	131,285,676	57,954,332	115,273,322	43,485,432
Age (in years)	39.3	31.9	39.7	53.3	40.1	55.1
0-5 years	0%	14.8%	0%	0%	0.0%	0.0%
6-15 years	0.3%	29.7%	0.1%	1.1%	0.0%	0.3%
16-25 years	16.6%	9.0%	15.5%	13.2%	14.3%	9.8%
26-64 years	80%	23.2%	81.4%	46.7%	82.6%	49.1%
>64 years	3%	21.1%	3.0%	39%	3.1%	40.7%
Sex						
Male	54.3%	43.2%	54.7%	38.2%	54.9%	39.6%
Female	45.7%	56.8%	45.3%	61.8%	45.1%	60.4%
Employment Status						
Full time	77.4%	NA	78.4%	NA	84.2%	NA
Part time	15.4%	NA	14.7%	NA	15.3%	NA
Multiple Jobs	0.3%	NA	0.5%	NA	0.5%	NA
Highest Education Level						
Highschool/less	39.4%	55.5%	36.6%	52.4%	36.6%	82.3%
Some college	30.4%	22.0%	30.4%	26.1%	31.8%	45.7%
Collegegraduate	21.0%	11.9%	21.3%	14.8%	22.3%	26.8%
Post graduate	11.6%	5.4%	11.8%	6.7%	12.2%	12.4%
Driver Status						
Driver	94.9%	74.7%	100%	100	100%	100%
Primary Driver	83.3%	31.5%	87.8%	75%	100%	100%
Daily Travel						
Trips/day	4.5	3.7	4.61	4.1	4.66	4.3
Work trips	1.4	0.1	1.4	0.1	1.4	0.1
Non-work trips	3.1	3.6	3.2	4.0	3.2	4.2
Miles Traveled	51.2	29.4	52.5	37.2	51.6	38.5
Minutes Traveled	92.2	65.8	93	76.7	91.8	77.9

Note: Workers are those who indicated that they are employed while non-workers indicated that they are not employed. The above table ignores persons who did not respond to specify their worker status.

79.5 percent of the households live in urban residential locations. About 64 percent of the households live in detached single houses while about 22 percent live in apartments or condominiums. Only about 5.4 percent of the households report having no licensed driver and most of those households do not own a vehicle as well. Socio-demographic attributes of a household and its residential location characteristics are important in determining its vehicle ownership level and combination.

Table 4.2 provides weighted analysis for an overview of person socio-demographic characteristics. At a further disaggregate level, characteristics of each person in the household and the inter-personal interactions play an important role in utilization patterns of the household vehicles for travel to perform various activities. Person characteristics are provided in Table 4.2 for various groups. There are a total of about 277 million persons of which about 50 percent are workers. Among all the persons, about 68.5 percent are drivers and about 57.5 percent are primary drivers of the vehicles owned by the household they belong to. Essentially about 85% of all drivers are primary drivers. 83.3 percent of workers are primary drivers while only 31.5 percent of non-workers are primary drivers, indicating that the working population that owns most of the vehicles. It could be either due to the purchasing power given by their income and/or other factors like requirement of driving to/in work. The working population in general, whether primary drivers or not, show very similar characteristics with average age of about 40 years and more than 80 percent falling in the 26-64 age range. A little over 50 percent of the workers are males and more than 75% percent are employed full time. Nearly all workers are licensed to drive and most of them are primary drivers. On an average each working person makes about 4.5 trips per day, travels about 50 miles per day and spend a total of about 90 minutes on the road. Non-workers on the other hand, show some differences based on primary driver status. Presumably, the population of all non-workers includes a large proportion of school-going children. Hence, we compare only those non-workers who are drivers to those who are primary drivers. There seem to be no huge differences due to most of the drivers are primary drivers even among non-workers. As expected, non-workers who declared that they are drivers (includes primary drivers) tend to be elderly and retired folks. As such the average age of non-worker primary drivers is about 55 years and 40 percent of the primary driver non-worker sample is 65 years or above. A majority of non-workers are female. In addition, it is found that non-workers exhibit a lower level of education achievement than workers, even among primary drivers. Primary driver non-workers make about 4.3 trips per day and are found to make a few more trips than driver non-workers (4.1). They travel about 38 miles per day and spend about 78 minutes per day on the road. These trends seem to indicate that most of the licensed drivers are primary drivers and in fact About 84 percent of the licensed drivers are primary drivers. The primary drivers' utilization trends are further discussed in the vehicle utilization section. The next section provides a detailed analysis and discussion of vehicle ownership patterns.

4.3 Vehicle Ownership

Unites States is an auto dependent nation. Currently there are about 203 million vehicles owned by all households in the U.S, which turns out to be an average of 1.9 vehicles per household. The distribution of such a huge vehicle fleet definitely warrants closer look and a careful analysis. The ownership of vehicles by type can skew the fuel consumption patterns of the fleet, which can have significant implications in the emissions and air quality related issues, thus making it important to analyze the vehicle ownership patterns by type. This section provides a detailed descriptive analysis of the household vehicle ownership patterns with an emphasis on the distinctions by vehicle type. First subsection presents a discussion on the distribution of vehicles by type in the overall vehicle fleet. An analysis of the trends in the recent acquisition of households by vehicle type is presented in the next subsection.

4.3.1 Vehicle Ownership by Type

The widespread ownership of household vehicles makes it important to understand the trends by type. This section provides such an analysis of household vehicle ownership by type. In order to understand the ownership of vehicles by type, table 4.3 shows the distribution of vehicles by type for different household types and lifecycles. Though a major share of about 56.9 percent of the 203 million vehicles in the U.S. are cars, a considerable portion of about 12 percent are SUVs, 18.2 percent are pickup trucks and 8.9 percent are vans. A 4.1 percent of other types of vehicles include medium/heavy trucks, recreational vehicles, motorcycles and other vehicle types. As households go through various lifecycle stages, one can expect the vehicle ownership patterns to differ. The working couple with children population segment shows the least percentage of cars and highest percentage of vans and SUVs. The population of working couple with no children shows the highest percentage of pickup trucks. Households with children and working status show a greater propensity to own vans and SUVs relative to other single person households, households without children, and households with no worker. As expected, the distributions show that households in rural areas are more likely to have pickup trucks than urban area households. Multi-vehicle households show higher ownership of vans, SUVs and pickup trucks. Considerable presence of larger vehicles such as vans, SUVs and pickup trucks makes it important to understand the household vehicle ownership by number vehicles of each vehicle type.

Table 4.3 Vehicle Type Distribution by Household Type

Characteristic	Households	Cars	Vans	SUVs	Pickup	Other	All
Household Lifecycle							
Single person	22.8%	69.7%	4.4%	8.3%	14.3%	3.3%	13.8%
Single parent	3.9%	65.5%	8.7%	12.1%	10.5%	3.1%	2.6%
Working couple/no child	30.9%	58.4%	6.1%	11.3%	19.8%	4.4%	36.4%
Working couple/child	32.5%	49.5%	13.2%	14.7%	18.5%	4.1%	38.3%
Multiperson/no worker	9.9%	60.4%	9.3%	6.8%	19.1%	4.3%	8.9%
Household Residential Area type							
Urban	78.6%	60.9%	9.1%	12%	14.6%	60.9%	74.8%
Rural	21.4%	45.2%	8.6%	11%	29.1%	45.2%	25.2%
No of vehicles							
1 vehicles	34.1%	77.6%	6.4%	8.2%	7.7%	.2%	16.5%
2 vehicles	40.3%	56.9%	10.4%	13.0%	18.5%	1.2%	39.1%
>2 vehicles	25.6%	49.3%	8.6%	12.0%	21.9%	8.2%	44.4%
Total	98,878,005	56.9%	8.9%	11.8%	18.2%	56.9%	203 Million

The tables 4.4 and 4.5 show the distributions of single vehicle households and two vehicle households by the vehicle fleet combination. It can be seen that almost 78 percent of the households with single vehicle have cars. Only 31.2 percent of two vehicle households have only cars. These trends also indicate that non-car types of vehicles are owned more by multi-vehicle households.

Table 4.4 Distribution of Single Vehicle Households by Vehicle Type

	Households with children	Households w/o child	All Households
Sample	1392	5675	7067
Population	7520806.199	26164018	33684824.32
Car	70.30	79.56	77.5
Van	12.19	4.78	6.4
SUV	11.34	7.31	8.2
Pickup Truck	6.00	8.21	7.7
Other	0.17	0.15	0.2

Table 4.5 Distribution of Two Vehicle Households by Fleet Combination

	Households with children	Households w/o child	All Households
Sample	4224	6371	10595
Population	17260061.57	22617995.44	39878057
Car-Car	24.18	36.56	31.20
Car-Van	18.52	7.46	12.25
Car-SUV	17.40	13.31	15.08
Car-Pickup	17.16	27.31	22.92
Car-Others	0.33	1.52	1.00
Van-Van	1.22	0.79	0.98
Van-SUV	3.36	0.90	1.97
Van- Pickup	6.84	3.00	4.66
Van-Others	0.17	0.19	0.18
SUV-SUV	2.21	1.25	1.67
SUV- Pickup	6.89	4.31	5.43
SUV-Others	0.20	0.37	0.30
Pickup- Pickup	1.25	2.09	1.73
Pickup -Other	0.14	0.78	0.51
Other-Other	0.13	0.16	0.15

4.3.2 Length of Ownership and Age of Vehicles

Table 4.7 shows the distribution of the number of years that a vehicle has been held by a household by vehicle type. Essentially this is an analysis of the time that has elapsed after the acquisition of the vehicle, based on the respondent's answer to the question about how long the vehicle was owned. On average, the number of years that a household has held a vehicle is 4.2 years. The average for SUVs is the least at 3.2, followed by vans at 3.8, cars at 4.3 and pickup trucks at 4.8 years. This indicates that SUVs and vans are recently acquired vehicles, while pickup trucks were acquired much former than cars. An examination of the distribution for each vehicle type shows that about 45 percent of the vehicles have been held for 1-2 years while another 21.5 percent have been owned for about 3-4 years. About 13.5 percent of the vehicles in all categories have been held or owned for 9 years or more with the exception of vans and SUVs that tend to be a bit newer with lower percentage of them falling in this category. While it would be certainly interesting to analyze the differences by vehicle type in total ownership length from purchase to disposal, the NHTS data cannot be used for such an analysis for it does not provide such information.

The length of time a vehicle is held may also be different from the actual age of the vehicle, which is based on its model year. Hence it is useful to discuss the age of the vehicles that households own and utilize. Table 4.8 looks at the distribution of vehicle age (obtained from the model year of the vehicle) by vehicle type. The average age is about 9 years for cars, 7.6 years for van, 6.5 years for SUV, and 10.1 years for truck. Thus, vans and SUVs appear to be newer vehicles in comparison to cars and trucks. It is possible that households like to keep newer, reliable, and good-looking vehicles as their family vehicles and do not mind having older vehicles for personal transportation. More than 55 percent of SUVs and more than 40 percent of vans are in the 0-5 year range. Only about 2-3 percent of these vehicles are more than 20 years old. On the other hand, about 5 percent of cars and about 10 percent of trucks are more than 20 years old. Combining table 4.4 with table 4.5 points to an interesting pattern where vans and SUVs tend to be newer vehicles and held/owned for slightly fewer years. It appears that people may be purchasing SUVs and vans in the more recent past as they dispose of older vehicles and purchase newer vehicles. This pattern is simply a manifestation of the vehicle acquisition process coupled with people's vehicle type choice.

The table 4.6 shows a cross tabulation of households by age of vehicles. There are about 4.9 percent of the two vehicle households that have both new vehicles and about 10.9 percent with both old vehicles. About 21 percent of two vehicle households have both vehicles with in 5 years of age.

Table 4.6 Cross Tabulation of Two Vehicle Households by Age of Vehicles

			Age of older vehicle				
			0-2yrs	3-5yrs	6-10yrs	11+yrs	Total
Age of newer vehicle	0-2yrs	Count	1917672	3715976	3997504	2329700	11960852
		% of Total	4.9%	9.4%	10.1%	5.9%	30.3%
	3-5yrs	Count		2844618	5812588	4235220	12892426
		% of Total		7.2%	14.7%	10.7%	32.7%
	6-10yrs	Count			4220508	6099470	10319978
		% of Total			10.7%	15.5%	26.1%
	11+yrs	Count				4300998	4300998
		% of Total				10.9%	10.9%
	Total	Count	1917672	6560594	14030600	16965388	39474254
		% of Total	4.9%	16.6%	35.5%	43.0%	100.0%

Table 4.7 Distribution of Number of Years of Ownership by Vehicle Type

Years Owned	Car	Van	SUV	Pickup Truck	Other	Total
1-2 years	43.6%	45.2%	55.1%	41.8%	43.1%	44.8%
3-4 years	21.7%	22.9%	22.9%	19.8%	19.7%	21.5%
5-6 years	13.1%	13.9%	9.6%	12.9%	11.4%	12.6%
7-8 years	8%	8.1%	5.5%	7.6%	7.4%	7.6%
9+ years	13.7%	9.9%	6.9%	17.8%	18.5%	13.5%
Mean	4.3	3.8	3.2	4.8	5.3	4.2
Total vehicles	57.4%	9.2%	11.9%	17.6%	3.8%	172,199,884

Table 4.8 Distribution of Vehicle Age by Vehicle Type

Age	Model year	Car	Van	SUV	Pickup Truck	Other	Total
0-5 years	1997-2002	35%	41.3%	55.5%	34.5%	34%	37.9%
6-10 years	1991-1996	31.2%	33.4%	25%	26.1%	16.9%	29.2%
11-15 years	1985-1990	21.2%	17.6%	11.8%	18.7%	11.2%	19%
16-20 years	1989-1984	7.4 %	5.4%	5.1%	10.8%	15.1%	7.9%
21+ years	Before 1984	5.2%	2.3%	2.6%	9.8%	23.7%	6.1%
Mean age		9.0	7.6	6.5	10.1	12.7	8.9
Total vehicles	195,854,080	57.2%	8.9%	11.9%	18.2%	3.7%	100%

4.3.3 Recent Vehicle Acquisitions

Households add a new vehicle to their fleet either to replace an older vehicle or to accommodate for an increase in their long-term travel requirements. Analysis of the recent vehicle purchases by households helps understand the trends in addition of new vehicles to the fleet. Table 4.9 shows the distribution of the households by the type of recent vehicle acquired. About 40 percent of the households have owned a new vehicle not former than a year. Only about 15% of the households (with vehicles) have not acquired a new vehicle in past 5 years. This indicates the increasing vehicle acquisition by households in the recent past. Though cars are being added most to the vehicle fleet, the share of SUVs, vans and pickup trucks being added to the fleet is increasing. Out of all the households with cars as their recent acquisitions, the percentage that acquired not former than a year is only about 37 percent, while it is 40 percent for vans, 44.7 percent for pickup trucks and 47% for SUVs. The changes in the vehicle acquisitions over time and the recent acquisition trends definitely warrant a closer look at the recent vehicle acquisition patterns.

Table 4.9 Distribution of Households by Recently Owned Vehicle Type

Newly Owned Vehicle	Car	Van	SUV	Pickup Truck	Total
With in 1 year before	37%	40%	47%	44.7%	39.7%
Before 1-2 years	19.6%	23.2%	23.5%	20.4%	20.6%
Before 2-5years	24.6%	26.3%	22%	23%	24.1%
Before 5+years	18.7%	11.6%	7.6%	12.5%	15.6%
Total Households	62.1%	9.5%	13.2%	15.2%	91,448,602

4.3.4 Leased Versus Owned Vehicles

One of the developments related to vehicle holding, over the past decade, is the leasing of vehicles. There could be many differences in the way people own and use leased vehicles because of differences in the initial payment and the salvage values etc. In addition to this, there could also be many differences in the way people own and use new cars to used cars. Bureau of Labor Statistics reports that leased vehicles are more likely to be luxurious in terms of having air conditioning, automatic transmissions, four wheel drive etc when compared to vehicles owned by consumers. They are also much more likely to be new when obtained by the consumer. According to their figures from the Consumer Expenditure Survey, 93 percent of the leased vehicles were new where as only 37percent of the owned vehicles were new when obtained by consumers in 1996. Leases now represent as much as 1 in 3 new car acquisitions by consumers.

Aizcorbe et. al., 1997 used the Federal Reserve Board's Survey of Consumer Finances (SCF) and the Bureau of Labor Statistics Consumer Expenditure interview Survey (CE Survey) for the year 1992 to analyze the vehicle holdings in terms of timing and financial terms of acquisitions and disposals of vehicles. They present evidence on the growth of auto leasing in recent years. Their analysis showed that the percentage of households that leased a vehicle was about 3.0 from SCF and 1.9 from CE survey. Both surveys indicated that the average number of leased vehicles was at 1.1 per household with leased vehicles. The average age of leased vehicles was about 1.6 years in 1992 when these surveys were conducted. Their analysis of the SCF shows that 43.6 percent of all vehicles owned by households were new when first acquired. The figure from CE survey is similar at 42.6 percent. Out of the vehicles that were bought used, the average age at acquisition was 6.5 years in SCF and 6.6 years in CE survey.

The vehicle acquisition trends may be influenced by lease-versus-buy, and new-versus-old decisions. Identifying and controlling for factors like lease-versus-buy, and new-versus-old can provide us better insights into the vehicle ownership and utilization patterns.

4.4 Vehicle Utilization

A total of 410,969,163,093 (about 411 billion) person trips are taken annually in United States, out of which 79% are on household vehicles. Household vehicles are utilized for a huge 96 percent of all the 235,506,624,828 (about 235.5 billion) vehicle trips driven annually. An analysis of utilization patterns of household vehicles is important to understand what type of vehicles are being driven by whom, how much and for what type of trips (length, purpose, occupancy, day of week, time of day). This section describes vehicle utilization patterns in the United States in the context of trip characteristics, daily travel, annual mileage and corresponding differences among the vehicle types. The primary driver allocation and utilization analysis provides insights into distinctions of vehicles by type based on their driving owners. It also gives an understanding of the extent to which primary drivers accomplish their travel needs in the primary vehicle and the extent to which households allocate/devote vehicles to different household members.

4.4.1 Vehicle Utilization Patterns

In order to understand the extent of vehicle usage, Table 4.10 provides the distribution of vehicles by type and annual mileage driven (estimated by a household respondent). Vans and SUVs show slightly higher average annual mileages than cars and trucks.

Table 4.10 Distribution of Annual Mileage by Vehicle Type

Vehicle Type	No. of Vehicles	Average Miles	0-5000 miles	5001-10000 miles	10001-15000 miles	15001-20000 miles	>20000 miles
Car	56.9%	10696	35.5%	27.0%	19.5%	9.3%	8.7%
Van	8.9%	12706	24.9%	26.8%	23.9%	12.3%	11.6%
SUV	11.8%	12869	22.3%	25.8%	25.5%	13.7%	12.6%
Pickup Truck	18.2%	11644	34.2%	25.0%	18.7%	10.0%	12.1 %
Other	4.1%	4920	82.3%	10.6%	3.2%	1.20%	2.7%
Total Vehicles	2,03,266,300	11,118	34.5 %	25.9%	19.9%	10%	9.8%

Average annual mileage on SUVs is the highest at about 12,900 miles followed by vans, pickup trucks and cars in that order. The differences are very clear in the percentage distributions. More than 10 percent of SUVs, vans and pickup trucks are driven more than 20,000 miles per year. The corresponding figure for cars is just 8.7%. Whereas 35.5 percent of cars are driven 0-5000 miles, only 22 percent of SUVs are driven in this small annual mileage range. These figures indicate that vans, SUVs and pickup trucks are driven more than cars on an annual mileage basis. When the differences are observed among different vehicle types, the annual mileage by vehicle type in the all households segment of table 4.11 shows that vans, SUVs, and pickup trucks are driven more per annum than cars.

However, a vehicle's utilization depends upon how old it is. Generally older vehicles are driven less compared to newer ones, which is quite evident from the annual mileage figures in the table 4.11. Hence it is possible that vans and SUVs being relatively new vehicles are being driven more because they are relatively new in the fleet. Given that cars are relatively new in the vehicle fleet, it is possible that these vehicles are driven less than relatively young vans and SUVs. However, given that pickup trucks are relatively older than cars and are still being driven more, one cannot expect that vans and SUVs may be driven less after controlling for age. Hence Table 4.11 compares the annual mileage differences among vehicle types after controlling for age as well as the vehicles to drivers ratio. The annual mileages of vans and SUVs are higher even after controlling for the age of the vehicle. This trend could be observed in all categories of household vehicle availability.

Households with larger number of vehicles than the drivers show the least mileage on vehicles of age 6 years or more. This may be because they have these older vehicles as contingency vehicles that may be used less compared to newer vehicles. Hence, the vehicle availability also plays an important role in the individual vehicle utilization.

Table 4.11 Annual Mileage After Controlling for Vehicle Availability and Age

Vehicles to Drivers Ratio	Vehicle Age (years)	Annual Mileage on the Vehicle Type (Miles)					
		Car	Van	SUV	P/U	Other	Total
< 1	0 to 2	13877	14343	16733	13368	11000	14240
	3 to 5	12998	14972	16579	12706	36263	13784
	6 to 10	11005	16018	16432	12675	NA	12347
	11 or more	9508	8965	8526	10902	96	9548
	All ages	11439	13694	15144	12236	20551	12188
= 1	0 to 2	13725	15257	14661	18154	6641	14717
	3 to 5	11868	13906	13729	14671	7203	12754
	6 to 10	11201	11699	13033	12171	6802	11548
	11 or more	8041	10833	9429	8652	5080	8392
	All ages	10844	12865	13256	12744	6034	11590
> 1	0 to 2	14447	17889	15002	17269	5396	14504
	3 to 5	13717	15910	14175	13782	7017	13424
	6 to 10	11016	11927	11236	11905	6398	11053
	11 or more	6882	7600	7407	6755	3087	6569
	All ages	10150	12132	11816	10507	4798	10139
All Households	0 to 2	13918	15950	14881	17531	5486	14612
	3 to 5	12408	14526	14050	14221	7212	13030
	6 to 10	11136	12243	12637	12085	6424	11461
	11 or more	7723	9094	8329	7625	3222	7621
	All ages	10696	12706	12869	11644	4920	11118

Tables 4.12 and 4.13 provide daily travel characteristics by vehicle type. Table 4.8 offers a detailed analysis of vehicle usage on a daily basis for weekdays (Monday to Friday). The first set of rows shows the total utilization of household vehicle by both household and the non-household members. The differences are quite apparent in that vans and SUVs show higher person trip rates than cars and pickup trucks. This is presumably due to the vans and SUVs serving multi-person family-oriented trips contributing to a larger average number of person trips on those vehicles. Indeed, a comparison of average vehicle occupancy (at the bottom of the table) shows that the average occupancy is 2.0 persons per vehicle in vans and 1.58 persons per vehicle in SUVs. Pickup trucks show the lowest vehicle occupancy level and correspondingly the lowest person trip rate. As expected, the bulk of the difference in person trip rates on vehicles occurs for non-work trip purposes. In order to control for vehicle occupancy, vehicle trip rates were compared across vehicle types. After controlling for vehicle occupancy rates, it is found that the differences among vehicle types are less pronounced due to a considerable decrease in non-work trips rates. Nevertheless, vans and SUVs show higher average vehicle trip rates and mileage when compared to cars and pickup trucks. Again, non-work trip rates showed the bulk of difference. As expected, Pickup trucks show much lower non-work trip rates compared to all other types of vehicles.

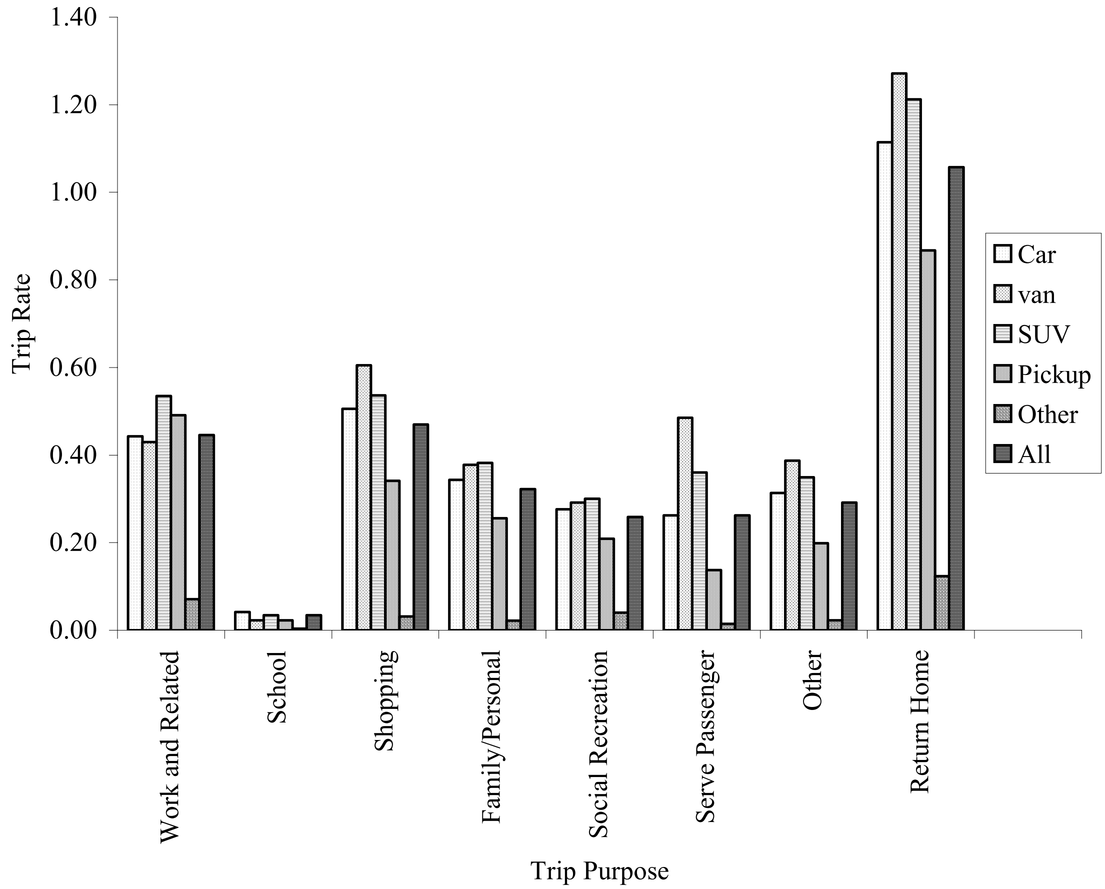
Table 4.12 Daily Travel Characteristics by Vehicle Type on Weekdays

	Characteristic	Car	Van	SUV	P/U Truck	Other	Total
Total Utilization of the Vehicle	Total person trips	4.47	6.76	5.42	3.23	0.17	4.42
	Work	1.05	1.03	1.22	1.10	0.15	1.05
	Non-Work	3.42	5.73	4.19	2.13	0.17	3.37
	Total driver trips	3.48	4.08	3.89	2.71	0.28	3.32
	Work	1.00	0.95	1.17	1.06	0.15	0.99
	Non-Work	2.48	3.13	2.72	1.66	0.13	2.33
	VMT (miles)	29.45	31.49	33.87	28.40	4.57	29.04
	Work	11.84	10.24	13.79	14.29	3.05	12.03
	Non-Work	17.61	21.26	20.09	14.11	1.52	17.01
	VTT (Vehicle Time Traveled -min)	60.46	65.40	65.58	51.63	7.82	57.96
	Work	22.15	19.96	25.26	24.49	4.89	22.08
	Non-Work	38.31	45.44	40.32	27.15	2.94	35.88
Vehicle Utilization by Primary Driver	Total vehicle trips	2.94	3.28	3.26	2.40	0.23	2.81
	Work	0.88	0.79	1.05	0.96	0.13	0.88
	Non-Work	2.05	2.49	2.22	1.44	0.10	1.93
	VMT (miles)	24.71	24.43	28.26	24.73	3.66	24.31
	Work	10.52	8.18	12.30	12.89	2.25	10.63
	Non-Work	14.19	16.25	15.96	11.84	1.41	13.68
	VTT (Vehicle Time Traveled -min)	50.97	50.93	55.15	44.91	6.36	48.67
	Work	19.60	16.07	22.65	22.09	3.77	19.48
	Non-Work	31.37	34.86	32.50	22.82	2.59	29.19
Total Primary Driver's Travel	Total Vehicle trips	3.79	4.38	4.20	3.90	3.78	3.89
	Work	1.16	1.11	1.36	1.50	1.46	1.24
	Non-Work	2.63	3.27	2.84	2.40	2.32	2.65
	VMT (miles)	35.21	36.16	39.99	45.52	51.75	37.38
	Work	15.28	12.90	18.07	23.01	25.35	16.66
	Non-Work	19.93	23.26	21.92	22.51	26.40	20.72
	VTT (Vehicle Time Traveled -min)	69.27	72.84	74.86	79.44	85.30	71.40
	Work	27.31	24.53	31.41	38.07	40.22	29.29
	Non-Work	41.96	48.31	43.45	41.37	45.08	42.11
	Average Vehicle Occupancy	1.44	2.0	1.58	1.37	1.15	1.51
	Average Trip Length (miles)	8.94	8.17	9.12	10.96	15.60	9.21
	Average Trip Length (min)	17.9	16.6	17.5	20.0	27.56	18.0
	Average Speed (Miles/Min)	0.413	0.404	0.439	0.465	0.483	0.423

Table 4.13 Daily Travel Characteristics by Vehicle Type on Weekends

	Characteristic	Car	Van	SUV	P/U Truck	Other	Total
Total Utilization of the Vehicle	Total person trips	4.18	7.08	5.29	3.05	0.51	4.24
	Work	0.30	0.26	0.30	0.33	0.08	0.30
	Non-Work	3.88	6.81	5.00	2.72	0.43	3.94
	Total driver trips	2.83	3.23	3.11	2.11	0.40	2.68
	Work	0.27	0.22	0.26	0.31	0.07	0.27
	Non-Work	2.56	3.01	2.84	1.80	0.33	2.41
	VMT (miles)	24.44	28.02	32.18	22.94	7.54	24.72
	Work	2.76	2.39	3.85	4.77	1.03	3.15
	Non-Work	21.68	25.63	28.32	18.16	6.51	21.57
	VTT (Vehicle Time Traveled -min)	48.01	54.42	58.61	41.04	14.37	47.24
	Work	5.25	4.30	6.35	7.40	1.82	5.54
	Non-Work	42.76	50.12	52.26	33.63	12.54	41.70
Vehicle Utilization by Primary Driver	Total vehicle trips	2.23	2.12	2.30	1.77	0.31	2.07
	Work	0.23	0.16	0.24	0.27	0.06	0.23
	Non-Work	2.00	1.96	2.06	1.50	0.25	1.84
	VMT (miles)	18.74	17.42	23.41	19.21	6.09	18.74
	Work	2.29	1.79	3.58	4.25	0.89	2.69
	Non-Work	16.46	15.63	19.83	14.96	5.21	16.06
	VTT (Vehicle Time Traveled -min)	37.06	34.34	42.89	34.64	10.65	36.01
	Work	4.37	3.17	5.86	6.56	1.48	4.71
	Non-Work	32.70	31.17	37.02	28.08	9.17	31.30
Total Primary Driver's Travel	Total Vehicle trips	3.05	3.05	3.08	3.27	3.40	3.06
	Work	0.30	0.27	0.30	0.42	0.42	0.31
	Non-Work	2.75	2.78	2.78	2.85	2.98	2.75
	VMT (miles)	27.71	27.80	35.98	38.89	51.94	30.43
	Work	3.46	4.74	6.78	6.96	7.47	4.26
	Non-Work	24.26	23.06	29.20	31.93	44.47	26.17
	VTT (Vehicle Time Traveled -min)	53.31	52.90	63.05	66.74	78.23	56.15
	Work	6.29	7.76	9.86	10.23	11.92	7.19
	Non-Work	47.02	45.14	53.19	56.51	66.31	48.97
	Average Vehicle Occupancy	1.87	2.89	2.14	1.77	1.21	2.01
	Average Trip Length (miles)	9.65	11.10	12.15	11.43	22.21	10.50
	Average Trip Length (min)	18.24	19.00	20.86	20.11	38.04	19.11
	Average Speed (Miles/Min)	0.419	0.436	0.453	0.471	0.510	0.435

Figure 4.1 Trip Rates by Purpose by Vehicle Type



Rows at the bottom of table 4.12 have average vehicle occupancy and trip lengths on weekdays. On a per trip basis, it is found that vans and SUVs exhibit higher vehicle occupancy rates as mentioned earlier. It is also found that the average trip length for vans is slightly lower than that for cars, SUVs and pickup trucks, presumably due to the higher non-work trip rate in these vehicle types. Generally on weekdays, non-work trips tend to be of shorter length than work trips due to the time constraints. More over, many non-work trips on a weekday tend to be shorter links of a trip chain. That trend was seen both in duration and distance. The average trip lengths for SUVs and pickup trucks are slightly on a higher side compared to that of cars. The average trip durations follow similar trends as trip lengths except that the SUVs show smaller trip durations than that of cars while they show higher trip distances than cars. This is perhaps due to their higher average speed.

Table 4.13 provides the same kind of information for weekends. Many of the trends seen on weekdays are once again seen on weekend days. As expected, all vehicles are used substantially less for the work purpose on weekend days. Also, it is seen that the difference between SUVs and vans on the one hand and cars and pickup trucks on the other is further amplified on weekends. As many weekend activities tend to be household oriented and joint activities, it is likely that vans and SUVs are used more relative to cars and pickup trucks on weekends. It is found that vehicle occupancy rates on weekends are so high relative to weekdays that, although the number of person trips on weekends and weekdays are quite similar, the number of vehicle trips on weekends is less than that on weekdays. Total vehicle VMT and travel duration are substantially larger for SUVs and vans on weekends. Unlike on weekdays, the average vehicle trip length of vans is higher than that of cars because the non-work trips on a weekend tend to be longer due to lower time constraints. However, it is primarily the number of trips and not the trip lengths that contribute to the differences across vehicle types in daily duration and VMT on weekends. (similar to weekdays).

Figure 4.1 shows the daily vehicle trip rates by purpose for each vehicle type (for all days of a week). The graph indicates that vans and SUVs have the highest trip rates for shopping, family/personal, social recreation and serve passenger trip purposes. Work and related trip purpose trip are carried the most by SUVs and pickup trucks. The trends indicate that vans and SUVs are used the most for non-work kind of trip purposes because of their use as personal vehicles and family vehicles. SUVs are also used for work trips indicating their higher use for all trip purposes.

4.4.2 Primary Driver Vehicle Allocation and Utilization Patterns

Vehicles are allocated to drivers for their use to perform household and individual activities. Only about 12 percent of all the household vehicles are not allocated to any specific primary driver. Rest of the 88 percent of the household vehicles are allocated to primary drivers. Primary driver characteristics are likely to be playing an important role in shaping the differences across the vehicle types. Hence it is useful to understand who primarily drives the vehicles in particular. Table 4.14 provides such an analysis through description of primary driver characteristics by vehicle type. In this table, the characteristics of those who reported themselves as primary drivers for different vehicle types are summarized. Although the average age of the different primary driver groups are similar across vehicle types, it is important to note the differences in age distributions. 17 percent of the car primary drivers are in the 16-25 years category, the corresponding percentage for vans is only 3.7 percent and that for SUVs and trucks is about 11 percent and 12 percent respectively. While about 85 percent of the van and SUV primary drivers are in the 26-64 year age group, only 66 percent of car primary drivers are in this age group. In general, the elderly show a greater propensity to be primary drivers for cars as opposed to larger vans, SUVs, and trucks. Interestingly, it was found that the majority of primary drivers for cars, vans, and SUVs are female. The big difference in gender distribution is noted for trucks where 88 percent of the primary drivers are male. The van shows a slightly higher percentage of females as primary drivers at about 60 percent as opposed to cars at about 56 percent and SUVs at about 53 percent. In general, a larger percentage of SUV and pickup truck primary drivers tend to be workers. About three-fourths of these drivers are workers; the corresponding percentage for cars and vans is about two-thirds. While the highest education level distribution shows similar trends across car, van, and SUV primary drivers, it is found that the pickup truck driver group is less educated, possibly suggesting that they may be using the truck for blue-collar service occupations. The SUV primary driver group exhibits the highest education level distribution. Many of these variables are correlated with one another. As SUVs cost more, individuals must be in higher paying jobs and have higher incomes to afford SUVs. Individuals in higher paying jobs and having higher income are likely to have higher education levels as well. Overall, there seem to be some clear patterns of vehicle allocation and choice that emerge from this table.

Table 4.14 Primary Driver's Socio-Demographic Characteristics by Vehicle Type

Characteristic	Car	Van	SUV	Pickup Truck	Other	Total
Vehicles	115,723,093	18,186,471	23,949,107	37,054,676	8,090,527	203,266,300
Primary drivers	98,370,224	15,771,170	21,933,753	31,711,971	5,910,345	158,795,853
Age						
Average age (yrs)	45.04	45.62	41.64	44.73	44.97	44.24
0-5 years	0%	0%	0%	0%	0%	0%
6-15 years	0.07%	0%	0.09%	0.05%	1.21%	0.11%
16-25 years	17.18%	3.68%	11.08%	12.09%	9.23%	14.76%
26-64 years	66.18%	85.26%	83.36%	75.98%	78.16%	71.74%
>=65 years	16.57%	11.07%	5.47%	11.88%	11.39%	13.39%
Gender						
Female	56.03%	60.81%	53.07%	11.77%	8.78%	49.32%
Male	43.97%	39.19%	46.93%	88.23%	91.22%	50.68%
Employment Status						
Unemployed	29.37%	33.66%	22.75%	22.17%	21.59%	27.38%
Employed	70.63%	66.34%	77.25%	77.83%	78.41%	72.62%
Education						
High school	37.39%	37.39%	31.80%	52.43%	44.99%	39.28%
Some college	29.98%	30.59%	30.56%	29.17%	31.72%	29.94%
College graduate	20.91%	20.59%	25.30%	12.91%	16.63%	20.14%
Post graduate	11.72%	11.42%	12.34%	5.49%	6.66%	10.64%

Out of about 235 billion vehicle trips that are made annually in the United States, about 96 percent (225.5 billion) vehicle trips are driven on household vehicles. On an average 80 percent of these driver trips on household vehicles carry primary drivers. Remaining 20 percent of the household vehicle trips are with out the primary diver in the vehicle. These figures give an idea of the extent to which household vehicles are being used for carrying primary drivers. Corresponding percentages for each vehicle type are given in table 4.15, which shows that pickup trucks are above average with 85.5 percent of the trips carrying primary drivers. Cars are closer to the average figure with 80.4% of the trips carrying primary drivers. Vans and SUVs are below the average with vans being the lowest at only 72.7 percent of the trips carrying primary drivers and SUVs at a below average figure of 78.5 percent carrying primary drivers.

Another way to look at the primary driver's utilization of the vehicle is the extent of driving done by the primary driver when he/she was in his/her vehicle on the trip. This gives an idea of the extent to which drivers other than primary drivers are driving vehicles even when the primary driver is actually present in the vehicle. In other words, this is an analysis of the role of primary driver in multi-occupant trips. Out of all the 411 billion trips made annually in the United States, 193 billion trips are done by primary drivers in their primary vehicles and 67.5 billion trips of them are multi-occupant trips. 82.5 percent of these trips are driven by the primary drivers them selves, implying that the remaining 17.5 percent of the multi-occupant trips that carried primary drivers were driven by other drivers. The corresponding percentages of primary driver's role in multi-occupant trips for each vehicle type are shown in figure 4.15. Pickup trucks have the highest percentage (91.9) of multi-occupant trips that carried primary driver were driven by the primary driver. Cars are 82.1 percent (close to the all vehicles figure of 82.5) and SUVs are at 80 percent (little lower than 82.5). The percentage of vans trips driven by primary driver is only 79.6 indicating that the remaining 20.4 percent of multi-occupant van trips that carried primary driver were driven by some one other than primary driver. The primary driver vehicle utilization analysis from table 4.15 indicates that pickup trucks are allocated the most (shared the least) to the primary drivers, while vans are shared the most. This is perhaps due to higher tendency of females and unemployed persons being the primary drivers of vans than any other vehicle type. Vans are used more on weekends and for high occupancy trips and it is possible that the household head (mostly an employed male) drives the vehicle irrespective of the primary driver status.

Table 4.15 Vehicle Utilization by Primary Drivers

Vehicle Type	Percentage of household vehicle trips that carried primary drivers	Primary driver's role in multi-occupant trips (Percentage driven by primary driver)
Car	80.4%	82.1%
Van	72.7%	79.6%
SUV	78.5%	80%
P/U truck	85.5%	91.9%
All vehicles	80%	82.5%
Total Trips	225,626,347,382	67,500,040,642

Tables 4.12 and 4.13 provide primary driver utilization analysis on a daily basis. Table 4.12 offers a comparison of total utilization of the vehicle to the primary driver's usage to gain an understanding of the extent to which primary drivers are using the vehicles for weekdays on a daily basis. Primary driver's total travel is also compared to his/her vehicle utilization. The first set of rows shows the total utilization of household vehicle by both household and the non-household members. The second set of rows shows the primary driver's utilization of their vehicles on weekdays. When the number of driver trips of primary drivers on their vehicle is compared to the total driver trips carried

by the vehicle, most of the vehicle trips carried by the vehicles are those of primary drivers. Overall, the vehicles are driven, on average, about 30 miles per day with about 60 percent of the mileage for non-work travel. Of the 30 miles that a vehicle is driven, it appears that the primary driver accounts for a large percentage of about 84 percent. A similar trend is found with respect to travel duration. The vehicles average about 58 minutes in travel time per day. The primary driver accounts for about 85 percent of that time. These findings show that vehicle allocation in a household tends to be quite strong and that people rarely deviate from the vehicle allocation pattern (at least on weekdays).

However, The primary driver's utilization, in terms of vehicle mileage, varies from about 77% for vans to about 87% for pickup trucks. This shows that pickup trucks are being strongly allocated to primary drivers and vans show comparatively weaker allocation to a single person. The third set of characteristics reveals the total primary driver's travel on weekdays. In general, primary drivers of vans and SUVs are found to have taken/driven slightly higher number of trips. When the total vehicle trips of primary driver are compared to the trips made on their vehicle (from primary driver's vehicle utilization) it is found that on an average not more than 70 percent of the primary drivers' travel (mileage) is accomplished using their own vehicle. This may be because either they are primary drivers of more than one vehicle or they are using the vehicle that they are not primary drivers of. This analysis has indicated a strong allocation of vehicles to their primary drivers on weekdays. One could expect a weaker allocation of vehicles to primary drivers on weekends due to lower constraints of work. Hence, same kind of analysis is done for weekends in table 4.13. It is found that the primary driver once again plays a large role in using the vehicle, but not as much as it was on weekdays. The primary driver accounts for about 75 percent of the total daily mileage on his vehicle on a weekend day compared to the 83 percent on weekdays. The percentage by vehicle type varies from about 62 percent for vans to 83 percent for pickup trucks.

The primary driver utilization patterns suggested very strong allocation of vehicles, even on weekends, to an individual rather than sharing that one could expect in a household. Much of shared usage of a vehicle appears to be in the form of shared riding but the primary driver did most of the driving on the vehicle. While it would certainly be interesting to understand the factors or constrains that imply these strong allocations even on weekends, it is beyond the scope of this study. In summary, these descriptives have suggested the possibility of differences in ownership and utilization patterns of cars, SUVs, vans and pickup trucks. The forthcoming models will explore the trends of vehicle ownership, fleet combination and utilization in detail in a multivariate setting.

CHAPTER 5
MODELING METHODOLOGY

This section describes the underlying mathematical framework, methodology of estimation and application of the model structures of structural equations modeling and discrete choice modeling frameworks that are used for the analysis.

5.1 Structural Equations Modeling

Structural Equations Model (SEM) systems haven been widely adopted in activity pattern and travel behavior Research and vehicle ownership and utilization patterns. (Golob. 2003). SEM offers a very high extent of flexibility in terms of handling simultaneous multivariate out comes, in other words, multiple inter-dependent exogenous variables.

5.1.1 Structural Equations Representation

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

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

This can be rewritten as,

$$Y = BY + \Gamma X + \varepsilon$$

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

where

Y is a column vector of endogenous variables,

B is parameters matrix 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.

5.1.2 Estimation

Single equations estimation methods like the OLS (Ordinary Least Squares), ILS (Indirect least Squares), 2SLS (Two-Stage least Squares) cannot be used for the estimation of simultaneous equation's parameters. Even the LIML (Limited Information Maximum likelihood) method of estimation cannot be used for these are not suitable to deal with limited dependent variables with different underlying distributions. Though the FIML (Full Information Maximum Likelihood) is an ideal method of estimation of the parameters of for system of equations, this tends to be computationally intensive hence making larger model systems almost impractical to estimate. More over, even a small mis-specification in any part of the model system affects all of the estimates rather than just a related few.

SEM uses covariance-based structural analysis for the parameter estimation. Essentially, the difference between the sample covariances and the model predicted covariances are minimized (Bollen, 1989). The fundamental hypothesis for this approach is that the covariance matrix of observed variables is a function of a set of parameters as shown below:

$$\Sigma = \Sigma(\theta)$$

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.

The above equation 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, namely, the covariance matrix of Y, the covariance matrix of X with Y, and the covariance matrix of X.

Let Φ = covariance matrix of X, and Ψ = covariance matrix of ε. Then it can be shown that:

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

After ensuring that the specified model system is mathematically identified (Bollen, (1989), Judge et al (1985) and Johnston et al (1997).), 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 has 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 $\Sigma(\theta)$.

5.1.3 Asymptotically Distribution Free – Weighted Least Squares Estimation

There are four widely used fitting methods; Maximum Likelihood (ML), Unweighted Least Squares (ULS), Generalized Least Squares (GLS) and Asymptotically Distribution-Free (ADF) fitting method. Any of the above methods of fitting can be used for the estimation for obtaining consistent parameters. However, the possibility that the endogenous variables specified in the system may have different underlying theoretical distributions precludes the use of ML, ULS and WLS fitting functions. Hence ADF-WLS method is employed to get consistent and asymptotically efficient parameter estimates (Golob 2003, Amos User's Guide, 1997)

The ADF-WLS estimation method proceeds in three distinct steps. First, it is assumed that each observed endogenous variable is generated by an unobserved normally distributed latent variable. If the latent variable is greater than a censoring level, it is observed; otherwise the censoring level is observed. Each latent variable is assumed to be conditional on the other variables in the system. The problem is to determine the conditional unknown mean and variance of each censored latent variable. This can be done using the Tobit model. An appropriate maximum likelihood estimation procedure for the Tobit model is described in Maddala (1983). Second, estimates of the correlations between the latent censored endogenous variables, and the correlations between each of the latent variables and the continuous exogenous variables in the system are derived. Finally, parameters of the structural equation model are estimated such that the model-implied correlation matrix is as close as possible to the sample correlation matrix, where the sample correlation matrix is determined in the previous steps. The fitting function is then:

$$F_{WLS} = [s - \sigma(\theta)]' W^{-1}[s - \sigma(\theta)]$$

where, s is a vector of censored correlation coefficients for all pairs of endogenous and exogenous variables, σ(θ) is a vector of model-implied correlations for the same variable pairs, and W is a positive-definite weight matrix. Minimizing F_{WLS} implies that the parameter estimates are those that minimize the weighted sum of squared deviations of s from σ(θ). This is analogous to weighted least squares regression, but here the observed and predicted values are variances and covariances rather than raw observations. The best choice of the weight matrix is a consistent estimator of the asymptotic covariance matrix of s:

$$W = ACOV(s_{ij}, s_{gh})$$

Under very general conditions:

$$W = \frac{1}{N}(s_{ijgh} - s_{ij}s_{gh})$$

is a consistent estimator, where s_{ijgh} denotes the fourth-order moments of the variables around their means, and s_{ij} and s_{gh} denote covariances. Browne (1998) demonstrated that F_{WLS} with such a weight matrix will yield consistent estimates, which are asymptotically efficient with correct parameter test statistics. These properties hold for very general conditions, and consequently such estimators are known as arbitrary distribution function, or asymptotically distribution free (ADF) estimators. ADF-WLS estimators are available in several structural equation model estimation packages including AMOS (Arbuckle, 2000) and LISREL (Joreskog et. al., 1993).

5.1.4 Evaluation

Many criteria are available for assessing overall goodness-of-fit of a Structural Equations Model. Most of these evaluation criteria are based on the chi-square statistic given by the product of the optimized. Fitting function and the sample size (Golob 2003). The asymptotic distribution of (N-1) F_{ADF} is χ^2 distribution with {(1/2) (G+K) (G+K+1)}-t degrees of freedom, where t is the number of free parameters. The null hypothesis of the chi-square test is $H_0 = \Sigma = \Sigma(\theta)$. This implies that the over- identifying restrictions for the model are correct. Rejection of H_0 suggests that at least one restriction is in error so that $\Sigma \neq \Sigma(\theta)$. The objective is to attain a non-significant model chi-square, since the statistic measures the difference between the observed and reproduced variance-covariance matrices. The level of statistical significance indicates the probability that the differences between the two matrices are due to sampling variation. One rule of thumb for good fit is that the chi-square should be less than two times its degrees of freedom (Ullman, 1996). However, for large samples it may be very difficult to find a model that cannot be rejected due to the direct influence of sample size (Golob 2003). For such large samples, Critical N (Hoetler, 1983) gives the sample size for which the chi-square value would correspond to $p= 0.05$. A rule of thumb is that critical N should be greater than 200 for an acceptable model (Tanaka, 1987).

One of the several other ways to calibrate the match of the variance-covariance matrices is the Goodness-of-Fit Index proposed by Joreskog., et. al. (1986). The goodness of fit index measures the relative amount of the variances and covariances in S that are predicted by $\hat{\Sigma}$. The Adjusted Goodness-of-Fit Index (AGFI) adjusts for the degrees of freedom of a model relative to the number of variables. Both the indices reach a maximum of one when $S = \hat{\Sigma}$.

5.2 Multinomial Logit Model

This section provides an overview of the methodology of multinomial logit models that are most widely used for modeling discrete choice phenomenon in transportation, economics, marketing and many other fields.

5.2.1 Random Utility Approach

Discrete choice models are based on random utility maximization hypothesis. The random utility theory which assumes that the decision-maker's preference for an alternative is captured by the value of an index, called utility. A decision-maker selects the alternative from the choice set that has the highest utility value. 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.

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

where, C_n is the set of alternatives available for the n^{th} choice maker (choice set).

Random utility models assume that decision-makers have perfect discriminating capability. However, the analyst will have limited information about an individual's utility level. The uncertainty introduced by introducing an error term in the utility of each alternative. Hence, the utility of an alternative 'U_i' is split into a deterministic term 'V_i' and a random term 'ε_i'. Then,

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

The deterministic utility V_{in} expressed as linear function of explanatory variables (X_k) is given by:

$$V_{in} = \beta_{0i} + \beta_{1i} X_{1in} + ... + \beta_{ki} X_{k\,in}$$

Alternative distributional assumptions about the joint probability distribution of the full set of disturbances (error terms) yield different probabilistic choice models. Assumption that the disturbances are 'Gumbel' distributed leads to the multinomial logit model with the 'Independence of Irrelevant Alternatives' (IIA) property. Multinomial logit model is the most popular form of discrete choice model in practical applications. It can be shown that the probability of individual 'n' choosing the alternative 'i' is given by logit formula

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \quad \text{(or)} \quad P_n(i) = \frac{e^{\beta' x_{in}}}{\sum_{j \in C_n} e^{\beta' x_{jn}}}$$

5.2.2 Estimation

Maximum Likelihood method is used to estimate the parameters (coefficients) of multinomial logit model. Maximum likelihood estimates are the value of the parameters for which the observed sample is most likely to have occurred.

The likelihood function for a general multinomial choice model is

$$L^* = \prod_{n=1}^{N} \prod_{i \in C_n} P_n(i)^{y_{in}}$$

where, N denotes the sample size and,

y_{in} = 1 if choice maker n chooses alternative 'i'
= 0 otherwise

Where, for the linear in parameters model:

$$P_n(i) = \frac{e^{\beta' x_{in}}}{\sum_{j \in C_n} e^{\beta' x_{jn}}}$$

Taking the logarithm provides the log-likelihood function as:

$$L = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} \left(\beta x_{in} - \ln \sum_{j \in C_n} e^{\beta x_{jn}} \right)$$

We can then solve to estimate the parameters, which maximize L.

5.2.3 Evaluation

Likelihood ratio test is used to compare the specified model with the baseline model, which assumes that the probability of an alternative being chosen by all the decision makers is equal its the market share. This is the case of all coefficients in the model except the constants being equal to zero. Under the null hypothesis that the all the coefficients, except the constants are zero, the statistic given by:

$-2[L(c) - L(\hat{\beta})]$ is χ^2 distributed with K-J+1 degrees of freedom.

Where,

$L(c)$ is the Log-likelihood at market share

$L(\hat{\beta})$ is the Log-likelihood at convergence of the specified model

K is the number of parameters

J is the number of alternatives.

$L(c)$ can be obtained by estimating a model with J-1 alternative specific constants:

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

One can also look at the goodness-of-fit measure given by:

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

This measure does not have any statistical interpretation unlike that of R^2 measure in linear regression. This measure is called the adjusted Rho-Square and gives an idea about the improvement of the log-likelihood function from the base model. Having provided a brief methodology of the models the next section describes the model estimation results.

CHAPTER 6
MODELS OF VEHICLE OWNERSHIP AND UTILIZATION

6.1 Background

This section is devoted to models of household vehicle ownership and utilization and vehicle type choice behavior of households and drivers in the context of household and person attributes. First subsection presents a Structural Equations Model of vehicle ownership and utilization in a unified framework. This joint model of vehicle ownership, combination and utilization is definitely advantageous over individual models of vehicle fleet combination and utilization. The next subsection has a multinomial logit model of vehicle type chosen by the households in their recent purchases. This model incorporates previous vehicle ownership level and type as explanatory factors, which are very important along with the socio-demographics in the choice making behavior of recent vehicle purchases. The last subsection presents a multinomial logit model of the type of vehicle chosen by the driver for a trip. These models are important in that they provide an interpretation of the effects of each factor in a *ceteris paribus* situation, hence separating the correlated factors to avoid confounding effects. Apart from confirming certain common perceptions about various vehicle types, the models also bring out some subtle differences that cannot be identified through simple descriptive analysis.

6.2 Structural Equations Model of Vehicle Ownership and Daily Utilization

The purpose of this model is to understand the effect of socio-demographic attributes on the household vehicle ownership and utilization patterns in a unified framework. The hypothesis of the model structure is shown figure 6.1, according to which the vehicle ownership and the fleet combination of a household is explained by its socio-demographic attributes. The vehicle utilization patterns are explained by the socio-demographics as well as the vehicle ownership and the fleet combination of the household. Analyzing the vehicle utilization patterns along with the ownership trends enables us to control for the vehicle ownership level and fleet combination, which can definitely influence the utilization patterns. This joint model system of model system of household vehicle ownership and utilization estimated in a simultaneous equations setting is definitely advantageous over analyzing the vehicle use patterns conditional upon the vehicle fleet.

The exogenous variables in this model system are socio-demographics attributes; number of adults in the household, number of children, number of working persons, annual household income, indicators for urban/rural area location of the household, housing type and the weekend travel day indicator. These exogenous variables are chosen based on previous literature review, preliminary exploratory analysis and judgment. Vehicle ownership, fleet combination and utilization are endogenous in the system. Vehicle ownership (endogenous) is taken as the number of vehicles owned by the household. Vehicle fleet combination or the ownership by type is the number of vehicles of each type owned by the household. The total daily Vehicle Miles Traveled (VMT) and the VMT on vehicles of each type give the vehicle utilization of the household. The socio-demographics are taken in as 6 exogenous variables; number of adults in the household, number of children, number of workers, number of drivers, annual household income, dummy variables for urban area location and detached single type of housing. The error terms of the equations for number of vehicles of each type are correlated among each other and similarly the error terms of the equations for the daily VMT on vehicles of each type are also correlated.

The endogenous variables specified in the model have different underlying theoretical distributions, thus precluding the possibility of the normal distribution assumption of the variables. Hence, this paper employs a structural equations estimation methodology that accommodates skewed non-normal endogenous variables. The ADF-WLS (Asymptotically Distribution-Free – Weighted Least Squares) method available in the Structural Equations Modeling Framework is used for the estimation, which reduces to Generalized Least Squares (GLS) estimation in the absence of non-normality and Maximum Likelihood (ML) estimation in the absence of heteroskedastcity or auto-correlation. The ADF-WLS procedure corrects for any source of non-normality like skewness, kurtosis and censoring of the variable distributions. Essentially the results presented use consistent estimators that are asymptotically efficient and provide corresponding test statistics that are asymptotically valid. However, the software package called AMOS (Analysis of Moment Structures) used for the estimation does not take into take into consideration the potential ordered-discrete nature of some of the endogenous variables (vehicle ownership) which is possible through extended forms of ADF-WLS estimation available in other packages available Hence, there is an implicit assumption here that all the endogenous variables are continuous.

The proposed model is estimated for the sample of households having at least one vehicle. The tables show the direct effects and total effects that constitute relationships among variables. The model estimates showed excellent goodness-of-fit measures with the χ^2 statistic indicating that the model cannot be rejected with a high degree of confidence (95 percent or higher) The critical N is above 200 hence avoiding the pitfall of not rejecting the hypothesis due to larger sample size. The Goodness-of-fit index (GFI) equal to unity and the Adjusted GFI is equal to 0.098. Thus the model framework is capable of capturing key relationships among the variables. The indications provided by the model are consistent with the expectations and are otherwise plausible. The regression coefficients significant at the 95 percent confidence level are retained. These regression coefficients show the direct effect of one variable on other and hence are also called direct effects. An arrow linking the two variables in the path diagram depicts a direct effect. On the other hand, an indirect effect is one where a variable influences another variable through a mediating variable. In some cases, a variable may have both a direct and an indirect effect on another variable. Then the total effect is the sum of the direct and indirect effects. The results presented for the model are from the final validated model after a series of exploratory analyses. The discussion is divided into two separate sections for vehicle ownership and utilization.

6.2.1 Vehicle Ownership

The estimates of direct effects (Table 6.1) show that vehicle ownership is higher in households with higher income, or larger number of workers, or larger number of licensed drivers. Households with larger number of adults show higher vehicle ownership while the households with more children tend to have lower vehicle ownership. Households in urban areas tend to have lesser number of vehicles while households living in detached single houses tend to have higher vehicle ownership. Both, housing type and residential location, have been described in the literature as a measure of the activity travel environment in the immediate neighborhood and the area the house is situated in respectively. In other words, these variables can also be interpreted as surrogates for urban form, neighborhood design and parking availability. Households in urban areas tend to have higher car ownership than any other vehicle type while households in urban areas show the least tendency to own pickup trucks with a negative coefficient indicating that rural area households tend to own more pickup trucks. SUV ownership is not significantly affected by the urban/rural area location of the household. Surprisingly, Van ownership is negatively affected by the urban area location of the household. Detached single type of housing favors higher pickup truck ownership followed by vans and SUVs. They show a negative effect on the car ownership. This may be because of the availability of parking space with detached houses that enables the ownership of larger vehicles like pickup trucks, Vans and SUVs.

Households with higher annual income tend to own more SUVs and less number of pickup trucks, which is consistent with expectations. Household income doesn't show a significant effect on the ownership of cars and vans. Number of adults in the household does not show a significant effect on the car ownership while it shows a positive effect on van ownership and a negative effect on SUV ownership and pickup truck ownership. This indicates that larger households show a higher tendency to own vans rather than SUVs and pickup trucks. Number of children in the household has a positive effect on the van ownership and SUV ownership while it has a negative effect on the car ownership and pickup truck ownership. This indicates the ownership of vans and SUVs for their use as family vehicles. Households with higher number of workers show higher ownership of SUVs and pickup trucks and a lower ownership of cars and vans. This indicates the ownership of SUVs and pickup trucks for their use by workers. Households with more number of drivers tend to have higher car ownership and lower van and pickup truck ownership. Total vehicle ownership also shows significant effect on the individual ownership of each vehicle type. The coefficients are positive and are less than unity as expected. These coefficients represent how an additional vehicle ownership contributes to the ownership of each vehicle type. The coefficients indicate that, keeping all else the same, households with larger number of vehicles have more cars followed by pickup trucks, SUVs and vans in that order. In other words, any extra vehicle in the household is most likely to be a car followed by a pickup truck, SUV and a van in that order.

In summary, cars are owned the most by households in urban areas, and households with more number of drivers. More over, each extra vehicle in a household is most likely to be a car. Households in urban areas and households living in detached single houses, with larger number of adults and children have higher van ownership. Households with larger number of workers and drivers tend to have lower van ownership.

Each extra vehicle in a household is least likely to be a van, indicating the smaller presence of vans in the households. Larger SUV ownership is in the households of higher income, households living in detached houses, and households with more children and working people. Pickup trucks are owned more by rural area households and households living in detached single houses and households with lower income, smaller size (adults and children), smaller number of drivers and larger number of workers. The intercepts indicate that, keeping everything else the same; the ownership of pickup trucks is most prevalent followed by cars and the ownership of vans and SUVs in less prevalent**.**

6.2.2 Vehicle Utilization

The exogenous variables explaining vehicle utilization include an additional dummy variable for weekend day for the utilization is on a daily basis. The direct effect of the weekend day on overall household VMT is negative indicating a lower household VMT on a weekend day compared to that of a weekday. However, the weekend effect on the VMT of the vans of a household is positive and that of pickup trucks is negative indicating that vans are used more and pickup trucks are used less on weekends. This is quite consistent with the expected results because households tend to make high occupancy trips of recreation and other purposes on more on weekends causing a higher mileage on vans and lower mileage on pickup trucks.

Urban area households show lower total VMT compared to those of rural areas. The total effects (Table 6.2) of the urban area dummy variable on the VMT by each type vehicle indicate that all types of vehicles; cars, SUVS, vans, and pickups is lower in urban areas. This may be because of the lower overall mileage by urban area households. But surprisingly, the urban area households show a positive direct effect on the VMT by pickup trucks. This indicates that even after controlling for all other relevant factors, including total household VMT and vehicle ownership and fleet combination, an urban area household tends to have more miles traveled on its pickup trucks compared to a household in a rural location. Households in urban areas show lower VMT on cars compared to those of rural area households, while the urban /rural area effect is not significant in the case of vans and SUVs. Households living in detached single houses do not show significant effect on total daily VMT. However, the total effect of this variable on the daily VMT is positive due to the higher vehicle ownership of the households living in detached single houses. The direct effects of this variable on VMT by individual vehicle type show lower car VMT and higher van VMT. The corresponding total effects indicate higher daily VMT on vans, SUVs and pick trucks and lower daily VMT on cars.

As expected, the direct effects of the higher income households show higher daily total VMT, van VMT and SUV VMT. Number of adults doesn't have any significant effect either on the total VMT or on the individual vehicle type VMT. The number of children shows a positive effect on the total VMT of the household while it does not have any significant effect on the VMT by each vehicle type. However, number of adults and children directly affect the vehicle ownership and hence indirectly affect the utilization. Number of workers in the household shows a positive effect on the total VMT of the household while it shows a negative effect on the VMT on vans of the household. This is perhaps due to every worker in the household requiring a separate vehicle for work. Number of drivers shows a positive effect on the total VMT and the pickup truck VMT of the household. Naturally, households with larger number of vehicles show higher total VMT but lower car VMT and pickup truck VMT. These households travel more on their vans and SUVs. However, this model doesn't control for the age of vehicles. Vans and SUVs may be relatively new in the vehicle fleet and hence being used more. The total VMT and the split among the vehicle types can also be affected by the fleet combination owned by the household. After controlling for the number of vehicles owned by a household, cars do not significantly increase the total daily vehicle mileage of the household on the other hand vans, SUVS and pickup trucks have a positive effect on the household VMT. This indicates lager amount of travel by households with SUVs, vans and pickup trucks even after all other factors are controlled for. Same argument holds for the higher positive effect of number of vans, SUVs and pickup trucks on their own VMTs while number of cars has a smaller positive effect on the car VMT of a household. As expected, the ownership of each vehicle type shows a negative effect on the VMT of other vehicles.

In summary, the VMT on cars is lower on households living in detached houses and urban area households. However, owing to a larger presence of cars in the households, the total VMT on cars tends to be higher. VMT on vans is higher on weekends and in households living in detached houses. Households with higher number of workers tend have lower VMT on vans. Higher annual income increases the van VMT and also the SUV VMT of a household. Pickup truck VMT is higher in urban households and households with larger number of drivers, while it is lower on weekends. The intercepts indicate that, keeping every thing else the same, the VMT on vans is lower than that of any other vehicle type. Vans, SUVs and pickup trucks show higher VMT on them selves as well as total household VMT when compared to that of cars.

Table 6.1 Direct Effects, Structural Equations Model of Vehicle Ownership and Utilization

		Endogenous variables - Ownership (Number of vehicles)					Endogenous variables -Utilization (Daily VMT – Vehicle Miles Traveled)				
		Total no of Vehicles	No of Cars	No of Vans	No of SUVs	No of Pickup Trucks	Household VMT	VMT on Cars	VMT on Vans	VMT on SUVs	VMT on Pickup Trucks
Exogenous Variables	Intercept	0.538	0.090	-0.095	-0.101	0.180	13.007	0.000	-1.338	0.000	0.000
	Weekend (d)	0.000	0.000	0.000	0.000	0.000	-10.504	0.000	1.573	0.000	-0.826
	Urban Household (d)	-0.395	0.249	0.021	0.000	-0.286	-13.772	-1.549	0.000	0.000	1.070
	Detached House (d)	0.232	-0.093	0.043	0.028	0.051	0.000	-1.136	1.070	0.000	0.000
	Annual income	0.004	0.000	0.000	0.003	-0.002	0.191	0.000	0.010	0.011	0.000
	No of Adults	0.054	0.000	0.068	-0.025	-0.026	0.000	0.000	0.000	0.000	0.000
	No of Children	-0.041	-0.126	0.115	0.025	-0.018	1.590	0.000	0.000	0.000	0.000
	No of Workers	0.141	-0.015	-0.028	0.025	0.038	10.263	0.000	-0.444	0.000	0.000
	No of Drivers	0.674	0.202	-0.024	0.000	-0.041	11.772	0.000	0.000	0.000	0.954
Endogenous variables	Total no of Vehicles	0.000	0.319	0.059	0.089	0.289	4.685	-2.222	0.000	0.000	-1.810
	No of Cars	0.000	0.000	0.000	0.000	0.000	0.000	16.65	-2.714	-3.502	-4.405
	No of vans	0.000	0.000	0.000	0.000	0.000	2.395	-12.363	26.916	-3.831	-5.139
	No of SUVs	0.000	0.000	0.000	0.000	0.000	3.386	-12.164	-3.521	25.968	-4.726
	No of Pickup Trucks	0.000	0.000	0.000	0.000	0.000	3.953	-9.432	-2.490	-3.631	20.765
	Household VMT	0.000	0.000	0.000	0.000	0.000	0.000	0.465	0.103	0.121	0.170

No of observations = 19,360 Households. $\chi^2[44] = 48.971$, Prob[χ^2>value] = 0.280. Adjusted Goodness-of-Fit Index = 0.998.
All effects significant at 95% level
Notes: (d) ≡ Dummy variable
Row variables affect column variables.

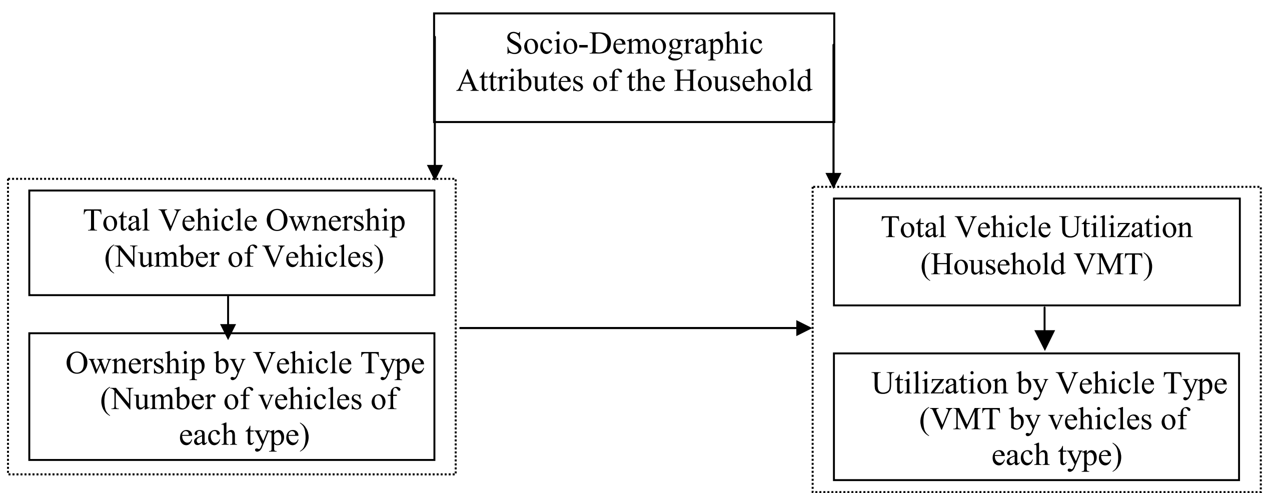
Table 6.2 Total Effects, Structural Equations Model of Vehicle Ownership and Utilization

		Endogenous variables - Ownership (Number of vehicles)					Endogenous variables -Utilization (Daily VMT – Vehicle Miles Traveled)				
		Total no of Vehicles	No of Cars	No of Vans	No of SUVs	No of Pickup Trucks	Household VMT	VMT on Cars	VMT on Vans	VMT on SUVs	VMT on Pickup Trucks
Exogenous Variables	Weekend (d)	0.000	0.000	0.000	0.000	0.000	-10.504	-4.889	0.493	-1.268	-2.609
	Urban Household (d)	-0.395	0.123	-0.003	-0.035	-0.400	-17.330	-2.447	-1.068	-1.969	-9.834
	Detached House (d)	0.232	-0.019	0.056	0.049	0.118	1.854	-3.507	2.355	0.918	1.915
	Annual income	0.004	0.001	0.000	0.003	-0.001	0.217	0.082	0.026	0.118	-0.014
	No of Adults	0.054	0.017	0.071	-0.021	-0.010	0.311	-0.221	1.995	-0.792	-0.600
	No of Children	-0.041	-0.139	0.113	0.022	-0.030	1.625	-2.840	3.578	0.923	-0.338
	No of Workers	0.141	0.029	-0.020	0.038	0.079	11.315	4.481	-0.219	2.036	3.096
	No of Drivers	0.674	0.417	0.016	0.060	0.154	15.775	10.418	0.319	1.376	3.405
Endogenous variables	Total no of Vehicles	0.000	0.319	0.059	0.089	0.289	6.269	1.468	0.330	0.667	3.135
	No of Cars	0.000	0.000	0.000	0.000	0.000	0.000	16.650	-2.714	-3.502	-4.405
	No of vans	0.000	0.000	0.000	0.000	0.000	2.395	-11.248	27.162	-3.541	-4.732
	No of SUVs	0.000	0.000	0.000	0.000	0.000	3.386	-10.588	-3.173	26.377	-4.151
	No of Pickup Trucks	0.000	0.000	0.000	0.000	0.000	3.953	-7.592	-2.084	-3.154	21.436
	Household VMT	0.000	0.000	0.000	0.000	0.000	0.000	0.465	0.103	0.121	0.170

Table 6.3 Estimated Variance-Covariance Matrix of the Disturbances of the Equations for Endogenous Variables

		No of cars	No of vans	No of SUVs	No of Pickup tucks
Ownership variables	No of Cars owned	0.482			
	No of Vans owned	-0.090	0.166		
	No of SUVs owned	-0.138	-0.036	0.222	
	No of Pickup tucks owned	-0.190	-0.031	-0.039	0.281
		VMT on Cars	VMT on Vans	VMT on SUVs	VMT on Pickup Trucks
Utilization variables	VMT on Cars	1081.578			
	VMT on Vans	-210.255	400.533		
	VMT on SUVs	-241.315	-55.813	462.473	
	VMT on Pickup Trucks	-340.708	-72.473	-91.962	624.689

Figure 6.1 Structural Equations Framework of Household Vehicle Ownership Trends and Daily Utilization Patterns



6.3 Multinomial Logit Model of Recent Vehicle Acquisitions

In addition to the vehicle fleet ownership by combination of number of each type, it is important to understand the recent vehicle acquisition trends. It is crucial to consider vehicle type choice behavior of households for recent vehicle purchases to understand the recent trends in vehicle ownership. Understanding of choice making behavior is also important in the assessment of demand for each type of vehicle and in the development of vehicle transactions models. This section provides such analysis in the context of household attributes.

To distinguish the four types of vehicles based on their addition to the household vehicle fleet, a multinomial logit model (Table 6.4) was estimated for the choice of the type (car, van, SUV and pickup truck) of vehicle recently acquired by the household. Model was estimated only for a sample of households that have acquired their recent vehicle not former than one year. This is because for the households that have purchased new vehicle former than a year, the socio-economic and the residential location and type attributes when they actually purchased the vehicle, which would have actually influenced the choice making, are not likely to be the same as current attributes. Given that the data has information of only current attributes, it is appropriate to model the vehicle acquisition of only those households that have recently bought vehicles. The observed utility was specified as a function of household structure and demographic attributes, annual income status, residential type and location variables and previous vehicle ownership. The explanatory variables set for previous vehicle ownership, which is very important in the new vehicle type choice, is generally not found in the literature. The utility of buying a car was taken to be the base case with zero value.

The model estimates show that households in urban areas show higher propensity to add a car to their vehicle fleet compared to any other vehicle type, whereas households living in detached single type of houses show the least tendency to add a car to their vehicle fleet. This is consistent with the results of the joint ownership and utilization model in the previous section. Households living in houses that are not detached and single houses do tend to own cars perhaps due to the parking space issues. These trends indicate the effect of urban form and immediate neighborhood design and dense environments on the vehicle type choice of the households. This also suggests a possibility of transportation control measures like parking pricing etc.

Higher average annual income favors addition of SUV followed by van. They are least likely to add a pickup truck to their vehicle fleet. This reiterates the fact that SUVs belong to higher income households. Children in the household increase the tendency of households to buy a van followed by SUV, pickup truck and car in that order. Households with retired people are most likely to acquire a car and are less likely to add SUV or pickup truck. Households of higher size are most likely to add van or SUV and least likely to add pickup truck. Higher number of workers in a household makes it least inclined towards buying a van. This is probably because each worker in the household might necessarily need a separate vehicle for work. The effect of number of workers in the household is not significantly different for cars, vans and SUVs. The first vehicle (if the household was previously in zero vehicle state) acquired by any household was mostly likely to be a car. It can also be inferred that multi-vehicle households are more likely to possess pickup trucks, vans and SUVs. Presence of van/SUV/pickup truck deters the acquisition of the same vehicle type. However, presence of a car doesn't deter the acquisition of another car. Presence of cars) does not show any statistically significant difference in the addition of van/SUV/car to the fleet. So, households with car are likely to buy any given type of vehicle. However, they are most likely to acquire a pickup truck. Households with car/van/SUV are more likely to add a pickup truck to their vehicle fleet. Previous vans or SUVs deter the addition of either type of them as a new vehicle in vehicle fleet. Presence of pickup truck doesn't significantly affect the acquisition of van/SUV in comparison to addition of a car. Thus, apart from the socio-economic and residential area attributes of a household, previous vehicle ownership of the household plays a vital role in the choice of the vehicle type to be added to the fleet. The alternative specific constants indicate that given all else the same, cars are given higher intrinsic preference by the households while making a purchase decision. The alternative specific constant term for pickup truck choice is not significantly different from that of car.

Essentially, the discrete choice model for the type of recently owned vehicle has shown the behavioral differences in choice making in the context of socio-demographic attributes and previous vehicle ownership combination. The model estimates have also confirmed the findings of the joint model of vehicle use ownership and utilization in the previous section. The ownership of different types of vehicles is for different types of trip making represented by the socio demographic attributes in this model. The forthcoming model of the type of vehicle chosen by a driver for his/her trip distinguishes the four vehicle types based on the attributes of the trips they are being driven for and also on the characteristics of the trip maker.

6.4 Multinomial Logit Model of Driver's Vehicle Type Choice for a Trip

Analysis of the vehicle type choice behavior of drivers for their trips can give further insights into the trends of vehicle utilization and the preferences of people amongst the opportunities provided and constraints imposed by their socio-demographics. It will also provide a better understanding of the vehicle utilization patterns in the context of driver attributes in a ceteris paribus situation. Hence, a multinomial logit model (Table 6.5) is estimated for the vehicle type (car, van, SUV, Pickup truck) chosen by a driver for his/her trip based on the trip attributes and driver attributes. The choice set was varied for trips from each household; i.e. the alternatives considered for a trip from a particular household were only the types of vehicles possessed by that household. Cases with no choice (only one alternative) were removed for they wouldn't provide any useful information in the logit model estimation. The base case utility of choosing car for a trip was specified as zero for identification purposes. Given that the outcome is just the probability of the type of the vehicle and not of the individual vehicle, the possibility of error term correlations due to common unobserved attributes of similar types of vehicles is eliminated.

The sign of the intercepts in the utility equations indicate that, given all else the same, cars are still driven the most compared to all other vehicle types. The coefficients indicate a higher tendency among drivers to choose comparatively new SUVs and older pickup trucks, perhaps due to the differences in the holding durations for these vehicles. Moreover, SUVs are comparatively newer vehicles of the fleet. The tendency to prefer vans, SUVs and pickup trucks increases with age of the driver. However, as indicated by the coefficients of age square term, drivers starting from the age of late 40s tend to revert back to cars. This implies that drivers in their mid age tend to drive non-car type of vehicles and elderly drivers tend to drive cars. On the other hand, one might question whether the elderly of tomorrow will behave like the elderly of today or like themselves today. That is, if people are accustomed to using minivans and SUVs during their working years, perhaps they will continue to do so in the future when they retire as well. Employed drivers choose to drive cars more compared to any other vehicle type. Employed drivers might choose to drive cars when compared to pickup trucks and vans. However, the tendency of unemployed drivers choosing to drive SUVs is counter intuitive. Female drivers tend to choose vans and male drivers tend to choose pickup trucks and SUVs. Drivers from high average income households tend to choose SUVs. Drivers from households with high vehicle to driver ratio are more likely to drive a car than any other vehicle. This is perhaps due to a larger presence of cars in the vehicle fleet.

As expected, there is a high tendency that trips of high vehicle occupancy are made in vans and SUVs rather than in cars. Pickup trucks are more likely to be used to make trips of lower occupancy. However, pickup trucks are most likely, and SUVs and vans are less likely to be driven for joint trip making with non-household members. There is also a high tendency that pickups are chosen for work trips and that they are chosen the least for recreational trips and for trips on weekend. SUVs and vans show positive coefficients for weekend trips but are statistically not significant. They are also more likely to be used for non-work trips, but the coefficients are not statistically significant. The coefficients of trip length in terms of duration are also negative and statistically significant for both vans and SUVs. They are more likely to be driven for comparatively shorter trips (trip time). The significant negative coefficient of trip length (minutes) on SUV choice was not expected as the descriptive analysis showed higher average trip lengths for SUVs when compared to cars. The tendency of vans to be driven for shorter trips, given that they are also being driven more (in terms of number of trips), has important implications to policy from the perspective of emissions and fuel consumption. Pickup trucks are more likely to be used in a non-urban setting. Even the coefficients of Vans and SUVs show negative signs for the urban indicator variable but they are not statistically significant. Vans are least likely to be used for trips that involve longer time spent at the destination. This might indicate the lower usage of vans for driving to perform activities of longer durations. As expected, there is no significant difference in the type of the vehicle driven for trips in different times of day. The vehicle type choice decisions are not such short-term decisions to be influenced by the time of day. Thus the vehicle type choice for a trip is dependent upon the type of the trip and the characteristics of the trip maker. The general trip making patterns of the household members shaped by the socio-demographics of the household will in turn play an important role in the vehicle ownership patterns.

Table 6.4 Multinomial Logit Model for the Recently Acquired Vehicle Type

	Variable	Coefficient	S.E	B/S.E	P
Van	Constant	-1.87217	0.21351	-8.769	0.000
	Urban HH (d)	-0.17600	9.03E-02	-1.949	0.051
	Detached single house (d)	0.29761	9.75E-02	3.052	0.002
	High income HH (d)	0.00000	3.29E-06	-1.307	0.191
	No of children (<18yrs)	0.36056	8.14E-02	4.427	0.000
	Retired people in HH (d)	0.09974	0.134845	0.740	0.460
	Household size	0.17418	7.66E-02	2.275	0.023
	No of workers in HH	-0.28964	6.13E-02	-4.727	0.000
	Previously zero vehicle HH (d)	-0.57669	0.152194	-3.789	0.000
	HH owns a car (d)	-0.10732	0.109913	-0.976	0.329
	HH owns a van (d)	-0.75020	0.137313	-5.463	0.000
	HH owns a SUV (d)	-0.47705	0.127639	-3.737	0.000
	HH owns a pickup truck (d)	-0.10531	0.10236	-1.029	0.304
SUV	Constant	-1.80841	0.168469	-10.734	0.000
	Urban HH (d)	-0.25802	7.31E-02	-3.529	0.000
	Detached single house (d)	0.31354	7.95E-02	3.945	0.000
	High income* HH (d)	0.00002	2.06E-06	9.703	0.000
	No of children (<18yrs)	0.17556	6.78E-02	2.591	0.010
	Retired people in HH (d)	-0.47263	0.116503	-4.057	0.000
	Household size	0.10498	6.38E-02	1.645	0.100
	No of workers in HH	-0.02400	5.20E-02	-0.461	0.645
	Previously zero vehicle HH (d)	-0.81720	0.128662	-6.352	0.000
	HH owns a car (d)	-0.05448	8.43E-02	-0.646	0.518
	HH owns a van (d)	-0.43223	0.103452	-4.178	0.000
	HH owns a SUV (d)	-0.12911	9.00E-02	-1.435	0.151
	HH owns a pickup truck (d)	-0.14461	7.87E-02	-1.838	0.066
Pickup Truck	Constant	-0.05339	0.157518	-0.339	0.735
	Urban HH (d)	-0.88050	6.46E-02	-13.627	0.000
	Detached single house (d)	0.35685	7.57E-02	4.716	0.000
	High income* HH (d)	-0.00001	2.32E-06	-3.227	0.001
	No of children (<18yrs)	0.14439	6.56E-02	2.200	0.028
	Retired people in HH (d)	-0.37967	0.104064	-3.648	0.000
	Household size	-0.17503	6.18E-02	-2.832	0.005
	No of workers in HH	-0.02188	4.90E-02	-0.446	0.655
	Previously zero vehicle HH (d)	-0.96006	0.127844	-7.510	0.000
	HH owns a car (d)	0.25480	7.92E-02	3.218	0.001
	HH owns a van (d)	0.09584	9.14E-02	1.049	0.294
	HH owns a SUV (d)	0.34809	8.20E-02	4.243	0.000
	HH owns a pickup truck (d)	-0.38434	7.47E-02	-5.147	0.000

#obs = 8651, Log-Likelihood function = -9581.852, $\chi^2[36]$ = 1061.076, Prob [χ^2>value] =.000

	Log-L fn	R^2	R^2_{Adj}
Model	-9581.852		
No coefficients	-11992.833	0.201	0.199
Constants only	-10112.390	0.052	0.051

Table 6.5 Multinomial Logit Model for Driver's Vehicle Type Choice for a Trip

	Variable	Coefficient	S.E	B/S.E	P
Van	Constant	-3.96361	0.151	-26.207	0.000
	Number of years vehicle owned	-0.00634	0.005	-1.319	0.087
	Drivers Age	0.17498	0.007	26.603	0.000
	Square of drivers age	-0.00173	0.000	-24.340	0.000
	Driver is employed (d)	-0.49307	0.042	-11.845	0.000
	Male driver (d)	-0.33169	0.033	-9.999	0.000
	Vehicle occupancy	0.46439	0.019	24.360	0.000
	Non-household passenger on trip (d)	-0.44134	0.060	-7.408	0.000
	Trip Length (min)	-0.00184	0.001	-2.150	0.032
	Time spent at destination of trip	-0.00036	0.000	-3.326	0.001
	Vehicles to drivers ratio	-0.12396	0.028	-4.418	0.000
SUV	Constant	-2.07397	0.113	-18.313	0.000
	Number of years vehicle owned	-0.07261	0.004	-16.646	0.000
	Drivers Age	0.10180	0.005	19.042	0.000
	Square of drivers age	-0.00106	0.000	-17.275	0.000
	Driver is employed (d)	-0.28025	0.036	-7.803	0.000
	Male driver (d)	0.22272	0.027	8.297	0.000
	Vehicle occupancy	0.22926	0.018	12.484	0.000
	Trip length (min)	-0.00224	0.001	-3.435	0.001
	Non-household passenger on trip (d)	-0.30950	0.051	-6.103	0.000
	Non-work trip (d)	0.05738	0.032	1.807	0.071
	Vehicles to drivers ratio in HH	-0.18872	0.024	-7.898	0.000
	Average household income	0.00001	0.000	6.368	0.000
Pickup Truck	Constant	-3.35042	0.108	-31.024	0.000
	Number of years vehicle owned	0.01105	0.004	3.141	0.002
	Drivers Age	0.11209	0.005	24.275	0.000
	Square of drivers age	-0.00123	0.000	-24.385	0.000
	Driver is employed (d)	-0.21907	0.037	-5.943	0.000
	Male driver (d)	2.95597	0.031	96.678	0.000
	Vehicle occupancy	-0.45727	0.021	-21.545	0.000
	Non-household passenger on trip (d)	0.35430	0.051	6.974	0.000
	Trip length (min)	-0.00097	0.001	-1.688	0.092
	Work trip (d)	0.22006	0.032	6.786	0.000
	Recreational trip (d)	-0.06896	0.033	-2.098	0.036
	Trip on a weekend (d)	-0.10531	0.030	-3.521	0.000
	Urban area household (d)	-0.12776	0.026	-4.997	0.000
	Vehicles to drivers ratio	-0.32036	0.021	-15.410	0.000

#obs = 71360, Log-L fn = -43952.678, χ^2 [34] = 96042.162, P[χ^2>value] = 0.000

	Log-L	R^2	R^2_{adj}
Model	-43952.678		
No coefficients	-98925.9656	.555	.555
Constants only	-66309.949	.454	.455

CHAPTER 7
CONCLUSIONS AND FUTURE RESEARCH

7.1 Conclusions

This thesis utilized the 2001 National Household Survey (NHTS) data to study the patterns of household vehicle ownership and utilization in the United States. Four vehicle types; cars, vans, SUVS and pickup trucks are distinguished based on how households own and use them for their travel needs. The NHTS data proved to be a rich source for such an analysis.

The thesis provided an extensive descriptive analysis of the data to assess the differences among the vehicle types in a univariate setting. The relevance and importance of socio-demographic factors is assessed in the context of the ownership, use and allocation of each vehicle type. The ownership analysis probed into aspects like vehicle fleet combination, length of ownership and trends in vehicle acquisitions across vehicle types. Vehicle utilization patterns are discussed in terms of the trip attributes and the extent of use and primary driver allocation. Vehicle miles traveled, person trips and driver trips served, occupancies and trip lengths were analyzed for weekdays and weekends to illuminate any differences in use across vehicle types. The primary driver allocation and utilization analysis offered insights into extent to which a vehicle is devoted to a primary driver and also the differences across vehicle types.

This study also analyzed the structural relationships among socio-demographics, ownership and utilization patterns of each vehicle type in a unified framework. The structural equations model developed in this context provides unconditional estimates by considering ownership and utilization simultaneously. The model considered the vehicle ownership and fleet combination as endogenous, which is better than an individual ownership model that considers the vehicle ownership as exogenous. The multinomial logit model for the type of recently acquired vehicle provided insights into the recent trends in the vehicle ownership patterns. The model estimates illustrated the importance of considering previous vehicle ownership in the decision making of the new vehicle type to be bought. Finally the multinomial logit model of the type of vehicle chosen by the driver for a trip offered an understanding of the choice making of the drivers in the context of person attributes and trip attributes. Essentially, this model has offered an understanding of who drives what type of vehicles for what purposes when and where.

Results of the analysis indicate that cars are still the dominant types of vehicles owned and recently purchased. Each additional vehicle in the household is more likely to be a car rather than any other vehicle. This may be because of their prevalence right from the beginning of the automobile era. Cars are still the prevalent type of vehicles present in the fleet. Urban area households have higher car ownership than that of a rural area household. Younger and elderly people and employed persons tend more to drive cars than any other vehicle.

Vans show the least presence in the vehicle fleet. These vehicles are being owned more by households in urban areas, households living in detached houses, and households of larger size and children count. Households with larger number of workers show lower van ownership tendency. Vans are relatively new vehicles in the fleet, essentially being used as family vehicles for trips of high occupancy, shorter length and are driven more by females and are being used more on weekends. These findings could have several implications. Vans, being owned more by households with children for their use as family vehicles, need to be better designed from safety perspective with child restraints etc. Given that they are being driven more by female drivers who are more prone to higher accident severity, vans need to be better designed for comfort of driving and safety with female driver as a basis. SUVs are also relatively new vehicles in the fleet, and are being owned by affluent households. SUVs are similar to in that they are also owned by households living in detached houses and larger households and are used as family vehicles for trips of higher occupancy.

Pickup trucks are being owned more by households in rural areas, households of smaller size and households living in detached houses, and households with lower income. Pickup trucks are not used as family vehicles; they are rather used as work vehicles. These vehicles are driven more by male drivers and are owned for longer time when compared to other vehicles. Pickup trucks are similar to vans and SUVs in that they are being driven more than cars and that people of mid-age are driving them more.

In addition to confirming many perceptions about the patterns in ownership and use of the four vehicle types, this study has brought out some subtle differences. In many ways, this analysis of the diverse personal vehicle fleet of United States has several implications to the transportation systems planning, policymaking and perhaps regulatory action. The finding that vans, SUVs and pickup trucks are driven over larger distances than cars can have several implications to emissions and energy consumption. These vehicles being larger than cars can actually take up more car equivalents on a road and on parking spaces hence pose capacity constraints on roads, at intersections and in parking lots. An important observation that could be made throughout the analysis is that the usage of vans and SUVs is similar to that of cars in similar ways. There is no indication of additional work travel on Vans and SUVs; these vehicles are in fact being used being used more than cars as personal vehicles. They are also being used as family vehicles for trips of high vehicle occupancy to various purposes. This evidence warrants the reconsideration of the light duty truck classification. Evidence of higher trip rates of primary drives of vans, SUVs and pickup trucks than that of cars, and the possibility of differences in the daily household VMT different vehicle fleet combination indicates that it may be necessary to incorporate the effect of vehicle fleet combination in addition to the total vehicle ownership in determining trip generation rates. However, a closer study is warranted in order to determine the causality of the relation between the amount of household travel and the vehicle fleet combination. Higher ownership of vans by female drivers, and their usage for high occupancy trips and by households with children indicates that these vehicles may need to be designed female driver friendly and be made more safer with better children restraints etc.

7.2 Future Research

This study offers a detailed analysis of the cross sectional data from the 2001 NHTS. However, patterns, preferences, and markets do change over time. Analysis of the temporal trends of vehicle ownership and utilization should certainly be undertaken for a panel data set in order to obtain better insights. Such study can illuminate much about the market share trends and inform policy in a better way. A thorough policy oriented research is required to understand the implications of the current vehicle ownership and utilization patterns in order to suggest appropriate regulatory action. Models of stated preference survey data are necessary in order to understand consumer and market responses and evaluate proposed policy measures.

The analysis in this study can be extended in many ways. It may be necessary to econometrically refine the models presented in this study. The structural equations model of vehicle ownership and utilization doesn't take into consideration the censored nature of endogenous variables. Vehicle ownership and utilization cannot be less than zero. The estimates could also be improved by considering the ordinal discrete nature of vehicle ownership variables. It would be certainly interesting to analyze the fractional split taken by vehicle of each type of the household's daily vehicle mileage (VMT) instead of the mileage itself in the structural equations framework. This kind of fractional split model would give insights into the structural relationships between the socio-demographic variables and the share of the daily household vehicle mileage taken by vehicles of each type. This fractional split could be further be extended to the work, non-work fractional split for each vehicle type in order to better understand the vehicle usage in a multivariate setting. The fractional split models in a logistic distribution framework can provide better predictions. The multinomial logit models presented could be saddled with the IIA (Independence of Irrelevant Alternatives) property. A random coefficients logit model can incorporate any form of error correlation across alternatives and heteroskedasticity through a general covariance matrix. Moreover, such general model can account for the heterogeneity of parameters, hence taste variations in the population. Current methodological advancements must be exploited to better analyze the trends before coming up with policy suggestions.

Not all aspects of ownership and utilization are covered in this analysis. One such unexplored aspect in the recent past is the vehicle holding durations. An in-depth analysis of the length of time a vehicle is used before it is disposed is necessary because older vehicles in the fleet cause more vehicular emissions. The descriptive analysis of the primary driver allocation can be extended to models of vehicle allocation patterns to primary drivers in order to study the trends in a multivariate setting. This study has concentrated on the socio-demographic factors, which are important determinants of vehicle ownership and utilization patterns. However, analysis should also be extended to many other important aspects; attitudinal factors, population density and other land use and urban form specific variables, vehicle ownership and operating costs, transportation system performance indicators like network level of service etc. which certainly have the potential to influence vehicle ownership and use. Future efforts require exploration of further complex structural relations introducing the effects of the above additional factors.

Given this analysis, results and implications to planning, policy and perhaps regulatory action, several cautions must be exercised before directly using the results. There could be many differences in the way households and people own and use leased vehicles and vehicles that are bought old. Vehicle ownership decisions may also depend upon the type of ownership; ex: lease-versus-own and new-versus-old vehicles. A household's vehicle purchase definitely depends upon the new-versus-old vehicle decision. Extended use of older vehicles may have implications to policy. Presence of older vehicles in the fleet may mask the effectiveness of certain policy and regulatory measures that are actually appropriate for new vehicles. Identifying and controlling for factors like lease-versus-buy, and new-versus-old can provide us better insights into the vehicle ownership and utilization patterns. Maturity of vehicle type is an issue that precludes the direct translation of current trends and differences in the ownership and use patterns of different types to future. The predictive values and trends may be influenced due to the fact relatively new vehicles like vans and SUVs have not yet matured in terms of their penetration into the market. Current ownership and use patterns may not be extrapolated to future with out considering the possibility of growth in market share of these vehicles and their maturity in terms of marker penetration. However, many commodities in the market may not see a maturity period due to the rapid changes in technology that accelerates the replacements of products. It may be possible that before SUVs see period, the new cross breed of SUVs and pickup trucks can take over the market share and so on.

For example, elderly of today show lower ownership of SUVs and vans. However, today's mid-age drivers, who will be the elderly of tomorrow, may be different because they are currently showing higher ownership of vans and SUVs. Hence it is possible that the elderly of tomorrow continue the use of their vans and SUVs. However, pickup trucks, which are relatively old in the fleet, have not shown such trend. Their increasing popularity in the recent years can perhaps make them popular among the elderly of tomorrow. Similar arguments can be extended to other implications discussed in this chapter.

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