ABSTRACT

Title of Document: MODELING CAR OWNERSHIP, TYPE AND USAGE FOR THE STATE OF MARYLAND

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Over the last few decades there has been a great increase in the number of cars in the United States. Given the importance of vehicle ownership on both transport and land-use planning and its relationship with energy consumption, the environment and health, the growth in the number of vehicles and their use has been one of the most intensely researched transport topics over many years.

This thesis presents a car ownership model framework for the State of Maryland. The model has been calibrated on publicly available data (2001 and 2009 National Household Travel Survey) without the burden and the consequent cost of collecting additional data. The sample has been sufficient to correctly estimate a number of relevant socio demographic and land use variables. The model has then been applied, for demonstration purposes, to test a number of sensitivity analysis concerning changes in housing density, income, urbanization, unemployment rates and fuel price.

MODELING CAR OWNERSHIP, TYPE AND USAGE FOR THE STATE OF MARYLAND

By

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Dedication

This thesis is dedicated to my loving parents.

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Chapter 1: Introduction

1.1 Background

The increasing energy cost and awareness about climate change are forcing citizens to reduce energy consumption and emissions and public authorities to study how policy might impact travel behavior.

Over the last few decades there has been a great increase in the number of cars in the United States. Both the average number of cars per household and the proportion of households with access to more than one vehicle have significantly grown.

Understanding and predicting consumers' preferences regarding car ownership and use is important given the consequent impacts on both transportation and land-use planning and its relationship with energy consumption, environment and health.

Vehicle ownership modeling is being used for a wide variety of purposes. Land use researchers and planners implement vehicle ownership models in trip generation for more accurate planning forecasting (Figure 1-1). In a typical four-step travel forecasting model, the first step is trip generation, which obtains the outputs from car ownership models. Departments of Transportation and Environment Departments develop vehicle ownership and vehicle use models to forecast transport demand, energy consumption and emission levels, as well as the likely impact of policy measures. Moreover, national governments (such as Finance Ministries) use car ownership models to forecast tax revenues and the regulatory impact of changes in the level of taxation. Car manufacturers apply models to the consumer valuation of attributes relative to cars that are not yet on the market, such as hybrid or electronic cars. Oil companies want to predict the future demand for their products and might benefit from car ownership models.

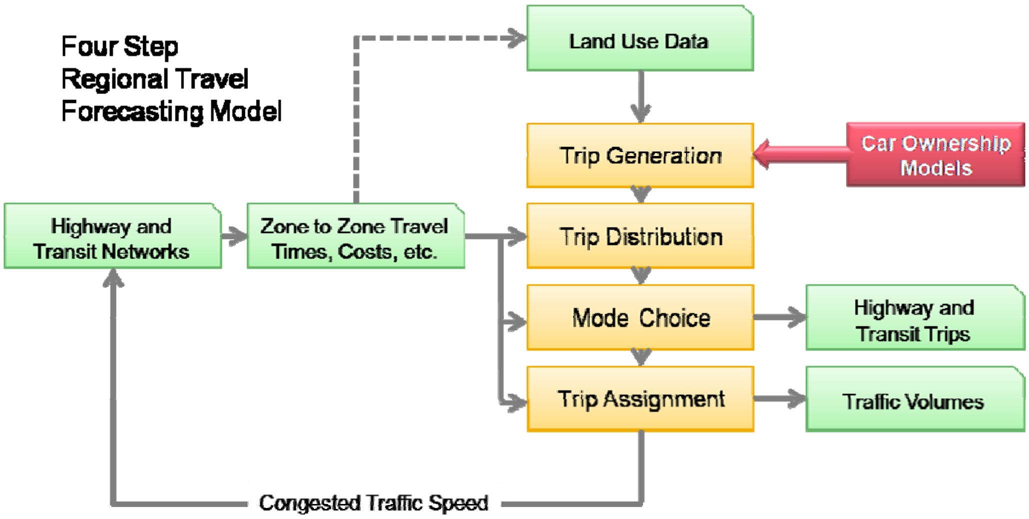


Figure 1- 1 Car Ownership Models in Four-Step Forecasting Model

1.2 Objective of Research

The aim of this research is to present the car ownership model framework developed for the State of Maryland. The modeling system aims to produce the tools needed to understand and predict consumers' preferences on vehicle ownership, as a function of:

- socio-demographic,
- economic,
- transportation system, and
- land development characteristics.

As shown in Figure 1-2, the modeling framework include three stages—vehicle quantity models, vehicle type models, and vehicle usage models. Each model is calibrated on data derived from the National Household Travel Survey (NHTS); two waves of data have been used for this analysis: NHTS 2001 and NHTS 2009. Due to the unavailability of the vehicle characteristics data for the years prior to 2001, it was not possible to estimate the 2001 vehicle type model. The framework developed for 2009 is complete as it contains the vehicle ownership model, the vehicle type and use models. However, the number of observations available for 2009 is quite low; this has limited the possibility to validate the models and to apply them for policy forecasts.

Overall, the models estimated have enabled the analysis of several policy scenarios and been demonstrated to be quite accurate when validated.

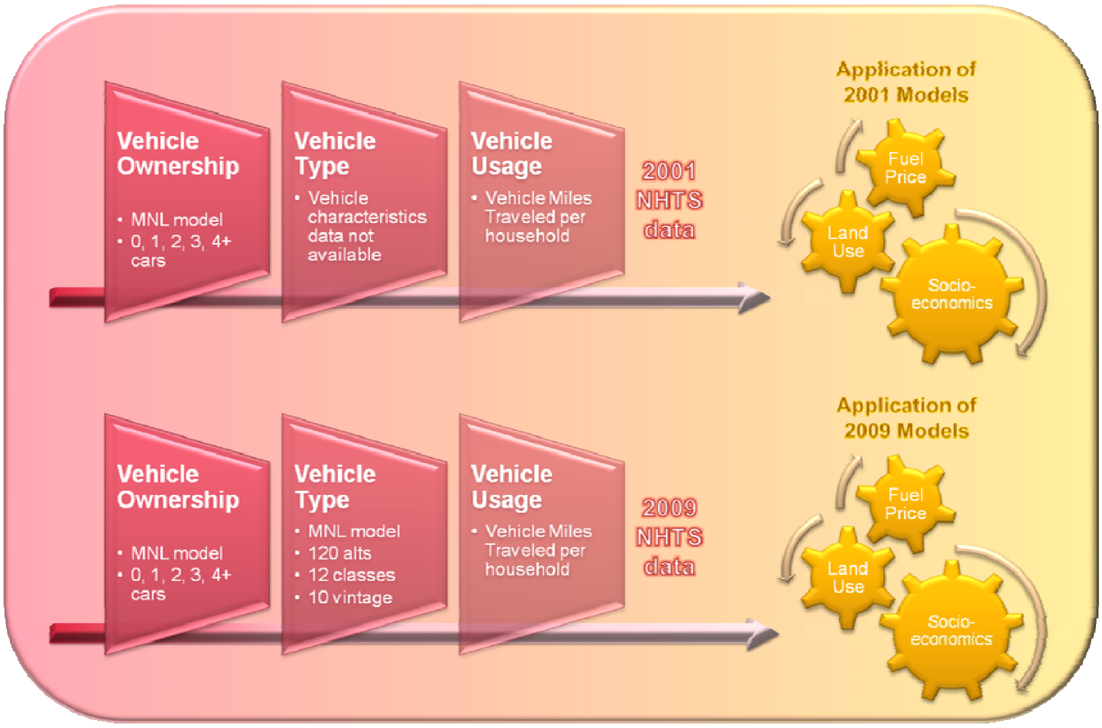


Figure 1- 2 Objective of Research and the Framework

1.3 Scope of Research

To place this research in context, a review of related literature is given in Chapter 2. First, an overview of car ownership related studies is provided and then previous research on vehicle quantity models, vehicle type models and vehicle usage models is elaborated. Finally some useful findings and conclusions are drawn for each Section.

In Chapter 3, methodologies that will be used in this research are described in detail, including discrete choice model and regression model. Chapter 4 describes the main data sources the some preliminary descriptive analysis. The National Household Travel Survey (NHTS) data and the information extracted from the *Consumer Report* *website* constitute the major databases used in this study. Some quantitative analysis are presented in this chapter, including the trends of major indicators for 2001 and 2009.

Having set the methodology, empirical results resulting from model calibration are given in Chapter 5 and Chapter 6. Chapter 5 is related to 2001 models and includes the estimation of vehicle quantity model and vehicle usage model. Model validation for vehicle quantity models is also conducted. Several policy scenarios are tested using 2001 models; they are based on changes in household income level, urbanization factor, unemployment rate, fuel price, etc.

Chapter 6 presents the results obtained with NHTS 2009. Policy scenario analyses similar to the one above have been carried out. Although the number of observations available for 2009 is rather limited, results obtained are statistically significant and produce reasonable forecasts when applied to future conditions. Finally a comparison between results obtained for 2001 and 2009 is summarized in the last section of this Chapter.

Final conclusions and challenges are presented in Chapter 7, where contributions, potential future research and main findings of this research are summarized.

Chapter 2: Literature review

2.1 Overview of Car Ownership Models

Models for predicting changes in the level of car ownership have been under development since the 1930s (e.g. Wolff, 1938; Rudd, 1951; Tanner, 1958). They are essential to the transport planning process and are of interest to government, vehicle manufactures, environmental protection groups, public transport authorities, and public transport operators.

A comprehensive review of car ownership models has been published by de Jong in 2004. In this paper, the models documented in the literature have been classified into nine types: (1) aggregate time series models, (2) aggregate cohort models, (3) aggregate car market models, (4) heuristic simulation method, (5) static disaggregate car ownership models, (6) indirect utility car ownership and use models (joint discrete-continuous models), (7) static disaggregate car type choice models, (8) (pseudo)-panel methods, and (9) dynamic car transaction models with vehicle type conditional on transaction.

Aggregate time series models usually contain a sigmoid-shape function for the development of car ownership over time; the growth function is usually related to income or gross domestic product (GDP). The function increases slowly in the beginning (at low GDP per capita), then rises steeply, and ends up approaching a saturation level. Examples along this line are the work done by Tanner (e.g. Tanner, 1983), Button et al. (1993), Ingram and Liu (1998), the National Road Traffic Forecasts (NRTF) in the UK (Whelan et al., 2000, Whelan, 2001), Dargay and Gately (1999a), etc. These models have the lowest data requirements and are attractive for application to developing countries.

Aggregate cohort models segment the current population into groups with the same birth year (often five-year cohort), and then shift these cohorts into the future, describing how the cohorts as they become older, acquire, keep and lose cars. Examples are the models of Van den Broecke (1987) for the Netherlands, cohort-based car ownership models in France (Madre and Pirotte, 1991) and Sweden. Aggregate cohort models are most suited for predicting the impact on car ownership of changes in the size and composition of the population. The demographic force behind car ownership growth can be expected to remain important in Western Europe for another couple of decades.

Examples of aggregate car market models are Mogridge (1983), the Cramer car ownership model (Cramer and Vos., 1985), Manski (1983), Berry et al. (1995), the TREMOVE model (KU Leuven and Standard & Poor's DRI, 1999), the ALTRANS model (Kveiborg, 1999), and those included in the software package THESIS (Hensher and Ton, 2002).

The FACTS model (NEI, 1989; AVG, 1999) and the UMOT model of Zahavi (1979) belong to the heuristic simulation method. The models use as starting point the assumption of stability of household money budget for transportation (as a fraction of the household's net income) over time. The FACTS model distinguishes 18 categories of passenger cars. For each household, annual income and annual car kilometrage are drawn at random from household-type-specific distributions, and the budget share of the income drawn is calculated for each category of passenger cars. The household then chooses the car category or categories for which the costs are close to the budget.

Static disaggregate car ownership models contain often discrete choice models that deal with the number of cars owned by a household. Examples are the work by Gunn et al. (1978/1979), which have been later implemented into the Dutch national model system (LMS) (Hague Consulting Group, 1989). Similar models have been developed by Bhat and Pulugurta (1998) and by Rich and Nielen (2001); real applications of static discrete methods include the model developed for the city of Sydney (Hague

Consulting Group, 2000), and the model for the National Roads Traffic Forecast (NRTF) in the UK (Whelan, 2001).

Joint discrete-continuous models explain household car ownership and car use in an integrated micro-economic framework. The models developed by Train (1986) for California, by Hensher et al. (1992) for Sydney and by De Jong (1989a, b and 1991) for The Netherlands belong to this category.

Static disaggregate car type choice models contain discrete choice models that deal with the households' choice of car type given car ownership. There are many publications on static and (pseudo)-dynamic vehicle type choice models, such as Berkovec (1985), Chandrasekharan et al. (1991), Hensher et al. (1992), Mannering and Winston (1985), Manski and Sherman (1980) and Train (1986). Among the car ownership models recently published we recall in particular those developed for new vehicle purchasing: Page et al. (2000), Brownstone et al. (2000), Hensher and Greene (2000) and Birkeland and Jordal-Jørgensen (2001).

The pseudo-panel approach is a relatively new econometric approach to estimate dynamic (transport) demand models that circumvents the need for panel data and their associated problems (e.g. attrition). A pseudo-panel is an artificial panel based on (cohort) averages of repeated cross-sections. Examples are work done by Kitamura (1987), Golob and van Wissen (1989), Kitamura and Bunch (1990), Meurs (1991), Hensher et al. (1992), Hanly and Dargay (2000), Golounuv et al. (2001), Dargay and Vythoulkas (1999, b), Nobile et al. (1996), Golounov, Dellaert and Timmermans (2002), Huang (2005), and Cao et al. (2007).

Early examples of vehicle transactions models were developed in the 80's (Hocherman et al. (1983), Smith et al. (1989) and Gilbert (1992)). More recent examples of this category include the Dutch DVTM (dynamic vehicle transactions model) (HCG, 1993, 1995a.b, De Jong 1996), and the work published by Brownstone et al (2000).

According to this comparison, aggregate time series, cohort models and aggregate car market models do not appear very promising for the development of a full-fledged car fleet model, since they lack vehicle types and policy variables. They could only be used to predict a total number of cars in the future year, which would then be used as a starting point for more detailed analysis. Heuristic simulation models of car ownership do not offer extensive possibilities to include many car types either. On the other hand they can fruitfully be used for predicting the total number of cars with some policy sensitivities. The static car ownership models and the discrete car type choice models with many car types are less suitable for short-run and medium-run predictions, due to the assumptions of an optimal household fleet in every period. For such time horizons it is much better to predict only the *changes* in the car fleet, instead of predicting the size and composition of the entire car fleet in each period. For a long term prediction of the number of cars and car type static models are well suited, though cohort effects on total car ownership might not be well represented. Discrete car type choice models can be integrated with panel models to account for the transition between car ownership states. Panel models could then be used to study the evolution of the fleet, starting from the present conditions. For medium and long term forecasts, the analysis of fleet evolution can only be carried out if there also is a mechanism for predicting changes in the size and composition of the population. Pseudo-panels offer an attractive way to get short and long-run policy-sensitive forecasts of the total number of cars (including the cohort effects), but cannot take over the role of a choice-based model for the number of cars and car type. Dynamic transaction models include duration models for the changes in the car ownership states of the households, and in this respect are a continuous time alternative of the discrete time panel models. They have been combined with detailed policy-sensitive type choice models. For short to medium term forecasts this combination seems a highly attractive option. For longer term forecasts (10-20 years ahead), as for panel models, a population refreshment procedure needs to be included. Long term changes in the supply of car types can be simulated through scenarios.

Since the objective of our research is to predict the vehicle quantity, vehicle type, and vehicle usage in State of Maryland, choosing a proper model framework is significant in our research. Relevant results and research findings that will be used in our model are therefore explained in the following subsection. Table 2-1 shows research work on car ownership that is highly related to our research.

Table 2- 1 Previous literature related to this study

Reference	Data Resource (Year)	Sample Size	Choices Examined	Model
Lave and Train (1979)	Seven US cities (1976)	541 new car buyers	Vehicle type choice	MNL
Manski and Sherman (1980)	US (1976)	1200 single-vehicle or two-vehicle households	Vehicle type choices in households holding one vehicle and two vehicles	MNL
Beggs and Cardell (1980)	Baltimore (1977)	326 households	Vehicle type choice	MNL
Hensher and Manefield (1982)	Sydney (1980)	151 households	Fleet-size choice, vehicle type choice	Nested Logit
Hocherman et al. (1983)	Haifa urban area, Israel, (1979)	800 households	Transaction, Vehicle type	Nested Logit
McCarthy (1983)	San Francisco (1973-1975)	269 households	choice between no transaction, replacing one auto, adding one auto, reducing one auto.	MNL
Mannering and Winston (1985)	US (1978-1980)	3842 households	quantity choice, type choice, utilization model	Nested Logit and OLS regression
Berkovec and Rust (1985)	US (1978)	237 single-vehicle households	Vehicle type choice	Nested Logit
Berkovec (1985)	US (1978)	1048 households	Vehicle quantity (0, 1, 2, 3), Vehicle type choice	Nested Logit
Hensher and Le Plastrier (1985)	Sydney (1980)	400 households	Fleet-size choice (0, 1, 2, 3), vehicle type choice	Nested Logit
Mannering (1986)	US (1978)	272 households, 554 vehicles	vehicle usage	3SLS-2 equations

Train (1986)	US (1978)	1095 households	Vehicle quantity, class/vintage, usage	MNL and Regression
McCarthy and Tay (1989)	US (1985)	726 households	choice of make/model for new vehicle purchases. Choice set is chosen plus 14 assigned alternatives.	MNL
Kitamura and Bunch (1992)	Dutch National Mobility Panel Data set	Panel, 605 HH, (1984-1987)	vehicle quantity	Ordered Probit
Colob (1990)	Dutch (1985-1988)	2119 households	choice between fleet size 0, 1, 2.	Ordered Probit
Henshier et al. (1992)	Sydney (1981-1985)	1444, 1295, 1251, 1197	Static Vehicle choice and type-mix choice, Static vehicle use, Dynamic vehicle choice and use	Nested Logit and 3SLS regression
De Jong (1996)	Dutch (Oct, 1992; Oct 1993)	Panel, 3241 respondents	Vehicle holding duration, Vehicle type choice, Annual kelometrage and fel efficiency	Hazard function, Nested logit, Regression
Golob et al. (1997)	California (1993)	4747 households	Vehicle use by type of vehicle	Structural equation model
Bhat and Purugurta (1998)	US (1991, 1990, 1991), Dutch (1987)	3665, 3500, 1822, 1807	vehicle quantity (0, 1, 2, 3, 4)	MNL and Ordered logit
Kitamura et al. (1999)	California, 1993	Panel (First wave), 4747 households	1 Vehicle holding model, and Num of Vehicle per household member and per driver, 2 Vehicle type choice, 3 Vehicle use	Ordered probit model, Tobit model; MNL; OLS regression
Dargay and Vythoulkas (1999)	UK, Family Expenditure Survey (1982-1993)	panel, cohort, 7200 hh	vehicle quantity	dynamic cohort (panel)
Hanly and Dargay (2000)	UK (BHPS) (1993-1996)	Panel, about 4000-5000 households	vehicle quantity (0, 1, 2, 3+)	Ordered Probit model
Mannering et al. (2002)	US (1995)	654 households	vehicle acquisition type (cash, non-cash (lease, finance)); Vehicle type choice	Nested Logit model
Choo and Mokhtarian (2004)	San Francisco, 1998	1904 households	Vehicle type choice	MNL

Huang (2005)	UK, Family Expenditure Survey (1957-2001)	Panel, 6,500 households	Number of cars owned or used by household (1+, 2+)	Dynamic Mixed Logit model with Saturation Level
Bhat and Sen (2006)	San Francisco (2000)	3500 households	Vehicle type holding and usage	MDCEV (multiple discrete–continuous extreme value model)
Whelan (2007)	UK, (1971-1996) and NTS (1991)	unknown	vehicle quantity (0, 1, 2, 3+)	Hierarchical logit model with saturation level
Cao et al. (2007)	Northern California, USA, 2003	1682 households	vehicle quantity (0, 1, 2, 3, 4, 5+)	Ordered probit and static-score model
Fang (2008)	NHTS (2001, CA)	2299 households	Vehicle choice and usage (BMOPT & MDCEV)	BMOPT (Bayesian Multivariate Ordered Probit & Tobit) and MDCEV
Bhat et al. (2009)	San Francisco (2000)	15,000 households	Vehicle type/vintage and use, vehcile make/model	MDCEV-MNL
Bhat and Eluru (2009)	San Francisco (2000)	15,000 households	residential neighborhood choice and daily VMT	copula-based approach
Spissu et al. (2009)	San Francisco (2000)	15,000 households	Vehicle type acquisition and VMT	copula-based approach

We next illustrate featured or recent studies on car ownership models. A comprehensive framework for vehicle ownership and use was developed by Train in 1986. This model system contains several sub-models:

- a vehicle quantity model,
- a class/vintage model for one-vehicle households,
- a class/vintage model for two-vehicle households,
- an annual vehicle miles traveled (VMT) model for one-vehicle households,
- an annual VMT model for each vehicle for two-vehicle households and
- models for the proportion of VMT in each of two categories (work and shopping) for one- and two- vehicle households, respectively.

Train’s model is characterized by the following features: (1) it is a behavioral model that is estimated using choices from a household survey; (2) each household’s choices depend on both vehicle class/vintage characteristics (such as vehicle purchase price) and household characteristics (such as household annual income); and (3) the model can be incorporated into a simulation framework to forecast the vehicles' demand and their use.

Compared to previous household vehicle demand models, Train's model presents some advantages: (1) the model is able to forecast the number of vehicle owned and the annual VMT for each car in the household; (2) it explicitly shows the interdependence between a household's choice of vehicle quantity and vehicle types (class/vintage); (3) it accounts for the relation between household's choice of how many and what vehicle(s) to own and how much the household drives, and vice versa; and (4) it does not need a pre-specified demand function for each make/model.

De Jong (1996) proposed a system in which he modeled: vehicle holding duration until replacement, vehicle type choice model (conditional on replacement), annual kilometrage and fuel consumption. Together these sub-models form a prototype version of a dynamic model system for vehicle holding and use. The prototype model system is estimated on a first wave of the Dutch national panel survey and then applied to a second wave of the same survey. Results are quite satisfactory, although the model predicts slightly less vehicle transactions than occurred in reality and forecasted changes in vehicle type were more pronounced than those observed. The model has also been used to simulate the impact of income growth and of a number of possible policy measures.

One disadvantage of the duration model is that it is not possible to include variation over time in the individual characteristics. Another limitation of the prototype described is that, although the duration and the type choice models are linked through the time-varying log-sum variable, the models are not estimated in a joint structure.

Bhat and Pulugurta (1998) compared two alternative behavioral choice mechanisms for household car ownership decisions: the ordered-response (ordered-response logit model) and the unordered-response (multinomial logit model). First, they presented the underlying theoretical structures and identified both advantages and disadvantages, then they compared their performances using several data sets. This comparative analysis provided strong evidence that the appropriate choice mechanism is the unordered-response structure.

When comes to vehicle type choices, taste variation could be explored with mixed logit (Brownstone and Train, 1999). Unfortunately, this is not possible here because classe/vintage sub-models are in general estimated on a subsample of alternatives. Consistent estimates for a multinomial logit model can be achieved from a sub-sample of alternatives, but this property is not shared by the mixed logit formulation (Mannering et al. 2002).

Whelan (2007) predicted the household's decision to own zero, one, two or three or more vehicles as a function of income (modified by eight household categories and five area types), license holding, employment, the provision of company vehicles, and purchase and use costs. The models were applied using a methodology known as prototypical sampling. This method allowed the application of disaggregate models to 1203 zones by taking into consideration changes in the demographic characteristics of each forecast area. The models were successfully validated at the household level and the model forecasts compared favorably with actual ownership information extracted from the 2001 Census.

Choo and Mokhtarian (2004) identified travel attitude, personality, lifestyle, and mobility factors that affect individual's vehicle type choices, using data from a 1998 mail-out/mail-back survey of 1904 residents in the three neighborhoods in the San Francisco Bay Area. Vehicle type was classified into nine categories based on make, model and vintage of a vehicle: small, compact, mid-size, large, luxury, sports, minivan/van, pickup, and SUV. The study developed a multinomial logit model for vehicle type choice to estimate the joint effect of the key variables on the probability of choosing each vehicle type. One of the major limitations is represented by the lack of detailed information on all the vehicles in the household, including their acquisition history. Most importantly, the data on vehicle characteristics were not available.

To conclude, a number of studies have been conducted to model car ownership. Most of them, however, have limitations. First, some studies concentrated on only one aspect of the household vehicle ownership choices (i.e. vehicle quantity, vehicle type and vehicle use). Second, some researches have several model components but important attributes are missing, due to data limitation. Household socio-demographic information, land use data, and vehicle specifications are all necessary for modeling vehicle quantity, vehicle type and usage choices. Third, some of the results reported are not very recent. Factors affecting vehicle ownership have changed significantly over time, which can lead to different decisional mechanisms or to different coefficient estimates. All those aspects should be taken into account when building a framework to predict household car ownership and use.

2.2 Review of Vehicle Quantity Models

In Table 2-2 we present several vehicle quantity models, in particular we describe the data source, the sample size, model type and the dependent variables used for the analysis. Most vehicle quantity models in the literature were based on MNL model, or Ordered logit model.

Table 2- 2 Comparison of vehicle quantity models

Reference	Data Resource (Year)	Sample Size	Model type	Dependent Variables
Hensher and Manefield (1982)	Sydney (1980)	151 households	Nested Logit	Choice between acquiring one vehicle given initial holdings
Mannering and Winston (1985)	US (1978-1980)	3842 single-vehicle or two-vehicle households	NL (choice between 1 and 2 vehicles for each period and combined periad)	# hh members, # worker, income, urban indicator, log sum of type choice models, choice indicator
Kitamura and Bunch (1990)	Dutch National Mobility Panel	Panel, 605 HH, (1984-1987)	Ordered Probit model	Num of workers, Num of adults, num of children, HH size, num of drivers, HH education

	Data set			
Colob (1990)	Dutch (1985-1988)	2119 households	Ordered Probit	HH income, # persons >18, # persons 12-17, # persons <12, # drivers, # workers, recidence location
Bhat and Purugurta (1998)	US (1991, 1990, 1991), Dutch (1987)	3665, 3500, 1822, 1807	ORL v.s. MNL	Num of non-working adults, Num of working adults, Annual HH income, Urban residential location, Suburban residential location, Single-family residential housing
Kitamura et al. (1999)	California, 1993	Panel (First wave), 4747 households	Ordered probit model, Tobit model	HH size, Num of drivers, num of workers, num of adults, dummy of couple, dummy of single person, dummy of income, owns home, dummy of parking space; accessibility, density
Dargay and Vythoulkas (1999)	UK, Family Expenditure Survey (1982-1993)	panel, cohort, 7200 hh	dynamic cohort (panel)	income, adults, children, % metropolitan, % rural, generation, car purchase cost car running cost, public transport fares
Hanly and Dargay (2000)	UK, British Household Panel Survey (BHPS) (1993-1996)	Panel, about 4000-5000 households	Ordered Probit model	household income, number of adults, number of children, number of worker, dummy of pensioner, regional dummy, population density
Huang (2005)	UK, Family Expenditure Survey (1957-2001)	Panel, 6,500 households	Dynamic Mixed Logit model with Saturation Level (GUASS)	Log of household disposable income, household size, number of workers, log of age of household head, log of index of real motoring costs, proportion of households living in Metropolitan area, proportion of households living in rural are, dummy of young household
Gerard Whelan (2007)	UK, family expenditure survey (FES) (1971-1996) and the national travel survey (NTS) (1991)	unknown	The hierarchical logit model with saturation level	household income, household structure, motoring costs, need/accessibility, company cars, time trend/license holding
Cao et al. (2007)	Northern California, USA, 2003	1682 households	Ordered probit and static-score model (Limdep 8.0)	Female, HH income, HH size, Num. of adults, Num. of workers, Driving disability, Transit disability, Residential tenure, Outdoor spaciousness, num of business types, accessibility, car dependent, safety of car

The vehicle quantity attributes adopted in existing studies can be classified into four categories: (1) information on the household, (2) information on the household head or primary driver, (3) land-use factors and (4) other unclassified information (see Figure 2-1).

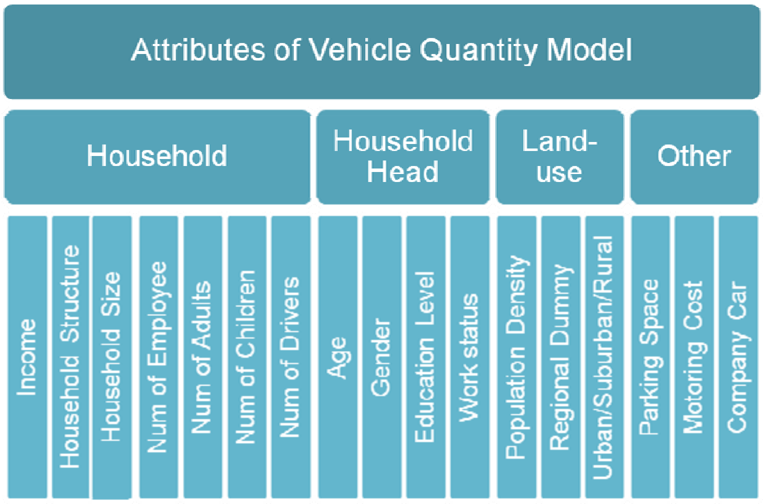


Figure 2- 1 Variables in the previous vehicle quantity models

Significant explanatory variables of the household includes the household's income, household structure, number of household members (household size), number of workers, number of adults, number of children, number of drivers (licensing holding) in the household. In terms of household income, usually the annual income is used in the model. In some studies, the logarithmic transformation of the income or the discretionary income (the amount of income left to the household after subtracting taxes and normal expenses) enter the model specification.

The estimation results showed that most of the household socio-economic characteristics have positive influence on car ownership. The positive coefficient of the income variable indicates that, for instance, a household is more likely to own more vehicles, with a higher household income. Same trends can be found in other attributes, such as the number of household members, number of workers, number of adults, number of children, and number of drivers in the household. All of the coefficients have considerable *t-statistics*. In most cases, especially, the coefficients of income and number of drivers have larger value of *t-statistics*, indicating income and the number of drivers take an important part in the decision making process. Few studies analyzed household structure variables, usually using the number of adults and the number of children in the household.

Significant explanatory variables about the household head or primary driver includes age, gender, education level and work status. The estimation results in the previous researches indicate that a household is likely to own fewer vehicles with older household head or female household head. With higher education level of the household head, a household is more likely to own more vehicles. Only few studies included household head's work status in the utility function.

In terms of land use information, previous researches mainly use population density, and location variables (urban, suburban, and rural). Estimation results indicate that households in the area with large density or in urban area own fewer vehicles. A few studies included the accessibility to transit; however this measurement is difficult to obtain in many real cases.

The other variables, which do not belong to any of the three categories above, include dummy variables describing parking availability and the influence of company car. These variables were mainly used in European studies; were parking space is limited and the number of company cars is quite high.

2.3 Review of Vehicle Type Model

In Table 2-3 we present several vehicle type models, in particular we describe the data source, the sample size, model type, vehicle classification and the dependent variables.

Table 2- 3 Comparison of vehicle type models

Reference	Data Resource (Year)	Sample Size	Model Type	Vehicle Classification	Dependent Variables
Lave and Train (1979)	Seven US cities (1976)	541 new car buyers	MNL	subsubcompact, sports, subcompact (A and B), compact (A and B), Intermediate, Standard (A and B) Luxury	purchase price/income, weight*age, # HH member, # vehicle
Manski and Sherman (1980)	US (1976)	1200 single-vehicle or two-vehicle households	MNL	Chosen alternative plus 25 alternative makes/models/vintage (randomly selected from 600 vehicle type)	purchase price, # seats, vehicle weight and age, acceleration time, luggage space, scrappage rate, transaction-search cost, operation cost
Beggs and Cardell (1980)	Baltimore (1977)	326 households	MNL	5 classes (subcompact, compact, mid-size, full-size, luxury), 4 vintage (1942-1971, 1972-1974, 1975-1976, 1977)	purchase price, operating cost, wheelbase, "depreciated luxury", age of vehicle, income, # hh members, distance to parking
Hocherman (1983)	Haifa urban area, Israel, (1979)	800 households	Nested Logit model	Chosen alternatives plus 19 alternative makes/models/vintages (randomly selected from 950 vehicle types)	purchase price, operating cost, engine size, vehicle age, income, brand loyalty, # same make cars, horsepower to weight
Mannering and Winston (1985)	US (1978-1980)	3842 single-vehicle or two-vehicle households	NL	Chosen alternative plus nine alternative makes/models/vintages (randomly selected from 2000 vehicles)	purchase price/income, operating cost/income, lagged utilization of same vehicle or same make
Berkovec and Rust (1985)	US (1978)	237 single-vehicle households	Nested Logit model	upper level: vehicle age groups (new, mid, old), lower level: 5 vehicle classes (subcompact, compact, intermediate, standard, luxury/sports)	purchase price, operating cost, # seats, vehicle age, turning radius in urban, housepower to weight, transaction

Berkovec (1985)	US (1978)	1048 households	Nested Logit model	131 alternatives=10 years (1969-1978) * 13 vehicle classes (domestic subcompact, compact, sporty, intermediate, standard, luxury, pickup truck, van and SUV; foreign subcompact, larger, sports, and luxury) + all models before 1969	purchase price, # seats, proportion of makes/models in class to total makes/models
Hensher and Le Plastrier (1985)	Sydney (1980)	400 households	Nested Logit	Holdings: Choice of make/model/vintage given fleet size. Single model for all levels. Choice set is chosen plus 2 reported alternatives. Transaction: choice of make/model/vintage given fleet size adjustment. Choice set is chosen plus 1 or 2 alternatives randomly selected.	Registration charge, service and repair expense, sales tax on purchase price, # seats, fuel efficiency, weight, luggage space, age of vehicle, age, # passenger, dummy (>600 miles per month, dummy (use for paid work)
De Jong (1996)	Dutch (Oct, 1992; Oct 1993)	Panel, 3241 respondents	Nested logit model (diesel and non-diesel cars)	133 make/model combinations; about 1000 make/model/age-of-car combinations (better); ALOGIT; 20 alternatives (the chosen one plus 19 random)	Log of remaining household income; fixed cost/income; fuel cost/income; dummy for brand loyalty, engine size, diesel, age
Kitamura et al. (1999)	California, 1993	Panel (First wave), 4747 households	MNL model	Four-door sedans, two-door coupes, Vans, wagons, sports car, SUVs.	dummy (same vehicle type), Age, male, education, employed, commuter, commute distance, other (same as the vehicle holding models)
Mannering et al. (2002)	US (1995)	654 households buying new vehicles	Nested Logit model	Chosen alternative plus 9 alternative makes and models (randomly selected from 175 vehicle types)	purchase price/income, passenger side airbag, horsepower, vehicle residual value, consecutive purchases
Choo and Mokhtarian (2004)	San Francisco, 1998	1904 households	MNL model (LIMDEP)	small, compact, mid-size, large, luxury, sports, minivan/van, pickup, SUV	objective mobility, subjective mobility, travel liking, attitudes, personality, lifestyle, demographics

The vehicle type classification methods mainly consists of five different categories: (1) models that only consider very general classes of vehicles, such as small car, compact car, large car, sporty car, etc; (2) models that consider general classes and vintages of vehicles, such as small old car, large new car, etc; (3) models that randomly select chosen alternative plus a certain number of alternatives from the total number of combination of makes and models (i.e. Toyota, Camry); (4) model that randomly select chosen alternative plus a certain number of alternatives from the total number of combination of make, model and vintage (i.e. 2003 Honda Civic); (5) model that consider vehicle classes and vintages, such as 2005 mid-size car, 2007 SUV, etc.

The previous studies have different standards for vehicle classification. Train (1986) distinguished domestic and imported vehicles, which reflects the brand loyalty. This is reasonable because when people make decisions they first consider new or used car, the class, and whether it is domestic or imported. Brand loyalty is becoming an important factor in vehicle ownership modeling.

Table 2- 4 Vehicle classification schemes

Sourse	Vehicle Classification	Basis
NHTS (FHWA, 2009)	Automobile (including wagon), van, SUV, pickup, other truck, RV, motorcycle, other	Function
NTS (BTS, 2009)	Subcompact car, compact car, intermediate car, full car, light pickup, large pickup, small van, large van, small utility, large utility	Size & function
EPA (2009)	Cars: two-seater, sedan(minicompact, subcompact, compact, mid-sized, large), station wagon (small, midsize, larg); Trucks: pickup (small & standard), van (cargo & passenger), minivans, SUV, special purpose vehicle	Size & function
Comsumer Reports (2009)	Convertible, small car, sedan, wagon, SUV, minivan, pickup, sporty car	Size & function

Notes: Vehicle function generally refers to engine size, wheel drive, and specialty.

BTS: Bureau of Transportation Statistics; EPA: Environmental Protection Agency; FHWA: Federal Highway Administration; NPTS: Nationwide Personal Transportation Survey; NTS: National Transportation Statistics.

In terms of vehicle classes, Table 2-4 shows some vehicle classification schemes found in statistical reports, which are focused on vehicle size, vehicle function, or both. Most schemes of vehicle classification first group vehicle by size, and then special categories such sports, pickup and SUV are added.

The explanatory variable in the previous vehicle type models can be categorized as in Figure 2-2.

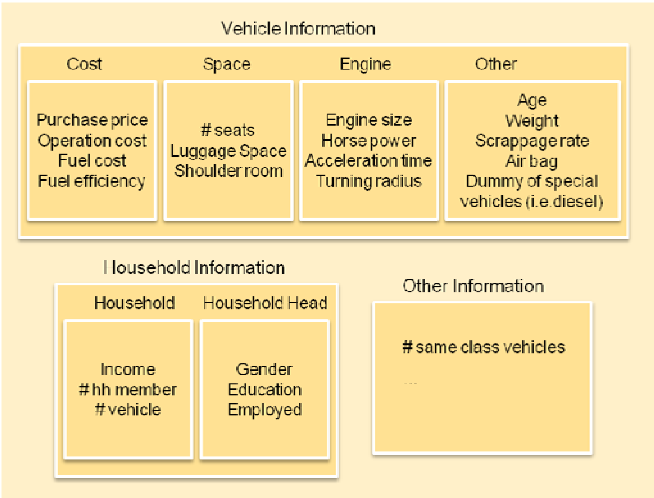


Figure 2- 2 Variables in the previous vehicle type models

There are mainly three kinds of variables in existing vehicle type models: (1) vehicle characteristics, (2) household characteristics, and (3) other unclassified characteristics. Purchasing price, operating cost, space and engine related variables are usually found to be significant in vehicle type models.

2.4 Review of Vehicle Usage Model

2.4.1 Traditional Regression Model

Early studies on vehicle usage mainly estimated VMT by general regression models; see Mannering and Winston (1985), Train (1986), Hensher et al. (1992), Kitamura et al. (1999). However, ordinary least square estimation for regression models is biased since some endogenous variables (such as operating cost) exist in the model. To solve this problem, instrumental variable estimation method has been used in the estimation, i.e. Train (1986).

Table 2- 5 Summary of Studies on Vehicle Usage with Regression Model

Reference	Data Resource (Year)	Variables in the regression model
Mannering and Winston (1985)	US (1978-1980)	Total fuel cost, income, 1/2 period lagged utilization of same vehicle, 1/2 period lagged utilization of same make vehicle, northeast indicator, urban indicator, age indicator, number of workers
Train (1986)	US (1978)	Log of household income, unit operating cost, log of household size, number of workers, number of transit trips per capita, dummy of urban, dummy of northeast, dummy of midwest, dummy of south.
Hensher et al. (1992)	Sydney (1981-1985)	Unit fuel cost, holding duration, vehicle age, age of driver, dummy of business car, vehicle weight, dummy of replacement, recurrent cost, maintenance cost, household income, newness dummy, no. of workers, residential location dummy, tow dummy, vehicle asset value, kilometers of other vehicles
Kitamura et al. (1999)	California, 1993	Vehicle attributes (dummy of van/wagon, dummy of own, dummy of new); attributes of primary user (age, work, distance, participated in acquisition decision); attributes of secondary user (dummy of secondary user, dummy of male, distance); household attributes (number of drivers, number of vehicles, dummy of single-parent, dummy of households with more than two adults, number of years in present address, income); residence zone characteristics (accessibility indices, retail employees per acre, inhabitants per acre)

Existing studies on vehicle usage with regression model mainly developed the model with vehicle variables, household variables, household head variables and land-use variables. Operating cost is a main factor to vehicle usage. There are two forms of operating cost in the literature: total operating cost and unit operating cost (cost per mile). Unit operating cost is better because total operating cost is endogenous with vehicle miles traveled. Significant household attributes in the regression model include household income, number or household members, number of drivers and number of employees. In terms of the attributes of household head, some studies used the age, work status, gender, distance to work in the model. Land use variables have significant influence to vehicle usage, since they have large impact on how people traveled. Population density, housing density, location dummies are always entering the vehicle usage regression model.

2.4.2 Discrete-Continuous Model in Consumer's Demand

Discrete-continuous models have been investigated in marketing studies since 1980's. Marketing researchers developed discrete-continuous models to determine household purchase decisions for frequently purchased packaged goods by the impact of marketing mix and demographic variables. Previous studies have predicted one or more of the purchasing decisions by proposing relationships between the observed choices of households and variables such as product price, price cuts, feature advertisements, special displays and observed and unobserved household characteristics (Chintagunta, 1993). Chintagunta summarized a partial list of previous studies dealing with household purchase behavior along with their important features (Table 2-6). Previous research has focused on three different household purchase decisions—(1) the timing of a purchase or the category purchase decision, (1) the brand choice decision and (3) the purchase quantity decision.

Table 2- 6 Several of Selected Empirical Studies on Purchase Behavior (Chintagunta, 1993)

Preference	Decisions Studied
Guadagni and Little (1983)	Brand choice
Neslin, Henderson and Quelch (1985)	Purchasing timing, Purchase quantity
Krishnamurthi and Raj (1989)	Brand Choice, Purchase Quantity
Tellis (1988)	Brand Choice, Purchase Quantity
Jones and Landwehr (1988)	Brand Choice
Gupta (1988)	Purchase Timing, Brand Choice, Purchase Quantity
Gupta (1991)	Purchase Timing
Bucklin and Lattin (1991)	Purchase Incidence, Brand Choice
Chiang (1991)	Purchase Incidence, Brand Choice
Jain and Vilcassim (1991)	Purchase Timing
Kamakura and Russell (1989)	Brand Choice
Helsen and Schmittlein (1990)	Purchase Timing

2.4.2 Discrete-Continuous Model in Transportation Activity Modeling

A number of discrete-continuous model have been applied in transportation field especially in activity analysis in the recent years. Bhat and Steed (2002) proposed a continuous-time hazard duration model for urban shopping trip departure time choice. The concept of a hazard rate originated in the Industrial Engineering and Biometrics fields and has been used in those fields for several decades now (see, for example, Berkson and Gage, 1952, and Goodman, 1953). Its use in the economics and transportation fields has been relatively recent, though much of the new advances in hazard models have emerged in these fields *(see Kiefer, 1988, Hensher and Mannering, 1994 and Bhat, 2000 for reviews of hazard-based models in the context of the economics and transportation fields)*.

Facing classical discrete and discrete–continuous models deal with situations where only one alternative is chosen from a set of mutually exclusive alternatives, Bhat (2005) formulated a new econometric model for multiple discreteness in demand that is based on utility maximization theory. Specifically, he assumed a translated non-linear, but additive, form for the specification of the direct utility function, as proposed by Kim et al. (2002). The translated non-linear form allows for multiple discreteness as well diminishing marginal returns (i.e., satiation) as the consumption of any particular alternative increases. This is in contrast to standard discrete and discrete–continuous choice models that allow only single discreteness and assume a linear utility structure (i.e., no satiation effects).

This multiple discrete– continuous extreme value (MDCEV) model is based on introducing a multiplicative log-extreme value error term into the utility function. The result of such a specification is a simple closed form expression for the discrete–continuous probability of not consuming certain alternatives and consuming given levels of the remaining alternatives. Further, the MDCEV model has the appealing property that it collapses to the familiar multinomial logit (MNL) choice model in the case of single discreteness, and represents an extension of the single discrete–continuous models of Dubin and McFadden (1984), Hannemann (1984), Chiang

(1991), Chintagunta (1993), and Arora et al. (1998). Finally, heteroschedasticity and/or correlation in unobserved characteristics affecting the demand of different alternatives can be easily incorporated within the MDCEV model framework. Such an extension represents the multiple discrete–continuous equivalent of the mixed multinomial logit (MMNL) model.

Two other limitations of the MDCEV approach relative to the more classic discrete-continuous approaches are concluded by Spissu et al. (2009). First, the MDCEV approach ties the discrete and continuous choices in a restrictive framework by having a single stochastic utility function (and therefore, a single error term) that underlies both the discrete and continuous choices. On the other hand, the classic approach allows separate error terms in the discrete and continuous equations, allowing a more flexible form of tie-up between the error terms in the discrete and continuous choices. Second, the MDCEV approach needs to have an exogenous total mileage budget of households for implementation. Bhat et al. (2009) develop this budget by aggregating the mileage across all vehicles held by a household and adding non-motorized mode mileage. However, the non-motorized mileage is a relatively negligible fraction of total mileage, effectively imposing the constraint that total motorized vehicle utilization is exogenous, and does not change in response to policies or fuel cost increases (though the MDCEV model allows substitution in vehicle mileage across different vehicle types). There is no such restriction imposed in the classic approach.

Habib et al. (2008) empirically investigated the relationship between the social context (measured by with whom the respondents interacted) and two key aspects of activity scheduling: start time and duration. This study developed a MNL model for the social context part and hazard duration model for start time and duration, with data collected by a seven-day activity diary survey.

Habib et al. (2009) also developed a discrete-continuous econometric model to investigate the joint decisions of trip timing and mode choice for commuting trips in the Greater Toronto Area (GTA). The joint model, with a multinomial logit model for mode choice and a continuous time hazard model for trip timing, allows for unrestricted correlation between the unobserved factors influencing these two decisions. Models are estimated by occupation groups using 2001 travel survey data for the GTA.

2.4.3 Discrete-Continuous Model in Car Ownership Models

As already stated, early studies on vehicle usage were mainly estimated by means of general regression models. More recently, discrete-continuous models are gaining acceptance amongst researchers in transportation.
Bhat and Sen (2006) applied a multiple discrete-continuous extreme value (MDCEV) model to analyze holding and use of multiple vehicle types. Data for the analysis is drawn from the 2000 San Francisco Bay Area travel survey. The model results indicated the important effects of household demographics, residence location variables and vehicle attributes on vehicle type holding and use. The model developed in the paper can be applied to predict the impact of changes in the main variables considered on vehicle type holding and usage. The predictions can also inform the design of proactive land-use, economic, and transportation policies and help to reduce traffic congestion and air quality problems.

In Fang's study in 2008, two models, a reduced-form Bayesian Multivariate Probit and Tobit (BMOPT) model and the Multiple Discrete–Continuous Extreme Value (MDCEV) model derived from utility maximization, are applied to model households' vehicle holding and usage decisions in California.

The system of BMOPT is composed of a multivariate ordered probit model and a multivariate Tobit model. The ordered probit is used to capture household decisions on number of vehicles in each category. Within this framework, vehicles are categorized into fuel efficient (cars) and fuel inefficient vehicles (trucks), which allow the analysis of possible environmental and energy saving policy implications.

Fang also highlighted the advantages and disadvantages of the two models. The BMOPT model is easy to implement and to apply in order to draw policy implications; it is also possible to handle a large number of vehicles, but it will become computationally intensive with increasing vehicle categories because the number of equations to be estimated increases proportionally with number of categories. The MDCEV is consistent with random utility maximization, and can accommodate hundreds of vehicle classifications, but one restriction is that the total utilization of vehicles are assumed to be fixed no matter how the policy changes. This assumption rules out the potential vehicle utilization reduction which we would expect to occur, or at least test, in response to particular policies. In addition, finer classification of vehicles to a degree that no one type of vehicle can be chosen twice for a household is a must for the model implementation.

Bhat et al. (2009) formulate and estimate a nested model structure that includes a multiple discrete-continuous extreme value (MDCEV) component to analyze the choice of vehicle type/vintage and usage in the upper level and a multinomial logit (MNL) component to analyze the choice of vehicle make/model in the lower nest. This study successfully estimated vehicle type, age, make and model together. However, the limitation is the two models in the nested model structure are not jointly formulated and estimated, which indicates the model may not capture the relationship between the two levels in the nest.

In the meantime, Bhat and Eluru (2009) modeled residential neighborhood choice and daily household vehicle miles of travel (VMT), using the 2000 San Francisco Bay Area Household Travel Survey (BATS). The sample selection hypothesis is that households select their residence locations based on their travel needs, which implies that observed VMT differences between households residing in neo-urbanist and conventional neighborhoods cannot be attributed entirely to the built environment variations between the two neighborhoods types. The approach is based on the concept of "copula", which is a multivariate functional form for the joint distribution of random variables derived purely from pre-specified parametric marginal distributions of each random variable.

The copula concept has been recognized in the statistics field for several decades now, but it is only recently that it has been explicitly recognized and employed in the econometrics field. The copula-based approach retains a parametric specification for the bivariate dependency, but allows testing several parametric structures to characterize the dependency.

Similarly, Spissu (2009) formulated a joint model of vehicle type choice and utilization and estimated the model on a data set of vehicles drawn from the 2000 San Francisco Bay Area Travel Survey by using copula-based approach. In contrast to these recent studies, this paper reverts to the treatment of household vehicle type choice as a simple multinomial choice variable by considering the most recent vehicle purchased by a household. The MDCEV model structure, although extremely useful to capture the mix of vehicle holdings at any given point in time, fails to capture the dynamics associated with vehicle acquisition. Thus, the unit of analysis is no longer a household as such, but the actual vehicle purchase itself. A copula-based methodology is adopted to facilitate model estimation without imposing restrictive distribution assumptions on the dependency structures between the errors in the discrete and continuous choice components. The copula-based methodology is found to provide statistically superior goodness-of-fit when compared with previous estimation approaches for joint discrete-continuous model systems. The model system, when applied to simulate the impacts of a doubling in fuel price, shows that individuals are more prone to shift vehicle type choices than vehicle usage patterns.

Figure 2- 3 Evolution of discrete-continuous model

In order to summarize the different approaches presented in this Section we report in Table 2-7 the main characteristics of the models reviewed.

Table 2- 7 Comparison of discrete-continuous models

	Example	Pros	Cons
Regression	Train (1986)	Simple and easy, Good for aggregated data	Biased, Not good for disaggregated data
MDCEV	Bhat (2006)	Multiple discreteness, closed form, collapses to MNL model, Heteroscedasticity and correlation	Single error term underlies both discrete and continuous choices, fixed total mileage budget for each household
BMOPT	Fang (2008)	Easy to implement, convenient to get inferences	Computationally intensive with increasing vehicle categories
Hazard model	Habib (2009)	Overcomes the limitations in discrete models, no mileage budget for households, joint model for discrete and continuous choices	Single discreteness

In synthesis, the following recommendation might serve as a guide to analysts working on vehicle holding and usage:

- Regression models are simple and easy to estimate, but the results might be biased; moreover regression models are not best suited for disaggregated data.
- The multiple discrete-continuous extreme value (MDCEV) models allow multiple discreteness. The specification is a simple closed form expression; heteroschedasticity and correlation in unobserved characteristics can be also incorporated in more complex specification forms. However, only a single error term ties the discrete and continuous choices, which limits the spectrum of the analyses. Moreover, MDCEV approach always allocate a total mileage budget to each household, as this approach was derived from economics models which assume consumers have a total budget for good purchasing. This assumption is realistic in marketing, but not limitative for vehicle usage, which is expected to change in response to policies or fuel price.

- Reduced-form Bayesian Multivariate Probit and Tobit (BMOPT) model is easy to implement and convenient to get inferences and draw policy implications. However, it becomes computationally intensive when the number of vehicle categories increases.
- Hazard duration model overcomes the limitations of classical discrete models and does not suffer from the fixed mileage budget allocated to households. The model is jointly estimated for discrete and continuous choices. Nevertheless, existing formulations do not allow multiple discretenesses.

Chapter 3: Methodologies

3.1 Discrete Choice Model

3.1.1 Why Discrete Choice Model

The emphasis in econometrics has shift from aggregate models to disaggregate models (Train, 1986). There are several reasons for this shift:

First, economically relevant behavior is necessarily at the individual level. Microeconomic theory provides a way of looking at the actions of individual decision making units, as well as rich set of hypotheses concerning these actions. The theory can be drawn upon in specifying and interpreting disaggregate econometric models to a degree that is not possible with aggregate models.

Second, survey data on households and individual firms are becoming more and more available, making it possible to estimate disaggregate models in situation that would previously have been impossible to examine at the individual level.

Furthermore, with these data on individual decision-making unites, more precise estimation of underlying parameters is possible. Data on individual units necessarily contain greater variation in each factor, and usually less covariation among factors, than aggregate data, simply because the latter are sums or averages of the former. This fact is important in estimating econometric models since the precision with which each parameter in a model can be estimated generally increases with the variance of the variable entering the model and decreases with the covariance among variables.

In conclusion, disaggregate models are often able to capture effects that cannot be incorporated accurately in aggregate models.

Standard econometric methods like regression were designed for analyzing variables that can assume any value within a range, that is, for continuous variables. These methods are usually appropriate for examining aggregate data. When the underlying behavior of the individual decision making units is examined, however, it is often found that the outcome of the behavior is not continuous and standard regression procedures are inappropriate.

A variety of methods have been developed for examining the behavior of individuals when continuous methods are inappropriate. Qualitative choice analysis is among theses. It is design for describing decision makers' choices in certain types of situations. These situations arise in a variety of contexts in such area as transportation, energy, telecommunications, housing, criminology, and labor, to name a few.

A qualitative choice situation, which qualitative choice models are used to describe, is defined as one in which a decision maker faces a choice among a set of alternatives meeting the following criteria: (1) the number of alternatives in the set is finite; (2) the alternatives are mutually exclusive: that is, the person's choosing one alternative in the set necessarily implies that the person does not choose another alternative; and (3) the set of alternatives is exhaustive: that is, all possible alternatives are included, and so the person necessarily chooses one alternative from the set.

In conclusion, qualitative choice models are used to analyze situations in which a decision maker can be described as facing a choice among a finite and exhaustive set of mutually exclusive alternatives.

3.1.2 Specification of Discrete Choice Models

Qualitative choice models calculate the probability that a decision maker will choose a particular alternative from a set of alternatives, given data observed by the researcher. The models differ in the functional form that relates the observed data to the probability. We first elaborate the notations of discrete choice models (Train, 1986).

Denote n is the number of decision maker in a qualitative choice situation. The set of alternatives that the decision maker faces, called the choice set, is J_n, which is subscripted by n to represent the fact that different decision makers might face different sets of alternatives in similar choice situations.

The alternatives that the decision maker faces differ in their characteristics, some of which are observed by the researcher and some are not. For all i in J_n, vector z_{in} are the observed characteristics of alternative i as faced by decision maker n. The characteristics of each alternative are subscripted by n to reflect the fact that different decision makers can face alternatives with different characteristics.

The decision maker's choice of alternative obviously depends on the characteristics of the available alternatives. Different decision makers, however, can make different choices when facing the same alternatives because the relative value that they place on each characteristic is different. The differences in the valuation of each characteristic of the alternatives depend on the characteristics of the decision maker, some of which can be observed by the researcher and some could not. Label the observed characteristics of decision maker n as s_n. Usually elements of s_n are socio-economic characteristics such as income, age, education level, etc.

The probability that decision maker n chooses alternative i from set J_n depends on the observed characteristics of alternative i compared with all other alternatives and on the observed characteristics of the decision maker (s_n). Qualitative choice models specify this probability as a function of the general form

$$P_{in} = f(z_{in,} z_{jn} \text{ for all } j \text{ in } J_n \text{ and } j \neq i, s_{n,} \beta) \qquad (1)$$

where f is the function that relates the observed data to the choice probabilities. This function if specified up to β, the vector of parameters. Al qualitative choice models have this general form. Specific qualitative choice models such as logit or probit, are obtained by specifying f.

Since decision maker n has a choice among the alternatives in set J_n, he or she would obtain some relative happiness or "utility" from each alternative if he or she were to choose it. Designate the utility from alternative i in J_n as U_{in}. This utility depends on various factors, including the characteristics of the alternative and the characteristics of the decision maker. Label the vector of all relevant characteristics of alternative i as faced by person n as x_{in} and the vector of all relevant characteristics of person n as r_n. Since x_{in} and r_n include all relevant factors, we can write utility as a function of these factors,

$$U_{in} = U(x_{in}, r_n), \text{ for all } i \text{ in } J_n, \tag{2}$$

where U is a function.

The decision maker chooses the alternative from which he or she derives the greatest utility. That is, the decision maker chooses alternative i in J_n if and only if

$$U_{in} > U_{jn}\,, \quad \text{for all } j \text{ in } J_n, \quad j \neq i\,.$$

Substituting (2), we have

$$n \text{ chooses } i \text{ in } J_n \qquad \text{if } \; U(x_{in}, r_n) > U(x_{jn}, r_n), \; \text{ for all } j \text{ in } J_n, \; j \neq i\,. \tag{3}$$

Then we are interested in predicting this decision maker's choice. If we observed all the relevant factors, i.e., x_{in} for all i in J_n and r_n, and knew the decision maker's utility function U, then we could use relation (3) perfectly to predict the decision maker's choice. However, we could not observe all the relevant factors and do not know the utility function exactly.

Decompose $U(x_{in}, r_n)$ for each i in J_n into two subfunctions, one that depends only on factors that the researcher observes and whose form is known by the researcher up to a vector of parameters, β, to be estimated, with this component labeled $V(z_{in}, s_n, \beta)$, and another that represents all factors and factors and aspects of utility that are known by the researcher, which is labeled e_{in}. Where vector z_{in} denotes the characteristics of the alternative that are observed by the researcher in x_{in} and s_n denotes the observed characteristics of the person in r_n. That is,

$$U_{in} = U(x_{in}, r_n) = V(z_{in}, s_n, \beta) + e_{in} \tag{4}$$

P_{in} denotes the probability that person n chooses alternative i. P_{in} is the probability that the utility of alternative i is higher that that of any other alternative, given the observed components of utility for each alternative.

$$P_{in} = \text{Prob}(U_{in} > U_{jn}, \quad \text{for all } j \text{ in } J_n, \quad j \neq i). \tag{5}$$

Substituting (4) and letting V_{in} denote $V(z_{in}, s_n, \beta)$,

$$P_{in} = \text{Prob}(V_{in} + e_{in} > V_{jn} + e_{jn}, \quad \text{for all } j \text{ in } J_n, \quad j \neq i).$$

Rearranging,

$$P_{in} = \text{Prob}(e_{jn} - e_{in} < V_{jn} - V_{in}, \quad \text{for all } j \text{ in } J_n, \quad j \neq i). \tag{6}$$

V_{in} and V_{jn} can be observed and we can calculate their difference. e_{in} and e_{jn} cannot be observed and they are random, varying across decision makers with the same observed components of utility. Since e_{in} and e_{jn} are random variables, their difference is also a random variable. So the right-hand side of (6) is simply a cumulative distribution. By knowing the distribution of the random e, we can derive the distribution of each difference $e_{jn} - e_{in}$ for all j in J_n, $j \neq i$, and by using equation (6) calculate the probability that the decision maker will choose alternative i as a function of $V_{jn} - V_{in}$ for all j in J_n, $j \neq i$.

All qualitative choice models are obtained by specifying some distribution for the unknown component of utility and deriving functions for the choice probabilities. Different qualitative choice models are obtained by specifying different distributions for the e's, giving rise to different functional forms for the choice probabilities. For more detail about the theory of discrete choice models please refer to Train, 1986.

3.1.3 Multinomial Logit Model

Logit is the most widely used qualitative choice model so far. The logit probabilities are derived under a particular assumption regarding the distribution of the unobserved portion of utility.

According to Train (1986), given the utility function $U_{in} = V_{in} + e_{in}$ and assuming that each e_{in}, for all i in J_i, is distributed independently and identically in accordance with the extreme value distribution, the probability that the decision maker will choose alternative i is:

$$P_{in} = \frac{e^{V_i}}{\sum_{j \in J_n} e^{V_{jn}}}, \quad \text{for all } i \text{ in } J_n. \tag{7}$$

Three important properties characterize the choice probabilities: (1) each of the choice probabilities is necessarily between zero and one; (2) the choice probabilities necessarily sum to one; (3) the relation of the choice probability for an alternative to the representative utility of that alternative, holding the representative utilities of the other alternatives fixed, is sigmoid, or S-shaped.

An important property of the logit model is the independence from irrelevant alternatives property (IIA). Consider the ratio of the choice probabilities for two alternatives, i and k:

$$\frac{P_{in}}{P_{kn}} = \frac{e^{V_{in}} \Big/ \sum_{j \in J_n} e^{V_{jn}}}{e^{V_{kn}} \Big/ \sum_{j \in J_n} e^{V_{jn}}} = \frac{e^{V_{in}}}{e^{V_{kn}}} = e^{V_{in} - V_{kn}} \ .$$

The ratio of these two probabilities does not depend on any alternatives other than i and k. That is, the ratios of probabilities are necessarily the same no matter what other alternatives are in J_n or what the characteristics of other alternatives are. Since the ratio is independent from alternatives other than i and k, it is said to be independent from “irrelevant alternatives”, that is, alternatives other than those for which the ratio is calculated.

While this property is inappropriate in some situations, it has several advantages. First, because of the IIA property, it is possible to estimate model parameters consistently on a subset of alternatives for each sampled decision maker. This fact is important because estimating on a subset of alternatives can save computer time, in analyzing choice situations for which the number of alternatives is large. Another practical use of this ability to estimate on subsets of alternatives arises when a researcher is only interested in examining choices among a subset of alternatives and not among all alternatives. The IIA property also allows to predict demand for alternatives that do not currently exits.

3.2 Regression Model

In statistics, regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps the analyst to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables —

that is, the average value of the dependent variable when the independent variables are held fixed. Less commonly, the focus is on a quartile, or other location parameter of the conditional distribution of the dependent variable given the independent variables. In all cases, the estimation target is a function of the independent variables called the regression function. In regression analysis, it is also of interest to characterize the variation of the dependent variable around the regression function, which can be described by a probability distribution (Sykes).

Regression analysis is widely used for prediction (including forecasting of time-series data). The use of regression analysis for prediction has substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables.

Classical assumptions for regression analysis include (Draper and Smith, 1998):

- The sample must be representative of the population for the inference prediction.
- The error is assumed to be a random variable with a mean of zero conditional on the explanatory variables.
- The variables are error-free. If this is not so, modeling may be done using errors-in-variables model techniques.
- The predictors must be linearly independent, i.e. it must not be possible to express any predictor as a linear combination of the others. See multi-collinearity.
- The errors are uncorrelated, that is, the variance-covariance matrix of the errors is diagonal and each non-zero element is the variance of the error.
- The variance of the error is constant across observations (homoschedasticity). If not, weighted least squares or other methods might be used.
- These are sufficient (but not all necessary) conditions for the least-squares estimator to possess desirable properties; in particular, these assumptions imply that the parameter estimates will be unbiased, consistent, and efficient in the class

of linear unbiased estimators. Many of these assumptions may be relaxed in more advanced treatments.

The regression equation deals with the following variables:

- The unknown parameters denoted as **β**; this may be a scalar or a vector of length k.
- The independent variables, **X**.
- The dependent variable, **Y**.

Regression equation is a function of variables **X** and **β**:

$$\mathbf{Y} = f(\mathbf{X}, \boldsymbol{\beta})$$

The user of regression analysis must make an intelligent guess about this function. Sometimes the form of this function is known; sometimes he must apply a trial and error process.

Chapter 4: Data Resources and Pre-Analysis

4.1 Introduction of Data Resource

4.1.1 National Household Travel Survey

The car ownership framework is developed using data from the 2001 and 2009 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration (FHWA). The NHTS collected travel data from a national sample of the civilian, non-institutionalized population of the United States. There are approximately a total of 70,000 households in the final 2001 NHTS dataset while 4,240 households in Maryland area, and 150,000 household in the final 2009 NHTS dataset while 355 household in Maryland area.

The NHTS was conducted as a telephone survey, using Computer-Assisted Telephone Interviewing (CATI) technology. The 2001 and 2009 NHTS dataset include the information that is needed in the models, but is not limited to:

- Household data on the relationship of household members, education level, income, housing characteristics, and other demographic information;
- Information on each household vehicle, including year, make, model, and estimates of annual miles traveled;
- Data about drivers, including information on travel as part of work.

4.1.2 Consumer Reports

The NHTS data does not have the detailed vehicle information needed for model estimation. Vehicle characteristics are computed from the *Consumer Reports (www.consumerreports.org).*

Consumer Reports shows the vehicle specification data on models tested within the past 10 years, having up to four model years by performance, crash protection, fuel economy, and specifications. It also has the market value or price of each new or used car.

We collected all the vehicle specifications and price for each make, model and year from *ConsumerReports.org*, including:

- Tested Model (i.e. 2003 SR5 4-door SUV 4WD, 4.0-liter V6, 4-speed automatic (Toyota 4Runner))
- Price
- Seating (front, rear, third)
- Engine size
- Transmission (manual or automatic)
- Acceleration
  - 0 to 30 mph, sec.
  - 0 to 60 mph, sec.
  - 45 to 65 mph, sec.
  - Quarter-mile, sec
  - Quarter-mile, mph
- Emergency handling
- Braking
  - Braking from 60 mph dry, ft.
  - Braking from 60 mph wet, ft.
- Comfort/convenience
  - Ride
  - Noise
  - Driving position
  - Seat comfort
  - Shoulder room, in
  - Leg room, in
  - Head room, in
  - Controls and display
  - Interior fit and finish
- Trunk/Cargo Area
- Luggage/cargo capacity, cu. ft.
- Climate System
- Fuel Economy (MPG)
- Cruising range, mi.
- Fuel capacity, gal.
- Fuel type
- Safety (Crash and rollover tests)
- Specifications
  - Length, in.
  - Width, in.

- Height, in.
- Turning circle, ft.
- Curb weight, lb.
- Max. load, lb.
- Typical Towing capacity, lb.

Then we aggregated all the information we collected by 12 vehicle classes and 10 vintages. Therefore, there are totally 120 alternatives (12 classes * 10 vintages), with detailed and aggregated vehicle specification and price information. The detail about the 12 classes and 10 vintages will be discussed in Chapter 6.

4.2 Descriptive Statistics

4.2.1 Trends of the National Household Travel Survey

This part is aim to highlight important travel trends in tabular and graphic format. Some of the results are from *Summary of Travel Trends* 2001 (Hu and Reuscher, 2004).

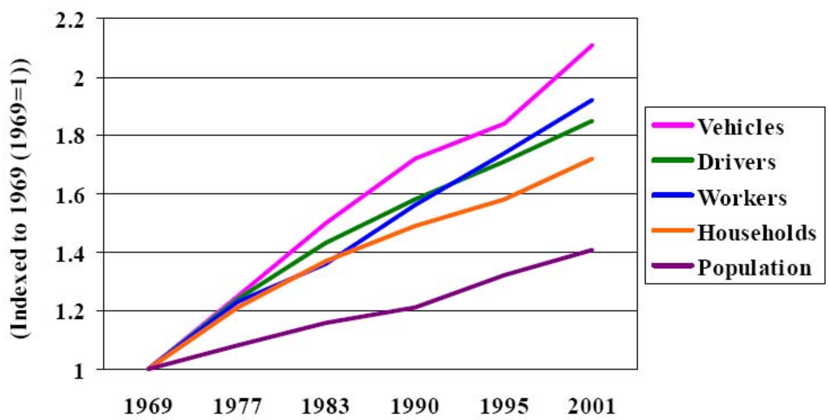


Figure 4- 1 Changes in Summary Demographics

1969, 1977, 1983, 1990, 1995 NHTS, and 2001 NHTS

During the past three decades, the number of vehicles increased at a steeper rate than most other demographic indicators. For example, it increased at an annual rate that was almost one and one-half times that of the total number of licensed drivers (Hu and Reuscher, 2004).

Table 4- 1 Summary of Demographic Trends

	1969	1977	1983	1990	1995	2001	2009
Persons per household	3.16	2.83	2.69	2.56	2.63	2.58	2.34
Vehicles per household	1.16	1.59	1.68	1.77	1.78	1.89	2.05
Licensed drivers per household	1.65	1.69	1.72	1.75	1.78	1.77	1.80
Vehicles per licensed driver	0.70	0.94	0.98	1.01	1.00	1.06	1.14
Workers per household	1.21	1.23	1.21	1.27	1.33	1.35	0.93
Vehicles per worker	0.96	1.29	1.39	1.40	1.34	1.39	2.20

Note: The 1969 survey does not include pickups and other light trucks as household vehicles.

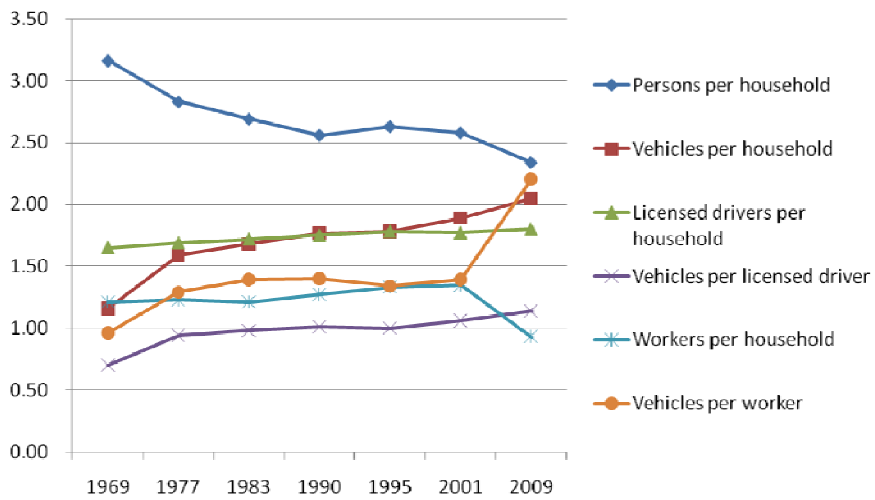


Figure 4- 2 Summary of Demographic Trends

The typical American household continues to own more vehicles. The percentage of households who own 3 or more vehicles increased from 19% in 1995 to 27% in 2009 (Table 4-2). The number of workers per household decreased sharply, probably reflecting the economic crisis in 2008.

Table 4- 2 Availability of Household Vehicles

Household with -	1969	1977	1983	1990	1995	2001	2009
No vehicle	12876	11538	11548	8573	7989	8716	7205
	20.60%	*15.30%*	*13.53%*	*9.18%*	*8.07%*	*8.12%*	*4.80%*
One vehicle	30252	26092	28780	30654	32064	33757	40527

	48.40%	*34.60%*	*33.71%*	*32.84%*	*32.39%*	*31.44%*	*26.99%*
Two vehicles	16501	25942	28632	35872	40024	39938	61711
	26.40%	*34.40%*	*33.54%*	*38.43%*	*40.43%*	*37.20%*	*41.10%*
Three or more vehicles	2875	11840	16411	18248	18914	24955	40704
	4.60%	*15.70%*	*19.22%*	*19.55%*	*19.11%*	*23.24%*	*27.11%*
All	62504	75412	85371	93347	98991	107366	150147
	100.00%	*100.00%*	*100.00%*	*100.00%*	*100.00%*	*100.00%*	*100.00%*
Vehicles per household	1.16	1.59	1.68	1.77	1.78	1.89	2.05

Note: The 1969 survey does not include pickups and other light trucks as household vehicles.

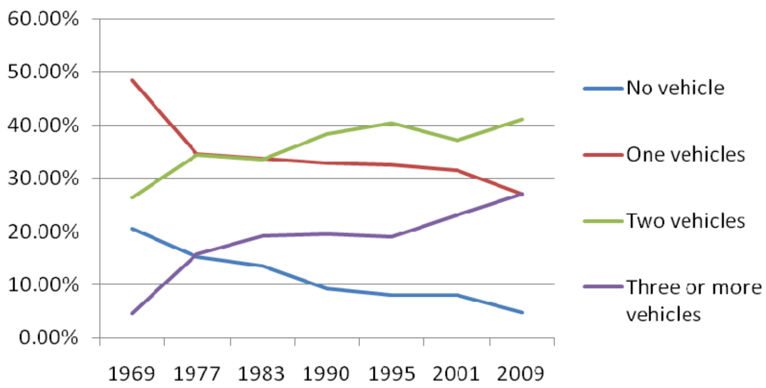


Figure 4- 3 Availability of Household Vehicles

About 70% of all households had 2 or more vehicles in 2009. Furthermore, not only were there more multi-vehicle households in 2009 than in 2001, they also owned more vehicles. There was a shift in 2009 from 1- to 2-vehicle households to 3+ vehicle households. Households owned an average of 2.05 vehicles in 2009, compared to1.89 in 2001. The *percent*age of households without a vehicle decreased to about 60% of 2001 level.

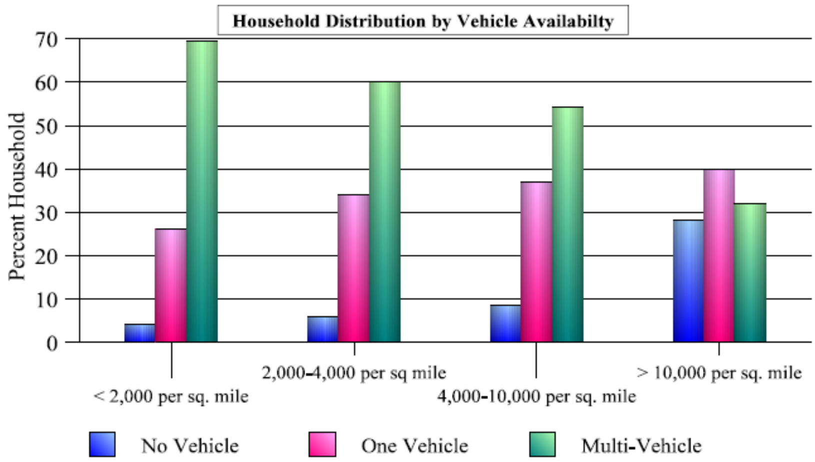


Figure 4- 4 Vehicle Ownership Statistics by Population Density

Population density seems to have little or no impact on households' decisions to own a vehicle, except in highly-populated areas with more than ten thousand persons per square mile. Almost thirty percent of the households in areas with a population density greater than 10,000 per square mile did not own a vehicle. On the other hand, almost 70% of the households in the least densely-populated areas owned more than two vehicles.

Table 4- 3 Percent of Households without a Vehicle within MSA Size Group

MSN size	% Households within an Area without a Vehicle						
	1977	1983	1990	1995	2001	2009	% Change 1977-2009
Not in MSA	12.20	10.50	7.70	5.30	5.80	4.04	-66.91%
<250000	13.70	10.10	8.60	4.80	5.80	4.49	-67.21%
250000 to 499999	12.20	8.10	5.70	7.30	5.20	4.44	-63.57%
500000 to 999999	14.00	14.30	8.40	6.30	7.00	4.35	-68.91%
1 to 2.9 million	14.20	12.10	8.20	6.90	6.40	6.30	-55.64%
3+ million	26.10	25.40	12.40	11.20	11.90	4.00	-84.66%
All	15.30	13.50	9.20	8.10	8.10	4.80	-68.64%

The percentage of households not owning a vehicle increases with increasing area size. In 2001, about 6% of the households in non-MSA areas or in small cities (< 250,000) were without a vehicle, representing a slight increase from 1995. The comparable percentage for areas with more than 3 million people was close to 12%. In large cities, such as New York, some zero-vehicle households are by choice due to the high cost and the inconvenience of owning a vehicle, and the availability of other modes. About 6 to 7 percent of the households in medium-size cities (with 500,000 to 3 million people) did not have a vehicle. In 2009, however, the percentage of households not owning a vehicle does not changes much with increasing area size

Table 4- 4 Vehicle Distribution and Average Vehicle Age by Vehicle Type

	1977	**1983**	**1990**	**1995**	**2001**	**2009**
Distribution of Vehicles						
Total	***100.0***	***100.0***	***100.0***	***100.0***	***100.0***	***100.0***
Auto	79.6	75.9	74.7	64.3	56.8	50.0
Van	2.8	3.6	5.5	7.8	9.0	7.9
Sport Utility	NA	NA	NA	6.9	12.1	17.7
Pickup	12.8	15.2	17.2	17.7	18.4	19.7
Other Truck	1.3	1.5	0.6	0.4	0.5	0.4
RV/Motor Home	0.4	0.5	0.5	0.5	0.7	0.7
Motorcycle	2.7	2.5	1.3	0.9	2.1	3.3
Moped	0.2	0.6	0.1	NA	NA	NA
Other	0.2	0.2	0.1	0.1	0.5	0.1
Average Vehicle Age						
Total	***6.6***	***7.6***	***7.7***	***8.3***	***8.9***	***8.6***
Auto	6.4	7.2	7.6	8.2	9.0	8.7
Van	5.5	8.5	5.9	6.7	7.6	8.0
Sport Utility	NA	NA	NA	6.6	6.4	6.8
Pickup	7.3	8.5	8.4	9.7	10.1	10.0
Other Truck	11.6	12.4	14.5	14.9	17.7	14.3
RV/Motor Home	4.5	10.7	10.4	13.2	13.5	12.8

Automobiles continued to lose their market share of private vehicles, from 80% in 1977 to about 50% in 2009. In the meantime, the market share for sport utility vehicles (SUVs) doubled between 1995 and 2001 and continues the increasing in 2009. Except for SUVs, the average age of vehicles in 2001 was greater than in the past and the average age of vehicle in 2009 was smaller than 2001.

In 2009, household vehicles remained in operation significantly longer than those in 1977, but shorter than 2001. In 1977, automobiles averaged 5.5 years of age while automobiles in 2001 averaged 9 years of age – an increase of almost 3.5 years. The average age of automobiles in 2009 decreased to 8.7 years comparing with 2001.

4.3.2 Statistics of 2001 NHTS Data

This Section presents data compiled from the 2001 National Household Travel Survey (NHTS) on vehicle ownership by households in State of Maryland, United States. Knowledge of vehicle ownership is useful in understanding the impact of socio-demographic and technological changes on household travel habits. This part is concerned with the characteristics of vehicles owned by or available to private households, along with characteristics of households that are major factors in vehicle ownership.

- Income

Not surprisingly, vehicle ownership increases directly with income. As shown in Figure 4-5, 67.14 percent of households with annual incomes under $5,000 own no vehicles, while only less than 5 percent of households with more than $45,000 income are without vehicles. Two-vehicle households are most commonly those with incomes of $20,000 to $30,000. Number of vehicles per household grows steadily with income, from 0.52 for households under $5,000 to 1.88 for households with $45,000 to $50,000 income to 2.66 for households over $100,000. The average for all households is 1.92 vehicles.

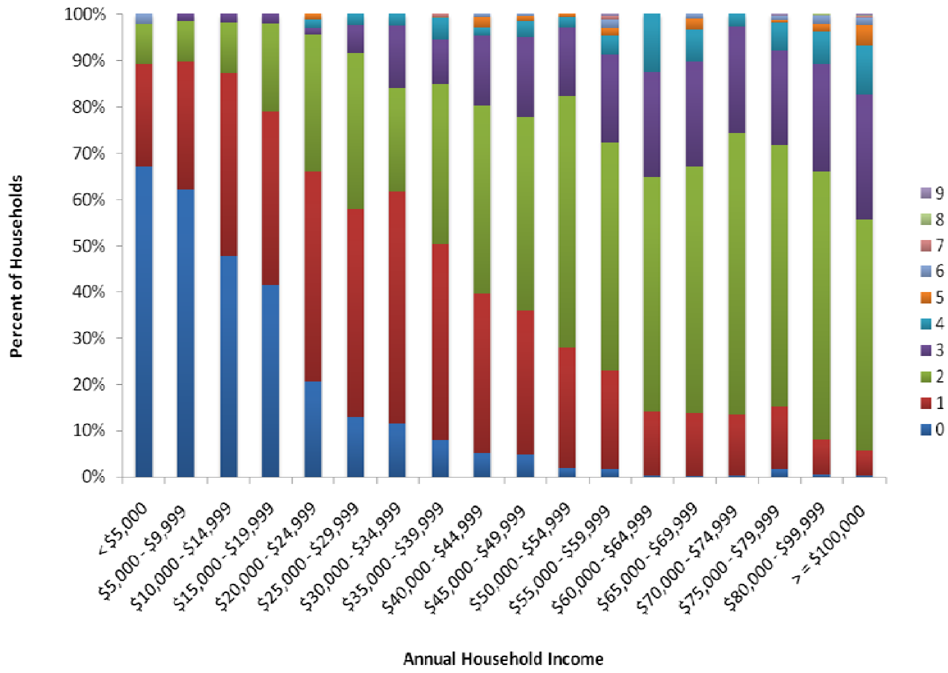


Figure 4- 5 Percent of Households Owning One or More Vehicles by Annual Household Income

- Household Composition

Household vehicle ownership is directly related to the number of adults (for the purpose of this study, adults are defined as persons 16 years of age and older) in the household. Figure 4-6 shows that incidence of vehicle ownership and number of vehicles owned increases with number of adults. Of all households with one adult, 29.37 percent do not own vehicles, while only 8.76 percent more or less of two-or-more-adult households do not own vehicles. Number of vehicles owned increase 0.88 vehicles for on-adult households, 2 for two-adult household, 2.57 for three-adult households and 3.29 more or less for households with four adults or more.

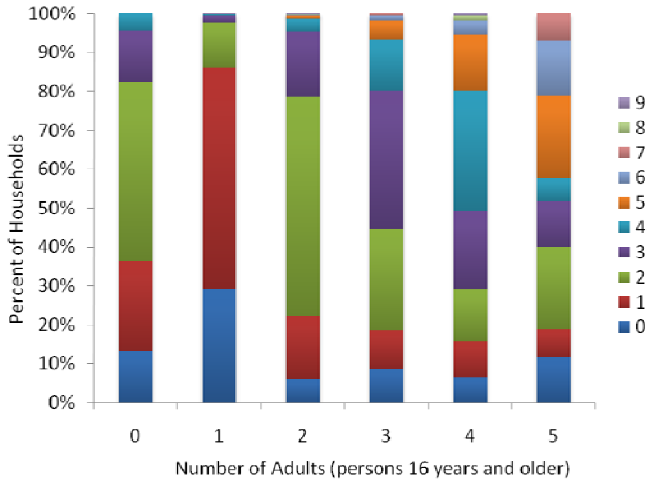


Figure 4- 6 Percent of Households Owning One or More Vehicles by Number of Adults per Household

As with household adults, the number of licensed drivers in household is closely related to vehicle ownership. Figure 4-7 shows that both the percent of household owning vehicles and the number of vehicles owned are linked to the number of drivers. Of one-driver households, 12.32 percent are without vehicles, while no households with three or more drivers are without vehicles. A somewhat surprising finding is that 2 percent of all households without any licensed drivers own at least one motor vehicle. Average number of vehicle per household closely follows the number of drivers, ranging from 1.05 for one-driver households, 2.13 for two-driver households, 3.00 for three-driver households, 4.00 for four-driver households, 4.86 for households with five or more drivers.

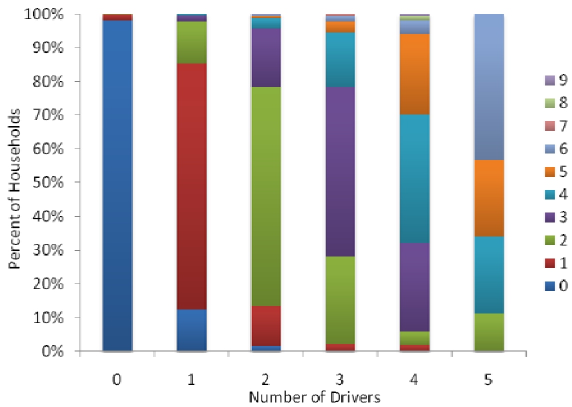


Figure 4- 7 Percent of Households Owning One or More Vehicles by Number of Drivers

As with household members with jobs, the number of members with job in household is closely related to vehicle ownership. Figure 4-8 shows that the percent of household owning vehicles is linked to the number of workers. Of zero-worker households, 28.77 percent are without vehicles, while no households with four or more workers are without vehicles. Average number of vehicle per household is a little more or less than the number of workers, ranging from 1.53 for one-worker households, 2.14 for two-worker households, 2.81 for three-worker households, 3.89 for four-worker households, 4.50 for households with five or more workers. 9.89 percent of all households without any members with job own more than one motor vehicle in average, mainly because it includes the retired people.

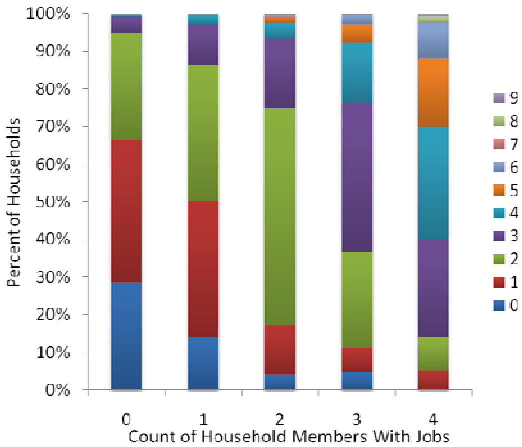


Figure 4- 8 Percent of Households Owning One or More Vehicles by Count of Household Members with Jobs

- Education of Household Head

Vehicle ownership increases with the level of educational attainment of the household head, principally because level of education is also tied to level of income. Both incidences of vehicle ownership and ownership rates increase with level of education. As shown in Figure 4-9, 43.51 percent of households whose head did not finish high school are without vehicles. This proportion drops to 15.64 percent for those attending high school, and 2.35 percent for those have Bachelor's degree. Average number of vehicles owned is 1.00 for those households where the household head did not finish high school, 1.82 for those that attended high school, and 2.14 for those with Bachelor's degree.

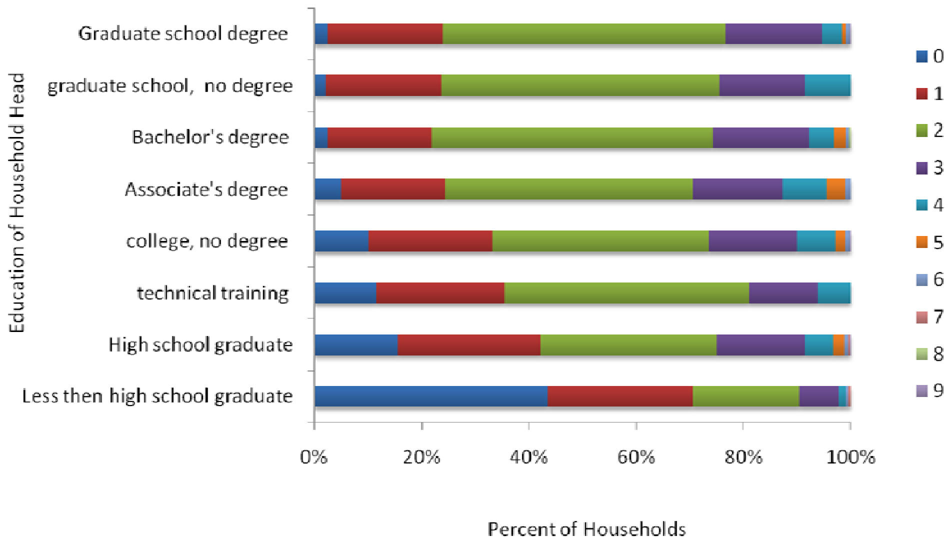


Figure 4- 9 Percent of Households Owning One or More Vehicles by Education of Household Head

- Housing Type

In the NHTS housing alternatives are categorized as single-family detached, single-family attached to one or more structures, single-family trailer or mobile home, and multifamily with either two to four units or more than four units. As shown in Figure 4-10, the majority of households (72 percent) reside in single-family detached homes. This group also has the highest incidence and rate of vehicle ownership. Only 3 percent of all households in single-family detached homes own no vehicles, which is comparable only to mobile home households at 2.13 percent. Households in department or condominium have the lowest incidence of vehicle ownership. Of households in department or condominium 30.53 percent have no vehicles. Households in single-family attached housing, typically townhouses and row-houses, display ownership characteristics midway between the single-family detached households and multiunit groups. Of households in this group, 16.86 percent own no vehicles. Expressed another way, ownership rates range from a low of 1.02 vehicles per household for apartment/condominium to a high of 2.40 vehicles for single-family detached, with an average for all housing types of 1.92. Even more revealing is the predominance of multivehicle ownership by single-family detached housing, 86 percent own two or more vehicles.

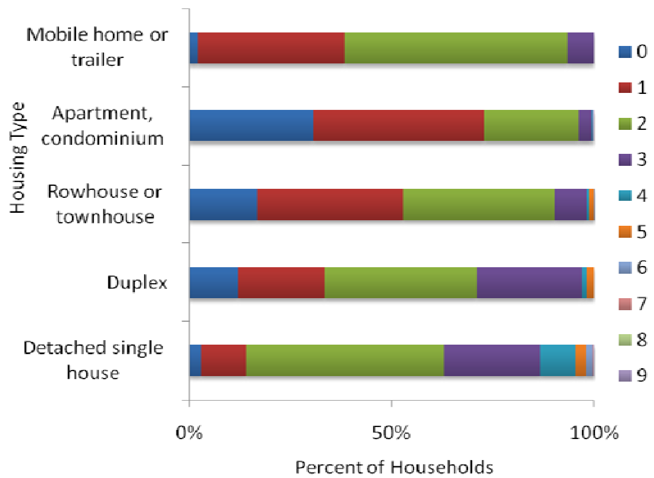


Figure 4- 10 Percent of Households Owning One or More Vehicles by Housing Type

- Access to Public Transportation

Access to public transportation may be measured in several ways. In the NHTS households were asked the general question of whether the public transportation, other than taxis, was available within two miles of their home. A comparison of access to public transportation with household vehicle ownership is shown in Figure 4-11.

The results show that 5.01 percent of all households think that public transportation is available according to the NHTS definition, while 94.16 percent do not, and 0.83 percent do not know. Only 7.59 percent of households where public transportation is considered not available owned no vehicles, while 54.07 percent of households with public transportation considered available are without a vehicle. Household with public transportation available average 0.77 vehicles per household, compared to 2.00 for households without public transportation. An important consideration in these relationships is that households residing in urban areas, and in particular within central cities where vehicle ownership rates are lower, are more likely to have public transportation available.

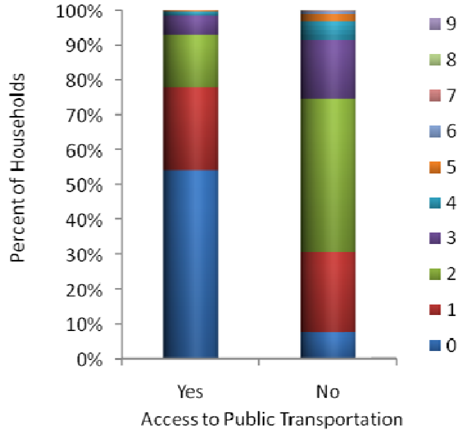


Figure 4- 11 Percent of Households Owning One or More Vehicles by Access to Public Transportation

- Household in Urban/Rural Area

Figure 4-12 show the relationship between vehicle ownership and whether household is in urban or rural area. The results show that the households in rural area own more cars in average. The average vehicles per household is 2.53 in an urban cluster, 1.77 in an urban area, while in an area surrounded by urban areas it is 2.51 and it is 2.83 in a non-urban area.

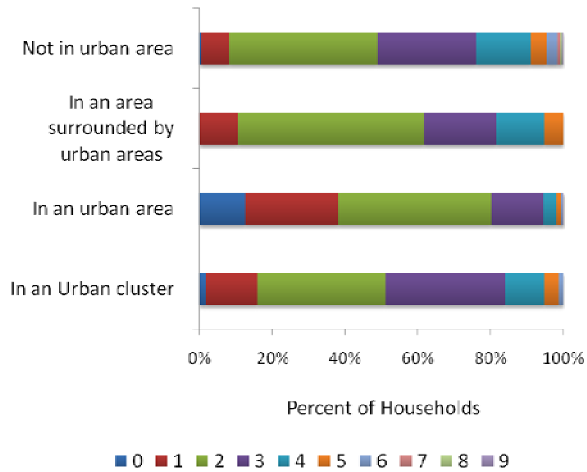


Figure 4- 12 Percent of Households Owning One or More Vehicles by Household in Urban/Rural Area

- Type of Vehicles Owned by Households

As seen in Table 4-5 and Figure 4-13, the vast majority of the vehicles are autos, including automobile, car and station wagon. The next largest share is sports utility vehicle. The third largest share is pickup truck. The fourth largest share is van, including minivan, cargo, and passenger.

Table 4- 5 Distribution of Household Vehicles by Type

Vehicle Type	Percent of Vehicles
Refused	0.06
Don't Know	0.11
Automobile/car/station wagon	64.72
Van (mini, cargo, passenger)	9.47
Sports utility vehicle	12.31
Pickup truck	10.97
Other truck	0.10
RV (recreational vehicle)	0.37
Motorcycle	1.78
Other	0.11
Total Vehicles	100.00

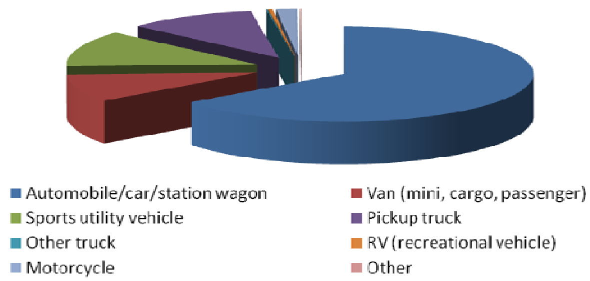
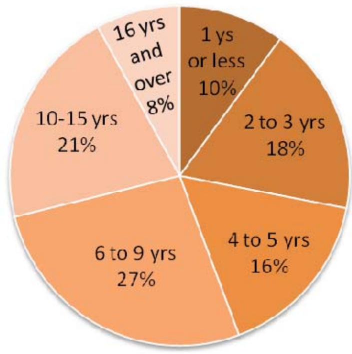


Figure 4- 13 Percent of Types of Vehicles Owned by Households

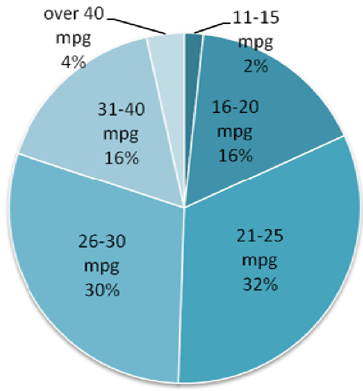
- Profile of Household Auto Characteristics

Figure 4-14-A shows that the average household auto in 2001 was 7.47 years old. Only 10 percent of all autos are late model (1year old or less), and 18 percent are 3 years old or under. The majority of autos, 56 percent, are more than 5 years old.

Aggregate fuel consumption (using combined city and highway driving conditions) for the 2001 stock is estimated at 26.6 miles per gallon (MPG). More than three quarters of the fleet (79 percent) have average fuel economy in excess of 15 MPG (Figure 4-14-B).



A Vehicle Age (Avg. Age = 7.47 Years)



B Average Combined Highwayand City MPG (Avg. MPG = 26.6)

Figure 4- 14 Auto Characteristics Profile

4.3.3 Statistics of 2009 NHTS Data

This part presents data compiled from the 2009 National Household Travel Survey (NHTS) on vehicle ownership by households in State of Maryland, United States. Similarly, this part is concerned with the characteristics of vehicles owned by or available to private households, along with characteristics of households that are major factors in vehicle ownership.

- Income

Vehicle ownership increases directly with income, as shown in Figure 4-15. The average for all households is 2.02 vehicles.

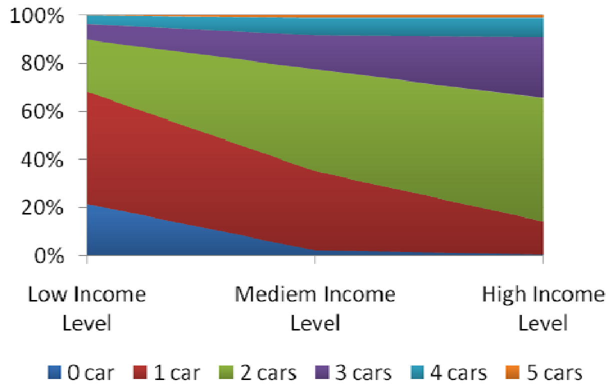


Figure 4- 15 Percent of Households Owning One or More Vehicles by Annual Household Income

- Household Composition

Household vehicle ownership is directly related to the number of adults (for the purpose of this study, adults are defined as persons 16 years of age and older) in the household. Number of vehicles owned increase 1.14 vehicles for on-adult households, 2.21 for two-adult household, 2.96 for three-adult households and 3.50 for households with four adults or more.

As with household adults, the number of licensed drivers in household is closely related to vehicle ownership. Figure 4-16 shows that the percent of household owning vehicles is linked to the number of drivers. Of one-driver households, 5 percent are without vehicles, while no households with three or more drivers are without vehicles. Average number of vehicle per household closely follows the number of drivers, ranging from 1.27 for one-driver households, 2.22 for two-driver households, 3.14 for three-driver households, 4.45 for four-driver households, 4.00 for households with five or more drivers.

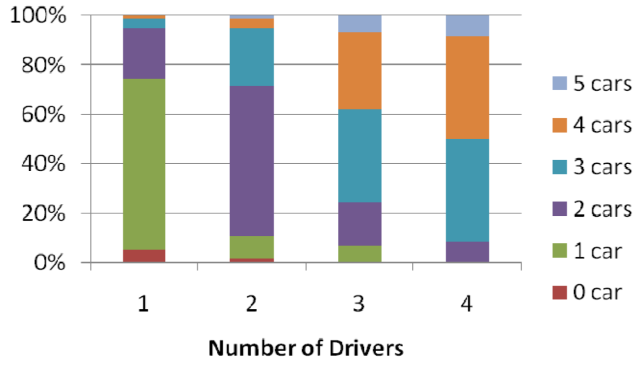


Figure 4- 16 Percent of Households Owning One or More Vehicles by Number of Drivers

As with household members with jobs, the number of members with job in household is closely related to vehicle ownership. Figure 4-17 shows that the percent of household owning vehicles is linked to the number of drivers. Of zero-worker households, only 8.49 percent are without vehicles, while no households with three or more workers are without vehicles. Average number of vehicle per household is a little more than the number of workers, ranging from 1.90 for one-worker households, 2.38 for two-worker households, 3.80 for three-or-more-worker households. Surprisingly, average number of vehicle per household is 1.61 for zero-worker households, mainly because this category may include a number of retired people.

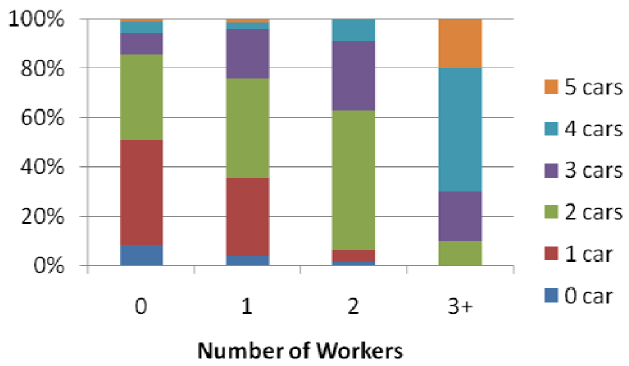


Figure 4- 17 Percent of Households Owning One or More Vehicles by Count of Household Members with Jobs

- Housing Type

As shown in Figure 4-18, the majority of households (74.22 percent) reside in single-family detached homes. This group also has the highest incidence and rate of vehicle ownership. Only 2.29 percent of all households in single-family detached homes own no vehicles. Households in department or condominium have the lowest incidence of vehicle ownership. Of households in department or condominium 17.95 percent have no vehicles. Expressed another way, ownership rates range from a low of 1.10 vehicles per household for apartment/condominium to a high of 2.22 vehicles for single-family detached, with an average for all housing types of 2.00. Even more revealing is the predominance of multivehicle ownership by single-family detached housing, 80.53 percent own two or more vehicles.

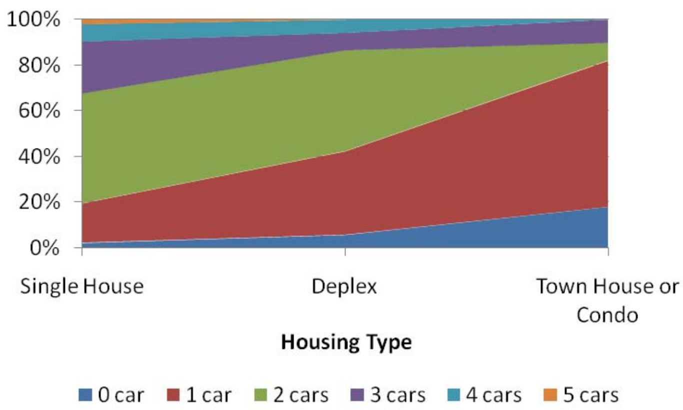


Figure 4- 18 Percent of Households Owning One or More Vehicles by Housing Type

- Household in Urban/Rural Area

Figure 4-19 show the relationship between vehicle ownership and whether household is in urban or rural area. The results show that the households in rural area own more cars in average. The average number of vehicles per household is 1.90 in an urban cluster, 2.22 in an urban area, while it is 2.35 in a non-urban area.

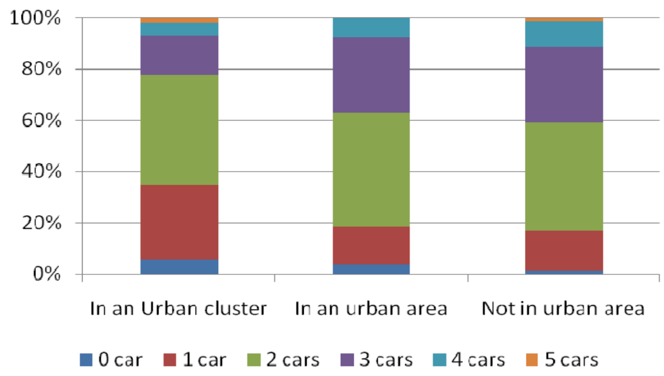


Figure 4- 19 Percent of Households Owning One or More Vehicles by Household in Urban/Rural Area

- Type of Vehicles Owned by Households

As seen in Figure 4-20, the vast majority of the vehicles are autos, including automobile, car and station wagon. The next largest share is sports utility vehicle. The third largest share is pickup truck. And the fourth largest share is van, including minivan, cargo, and passenger.

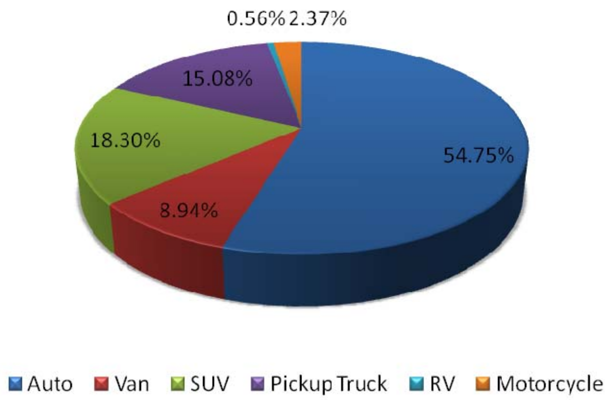


Figure 4- 20 Percent of Types of Vehicles Owned by Households

- Profile of Household Auto Characteristics

Figure 4-21 shows that the average household auto in 2001 was 8 years old. Only 4.76 percent of all autos are late model (1year old or less), and 13.69 percent are 3 years old or under. The majority of autos, 63.54 percent, are more than 5 years old.

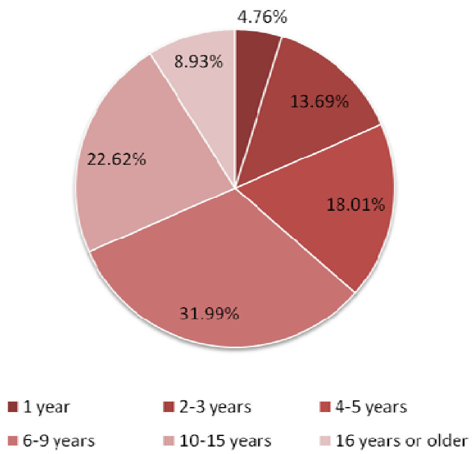


Figure 4- 21 Auto Characteristics Profile (Vehicle Age)

Chapter 5: Empirical Results for the Year 2001

In this Chapter we estimate vehicle ownership and use by using data derived from the National Household Travel Survey collected in 2001. At this stage vehicle type model is not part of the modeling framework given that the vehicle characteristics are not available in the consumer report for years prior to 1999. The structure of the framework applied is shown in Figure 5-1.

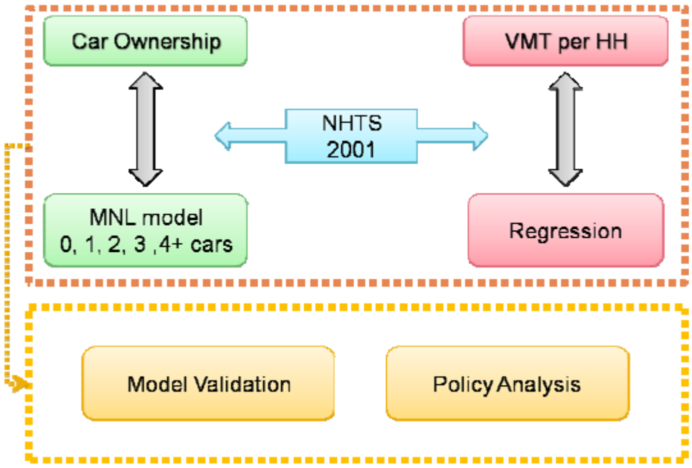


Figure 5- 1 Structure of the Modeling Framework for the year 2001

According to the structure above, the number of vehicles that the household owns (zero, one, two, three, four or more cars) is predicted by means of Multinomial Logit model (MNL). If the household is predicted to own no vehicles, then no further calculations are made. If the household is predicted to own one or more vehicles, the annual mileage traveled by all the vehicles in the household is then predicted. The models estimated are then used for validation and to test a number of policy scenarios.

5.1 Empirical Results for Vehicle Quantity Model

5.1.1 Model Specification

Having set the modeling framework, we firstly identify the relevant decision-maker, the alternatives available, and the functional form of the vehicle quantity model.

Although it can be argued that it is the individual (or the individual's employer in the case of company vehicles) who is responsible for specific ownership decisions, it is assumed that the household has overall responsibility for the number of vehicles owned. This assumption is not only reasonable but it is necessary given that the data does not identify the actual decision-maker.

The choice set for the household is well defined and includes zero, one, two, three and four or more vehicles. Consideration was given to extending the choice set to include five or more cars but examination of the data showed this to account for less than 2% of households. Although ownership levels are increasing, household size is also decreasing and therefore this sector of the market is not likely to be significant.

Following the systematic assessment of each of the research issues, a final set of model was specified. The overall structure of the model assesses the household's decision to own zero, one, two, three or four or more vehicles by way of a Multinomial Logit Model. The final model specifications are shown below (follow equation (7)):

$$P_i = \frac{e^{V_i}}{\sum_{j=0,1,2,3,4+} e^{V_j}}$$

Where, P_i is the probability of owning each number of vehicles in the choice set (0, 1, 2, 3, 4+); P_i depends on the factors that reflect the households' need for vehicles and its willingness or ability to purchase vehicles. V_i (the utility of ownership) denote the weighted sum of factors that affect households' decisions.

$$V_0 = 0$$

$$V_1 = ASC_1 + a_1 \times Inc + b_1 \times HS + c_1 \times Cld + e_1 \times Dri + f_1 \times Edu + g_1 \times Loc + h_1 \times HD + m_1 \times Rnt$$

$$V_2 = ASC_2 + a_2 \times Inc + b_2 \times HS + e_2 \times Dri + f_2 \times Edu + g_2 \times Loc + h_2 \times HD + m_2 \times Rnt$$

$$V_3 = ASC_3 + a_3 \times Inc + b_3 \times HS + d_3 \times Wrk + e_3 \times Dri + f_3 \times Edu + g_3 \times Loc + h_3 \times HD + m_3 \times Rnt$$

$$V_{4+} = ASC_4 + a_4 \times Inc + b_4 \times HS + d_4 \times Wrk + e_4 \times Dri + f_4 \times Edu + g_4 \times Loc + h_4 \times HD + m_4 \times Rnt$$

Where: ASC_i is alternative specific constant; ***Inc*** is the annual income of the household; ***HS*** is the household size; ***Cld*** is number of children in the household; ***Wrk*** is the number of workers in the household; ***Dri*** is the number of licensed drivers in the household; ***Edu*** is the education level of household head; ***Loc*** is the household location (five levels: 1 for urban, 2 for second city, 3 for suburban, 4 for town, 5 for rural); ***HD*** is the household density at block level; ***Rnt*** is the percent renter-occupied housing at block level; ***a***, ***b***, ***c***, ***d***, ***e***, ***f***, ***g, h, m*** are parameter vectors to be estimated.

5.1.2 Model Estimation

Table 5-1 presents the estimated model of vehicle ownership. The model is estimated on 3320 observations and has very good level of fit with ρ^2 value with respect to constants of 0.4402.

In terms of the estimated coefficients, most of them have the expected sign and values. For those which present significant t-statistics, the coefficients have intuitive meaning:

(1) Coefficients of household income are positive and very significant. Meanwhile, the value of the coefficients is larger with respect to the households with more cars. Therefore households with higher income tend to own multiple cars, and the higher their income, the more likely that they will own more cars.

Table 5- 1 Vehicle ownership model estimation

Explanatory Variables	**Alternatives**	**Estimated coefficient**	**Standard Error**	***t*-statistic**
Alternative Specific Constant	1 Vehicle	-1.304	0.647	-2
	2 Vehicle	-7.366	0.758	-9.7
	3 Vehicle	-12.02	0.909	-13.2
	4+ Vehicle	-13.45	1.190	-11.3
Household Income	1 Vehicle	0.1735	0.0370	4.7
	2 Vehicle	0.3071	0.0403	7.6
	3 Vehicle	0.3854	0.0436	8.8
	4+ Vehicle	0.3890	0.0513	7.6
Household Size	1 Vehicle	-0.7756	0.156	-5.0
	2 Vehicle	-0.2036	0.126	-1.6
	3 Vehicle	-0.2110	0.138	-1.5
	4+ Vehicle	-0.2932	0.167	-1.8
Number of Children	1 Vehicle	0.5131	0.157	3.3
Number of Employees	3 Vehicle	0.3489	0.100	3.5
	4+ Vehicle	0.4725	0.176	2.7
Number of Drivers	1 Vehicle	3.912	0.299	13.1
	2 Vehicle	6.409	0.346	18.5
	3 Vehicle	7.591	0.378	20.1
	4+ Vehicle	8.033	0.417	19.3
Education Level of Household Head	1 Vehicle	0.06871	0.0567	1.2
	2 Vehicle	0.02271	0.0656	0.3
	3 Vehicle	-0.09585	0.0718	-1.3
	4+ Vehicle	-0.15570	0.0860	-1.8
Household Location	1 Vehicle	0.1887	0.149	1.3
	2 Vehicle	0.4301	0.169	2.6
	3 Vehicle	0.5743	0.186	3.1
	4+ Vehicle	0.5019	0.230	2.2
Housing Density	1 Vehicle	-0.00006309	0.000080	-0.8
	2 Vehicle	-0.00017750	0.000092	-1.9
	3 Vehicle	-0.00032050	0.000108	-3.0
	4+ Vehicle	-0.00071770	0.000175	-4.1
Percent renter-occupied housing	1 Vehicle	-0.02100	0.00478	-4.4
	2 Vehicle	-0.02671	0.00556	-4.8
	3 Vehicle	-0.03087	0.00644	-4.8
	4+ Vehicle	-0.04298	0.01010	-4.3

Likelihood with Zero Coefficients = -4218.3368

Likelihood with Constants only = -3643.9357

Final value of Likelihood	=	-2039.6993
"Rho-Squared" w.r.t. Zero	=	0.5165
"Rho-Squared" w.r.t. Constants	=	0.4402

(2) The variables relative to the number of household members have negative coefficients but turn out to be not significant.

(3) Number of children in a household is a significant factor entering one-vehicle-alternative.

(4) Households with more employees and drivers own more vehicles. The coefficients of number of drivers are extremely significant, which means that this attribute greatly influences the vehicle ownership in the household. Number of employees result to be significant in three-vehicle and four-or-more-vehicle alternatives only.

(5) When comes to the characteristics of the household head, the coefficients associated with household head's education level is significant. The coefficients in one-vehicle and two-vehicle alternatives are positive, as the higher the education level, the more likely that the household owns more cars. The coefficients in three-vehicle and four-or-model-vehicle alternative are negative. All the education coefficients are not significant at the 95% level of significance.

(6) We estimate three land use factors: location of the household (from urban to rural area), housing density and percent of rental properties. These variables have strong influence on household vehicle ownership. In particular, moving from urban to rural areas has a positive effect on the number of cars owned (as expected); housing density has a negative effect as well as the percent of rental properties.

5.1.3 Model Validation

For validation purpose (which is extremely important when the model is used to test policies), we re-estimate the model on 80% of the available observations in the dataset and we apply the model estimates on the hold out sample. The results show that the model does well in prediction. In Table 5-2 we report the actual choices, the choices predicted by the model and the difference between observed and predicted choices. It can be noted that we slightly under-predict the number of households with zero car and over-predict the number of the household with 1 or 2 vehicles. Differences are extremely small and less than 2.5%. We also apply the model by considering the dimension location of the household which is on 5 levels of variation (urban, second city, suburban, town, rural); this is done because the low number of observations in rural areas might potentially compromise the ability of the model to correctly recover the choices in remote areas, see Table 5-3.

Table 5- 2 Model Validation

	Actual	Forecast	Difference
0 Vehicle Household	28.04%	25.75%	-2.29%
1 Vehicle Household	41.06%	42.75%	1.69%
2 Vehicle Household	24.32%	25.05%	0.73%
3 Vehicle Household	6.01%	5.67%	-0.34%
4+ Vehicle Household	0.57%	0.77%	0.20%
Cars per household	1.10	1.13	0.03
Number of Household	699	699	0
Number of Cars	769	789.4	20.4

Again the differences in the number of cars observed and predicted for each area type are small; this attests the goodness of the model and the possibility to apply the model calibrated to test different policies.

Table 5- 3 Model Validation (by land use categories)

	Urban	Second City	Suburban	Town	Rural	Total
Actual						
0 Veh HH	32.03%	18.75%	1.64%	0.00%	0.00%	28.04%
1 Veh HH	42.54%	34.38%	36.07%	23.08%	0.00%	41.06%
2 Veh HH	20.85%	40.63%	44.26%	38.46%	66.67%	24.32%
3 Veh HH	4.41%	6.25%	14.75%	30.77%	33.33%	6.01%
4+ Veh HH	0.17%	0.00%	3.28%	7.69%	0.00%	0.57%
Cars per household	0.98	1.34	1.82	2.23	2.33	1.10
Number of Household	590	32	61	13	3	699
Number of Cars	579	43	111	29	7	769
Forecast						
0 Veh HH	29.37%	12.81%	4.10%	0.77%	0.00%	25.75%
1 Veh HH	44.02%	47.19%	33.44%	26.92%	6.67%	42.75%
2 Veh HH	22.36%	32.50%	42.30%	38.46%	63.33%	25.05%
3 Veh HH	3.97%	6.56%	16.89%	24.62%	23.33%	5.67%
4+ Veh HH	0.29%	0.94%	3.28%	9.23%	6.67%	0.77%
Cars per household	1.02	1.36	1.82	2.15	2.30	1.13
Number of Household	590	32	61	13	3	699
Number of Cars	600.5	43.4	110.9	27.9	6.9	789.4
Difference						
0 Veh HH	-2.66%	-5.94%	2.46%	0.77%	0.00%	-2.29%
1 Veh HH	1.47%	12.81%	-2.62%	3.85%	6.67%	1.69%
2 Veh HH	1.51%	-8.13%	-1.97%	0.00%	-3.33%	0.73%
3 Veh HH	-0.44%	0.31%	2.13%	-6.15%	-10.00%	-0.34%
4+ Veh HH	0.12%	0.94%	0.00%	1.54%	6.67%	0.20%
Cars per household	0.04	0.01	0.00	-0.08	-0.03	0.03
Number of Household	0	0	0	0	0	0
Number of Cars	21.5	0.4	-0.1	-1.1	-0.1	20.4

5.1.4 Model Application

The model has then been applied to test a number of policies and to measure their effects on car ownership in the State of Maryland. We have tested the following scenarios:

1. Change in housing density and in particular the effect of the increase in the actual values of density by 20%, 50%, 100%, 200%, 500%;
2. Change in household income; we tested both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
3. Change in land use; we assume that rural areas and towns become suburban area and that suburban areas become second city type area;
4. Change in land use: all areas become urban areas;
5. Unemployment: 10% of the household loose one worker and all the households loose one worker.

Table 5-4 summarizes results obtained from scenario 1; it can be observed that small changes in housing density do not affect too much car ownership and that we obtain a 4% reduction in the total number of cars in Maryland by doubling the actual density. Fang (2008) have the similar conclusion that increasing residential density within feasible ranges will have a very small impact on household vehicle holdings and vehicle fuel usage. This result can be explained by the fact that we are increasing density overall the State and that more focused interventions could result in being more effective. In general we can observe that the number of household with zero or one car is increasing while household with multiple cars are decreasing in percentage.

Table 5- 4 Scenario 1: Housing density

	Actual	**+20%**	**+50%**	**+100%**	**+200%**	**+500%**
0 Veh Household	14.70%	14.47%	14.87%	15.55%	17.00%	21.79%
1 Veh Household	33.25%	33.93%	34.56%	35.55%	37.29%	39.86%
2 Veh Household	35.48%	35.28%	34.95%	34.23%	32.46%	27.45%
3 Veh Household	13.31%	12.98%	12.49%	11.79%	10.69%	8.71%
4+ Veh Household	3.25%	3.34%	3.13%	2.88%	2.56%	2.20%
Cars per household	1.57	1.57	1.54	1.51	1.45	1.30
Number of Household	3320	3320	3320	3320	3320	3320
Number of Cars	5218	5205.5	5128.1	5009.2	4798.1	4304.7
Diff of Num of Cars	0	-0.24%	-1.72%	-4.00%	-8.05%	-17.50%

Income scenarios are presented in Table 5-5. As expected a decrease in household income will produce a decrease in the total number of cars owned by households in

Maryland; 25% decrease in household income is expected to lower the number of cars by about 4.5%.

Table 5- 5 Scenario 2: Income Factor

	Actual	Income -25%		Income +25%	
		Value	**Difference**	**Value**	**Difference**
0 Veh Household	14.70%	15.27%	0.58%	13.34%	-1.36%
1 Veh Household	33.25%	36.04%	2.78%	31.40%	-1.86%
2 Veh Household	35.48%	34.88%	-0.60%	35.78%	0.30%
3 Veh Household	13.31%	10.96%	-2.35%	15.71%	2.40%
4+ Veh Household	3.25%	2.84%	-0.41%	3.77%	0.51%
Cars per household	1.57	1.50	-0.07	1.65	0.08
Number of Household	3320	3320	0	3320	0
Number of Cars	5218	4981.9	-4.52%	5483.2	5.08%

An increase in household income of 25% will result into 5.1% more cars in our State. The most affected by this scenario are households with three cars.

Similar analyses have been conducted by varying urbanization factors and unemployment rates; results relative to these cases are in Table 5-6. To facilitate the analysis of the results, we just report the total number of cars in the dataset, those predicted by the model under each of the scenario considered and the differences. When increasing urbanization the total number of car and the number of cars per household decrease; an increase of the urbanization will determine a decrease in car ownership in suburban areas and towns, a relatively small increase is predicted for urban areas. These results are consistent for scenario 3 and 4; in the latter case differences between actual and future conditions are very different which is justified by the strong hypothesis that Maryland will become all urban. Raising rate of unemployment will produce a decrease of cars in suburban areas and town, but the scenario 10% rate of unemployment does not produce an overall decrease in the total number of cars. In order to quantify the effect on the population of Maryland in the last column of Table 5-6 we compare the actual number of cars in the State of Maryland and the predictions calculated by applying our model; it can be seen that even small effects predicted by our scenarios have strong effects on the total number of cars.

Table 5- 6 Scenario 3-4-5 : Urbanization and unemployment effects

Number of Cars	Urban	Second City	Suburban	Town	Rural	Total Sample	Total Cars in State of Maryland(*)
Urbanization - Scenario 3							
Forecast	1415.5	508.6	1841.8	1190.7	199.1	5155.3	3,151,107
Actual	1395	504	1887	1231	201	5218	3,189,432
Difference	20.50	4.60	-45.20	-40.30	-1.90	-62.70	-38,325
Urbanization - Scenario 4							
Forecast	1415.5	494.1	1792.5	1137.1	189.6	5029	3,073,908
Actual	1395	504	1887	1231	201	5218	3,189,432
Difference	20.50	-9.90	-94.50	-93.90	-11.40	-189.00	-115,524
10% Households loose one worker							
Forecast	1414.4	506.3	1881.2	1210.9	206.6	5220	3,190,654
Actual	1395	504	1887	1231	201	5218	3,189,432
Difference	19.40	2.30	-5.80	-20.10	5.60	2.00	1,222
All Households loose one worker							
Forecast	1398.5	496.2	1837.6	1175.6	201.2	5108.9	3,122,746
Actual	1395	504	1887	1231	201	5218	3,189,432
Difference	3.50	-7.80	-49.40	-55.40	0.20	-109.10	-66,686

* From Census 2000, the population in State of Maryland was 5,296,486 and the average household was 2.61 persons/household. Total number of households is 2,029,305.

5.2 Empirical Results for Vehicle Usage Model

5.2.1 Model Specification

The regression model predicts the annual vehicle miles traveled per household in 2001. It is specified as linear regression models with a function of household socio-economic variable, land use attributes and vehicle specifications. The formulation of the model is:

$$\log(VMT) = f(\log(Inc), HS, Cld, Wrk, Dri, Edu, Loc, \log(HD), Rnt, \log(Cost))$$

Where ***VMT*** is annual vehicle miles traveled per household; ***Inc*** is the annual household income; ***HS*** is the household size; ***Cld*** is number of children in the household; ***Wrk*** is the number of workers in the household; ***Dri*** is the number of licensed drivers in the household; ***Edu*** is the education level of household head; ***Loc*** is the household location (on five level of variation ranging from urban to rural area); ***HD*** is the household density at block level; ***Rnt*** is the percent renter-occupied housing at block level; ***Cost*** is the operating cost which is represented by cents per mile.

The parameters are estimated with an instrumental variable approach. This approach is required, rather than ordinary least square because the operating cost is entering the regression equation as an explanatory variable. Since the household chooses which vehicle(s) it owns, it effectively chooses the operating cost that it faces when driven, namely, the operating cost of it chosen vehicle(s) (Train, 1986). Therefore, the operating cost is endogenous in the model, and the ordinary least squares estimation is biased. To avoid this bias, instrumental variable estimation is applied. The exogenous variables used to predict operating cost are:

- Household income;
- Household size;
- Housing density;
- Number of adults;
- Number of workers.

5.2.2 Model Estimation

Table 5-7 presents the estimated regression model of vehicle use (VMT per household). The models have pretty good level of fit with R^2 value of 0.194.

In terms of the estimated coefficients, most of them have expected sign and values. For those which are significant from t-statistics, the estimated coefficients have intuitive meanings:

(1) All the coefficients of the household social-economic variables have the similar intuitive explanatory meaning as the vehicle quantity model. Household income, number of children, number of workers, and number of drivers have positive influence on vehicle use. Especially, number of workers in the household significantly contributes to household vehicle use. Coefficient of number of children is significant at 90% level. Coefficient of household size is negative but it is not significant in model.

(2) Among land use factors, variables of household location and population density are significant at 90% level. Households tend to drive less in more dense area as the coefficient of log of population density is negative. Household location is measured by level one to five which represents urban area, second city, suburban, town, rural. The positive coefficient means people drive more in the more rural area.

(3) As expected, households drive less when the operating cost increases. Another nice result is that the estimated coefficient of operating cost is exactly the elasticity[1].

(4) In terms of household head characteristic, education level of household head is very significant at this stage. We assume the households with higher education level usually have higher income. The resulting estimated coefficient confirms our result, that households have higher vehicle usage with higher education level.

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[1] $$\log(VMT) = \beta_{GC}\log(GC) + ... \Rightarrow \frac{\partial(\log(VMT))}{\partial VMT} = \frac{\partial(\beta_{GC}\log(GC))}{\partial GC}$$

$$\Rightarrow \frac{1}{VMT}\partial VMT = \beta_{GC}\frac{1}{GC}\partial GC \Rightarrow \beta_{GC} = \frac{\partial VMT}{VMT}\Big/\frac{\partial GC}{GC} = e_{GC}$$

Table 5- 7 Estimation Results of Regression Model

Variable	Estimated coefficient	std. Error	t-statistic	p-value
Intercept	10.1	1.7	6.03	<.0001
log(household income)	0.501	0.073	6.89	<.0001
household size	0.06	0.11	0.61	0.5447
number of children	-0.01	0.10	-0.06	0.953
number of workers	0.193	0.036	5.35	<.0001
number of drivers	0.151	0.056	2.69	0.0073
Education level of household head	0.0334	0.0080	4.17	<.0001
Urbanized level	0.061	0.026	2.34	0.0192
log(Population per sq mile)	-0.062	0.027	-2.32	0.0205
Percentage of Rental Properties	-0.00033	0.00096	-0.35	0.7281
log(operating cost by cents/mile)	-0.45	0.35	-1.26	0.2096

*R-Square=0.194

**Number of Observations Used: 2397

5.2.3 Model Application

The model has been applied to test a number of sensitivity analyses in order to measure their effects on vehicle usage. The scenarios we have tested are:

1. Change in household income; we tested both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
2. Unemployment: 10% of the household loose one worker and all the households loose one worker.
3. Change in land use: all areas become urban areas;
4. Change in housing density and in particular the effect of the increase in the actual values of density by 100%;

5. Change in Fuel cost: assume the highest fuel cost was $4 per gallon in 2008[2] ($3.16 per gallon in 2001 dollar with inflation rate of 3% per year).

Table 5-8 and Figure 5-2 summarized the results obtained from the scenarios above. Vehicle miles traveled increases a lot (18.61%) with the increase of income-the amount of change is almost 75 percent as the change of income. This is true because people tend to spend more money to improve the living quality when they earn more money. However, when the income decreases, VMT decreases with much less proportion (-8.15% when income decreases by 25%). This is because people still need to travel and to satisfy their basic living requirement even they have less money.

In terms of the employment situation, vehicle miles traveled does not change much (-1.91%) when 10% household loose worker. But it decrease a lot (-17.54%) when all households loose one worker. It means the bad unemployment does not change the vehicle usage a lot, but once the unemployment is super bad (every household looses one worker) people will use vehicles much less.

Changes of urban level of household location and housing density are used to measure the influence of urbanization. The results show even if the housing density is doubled or all area in Maryland becomes urban area, VMT does not decrease a lot (-8.05% and -9.46% respectively). This occurs because the United State is a "mobile society" and the city life in Maryland depends a lot on the highway network. People have to use vehicle for commuting or traveling purposes even if the state is much denser.

When comes to the operating cost, we see people are very sensitive to mobile cost. We take the historical data of fuel price and the highest price is around $4 which is occurred in 2008. We re-calculate the operating cost by this fuel price. After removing the inflation factor, we see vehicle usage is about one quarter less (-

[2] Information of historical fuel price (excluding tax) is from U.S. Energy Information Administration (EIA). Information of fuel tax is from Federal Highway Administration.

25.92%). This is realistic because in reality people did travel much less in 2008 when the fuel price was very high and the economic crisis was taken place.

Table 5- 8 Application Results of Regression Model

Policy	Income +25%	Income -25%	10% households loose one worker	All households loose one worker	Highest urban level	Housing Density +100%	Fuel Price +250% (from \$1.6 to \$4)
Percent change of VMT	18.61%	-8.15%	-1.91%	-17.54%	-9.46%	-8.05%	-25.92%

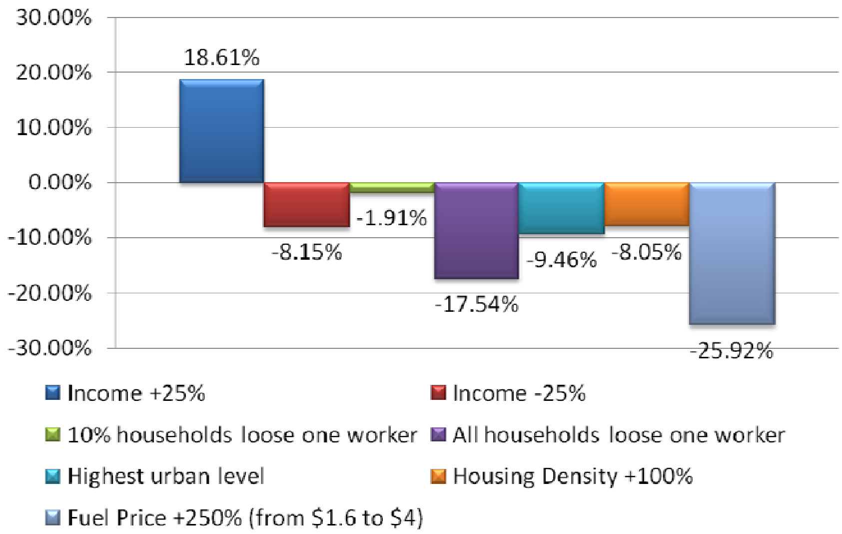

Figure 5- 2 Application Results of Regression Model

Chapter 6: Empirical Results for the Year 2009

The model framework applied to NHTS 2009 consists of three sub-models that separately describe the number of vehicles owned, vehicle type and vehicle miles traveled. The first model predicts how many vehicles do a household own. The second part measures preferences over vehicle types (class and vintage). The final part estimates vehicle usage at household level. The structure of the framework is shown in Figure 6-1.

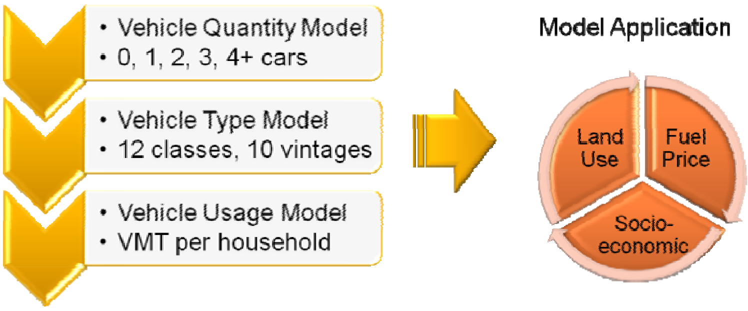

Figure 6- 1 Structure of the Modeling Framework for the year 2009

According to the structure above, the number of vehicles that the household owns (zero, one, two, three, four or more cars) is predicted by a Multinomial Logit model (MNL). If the household is predicted to own no vehicles, then no further calculations are made. If the household is predicted to own one or more vehicles, the preference of vehicle class and vintage and the annual mileage traveled by all the vehicles in the household is then predicted. The models estimated are then used to test a number of policy scenarios. Due to the limited number of observations available for the State of Maryland, model validation could not be conducted.

6.1 Empirical Results for Vehicle Quantity Model

6.1.1 Model Specification

Similarly to the model developed in the previous chapter, we assume that the households are the decision makers for car ownership. The choice includes zero, one, two, three and four or more vehicles. The model specification is shown below:

$$P_i = \frac{e^{V_i}}{\sum_{j=0,1,2,3,4+} e^{V_j}}$$

where, P_i is the probability of owning each number of vehicles in the choice set (0, 1, 2, 3, 4+); P_i depends on the factors that reflect the households' need for vehicles and its willingness or ability to purchase vehicles. V_i (the utility of ownership) denote the weighted sum of factors that affect households' decisions.

$$V_0 = 0$$
$$V_1 = ASC_1 + a_1 \times Inc + b_1 \times Cld + c_1 \times Dri$$
$$V_2 = ASC_2 + a_2 \times Inc + b_2 \times Cld + c_2 \times Dri + d_2 \times Wrk + e_2 \times Home + f_2 \times Loc$$
$$V_3 = ASC_3 + a_3 \times Inc + b_3 \times Cld + c_3 \times Dri + d_3 \times Wrk + e_3 \times Home + f_3 \times Loc$$
$$V_{4+} = ASC_4 + a_4 \times Inc + c_4 \times Dri + d_4 \times Wrk + f_4 \times Loc$$

where: ASC_i is alternative specific constant; ***Inc*** is the annual income of the household; ***Cld*** is number of children in the households with more than one child; ***Dri*** is the number of licensed drivers in the household; ***Wrk*** is the number of workers in the households with more than one worker; ***Home*** is a dummy variable which 1 is for owned home and 0 is for rental home; ***Loc*** is the household location on six level of variation ranging from 1 (for non-urban area) to 6 (most dense urban area); ***a***, ***b***, ***c***, ***d***, ***e***, ***f*** are parameter vectors to be estimated.

6.1.2 Model Estimation

Table 6-1 presents the estimated model of vehicle ownership. The model is estimated on 335 observations and has good level of fit with ρ^2 value with respect to constants of 0.2891.

In terms of the estimated coefficients, all of them have the expected sign and values. For those which present significant t-statistics, the coefficients have intuitive meaning:

(1) Coefficients of household income are positive and very significant. Meanwhile, the value of the coefficients is larger with respect to the households with more cars. Therefore households with higher income tend to own multiple cars, and the higher their income, the more likely that they will own more cars.

(2) Number of children in the households with more than one child is entering one-vehicle, two-vehicle and three-vehicle alternatives. The coefficients are positive except the one in one-vehicle alternative. Although the coefficients are not significant at 95% significance level, the signs are correct because households with more children usually have multiple cars rather than only one car. In other words, households with more children tend to own two or more cars.

(3) Households with more employees and drivers own more vehicles. The coefficients of number of drivers are very significant, which means that this attribute greatly influences the vehicle ownership in the household. Number of employees is significant in two-vehicle, three-vehicle and four-or-more-vehicle alternatives only.

(4) Home owned or rent variable is only significant in two-vehicle and three-vehicle alternatives. The positive sign means households with owned home are more likely to own more cars.

(5) In terms of land use factors we use the urban size in the location of the household. This variable is ranging from 1 to 6: 1 is for non-urban area, 2 to 6 represent five density levels in which 2 is for the least dense urban area and 6 is for the most dense urban area. This variable has strong influence on household vehicle ownership. Especially, it is very significant in two-vehicle, three-vehicle and four-or-more-vehicle alternatives. As we expected, urban size has a negative effect on car ownership and the effect becomes larger with three-or-more-vehicle households.

Table 6- 1 Vehicle ownership model estimation

Explanatory Variables	**Alternatives**	**Estimated coefficient**	**Standard Error**	***t*-statistic**
Alternative Specific Constant	One	-1.494	0.767	-1.9
	Two	-5.635	1.12	-5
	Three	-8.639	1.41	-6.1
	Four+	-10.9	1.61	-6.8
Household Income	One	0.1755	0.0802	2.2
	Two	0.2648	0.0849	3.1
	Three	0.3117	0.0915	3.4
	Four+	0.289	0.0999	2.9
Number of Children	One	-0.1917	0.244	-0.8
	Two	0.1512	0.204	0.7
	Three	0.1409	0.215	0.7
Number of Drivers	One	1.875	0.706	2.7
	Two	3.568	0.779	4.6
	Three	4.879	0.834	5.8
	Four+	5.844	0.866	6.7
Number of Workers	Two	0.4239	0.261	1.6
	Three	0.3961	0.284	1.4
	Four+	0.5075	0.334	1.5
Home Owned or Rent	Two	1.637	0.58	2.8
	Three	1.07	0.758	1.4
Urban Size	Two	-0.206	0.0863	-2.4
	Three	-0.3884	0.106	-3.7
	Four+	-0.3406	0.141	-2.4

Likelihood with Zero Coefficients = -523.0673
Likelihood with Constants only= -445.3020
Final value of Likelihood= -316.5486
"Rho-Squared" w.r.t. Zero = 0.3948
"Rho-Squared" w.r.t. Constants = 0.2891

6.1.3 Model Application

The model has then been applied to test a number of sensitivity analyses and to measure their effects on car ownership in the State of Maryland. We have tested the following scenarios:

1. Change in household income; we tested both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
2. Change in urban density and in particular the effect of the increase in the actual values of density by 100%;
3. Unemployment: we assume 10% of the household loose one worker.

Table 6- 2 Application Results for 2009 Vehicle Quantity Model

	Actual	Income +25%	Income -25%	Urban Density+100%	10% households loose one worker
0 car households	4.92%	4.12%	6.06%	5.35%	4.95%
1 car households	24.92%	22.71%	27.23%	34.98%	26.86%
2 car households	43.38%	43.60%	42.65%	40.71%	42.03%
3 car households	19.08%	21.75%	16.55%	12.68%	19.26%
4+ car households	7.69%	7.85%	7.51%	6.25%	6.86%
Total	100.00%	100.00%	100.00%	100.00%	100.00%
Average car ownership per household	**2.00**	**2.07**	**1.92**	**1.79**	**1.96**
Total car ownership in State of Maryland	4,334,703	4,483,646	4,172,402	3,894,554	4,257,894
Change of total cars in State of Maryland	-	148,943	-162,301	-440,149	-76,809
Percent change of total cars in State of Maryland	-	3.44%	-3.74%	-10.15%	-1.77%

* From Census 2000, the estimated population in State of Maryland was 5,296,486 in 2009 and the average household was 2.44 persons/household. So total number of households is 2,170,691.

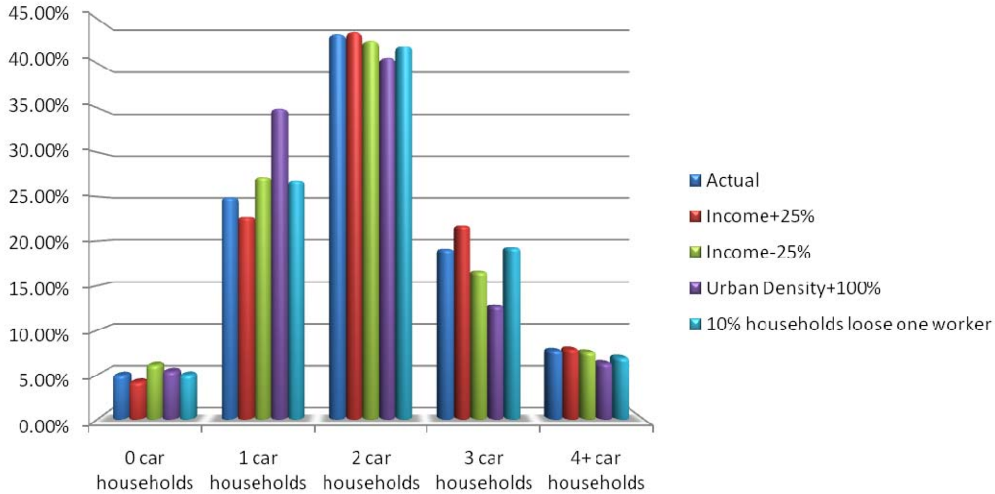

Figure 6- 2 Application Results for 2009 Vehicle Quantity Model

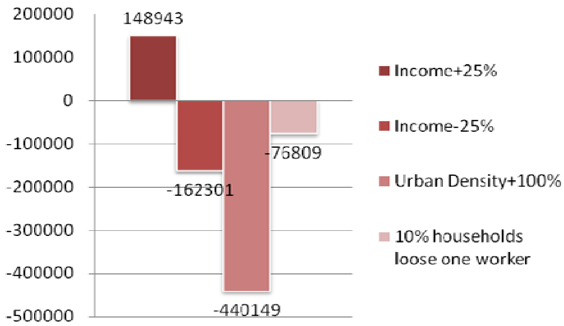

Figure 6- 3 Total Change of Cars in State of Maryland in Four Scenarios

As expected a decrease in household income will produce a decrease in the total number of cars owned by households in Maryland; 25% decrease in household income is expected to lower the number of cars by about 3.74%. An increase in household income of 25% will result into 3.44% more cars in our State. The most affected by this scenario are households with one car or households with three cars.

It can be observed that changes in urban size affect car ownership and that we obtain a 10% reduction in the total number of cars in Maryland by doubling the actual density. In general we can observe that the number of household with zero or one car is increasing while households with multiple cars are decreasing in percentage. Especially, there is a large increase of one-car households and a large decrease of three-car households. Households with zero-car only increase slightly. We can conclude that the increasing density will result in owning less cars in the household, but still people need to have at least one car per household.

When comes to the unemployment effect, 10% households loose one worker not affect car ownership very much—only decrease the car ownership by 1.77%. Though the effect is not as significant as income or urban size, the total amount of cars in State of Maryland still decreases 76,809.

6.2 Empirical Results for Vehicle Type Model

6.2.1 Model Specification

The vehicle type choice model calculates individuals' preferences over classes and vintages. The probability and the utility function can be written similarly:

$$P_i = e^{Vi} / \sum_j e^{Vji}$$

$$V_i = \beta_i \cdot z_i$$

Where V_i is a weighted sum of factors affecting the desirability to the household of owning a vehicle of class and vintage combination. z_i is a vector of characteristics of vehicles in class/vintage i and characteristics of household, and β_i is a vector of parameters to be estimated.

For estimation, each household is assumed to have a choice among 12 classes of vehicle for each 10 vintages, making a total of 120 alternatives. The classes of vehicles are

1. small domestic car;
2. compact domestic car;
3. mid-size domestic car;
4. large domestic car;

5. luxury domestic car;
6. small import car;
7. mid-size import car;
8. large import car;
9. sporty car;
10. minivan/van;
11. pickup trucks;
12. SUVs.

The 10 vintages are pre-1999 and the years 2000 through 2008 for the 2009 NHTS dataset.

For each observation, the vehicle type choice-set has 120 alternatives. Because of the large number of alternatives, estimation of this model on the full set of alternatives is considered infeasible. We took advantage of the multinomial logit IIA property and estimated the type-choice models by random sub-sampling of 21 alternative vehicles including the chosen alternative. A subset of alternatives is selected for each household. These alternatives included the household's chosen alternative and 20 alternatives randomly selected from the 120 available. Tests (Train, 1986) indicate that, beyond a minimal number of alternatives, the estimated parameters are not sensitive to the number of alternatives included in estimation.

The variables entering this model are:

Vehicle purchase price (in $1000),
Shoulder room (inch) for household with four or more members,
Engine size (liter),
Log of the number of makes and models in the class/vintage,
Foreign car dummy,
Dummy of New car (equal or less than 3 years),
Dummy of vehicle age from 4 to 6 years,
Dummy of SUV for households with four or more members,

Dummy of Auto for household with one adult,

Miles per Gallon (MPG),

Acceleration time from 0 to 60mph (second) if the household is in urban area.

6.2.2 Model Estimation

The estimation result is given as Table 6-3. The estimation is based on 540 observations. All of the variables are significant and have the expected sign:

- Purchase price is negative—people prefer cheaper cars;
- Shoulder room is positive—people in households with four or more members prefer cars with more room;
- Engine size is positive—people like vehicles with larger engines and better performance.
- Log of the number of makes and models in the class/vintage is positive—people tend to choose the class/vintage with more choices (more makes and models);
- Dummy of foreign car is positive—people would like to buy a foreign car instead of domestic car.
- Dummies of vintages are positive—the larger value of new car dummy indicates that people prefer new cars. The smaller value for medium age cars indicates that vehicle with age 4-6 still acceptable.
- Dummy of automobile is positive—single-adult households usually choose automobile as they don't need large model and they don't have other special needs.
- Dummy of SUV is positive—people in a household with four or more members need SUVs. It shows that larger families usually have SUVs because of its larger capacity, good performance and reliability for commuting or traveling purposes.
- MPG (miles per gallon) is positive—people are more likely to choose more fuel efficient vehicles. This is consistent with the positive coefficient of foreign car dummy.

- Acceleration time is negative—the negative coefficient means the less time that the vehicle accelerates from 0 to 60 mph, the better. It reflects the fact that people like good performance cars in urban areas because stop-and-go is very frequent in dense areas. This result is also consistent with the positive coefficient of engine size since bigger engine size provides better acceleration.

Table 6- 3 Estimation Results of Vehicle Type Model

Explanatory Variables	Estimated coefficient	Standard Error	*t-statistic*
Purchase Price (in $1000)	-0.2686	0.0193	-13.9
Shoulder room for household with four or more members	0.02924	0.0153	1.9
Engine size (liter)	0.6186	0.1060	5.8
Log of the number of makes and models in the class/vintage	1.007	0.0922	10.9
Foreign car dummy	0.7423	0.1480	5.0
Dummy of New car (equal or less than 3 years)	1.711	0.1930	8.9
Dummy of vehicle age from 4 to 6 years	0.4464	0.1240	3.6
Dummy of auto for household with one adult	0.6595	0.2680	2.5
Dummy of SUV for households with four or more members	0.4474	0.2440	1.8
Miles per Gallon (MPG)	0.0508	0.0270	1.9
Acceleration time from 0 to 60mph (in urban area)	-0.2608	0.0766	-3.4

Estimation based on 540 observations
Likelihood with Zero Coefficients = -1644.0421
Likelihood with Constants only= 0.0000
Final value of Likelihood= -1332.7628
"Rho-Squared" w.r.t. Zero= 0.1893
"Rho-Squared" w.r.t. Constants = 0.0000

6.3 Empirical Results for Vehicle Usage Model

6.3.1 Model Specification

The regression model predicts the annual vehicle miles traveled per household in 2009. Similarly to the one in 2001, it is specified as a linear regression model with a function of household socio-economic variable, land use attributes and vehicle specifications. The formulation of the model is:

$$\log(VMT) = f(\log(Inc), Hmtp, Cld, Wrk, Dri, Loc, \log(Cost))$$

Where ***VMT*** is annual vehicle miles traveled per household; ***Inc*** is the annual household income; ***Hmtp*** is the household housing type (1 for single house, 2 for townhouse, 3 for condo or apartment); ***Cld*** is number of children in the household; ***Wrk*** is the number of workers in the household; ***Dri*** is the number of licensed drivers in the household; ***Loc*** is the household location on six level of variation ranging from 1 (for non-urban area) to 6 (most dense urban area); ***Cost*** is the operating cost which is represented by cents per mile.

6.3.2 Model Estimation

Table 6-4 presents the estimated regression model of vehicle use (VMT per household). The models have pretty good level of fit with R^2 value of 0. 3485.

In terms of the estimated coefficients, most of them are significant and have the expected sign:

(1) All the coefficients of the household social-economic variables have the similar intuitive explanatory meaning with vehicle quantity model. Household income, number of children, number of workers, and number of drivers have positive influence on vehicle use. Especially, number of workers in the household significantly contributes to household vehicle use. Coefficient of household housing type is negative because households owning condos or apartments usually have lower income and travel less than the ones owning single house.

(2) When comes to land use factors, variable of urban size is significant at 95% level. This variable is ranging from 1 to 6: 1 is for non-urban area, 2 to 6 represent five

density levels in which 2 is for the least dense urban area and 6 is for the most dense urban area. Households tend to drive less in denser area since the coefficient is negative.

(3) As expected, households drive less when the operating cost goes higher. Similarly, the estimated coefficient of operating cost is exactly the elasticity.

Table 6- 4 Estimation Results of Regression Model

Variable	Estimated coefficient	std. Error	t-statistic	p-value
Intercept	7.37453	0.81101	9.09	<.0001
log(household income)	0.59286	0.10456	5.67	<.0001
Housing Type	-0.11583	0.08241	-1.41	0.1614
number of children	0.09003	0.05394	1.67	0.0966
number of workers	0.24085	0.07811	3.08	0.0023
number of drivers	0.09156	0.0865	1.06	0.2911
Urban size	-0.05281	0.0254	-2.08	0.0388
log(gas cost)-cents/mile	-0.18628	0.24388	-0.76	0.4459

*R-Square=0.3485

**Number of Observations Used: 211

6.3.3 Model Application

The model has been applied to test a number of sensitivity analyses in order to measure their effects on vehicle usage. The scenarios we have tested are:

1. Change in household income; we tested both a 25% decrease (reflecting a possible economic downturn) and a 25% increase;
2. Unemployment: 10% of the household loose one worker and all the households loose one worker.
3. Change in housing density and in particular the effect of the increase in the actual values of density by 100%;

4. Change in fuel cost: we tested both a 50% decrease and a 50% increase..

Table 6-5 and Figure 6-2 summarized the results obtained from the scenarios above. Vehicle miles traveled increases a lot (14.14%) with the increase of income—the amount of change is almost 60 percent as the change of income. People tend to spend more money to improve the living quality when they earn more money. However, when the income decreases, VMT decreases much less relatively (-3.75% when income decreases by 25%). This is because people still need to travel and to satisfy their basic living requirement even when they have less money.

In terms of the employment situation, vehicle miles traveled do not change much (-2.38%) when 10% household lose worker. But it decrease a lot (-21.40%) when all households lose one worker. It means the bad unemployment does not change the vehicle usage a lot, but once the unemployment is very bad (every household loses one worker) people will use vehicles much less.

Urban size is used to measure the influence of urbanization. The results show even if the housing density is doubled, VMT does not decrease a lot (-12.31%). It is because the United State is still a "mobile society" and the city life in Maryland depends on highway network a lot. People have to use vehicle for commuting or traveling purposes even if the state is much denser.

For the operating cost, we see people are not as sensitive to mobile cost in 2009 as in 2001. We suppose the price would either increase or decrease by 50 percent and then re-calculate the vehicle usage. The vehicle usage increases 13.78% as the fuel price decreased by 50 percent which is reasonable. When the fuel price increases by 50% percent, the vehicle usage does not decreases a lot (only -7.27%) because the fuel price in 2008 is already very high and people could not reduce their traveling activities much.

Table 6- 5 Application Results of Regression Model

Policy	Income +25%	Income - 25%	10% households loose one worker	All households loose one worker	Population Density +100%	Fuel Price -50%	Fuel Price +50%
Percent change of VMT	14.14%	-3.75%	-2.38%	-21.40%	-12.31%	13.78%	-7.27%

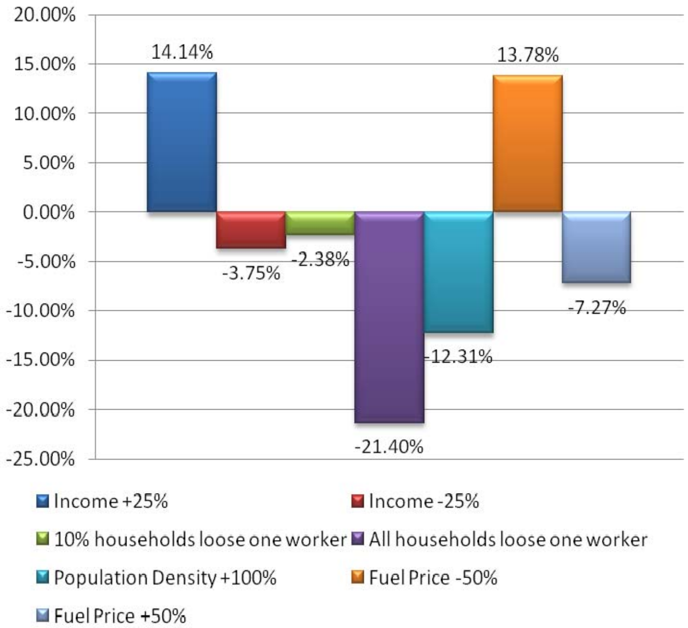

Figure 6- 4 Application Results of Regression Model

6.4 Comparison of 2001 and 2009 Car Ownership Models

I finally summarize the prediction results of both 2001 and 2009 models. As Table 6-6 and Figure 6-4, we conclude that:

- As a major socio-economic characteristic, household income has more effect on vehicle usage than vehicle quantity decision. When the income changes, people will change their vehicle usage patterns respectively rather than buy or sell cars. The amount of vehicle usage increase is much larger than the decrease facing the increasing or decreasing income. The reason is that people use their vehicles more for shopping, traveling, social purposes when they have more money. Although they have much less money, they still have to commute or travel to maintain the basic living level. Income is less sensitive in 2009 than in 2001 mainly because the economic crisis was taken place in 2009 and the average income is comparatively low at that time.
- In terms of land-use factor, people change their vehicle usage more than the vehicle quantity when the area's density changes. The change is relatively low even we double the density. In 2009, the decrease of both vehicle quantity and usage are much higher than 2001 when we increase the density. It is because public transportation has been improved dramatically in the past decade. The public transit system now is much better than ten years ago. People are willing to switch from cars to public transit when the cities and towns are much denser in 2009.
- Facing the high unemployment rate, people seem not be sensitive to it at all. Even if ten percent households loose one worker (it means the unemployment rate increases by more than 10 percent) people still stick on their vehicle and keep the same usage.
- Especially for the vehicle usage, we compare the results from changing the fuel price. If we change the price to 2009 level in 2001 model, the vehicle usage sharply decreases by about 25 percent. It is realistic since it is a huge change from \$1.6 to \$4. As a comparison, in 2009 model, people will not travel that much more (about only 14%) with decreasing the fuel price by 50% percent.

People are not that sensitive to it because it is slower to change the traveling behavior with lower fuel price than higher fuel price. When we increase the fuel price by 50% percent, people will not cut their traveling much (about only 7%), as the fuel price in 2008 was already very high.

Table 6- 6 Comparison of 2001 and 2009 Car Ownership Models

	2001	2009
Vehicle Quantity		
Income+25%	5.08%	3.44%
Income-25%	-4.52%	-3.74%
Density+100%	-4.00%	-10.15%
10% households loose one worker	0%	-1.77%
Vehicle Usage		
Income+25%	18.61%	14.14%
Income-25%	-8.15%	-3.75%
Density+100%	-8.05%	-12.31%
10% households loose one worker	-1.91%	-2.38%
All households loose one worker	-17.54%	-21.40%
Fuel Price	-25.92% (from \$1.6 to \$4)	-7.27% (increase by 50%) 13.78% (decrease by 50%)

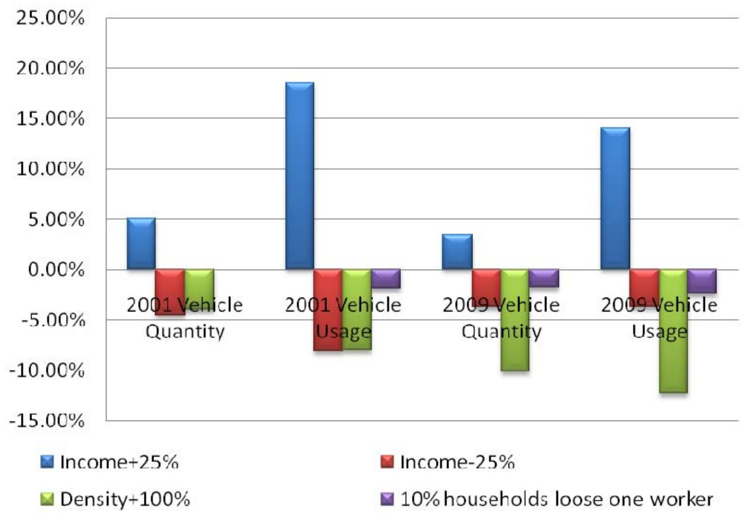

Figure 6- 5 Comparison of 2001 and 2009 Car Ownership Models

Chapter 7: Conclusions and Challenges

This study has presented a car ownership modeling framework for the State of Maryland. To my best knowledge this is the first model of this type developed for our State. The car ownership framework includes three stages—vehicle quantity model, vehicle type model and vehicle usage model.

A Multinomial Logit Model is used in the vehicle quantity models and vehicle type model. Recent studies clearly show that MNL models are better than Ordered Logit models and Mixed Logit models for car ownership modeling. A regression model and instrumental variable estimation approach are used for vehicle usage model.

Car ownership models are calibrated using two waves of the National Household Travel Survey: 2001 and 2009. NHTS 2001 dataset contains information from 4240 households residing in the State of Maryland; while NHTS 2009 only contains data relative to 355 households. The framework developed for 2001 include vehicle quantity and vehicle usage models; while the 2009 model system is composed by vehicle quantity, vehicle type and vehicle usage models.

The system of models developed for both 2001 and 2009 contains a wide variety of coefficients estimated, including socio-demographics, land use variables, vehicle characteristics and fuel price. The majority of the coefficients estimated turn out to be statistically significant.

The models were then applied to study individual preferences over car ownership and use under a number of policy scenarios. Predictions, not always intuitive, provided a good ground for discussions and are found to be significant to understand travel behavior and attitude.

To conclude, the main findings from this research work can be summarized into the following points:

- As a major socio-economic characteristic, household income has more effect on vehicle usage than on vehicle quantity decisions. When the income changes, people will change their vehicle usage patterns rather than buy or sell cars. The increase in vehicle miles travelled is much larger than the decrease, when calculating the effects of equivalent upward and downward changes in household income. The sensitivity to income is much less in 2009 than in 2001, possibly because of the effect of the economic crisis registered in 2009.
- In terms of land-use factor, density is found to affect more vehicle usage than vehicle quantity. In particular, when doubling the density, just a 4% decrease in car ownership is calculated. In 2009, denser development causes much higher decrease in both vehicle quantity and usage than in 2001. It would be interesting to analyze density effects by area type, if data allows such a disaggregate analysis.
- When facing higher unemployment rate, people seem not to be sensitive at all. Even if ten percent of households in Maryland lose one worker (it means the unemployment rate increases by more than 10 percent) people won't change their attitude versus vehicle ownership and use.
- Especially for the vehicle usage, if we change the fuel price from \$1.6 to \$4 (2008 level) in 2001 model, the vehicle usage sharply decreases by about 25 percent. As comparison, in 2009 model, when we increase the fuel price by 50% percent, people will cut their travel only by about 7%; probably because fuel price in 2008 was already very high. When decreasing the fuel price by 50% percent people will not travel that much more (only about 14%).
- Finally, from the analyses performed it results that changing habits and preferences over car ownership and use, is extremely difficult. In order to obtain significant effects on the average number of cars owned by the households in Maryland and their use extraordinary measures in land use and pricing are necessary.

In addition to the empirical findings, this study has contributed to:

- Provide a systematic and comprehensive review of previous studies and researches on car ownership modeling. The literature review in this study collects information of research in the past several decades and summarized them into different categories. Comparison and discussion of difference approaches are also elaborated in the review.
- Consolidate a database of vehicle characteristics information by using the resource of ConsumerReport.org. The database includes all vehicle characteristics information from year 1999 to 2009 including vehicle performance, crash protection, fuel economy, and specifications.
- Establish the first car ownership modeling framework for State of Maryland. This car ownership modeling framework would possibly contribute to the state-wide model for the State of Maryland.
- Formulate a car ownership modeling framework which sequentially estimates the vehicle quantity, vehicle type and vehicle usage. Meanwhile, it has parallel models for both years 2001 and year 2009, which gives handy comparison between these two periods.
- Perform a number of sensitivity analyses that provide the policy makers with a valid tool to study individuals' preferences and their traveling behavior.

However, this study has no vehicle type model for 2001, because of the shortage of vehicle characteristic data, and the 2009 NHTS dataset only has limited observations (355 households). Moreover, the limited number of variables and observations in this dataset restricts 2009 models specification and validation.

In the near future, more accurate models will be generated conditionally on the availability of better data. Vehicle quantity model, vehicle type model and vehicle usage model will be jointly estimated. The use of advanced models for vehicle usage and their integration into this framework is under consideration.

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