# Modeling Vehicle Ownership Decisions for the State of Maryland

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# 1 Introduction

Different car ownership models are being used for a wide variety of purposes. National governments (notably the Ministries of Finance) make use of car ownership models for forecasting tax revenues and the regulatory impact of changes in the level of taxation. National, regional and local governments (particularly traffic and environment departments) use car ownership models to forecast transport demand, energy consumption and emission levels, as well as the likely impact on this of policy measures. Car manufacturers apply models on the consumer valuation of attributes of cars that are not yet on the market. Oil companies want to predict the future demand for their products and might benefit from car ownership models. International organizations, such as the World Bank, use aggregate models for car ownership by country to assist investment decision-making (de Jong et al., 2004).

This project develops a modeling framework for vehicle ownership in 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.

This report is organized as following. Chapter 2 discusses literature related to car ownership models. Methods usually used for car ownership modeling are described in Chapter 3. Data resources and basic analysis based on 2001 NHTS (US National Household Travel Survey) data are presented in Chapter 4. Chapter 5 describes the survey, including the organization and the survey design. Finally, future work and results expected are discussed in Chapter 6.

# 2 Literature review

## *2.1 Car Ownership Models*

Models to predict 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.

In 2004 de Jong published a comprehensive review of car ownership models. In this paper, the models found 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 as a function of 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 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 (1999), 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 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 transport (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 of which the costs are closet to the budget.

Static disaggregate car ownership models contain discrete choice models that deal with the number of cars owned by a household. Examples are the work by Gunn et al. (1978/1979), the Dutch national model system (LMS) for transport (Hague Consulting Group, 1989), Bhat and Pulugurta (1998), the car ownership model for Sydney (Hague Consulting Group, 2000), the disaggregate model within the NRTF (Whelan, 2001) and Rich and Nielen (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 are Hocherman et al. (1983), Smith et al. (1989) and Gilbert (1992). More recent examples of this category are Bunch et al. (1996) and the Dutch DVTM (dynamic vehicle transactions model) (HCG, 1993, 1995a.b, De Jong 1996), Brownstone et al (2000).

De Jong (2004) also compared the nine model types based on sixteen criteria (Table 1).

TABLE 1 Comparison of types of car ownership models (De Jong, 2004)

| Aspect | Aggregate time series model | Cohort models | Aggregate market models | Heuristic simulation models | Static disaggregate ownership models | Indirect utility models | Static disaggregate type choice models | Panel models | Pseudo panel | Dynamic models transaction models |
|---|---|---|---|---|---|---|---|---|---|---|
| Demand-supply | Usually only demand | Demand | Demand and supply of 2nd hand cars; Equilibrium mechanism | Demand and supply of 2nd hand cars; Equilibrium mechanism | Demand | Demand | Demand | Demand | Demand | Demand |
| Level of aggregation | Aggregate | Aggregate | Aggregate | Disaggregate | Disaggregate | Disaggregate | Disaggregate | Disaggregate | Aggregate | Disaggregate |
| Dynamic or static model | Dynamic | Dynamic | Dynamic | Static, but shift from new to old cars over time | Static | Static | Static | Dynamic | Dynamic | Dynamic |
| Long or short run forecasts | Short, medium and long (saturation) | Medium and long | Short, medium and long | Medium and long | Long | Long | Long | Short and long | Short and long | Short & medium |
| Theory | No strong links | No strong links | Economic market equilibrium theory | Strong basic assumptions, can be at odds with theory | Can be based on random utility theory | Strong links | Can be based on random utility theory | Can be based on random utility or lifetime utility theory | Weak links with random utility theory | Parts can be based on random utility |
| Car use | Not included | Not included | Not included | Can be included, but insensitive (can be amended) | Included in some models (logsum) | Included | Included in some models (logsum) | Sometimes included, but in ad hoc way | Not included, but can be | Sometimes included, but in ad hoc way |
| Data requirements | Light | Light | Light | Moderate | Moderate | Heavy | Heavy | Very heavy | Moderate | Very heavy |

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|---|---|---|---|---|---|---|---|---|---|---|
| Special treatment of business cars | Usually not, but possible | Usually not, but possible | Usually not, but possible | Usually | Done in recent models | Usually not, but possible | Usually not, but possible | Usually not, but possible | Usually not, but possible | Usually not, but possible |
| Car types | No car types | No car types | Limited number of car types | Limited number of car types | Very limited number | Very limited number of car types possible | Often very many car types (brand-model-age) | Very limited number of car types possible, but could be combined with a type choice model | Very limited number of car types possible | Very limited number in duration model, but very many in car type choice model |
| Impact of income | Yes | Yes | Yes (average and distribution) | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Impact of car cost | Fixed and or variable cost sometimes included | None | Fixed and variable | Fixed and variable | Fixed cost often included; logsum includes variable cost | Fixed and variable (also on car use) | Purchase cost and fuel efficiency often included | No policy runs reported, but might be possible | Fixed and variable | Fixed and variable |
| Car quality impacts | No | No | No | Can be included, might have to work through cost | No | No | Yes | No, unless type choice added | No | Yes in type choice |
| Impact of licence holding | No | Yes | Yes | No | Possible | Possible | No | No, but possible | No, but possible | No, but possible |
| Socio-demographic impacts | Limited | Many possible | Limited | Many possible | Many possible | Many possible | Many possible | Many possible | Limited | Many possible |
| Attitudinal variables | Hard to include | Cohort-specific attitudes can be included | Hard to include | Hard to include | Can be included if specific questions in dataset | Hard to include | Can be included if specific questions in dataset | Can be included if specific questions in dataset | Can be included if specific questions in dataset | Can be included if specific questions in dataset |
| Scrappage included | No | No | Can be included | Can be included | No | No | No | Can be included | No | Can be included |

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 in other more detailed models. Heuristic simulation models of car ownership do not offer extensive possibilities for including 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 fleet. For medium and long term forecasts, this 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 can not 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 and vehicle type 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 shows research work about car ownership related to our research.

TABLE 2 Previous literatures related to this study

| Reference | Data Resource (Year) | Sample Size | Choices Examined |
|---|---|---|---|
| Lave and Train (1979) | Seven US cities (1976) | 541 new car buyers | Vehicle type choice |
| Manski and Sherman (1980) | US (1976) | 1200 single-vehicle or two-vehicle households | Vehicle type choices in households holding one vehicle and two vehicles |
| Beggs and Cardell (1980) | Baltimore (1977) | 326 households | Vehicle type choice |
| Hocherman (1983) | Haifa urban area, Israel, (1979) | 800 households | Transaction, Vehicle type |
| McCarthy (1983) | San Francisco (1973-1975) | 269 households | choice between no transaction, replacing one auto, adding one auto, reducing one auto. |
| Mannering and Winston (1985) | US (1978-1980) | 3842 single-vehicle or two-vehicle households | quantity choice, type choice, utilization model |
| Berkovec and Rust (1985) | US (1978) | 237 single-vehicle households | Vehicle type choice |
| Berkovec (1985) | US (1978) | 1048 households | Vehicle quantity (0, 1, 2, 3), Vehicle type choice |
| Hensher and Le Plastrier (1985) | Sydney (1980) | 400 households | Fleet-size choice (0, 1, 2, 3), vehicle type choice |
| Mannering (1986) | US (1978) | 272 households, 554 vehicles | vehicle usage |
| McCarthy (1989) | US (1985) | 726 households | choice of make/model for new vehicle purchases. Choice set is chosen plus 14 assigned alternatives. |
| Kitamura and Bunch (1990) | Dutch National Mobility Panel Data set | Panel, 605 HH, (1984-1987) | vehicle quantity |
| Colob (1990) | Dutch (1985-1988) | 2119 households | choice between fleet size 0, 1, 2. |
| De Jong (1996) | Dutch (Oct, 1992; Oct 1993) | Panel, 3241 respondents | Vehicle holding duration, Vehicle type choice, Annual kelometrage and fuel efficiency |
| Golob et al. (1997) | California (1993) | 4747 households | Vehicle use by type of vehicle |
| Bhat and Purugurta (1998) | US (1991, 1990, 1991), Dutch (1987) | 3665, 3500, 1822, 1807 | vehicle quantity (0, 1, 2, 3, 4) |
| 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 |

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|---|---|---|---|
| | | | Vehicle use |
| Dargay and Vythoulkas (1999) | UK, Family Expenditure Survey (1982-1993) | panel, cohort, 7200 households | vehicle quantity |
| Hanly and Dargay (2000) | UK, British Household Panel Survey (BHPS) (1993-1996) | Panel, about 4000-5000 households | vehicle quantity (0, 1, 2, 3+) |
| Mannering et al. (2002) | US (1995) | 654 households buying new vehicles | vehicle acquisition type (cash, non-cash (lease, finance)); Vehicle type choice |
| Choo and Mokhtarian (2004) | San Francisco, 1998 | 1904 households | Vehicle type choice |
| Huang (2005) | UK, Family Expenditure Survey (1957-2001) | Panel, 6,500 households | Number of cars owned or used by household (1+, 2+) |
| Gerard Whelan (2007) | UK, family expenditure survey (FES) (1971-1996) and the national travel survey (NTS) (1991) | unknown | vehicle quantity (0, 1, 2, 3+) |
| Cao et al. (2007) | Northern California, USA, 2003 | 1682 households | vehicle quantity (0, 1, 2, 3, 4, 5+) |

We especially follow the model developed by Train (1986) who uses a hierarchical structure to model auto ownership and use. This model has several sub-models: a vehicle quantity sub-model, a class/vintage sub-model for one-vehicle households, a class/vintage sub-model for two-vehicle households, and annual vehicle miles traveled (VMT) submodel for one-vehicle households, an annual VMT submodel for each vehicle for two-vehicle households, and submodels for the proportion of VMT in each of two categories (work and shopping) for one- and two vehicle households, respectively.

Train's model has much in common with previous models: (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 demand for and use of vehicles.

Compared to previous household vehicle demand models, Train's model has some advantages: (1) the model can forecast the number of vehicle owned and the annual VMT for each vehicle class/vintage; (2) it explicitly shows the interdependence between a household's choice of how many vehicles to own and its choice of which vehicle class/vintage to own; (3) it explicitly indicates that a household's choice of how many and what vehicle(s) to own closely relates to how much the household drives, and vice versa; and (4) it shows that each household chooses a particular make/model from within its chosen vehicle class without asking for a specification of the demand of each make/model.

De Jong (1996) estimated duration models for vehicle holding duration until replacement, as well as a vehicle type choice model conditional on replacement and regression equations for annual kilometrage and fuel efficiency. Together these submodels form a prototype version of a dynamic model system for vehicle holdings and use. The prototype model system, as estimated on wave 1 of the car panel has been applied to forecast autonomous changes between wave 1 and wave 2 of the car panel, which gave quite satisfactory results. The model gave slightly less vehicle transactions than occurred in reality, whereas predicted vehicle type changes were mostly somewhat more pronounced than those observed. The model has also been used to simulate the impact of a number of possible policy measures and income growth.

One disadvantage of the duration models is that there is no variation over time in the individual characteristics. Another limitation of the present prototype version is that, although they are linked through the time-varying logsum variable, the duration and the type choice models are not estimated as a joint model. Both limitations can to some extent be removed by estimation on data for several waves and by using more sophisticated duration models.

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

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 to the year 2031 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 (2004) identified travel attitude, personality, lifestyle, and mobility factors that 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.

This study has some limitations. The available data did not have detailed information on all the vehicles in a household, including their acquisition history. Most importantly, they did not have data on vehicle characteristics available.

To sum up, a number of researches have been done in this area. Most of them, however, have limitations. First, some studies only concentrated on one part of the household vehicle ownership choices, which are vehicle quantity and vehicle type models. Second, some researches have both of the models but some important attributes in the models were missing. Household socio-demographic information, land use data, and vehicle specifications are all necessary for modeling vehicle quantity and vehicle type choices. Most of the previous studies, however, did not have comprehensive data in the model. Third, some of the results in the studies are not very recent. The attributes in the model have been changed significantly, which is result in changes in the model and different results. Consequently, it recalls the objective of the research, which aims to build a framework to predict the household vehicle quantity and vehicle type choices, using household socio-demographic information, land-use data and vehicle specification information.

### *2.2 Vehicle Quantity Models*

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

TABLE 3 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 |
| Hocherman (1983) | Haifa urban area, Israel, (1979) | 800 households | Nested Logit model | unknown |
| 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 |
| Hensher and Le Plastrier (1985) | Sydney (1980) | 400 households | Nested Logit | |
| Kitamura and Bunch (1990) | Dutch National Mobility Panel Data set | Panel, 605 HH, (1984-1987) | Ordered Probit model | Num of workers, Num of adults, num of children, HH size, num of drivers, HH education |
| Colob (1990) | Dutch (1985-1988) | 2119 households | Ordered Probit | HH income, # persons >18, # persons 12-17, # persons <12, # drivers, # workers, recidence location |
| De Jong (1996) | Dutch (Oct, 1992; Oct 1993) | Panel, 3241 respondents | Hazard function | Primary driver's age, gender, work status, education level, Household size, other cars in household, annual |

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|---|---|---|---|---|
| | | | | kilometrage of previous car |
| 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 in the previous research mainly consists of four kinds of information—information on the household, information on the household head or primary driver, land-use factors and other unclassified information, shown in Figure 1.

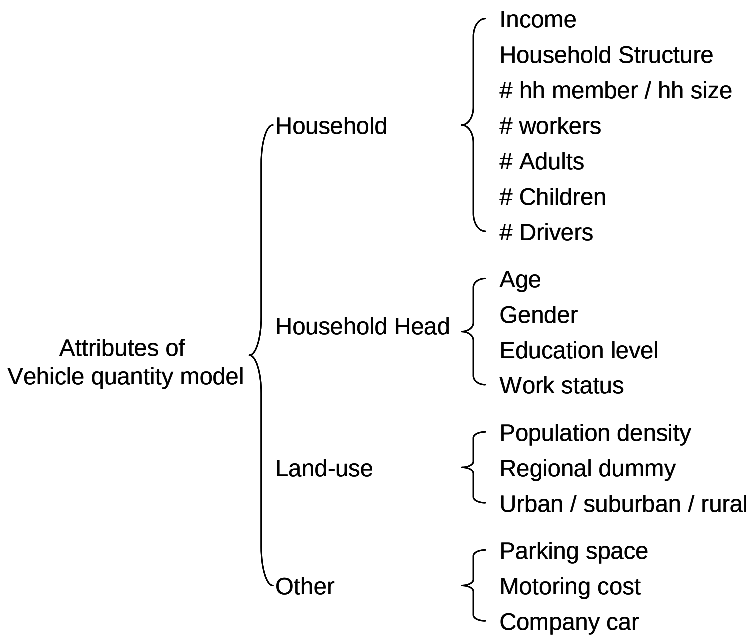


FIGURE 1 Variables in the previous vehicle quantity models

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. Some studies use the log of income or disposable income (income subtracts cost) in their model.

The estimation results showed most of the household socio-economic characteristics have positive influence on car ownership. The positive coefficient of income variable in the model 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 variable, for it is hard to measure many kinds of household structures. Household structure mainly shows how many adults and children in the household, consequently, this factor can be measured by estimating the number of adults and the number of children in the household equally.

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 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, since it can be measured by the number of workers in the household.

In terms of land use information, previous researches mainly use population density, and regional variable (urban, suburban, and rural).  Estimation results indicate that households in the area with large density or in urban area own more vehicles. A few studies included the accessibility of transit in the attributes; however the measurement is not quantitative enough.

The other variables, which do not belong to any of the three categories, include the dummy variable of the parking space, motoring cost and the influence of company car. All of the variables showed significance in the estimation with large t-statistics. Variables of the parking space and the company car were used in the situation of other countries (such as Europe). However, they are not adaptable to the situation in the United States because parking is not a problem in this country and almost every household have a place to park cars. Also in the State the companies is not responsible to provide cars. Consequently, these two variables are not significant in our model.

### *2.3 Vehicle Type Models*

In Table 4 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 4 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 mumber, # 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 |
| Hensher and Manefield (1982) | Sydney (1980) | 151 households | Nested logit | choice of fuel consumption level type (low, medium, high) given an acquisition | |
| 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 (Separate models for 1 and 2 vehicle households) | 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 |

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|---|---|---|---|---|---|
| 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) |
| McCarthy (1989) | US (1985) | 726 households | MNL | | |
| 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 in the previous research 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.

In terms of vehicle classes, table 5 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.

TABLE 5 Vehicle classification schemes (Choo and Mokhtarian, 2004)

| Sourse | Vehicle Classification | Basis |
|---|---|---|
| NPTS (FHWA, 1997) | Automobile (including wagon), van, SUV, pickup, other truck, RV, motorcycle, other | Function |
| NTS (BTS, 1999) | Minicompact, subcompact, compact, mide-sized, large, two-seater, small pickup, large pickup, small van, large van, small utility, large utility | Size & function |
| EPA (1996) | two-seater, minicompact, subcompact, compact, mid-sized, large, station wagon (small & mid-sized), pickup (small & standard by 2wd &4wd), van (cargo & passenger type), special purpose vehicle (2wd & 4wd) | Size & function |
| *Comsumer Reports* (1995) | small, mid-sized, large, luxury, sports, minivan, SUV, pickup | 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.

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

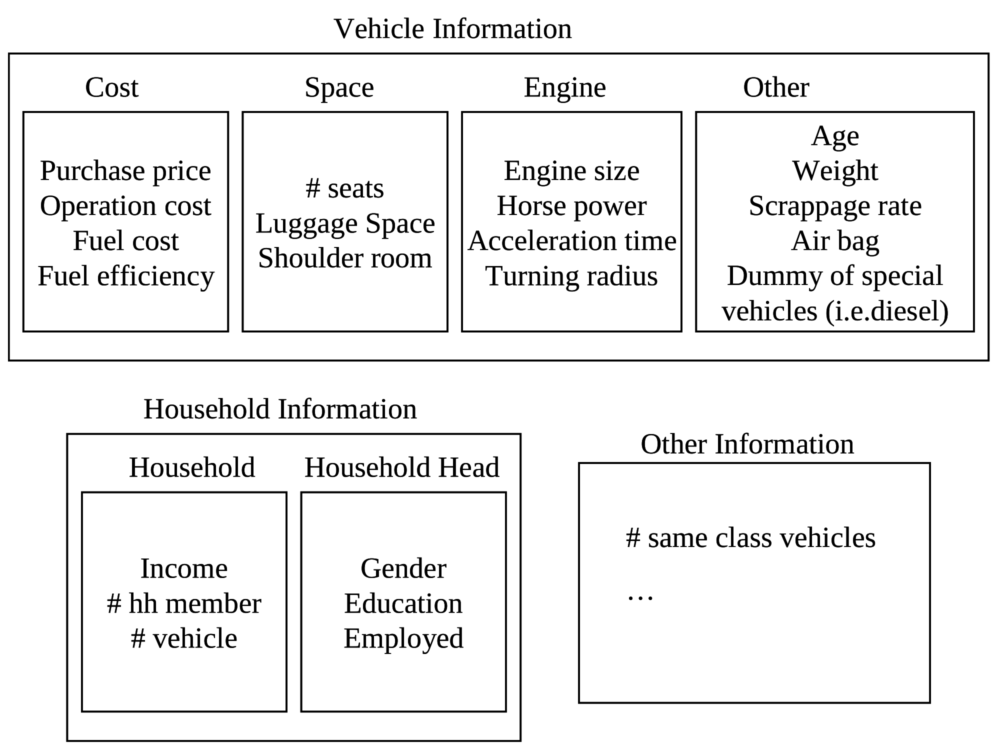



FIGURE 2 Variables in the previous vehicle type models

There are mainly three kinds of variables in the previous vehicle type models—vehicle information, household information, and other unclassified information. For vehicle information, the cost, space, engine related and other specifications were usually estimated in the model. And similar to the vehicle quantity models, information of the household and household head was also considered in the vehicle type models. Some specific information such as the number of same class vehicles was also included in the attributes.

# 3 Methodologies

## *3.1 Discrete Choice Model*

### 3.1.1 Why Discrete Choice Model and the Criteria

In recent years 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 methods to analyze the actions of individual decision making units; these methods are based on strong mathematical and statistical foundations. Individual behavior can be explained by disaggregate econometric models to a degree that is not possible to achieve with aggregate models.

Second, survey data on households and individual behavior 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 co-variation 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 those and it is conceived to describe 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.

Denote $n$ if the number of decision makers 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 nmakers can face alternatives with different characteristics.

The decision maker's choice of alternative obviously depends on the characteristics of each 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

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

where $f$ is the function that relates the observed data to the choice probabilities. This function if specified up to $\beta$, the vector of parameters. 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,

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

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

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

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 sub-functions, one that depends only on factors that the researcher observes and whose form is known by the researcher up to a vector of parameters, $\beta$, 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. More detail about the theory can be found in Train's (1986) book.

### *3.2 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 the description in Train's book (1986), given the utility function $U_{in} = V_{in} + e_{in}$, assume that each $e_{in}$ , for all $i$ in $J_i$, is distributed independently, identically in accordance with the extreme value distribution. Given this distribution for the unobserved components of utility, the probability that the decision maker will choose alternative $i$ is

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

There are three important properties of 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.

Another important property is 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.

### *3.3 Nested Logit Model*

In some situations, independence from irrelevant alternatives (IIA) holds for some pairs of alternatives but not all. Logit is inappropriate in these situations since it assumes there is IIA between each pair of alternatives. Nested logit model is used when the set of alternatives can be partitioned into subsets such that the ratio of probabilities for any two alternatives that are in the same subset is independent of the existence or characteristics of other alternatives. That is, in nested logit model, IIA holds within subsets but not across subsets (Train, 1986).

The nested logit model, first derived by Daly (1987), is an extension of the multinomial logit model designed to capture correlation among alternatives. The nested logit model is specified as follows. Let the set of alternatives $J_n$ be partitioned into $K$ subsets denoted

$B_n^i, \ldots, B_n^K$. The utility that person *n* obtains from alternative *i* in subset $B_n^K$ is denoted, as usual, as $U_{in} = V_{in} + e_{in}$, where $V_{in}$ is observed by the researcher and $e_{in}$ is a random variable whose value is not observed by the researcher. Nested logit model is obtained by assuming that $e_{in}$, for all elements *i* in $J_n$, are distributed in accordance with a generalized extreme value (GEV) distribution. That is, the joint cumulative distribution of the random variables $e_{in}$, for all *i* in $J_n$, is assumed to be:

$$\exp\left\{ -\sum_{k=1}^{K} \alpha_k \left( \sum_{i \in B_n^K} e^{-e_{in}/\lambda_K} \right)^{\lambda_K} \right\}.$$

This distribution is a generalization of the distribution that gives rise to the logit model. For logit, each $e_{in}$ is independent with an extreme value distribution. For GEV, the marginal distribution of each $e_{in}$ is extreme value, but all $e_{in}$ within each subset are correlated with each other. The parameter $\lambda_K$ is a measure of the correlation of unobserved utility within subset $B_n^K$. More exactly, $(1-\lambda_K)$ is a measure of correlation since $\lambda_K$ itself drops as the correlation rises. For any *i* and *j* in different subsets, there is no correlation between $e_{in}$ and $e_{jn}$.

The choice probability for alternative *i* in subset $B_n^K$ is:

$$P_{in} = \frac{e^{V_{in}/\lambda_K} \left( \sum_{j \in B_n^K} e^{V_{jn}/\lambda_K} \right)^{\lambda_K - 1}}{\sum_l \left( \sum_{j \in B_n^l} e^{V_{jn}/\lambda_l} \right)^{\lambda_l}}. \tag{8}$$

When $\lambda_K = 1$ for all *k*, the choice probabilities become simply logit. Consequently, nested logit model is a generation of logit that allows for particular patterns of correlation in unobserved utility.

The utility of nested logit model can be decomposed into two parts. First, a part is constant for all alternatives within a subset. Second, a part is not constant within subsets. It can be denoted as

$U_{in} = W_n^k + \lambda_k Y_{in}^k + e_{in}$, for all *i* in $B_n^K$, Where $W_n^k$ is the mean of $V_{in}$ over all alternatives in subset $B_n^K$; $Y_{in}^k$ (defined as $(V_{in} - W_n^k)/\lambda_k$) is the deviation of $V_{in}$ from the mean $W_n^k$; and $\lambda_K$ is a normalizing constant whose meaning will become evident.

The probability of choosing alternative $i$ in subset $B_n^K$ is expresses as the product of the probability that an alternative within subset $B_n^K$ is chosen and the probability that alternative $i$ is chosen (given that an alternative in $B_n^K$ is chosen). That is,

$$P_{in} = P_{in|B_b^K} \cdot P_{B_b^K},$$

where $P_{in|B_b^K}$ is the conditional probability of choosing alternative $i$ given that an alternative in the subset $B_n^K$ is chosen, and $P_{B_b^K}$ is the marginal probability of choosing an alternative in $B_n^K$.

The marginal and conditional probabilities can be expressed as

$$P_{in|B_b^K} = \frac{e^{Y_{in}^k}}{\sum_{j \in B_n^k} e^{Y_{jn}^k}},$$

$$P_{B_b^K} = \frac{e^{W_{in}^k + \lambda_k I_k}}{\sum_{l=1}^{K} e^{W_{in}^l + \lambda_l I_l}}, \text{ where } I_k = \ln \sum_{j \in B_n^k} e^{Y_{jn}^k}.$$

The conditional probability of choosing $i$, given that an alternative in $B_n^K$ is chosen, is expressed as logit with variables that vary over alternatives within each subset entering representative utility in the logit formula. The marginal probability of choosing an alternative in $B_n^K$ is also expressed as logit with the variables that vary over subsets of alternatives entering representative utility. In addition, the representative utility in the marginal probability includes a term $I_k$ which is the log of the denominator of the conditional probability. This term denotes the average utility that the person can expect from the alternatives within the subset.

It is clear that IIA holds within each subset but not across subsets. Consider two alternatives, $i$ and $m$, both of which are in subset $B_n^K$.

$$P_{in} / P_{mn} = \frac{P_{in|B_b^K} \cdot P_{B_b^K}}{P_{mn|B_b^K} \cdot P_{B_b^K}} = \frac{P_{in|B_b^K}}{P_{mn|B_b^K}} = \exp(Y_{in}^k) / \exp(Y_{mn}^k) \,,$$

which is independent of alternatives other than $m$ and $i$. However, for two alternatives in different subsets, say $i$ in $B_n^K$ and $r$ in $B_n^h$,

$$P_{in} / P_{rn} = \frac{P_{in|B_b^K} \cdot P_{B_b^K}}{P_{rn|B_b^h} \cdot P_{B_b^h}} \,,$$

which depends on the characteristics of all alternatives in $B_n^K$ and $B_n^h$.

### *3.4 The Car Ownership Model*

#### 3.4.1 Structure of the Model

The car ownership model is based on Nested logit model. The model consists of sub-models that separately describe the number of vehicles owned, and the class and vintage of each vehicle. The first level is to predict how many vehicles a household owns. The second level is to decide which class and vintage a household chooses. The structure of the model is shown in Figure 3.

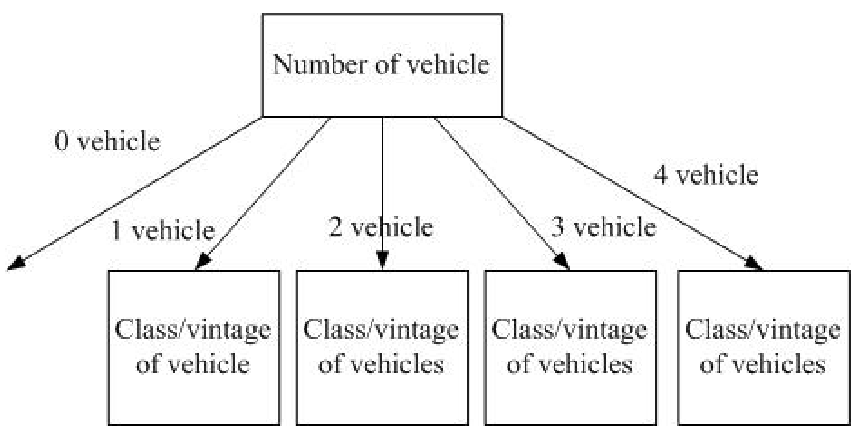



FIGURE 3 Structure of the Model

According to the structure of the model, first, the number of vehicles that the household owns is predicted. If the household is predicted to own no vehicles, then no further calculations are made. If the household is predicted to own one vehicle, the class and vintage of its vehicle is then predicted. If a household is predicted to own more than one vehicle, then the model predicts the class and vintage of each of the vehicles.

### 3.4.2 Vehicle Quantity Model (1st level)

The vehicle quantity model calculates the probability that a household will choose to own a certain number of vehicles. The choice set that a household faces is zero, one, two, three, four or more vehicles. The probability of owning each number of vehicles depends on factors that reflect the household's need for vehicles and its willingness or ability to purchase vehicles..

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{4} e^{Vj}} \quad i=1, 2, 3, 4$$

Where, $V_i$ denote the weighted sum of factors that reflect a household need or willingness to own $i$ vehicle.

$$V_i = \beta_i \cdot z_i$$

Where, $z_i$ are vectors of variables and $\beta_i$ are vectors of parameters to be estimated.

In our model, the variables are household socio-economic characteristics (such as household income, household size, number of workers, number of adults and number of drivers in the household, gender, age and education level of the household head), land-use characteristics and average utility in class/vintage choice given $i$ vehicle.

### 3.4.3 Vehicle Type Choice Model (2nd level)

The vehicle type choice model calculates which class and vintage vehicle(s) a household owns, given the number of vehicles. The probability and the utility function can be written similarly:

$$P_i = e^{Vi} / \sum_{j \in J} e^{Vj}$$

$$V_i = \beta_i \cdot z_i$$

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 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 from which to choose. In our models the vehicles are classified as follow:

1. small domestic car;
2. compact domestic car;
3. mid-size domestic car;
4. large domestic car;
5. luxury domestic car;
6. small imported car;
7. mid-size imported car;
8. large imported car;
9. sporty car;
10. minvan/van;
11. pickup trucks;
12. SUVs.

The 10 vintages are pre-1993 and 1993 through 2001 for the 2001 NHTS dataset, or pre-1999 and 2000 through 2008 for the 2008 NHTS dataset.

For the households with *i* vehicle(s), the vehicle type choice-set has $120^i$ alternatives. Because of the large number of alternatives, estimation of this model on the full set of alternatives is considered infeasible. A subset of alternatives is selected for each household. These alternatives included the household's chosen alternative and the alternatives randomly selected. Tests indicate that, beyond a minimal number of alternatives, the estimated parameters are not sensitive to the number of alternatives included in estimation.

The attributes of this model are vehicle purchase price, operating cost, front and rear shoulder room, luggage space, engine size, horsepower, number of makes and models in the class/vintage, household size, gender of household head, education level of household head, number of household vehicles, dummy of vintage (new, mid, old), dummy of selected class (sports, van, pickup, SUV). Additionally, for the households with more than one vehicle, the attributes also include sum or difference of selected specifications, such as the sum of the purchase price, the difference of the shoulder room, etc.

## 4 Data Resources and Analysis

### *4.1 NHTS data*

The car ownership model is developed using data from the 2001 Nationwide 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.

The NHTS was conducted as a telephone survey, using Computer-Assisted Telephone Interviewing (CATI) technology. The 2001 NHTS interviews for the national sample and New York and Wisconsin add-ons were conducted from March 19, 2001 through May 9, 2002. Interviews for households in the seven Morpace add-ons were conducted between May 31, 2001 and July 5, 2002.

The 2001 NHTS data set includes the information that is needed in the model, 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.

### *4.2 Data from Consumer Reports*

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

*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*. 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 next chapter.

### *4.3 Data Analysis*

#### 4.3.1 Trends of the National Household Travel Survey data

This part aims to highlight important travel trends in tabular and graphic format. Most of the results are from one of NHTS' reports—*Summary of Travel Trends* (2001).

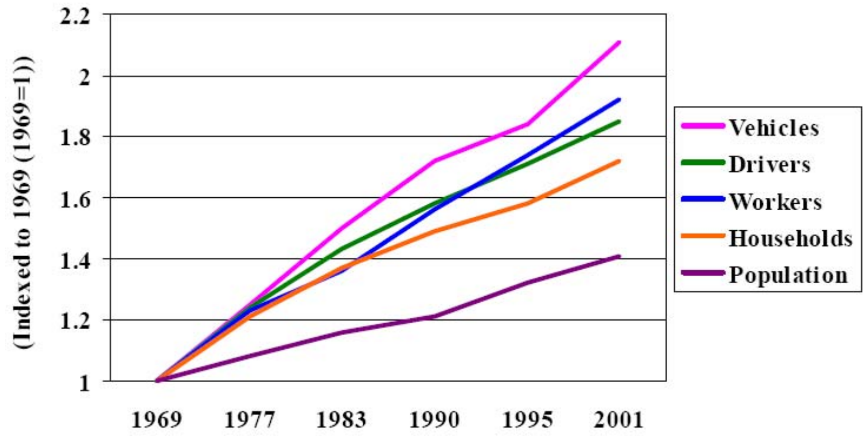



FIGURE 4 Changes in Summary Demographics 1969, 1977, 1983, 1990, 1995 NHTS, and 2001 NHTS

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.

TABLE 6 Summary of Demographic Trends

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

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

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 23% in 2001 (Table 7). The number of workers per household increased slightly, probably reflecting the trend in which retirees return to the labor market.

TABLE 7 Availability of Household Vehicles

| Households with -- | 1969 | 1977 | 1983 | 1990 | 1995 | 2001 |
|---|---|---|---|---|---|---|
| No Vehicle | 12,876 *(20.6%)* | 11,538 *(15.3%)* | 11,548 *(13.5%)* | 8,573 *(9.2%)* | 7,989 *(8.1%)* | 8,716 *(8.1%)* |
| One Vehicle | 30,252 *(48.4%)* | 26,092 *(34.6%)* | 28,780 *(33.7%)* | 30,654 *(32.8%)* | 32,064 *(32.4%)* | 33,757 *(31.4%)* |
| Two Vehicles | 16,501 *(26.4%)* | 25,942 *(34.4%)* | 28,632 *(33.5%)* | 35,872 *(38.4%)* | 40,024 *(40.4%)* | 39,938 *(37.2%)* |
| Three or More Vehicles | 2,875 *(4.6%)* | 11,840 *(15.7%)* | 16,411 *(19.2%)* | 18,248 *(19.6%)* | 18,914 *(19.1%)* | 24,955 *(23.2%)* |
| **ALL** | **62,504** ***(100.0%)*** | **75,412** ***(100.0%)*** | **85,371** ***(100.0%)*** | **93,347** ***(100.0%)*** | **98,990** ***(100.0%)*** | **107,365** ***(100.0%)*** |
| **Vehicles Per Household** | **1.16** | **1.59** | **1.68** | **1.77** | **1.78** | **1.89** |

Note:

- The 1969 survey does not include pickups or other light trucks as household vehicles.

More than 60% of all households had 2 or more vehicles in 2001. Furthermore, not only were there more multi-vehicle households in 2001 than in 1995, they also owned more vehicles. There was a shift in 2001 from 1- to 2-vehicle households to 3+ vehicle households. Households that owned at least one vehicle owned an average of 2.05 vehicles in 2001, compared to 1.93 in 1995. The *percent*age of households without a vehicle remained at the 1995 level, though the *number* of households without a vehicle increased - from 8 million households in 1995 to more than 8.7 million in 2001.

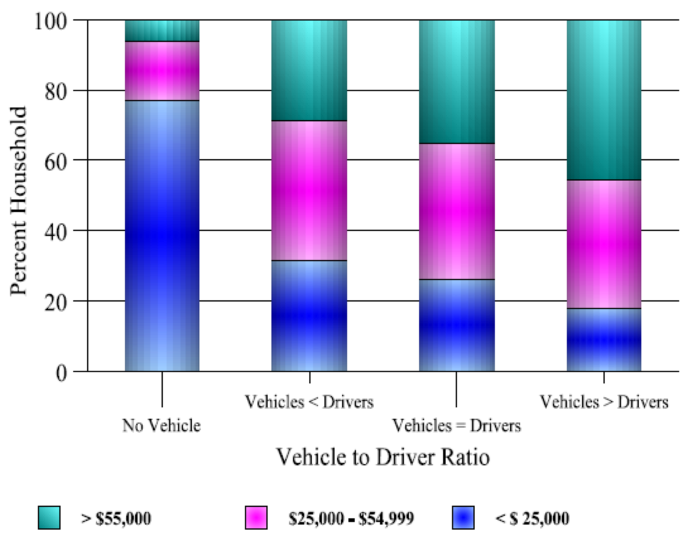



FIGURE 5 Household Distribution by Household Income and Vehicle to Driver Ratio

There were significantly more households in 2001 than in 1995 who owned a greater number of vehicles than there were drivers in the household. More than eighty percent of the households had at least one vehicle for each of their drivers in 2001. It is clear that income affects vehicle ownership and availability. Three out of every four low-income families did not own a vehicle, while one in two families with household income more than $55,000 had more vehicles than licensed drivers in their households.

TABLE 8 Distribution of Household Vehicle Availability and Population Density

| Household Vehicle Availability | Population Density (Persons per Square Mile) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Less than 2,000 | | | 2,000 to 4,000 | | | 4,000 to 10,000 | | | 10,000 or more | | |
| | 1990 | 1995 | 2001 | 1990 | 1995 | 2001 | 1990 | 1995 | 2001 | 1990 | 1995 | 2001 |
| ALL | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% |
| No Vehicle | 6.1% | 3.9% | 4.2% | 7.6% | 6.2% | 5.9% | 10.9% | 8.5% | 8.7% | 35.1% | 31.0% | 28.1% |
| One Vehicle | 30.4% | 27.3% | 26.2% | 33.4% | 33.8% | 34.1% | 38.2% | 38.6% | 37.0% | 40.0% | 41.7% | 39.9% |
| Two Vehicles | 41.0% | 44.5% | 40.1% | 41.5% | 42.3% | 38.6% | 34.9% | 38.6% | 36.5% | 18.4% | 21.3% | 23.1% |
| Three or More Vehicles | 22.5% | 24.3% | 29.5% | 17.5% | 17.7% | 21.4% | 16.0% | 14.4% | 17.7% | 6.5% | 6.0% | 8.9% |

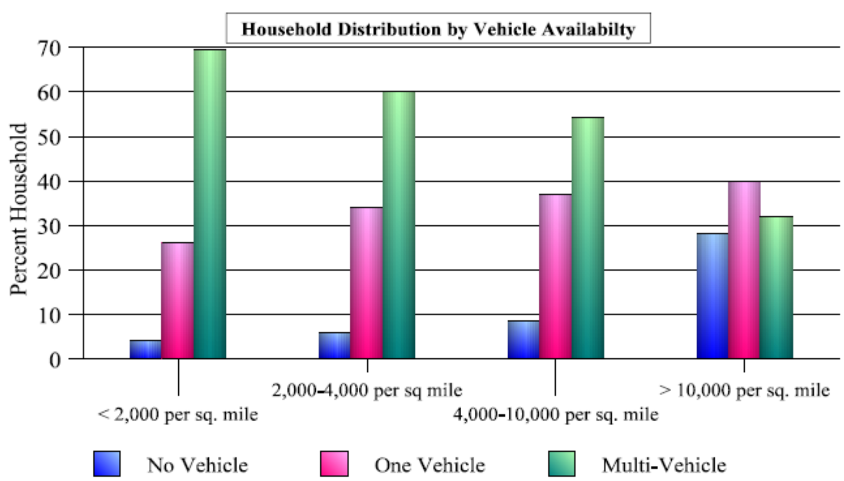



FIGURE 6 Vehicle Ownership Statistics by Population Density

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 9 Percent of Households without a Vehicle within MSA Size Group

| (S)MSA Size | % Households Within An Area Without a Vehicle | | | | | |
|---|---|---|---|---|---|---|
| | 1977 | 1983 | 1990 | 1995 | 2001 | % Change 1977-2001 |
| Not in (S)MSA | *12.2* | *10.5* | *7.7* | *5.3* | *5.8* | *-52%* |
| < 250,000 | *13.7* | *10.1* | *8.6* | *4.8* | *5.8* | *-58%* |
| 250,000 to 499,999 | *12.2* | *8.1* | *5.7* | *7.3* | *5.2* | *-57%* |
| 500,000 to 999,999 | *14.0* | *14.3* | *8.4* | *6.3* | *7.0* | *-50%* |
| 1 to 2.9 million | *14.2* | *12.1* | *8.2* | *6.9* | *6.4* | *-55%* |
| 3+ million | *26.1* | *25.4* | *12.4* | *11.2* | *11.9* | *-54%* |
| **ALL** | ***15.3*** | ***13.5*** | ***9.2*** | ***8.1*** | ***8.1*** | ***-47%*** |

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.

TABLE 10 Vehicle Distribution and Average Vehicle Age by Vehicle Type

| | 1977 | 1983 | 1990 | 1995 | 2001 |
|---|---|---|---|---|---|
| | Distribution of Vehicles | | | | |
| **TOTAL** | ***100.0*** | ***100.0*** | ***100.0*** | ***100.0*** | ***100.0*** |
| Auto | *79.6* | *75.9* | *74.7* | *64.3* | *56.8* |
| Van | *2.8* | *3.6* | *5.5* | *7.8* | *9.0* |
| Sport Utility | *NA* | *NA* | *NA* | *6.9* | *12.1* |
| Pickup | *12.8* | *15.2* | *17.2* | *17.7* | *18.4* |
| Other Truck | *1.3* | *1.5* | *0.6* | *0.4* | *0.5* |
| RV/Motor Home | *0.4* | *0.5* | *0.5* | *0.5* | *0.7* |
| Motorcycle | *2.7* | *2.5* | *1.3* | *0.9* | *2.1* |
| Moped | *0.2* | *0.6* | *0.1* | *NA* | *NA* |
| Other | *0.2* | *0.2* | *0.1* | *0.1* | *0.5* |
| | Average Vehicle Age | | | | |
| **TOTAL** | **6.6** | **7.60** | **7.71** | **8.33** | **8.87** |
| Auto | 6.4 | 7.20 | 7.61 | 8.24 | 8.98 |
| Van | 5.5 | 8.45 | 5.88 | 6.68 | 7.56 |
| Sport Utility | NA | NA | NA | 6.56 | 6.44 |
| Pickup | 7.3 | 8.54 | 8.43 | 9.65 | 10.05 |
| Other Truck | 11.6 | 12.39 | 14.48 | 14.93 | 17.72 |
| RV/Motor Home | 4.5 | 10.69 | 10.44 | 13.21 | 13.49 |

Note:

- The 1977, 1983, and 1990 surveys do not include a separate category for sports utility vehicles, while the 1995 and 2001 surveys do. In 1990 survey, most SUVs were classified as automobiles. The 1995 and 2001 surveys do not include a separate category for mopeds

Automobiles continued to lose their market share of private vehicles, from 80% in 1977 to less than 60% in 2001. In the meantime, the market share for sport utility vehicles (SUVs) doubled between 1995 and 2001. Except for SUVs, the average age of vehicles in 2001 was greater than in the past.

TABLE 11 Distribution of Vehicles by Vehicle Age and Vehicle Type

| | 1977 | | | 1983 | | | 1990 | | | 1995 | | | 2001 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Vehicle Age | Auto | Truck/ Van | All | Auto | Truck/ Van | All | Auto | Truck/ Van | All | Auto | Truck/ Van | All | Auto | Truck/ Van | All |
| 0 to 2 years | *27.3* | *29.9* | *27.8* | *20.0* | *16.6* | *19.2* | *15.6* | *19.7* | *16.6* | *14.9* | *19.2* | *16.2* | *13.27* | *18.59* | *15.41* |
| 3 to 5 years | *30.4* | *25.6* | *29.6* | *28.0* | *26.6* | *27.6* | *27.7* | *27.2* | *27.5* | *21.7* | *21.6* | *21.5* | *20.37* | *23.47* | *21.51* |
| 6 to 9 years | *26.7* | *21.1* | *25.7* | *27.4* | *25.0* | *26.9* | *26.8* | *20.9* | *25.3* | *30.3* | *25.5* | *28.5* | *25.45* | *22.59* | *24.08* |
| 10 or more years | *15.6* | *23.4* | *16.9* | *24.6* | *31.8* | *26.3* | *29.9* | *32.2* | *30.6* | *33.1* | *33.7* | *33.8* | *40.91* | *35.36* | *39.00* |
| **Total** | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* | *100.0* |
| Average Age | 5.5 | 6.4 | 5.6 | 6.7 | 7.8 | 6.9 | 7.6 | 8.0 | 7.7 | 8.2 | 8.3 | 8.3 | 9.0 | 8.5 | 8.9 |

Note:

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

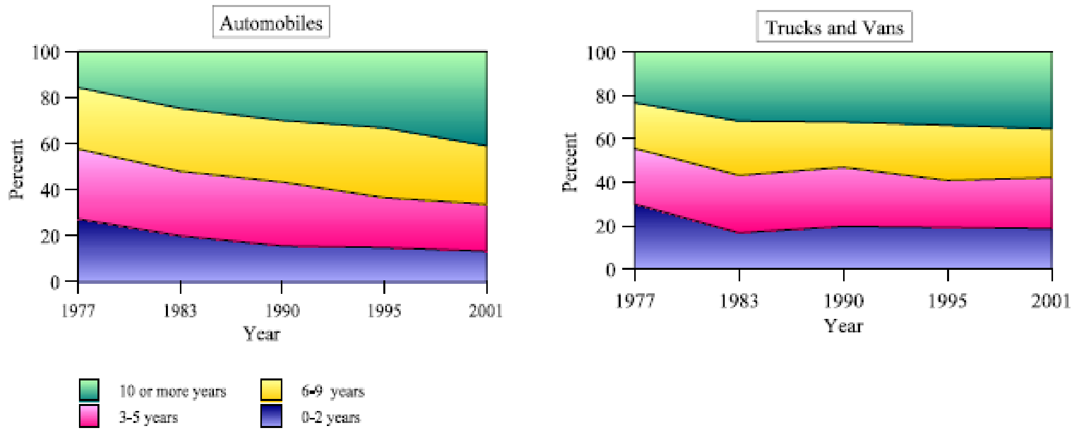



FIGURE 7 Distribution of Vehicle by Vehicle Age

In 2001, household vehicles remained in operation significantly longer than those in 1977. 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. In 2001, two out of every five vehicles were at least 10 years old. In the past, trucks and vans tended to be in operation longer than automobiles. However, this trend was no longer true by 2001.

**4.3.2 Data Analysis of Car Ownership in Maryland**

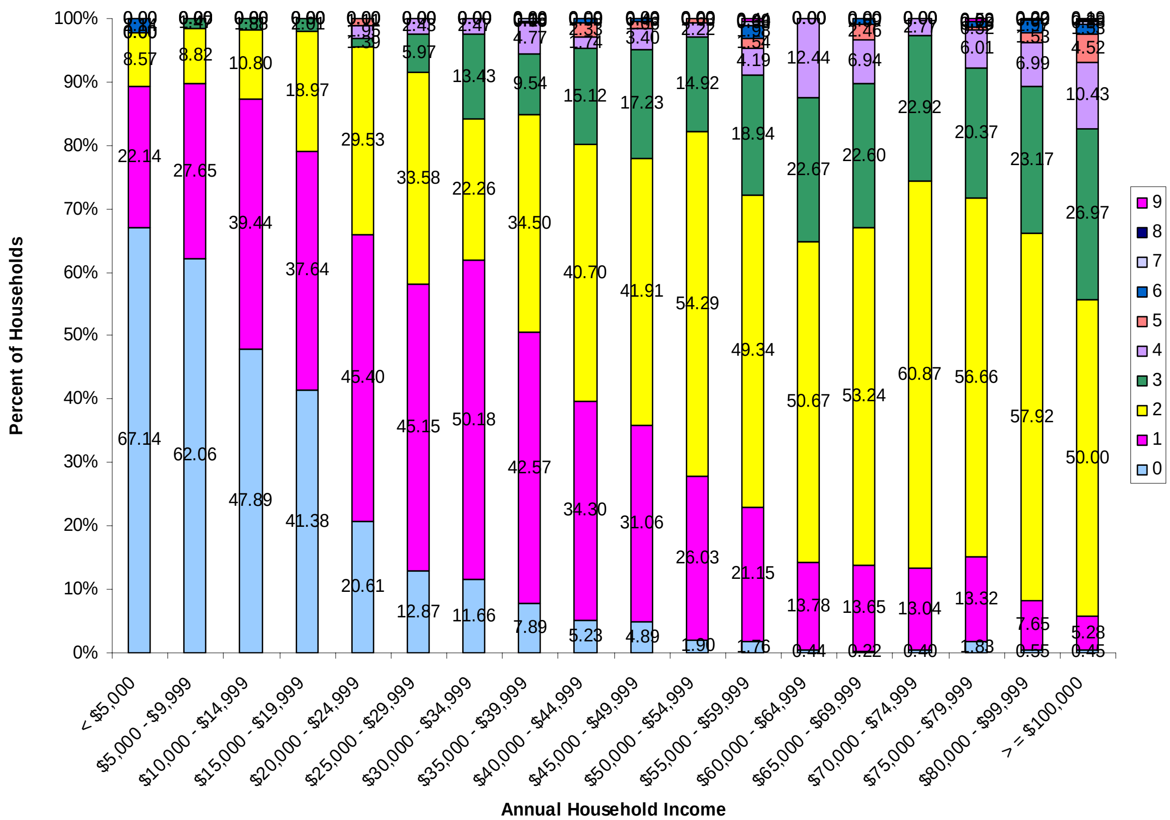
This part presents data compiled from the 2001 Nationwide Household Travel Survey (NHTS) on vehicle ownership for households in Maryland, United States. Knowledge of vehicle ownership is useful in understanding the impact of socio demographic and technological changes on household travel habits. This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

- Income

Not surprisingly, vehicle ownership increases directly with income. As shown in Figure 2, 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.

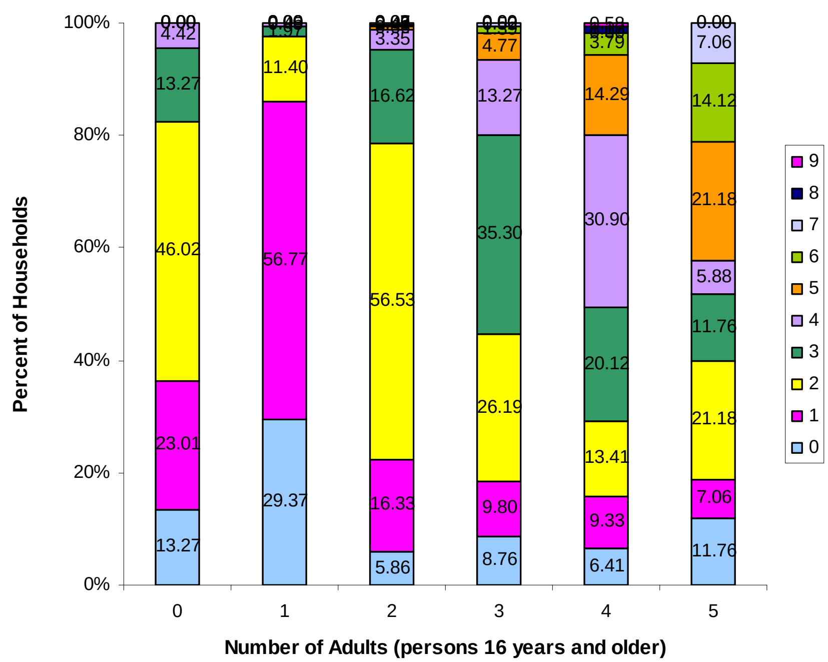
**Figure 2 Percent of Households Owning One or More Vehicles by Annual Household Income**



- Household Composition

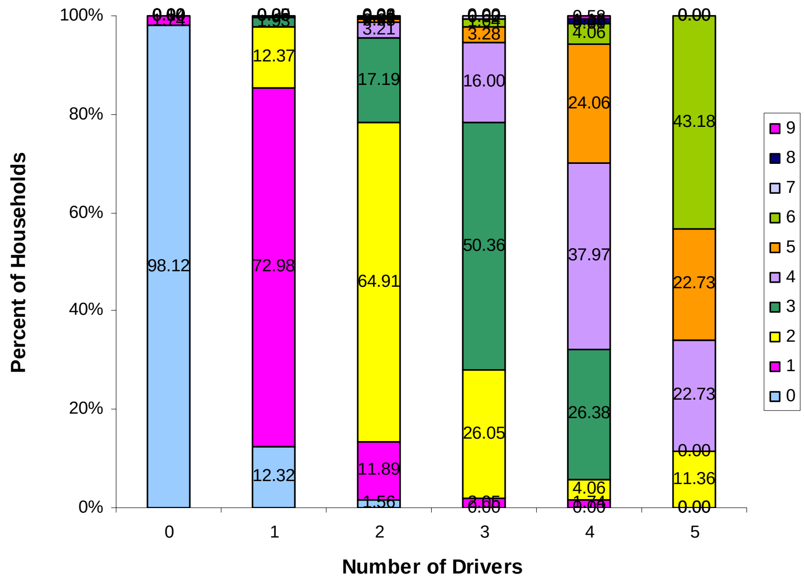
Household vehicle ownership is directly related to the number of adults (for the purpose of this study, adults are defined as persons 16 years of age and older) in the household. Figure 3 shows that incidence of vehicle ownership and number of vehicles owned increases with number of adults. Of all households 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 3 Percent of Households Owning One or More Vehicles by Number of Adults per Household**



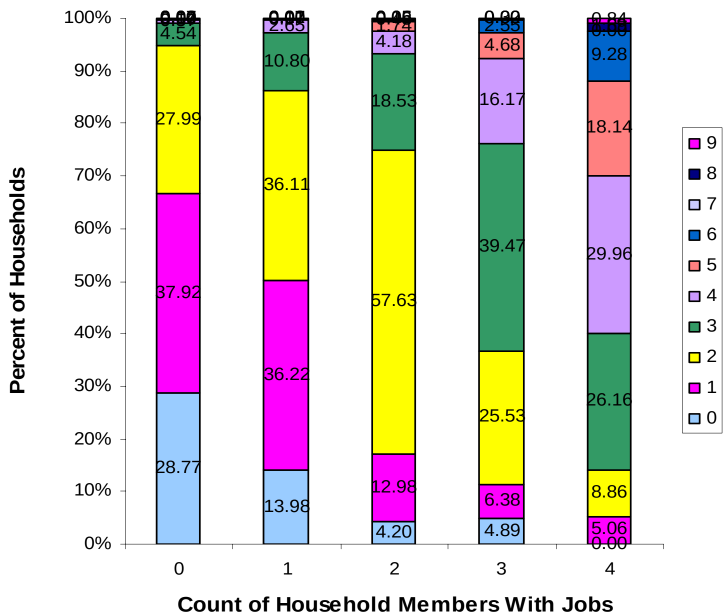

As with household adults, the number of licensed drivers in household is closely related to vehicle ownership. Figure 4 shows that both the percent of household owning vehicles and the number of vehicles owned are linked to the number of drivers. Of one-driver households, 12.32 percent are without vehicles, 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 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 5 shows that both the percent of household owning vehicles and the number of vehicles owned are linked to the number of drivers. Of zero-driver households, 28.77 percent are without vehicles, while no households with four or more drivers are without vehicles. Average number of vehicle per household is a little more or less than the number of drivers, ranging from 1.53 for one-worker households, 2.14 for two-driver households, 2.81 for three-driver households, 3.89 for four-driver households, 4.50 for households with five or more drivers. 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.

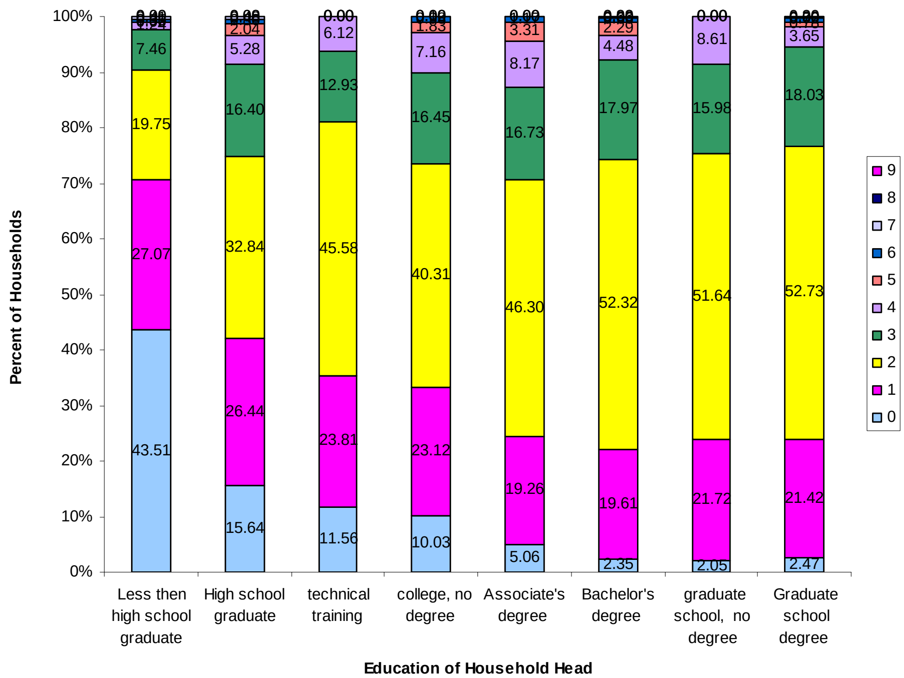
**Figure 5 Percent of Households Owning One or More Vehicles by Count of Household Members With Jobs**




- 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 8, 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.

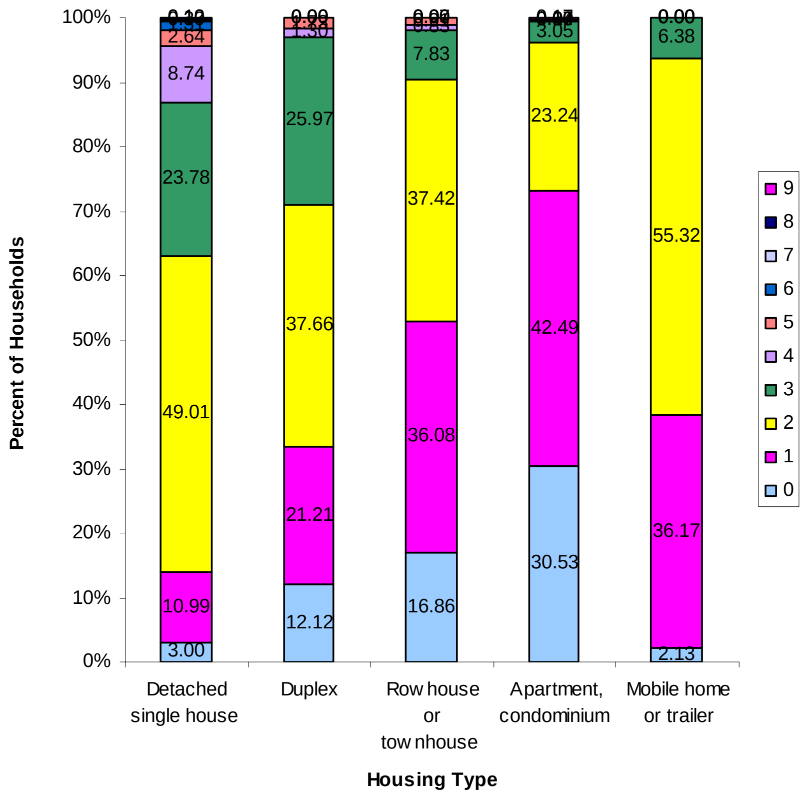
Figure 8 Percent of Households Owning One or More Vehicles
by Education of Household Head




- 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 11, 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 have no vehicles. Households in single-family attached housing, typically townhouses and rowhouses, 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 11 Percent of Households Owning One or More Vehicles by Housing Type**

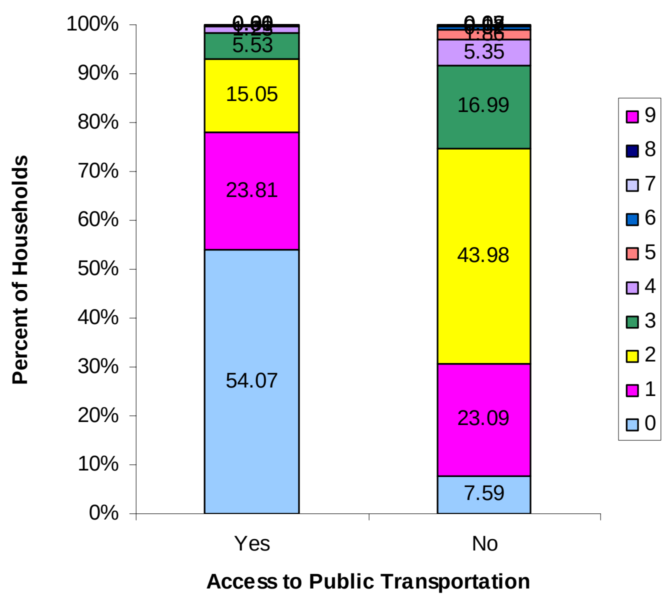



- Access to Public Transportation

Access to pubic 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 10.

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 10 Percent of Households Owning One or More Vehicles by Access to Public Transportation**




- Type of Vehicles Owned by Households

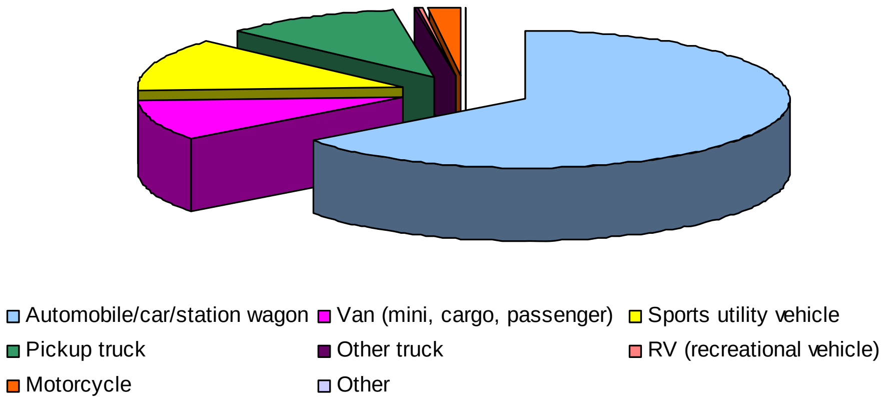
As seen in Table 12, the vast majority of the vehicles are autos, including automobile, car and station wagon. The next largest share is sports utility vehicle. The third largest share is pickup truck. The forth largest share is van, including minivan, cargo, and passenger.

Table 12 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 |

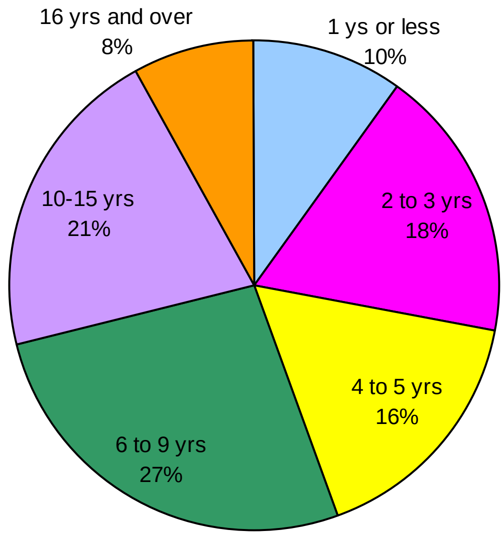
**Figure 12 Percent of Types of Vehicles Owned by Households**



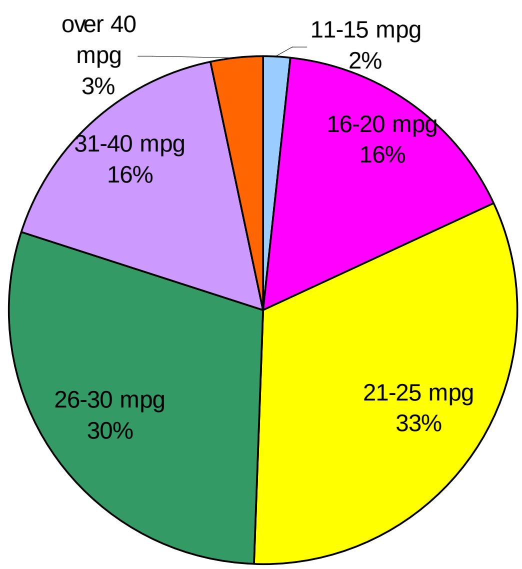

- Profile of Household Auto Characteristics

Figure 13-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 13-B).




A Vehicle Age ( Avg. Age = 7.47 Years)




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

Figure 13 Auto Characteristics Profile

## 5 The Survey

### *5.1 Survey description*

The vehicle ownership survey aims at identifying factors affecting household's vehicle choice decisions under hypothetical scenarios describing possible future market conditions. The survey focuses on the different factors that possibly affect customers' vehicle choice. In particular, we study the market penetration of different vehicle technologies and the effect of fuel prize, taxes and toll incentives on vehicle ownership rate (Figure 14). Each survey game consists of questions related to the actual household conditions in terms of car ownership (revealed preference - RP) and questions related to future choices (stated preference - SP).

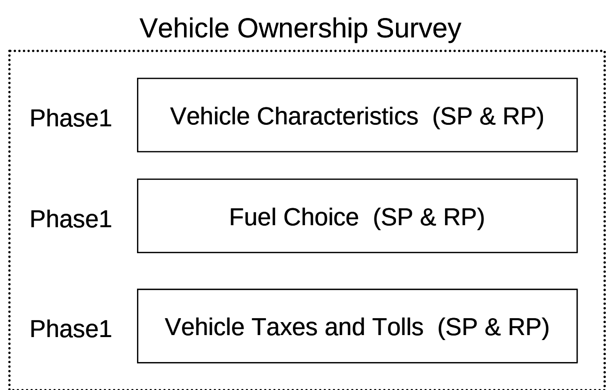



FIGURE 14 Vehicle Ownership Survey Phases

### *5.2 RP and SP Questions*

5.2.1 Revealed preference (RP)

The RP questionnaire aims to collect information on households' socioeconomic characteristics and on the vehicles owned. The socioeconomic characteristics consist of household head's sex, age, occupation, education level, car access to work, and household income range, number of driving license, number of vehicle in the household and residential zip code.

5.2.2 Stated preference (SP)

The SP questionnaire collects responses in terms of choices; five choices are proposed: (1) maintaining the current vehicle, replacing the current vehicle with the three hypothetical vehicles which are (2) gasoline, (3) hybrid, and (4) electric vehicle or (5) selling the current vehicle without any replacement. The scenarios provided in the SP questionnaire are adapted from each respondent's RP data. The advantage of using RP data for the SP design is the ability to provide respondent with scenarios that are realistic to each of them. Respondents then indicate which one of the choice he/she would prefer.

The hypothetical scenarios in the SP questionnaire are constructed as follows. The vehicle attributes for each vehicle type are collected twice for each future year (first semester and second semester of the year) from 2009 to 2015. We allow attributes in the year 2015 to have 5 levels of variation with respect to the actual value (reference value at 2009): (a) no variation, (b) 10% variation, (c) 20% variation, (d) 30% variation, and (e) 50% variation. The sign of the variation depends on the attribute under consideration. The variation is introduced in a way that the respondents experience a greater improvement over time. For each attribute of each vehicle type, the 2015 level will be randomly drawn from the 5 levels. Then, based on the level drawn for the year 2015, the levels for intermediate years between 2009 and 2015 are calculated assuming that in 2009 the level of variation is zero and that variation linearly increases until 2015. Respondent will face in total 14 scenarios. Three games have been prepared to the scope.

### *5.3 Survey Games*

#### 5.3.1 Survey Game 1: Vehicle characteristics

The first Game of the survey aims at understanding how vehicle characteristics affect vehicle choice selection. The questionnaire is divided into three parts (Figure 15): (a) respondent's socioeconomic information, (b) characteristics of the vehicle currently owned by the households, and (c) the SP vehicle choice questionnaire. Each alternative has 5 attributes: (1) Vehicle price, (2) Vehicle consumption MPG (mile per gallon), (3) Range between refueling (mile), (4) Carbon dioxide emission (g/km), and (5) Vehicle seat capacity (number of passenger).

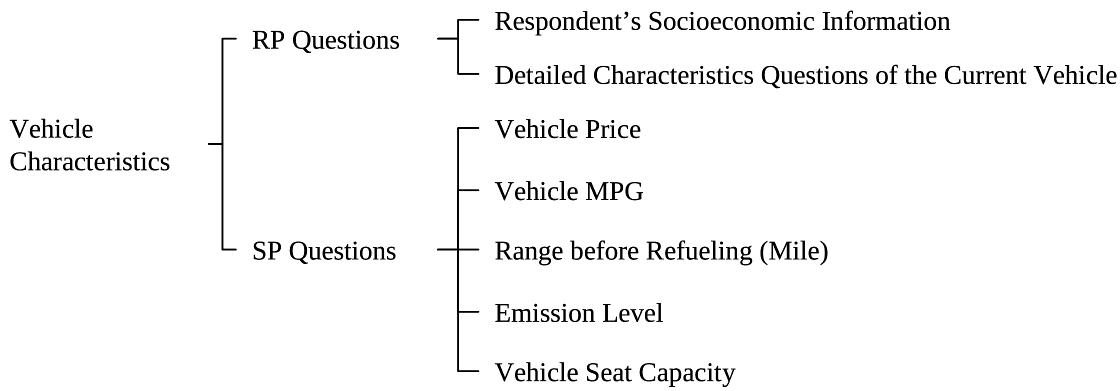



FIGURE 15 Game 1: Vehicle technology

Four vehicle types are considered: Hybrid, Electric, Diesel, and Gasoline.

*Gasoline Cars:* Gasoline vehicle works by burning the gasoline inside an engine in which an engine combustion takes place internally. Table13 describes the average characteristics of a Gasoline Car in the US in 2009.

TABLE 13 Example of gasoline vehicle characteristics

| Gasoline Cars | SUMMARY | | |
|---|---|---|---|
| Consumption city/highway/average (MPG) | 17/26/21 | 13/18/14 | 14/19/15 |
| Price MSRP ($) | 33483 | 49844 | 27254 |
| Curb Weight (lb/kg) | 3830/1737 | 5708/2589 | 5191/2355 |
| Dimensions Overall Height/Width/Length (in/m) | 58/71.7/200.3 / 1.47/1.82/5.09 | 76.7/78.9/204 / 1.95/2/5.18 | 74.3/78.7/225.7 / 1.89/2/5.73 |
| Seating Capacity | 5.25 | 7.5 | 5.5 |
| Passenger Volume (cu ft/m3) | 104.5/2.96 | 145.3/4.11 | 106.2/3 |
| Luggage capacity (cu ft/m3) | 17.25/0.49 | 24.25/0.69 | 48/1.36 |
| Fuel tank (gal/L) | 17.85/68 | 28.25/107 | 29.1/110 |
| Acceleration | 0->60 mph in 7.6s | 0->60 mph in 7.25s | 0->60 mph in 7.35s |
| Max speed or Top speed(mph) | 133 | 118 | 113 |
| CO2 Emissions (g/km) | 244 | 335 | 338 |
| Horsepower (hp) | 226 | 354 | 306 |
| Displacement(cu.in/cm3) | 229/3753 | 344/5637 | 309/5064 |
| Type | Average Mid-size gasoline car | Average Large gasoline car | Average gasoline Truck |

*Diesel Cars*: Diesel cars typically have higher exhaust levels of nitrogen oxide than gasoline cars. Automakers cite the high cost of developing an engine clean enough to meet the US standards. Understandably, this has made a lot of them lukewarm about diesel engines as a solution for boosting fuel economy. That, along with the fact that diesel cars have never really been a mainstream choice here in the United States. Table14 describes the main specifications of a Diesel Car in the US in 2009.

TABLE 14 Example of diesel vehicle characteristics

| Diesel cars | SUMMARY | | |
|---|---|---|---|
| Consumption city/highway /average (MPG) | 23/30/26 | 17/23/20 | 14/19/16 |
| Price MSRP ($) | 41191 | 47669 | 28320 |
| Curb Weight (lb/kg) | 4040/1833 | 5029/2281 | 5946/2697 |
| Dimensions Overall Height/Width/Length (in/m) | 59.3/76.6/187.9 / 1.51/1.95/4.77 | 71/84.3/194.3 / 1.8/2.14/4.94 | 77.6/84.8/235.7 / 1.97/2.15/5.97 |
| Seating Capacity | 5,5 | 6 | 6 |
| Passenger Volume (cu ft/m3) | 107.3/3.04 | 129.6/3.67 | 128.3/3.63 |
| Luggage capacity (cu ft/m3) | 14.5/0.41 | 22.3/0.93 | 67.4/1.91 |
| Fuel tank (gal/L) | 18.2/69 | 24.7/93.6 | 35/132.5 |
| Acceleration | 0->60 mph in 7.4s | 0->60 mph in 8.7s | 0->60 mph in 8.17s |
| Max speed or Top speed(mph) | 145 | 136 | 117 |
| CO2 Emissions (g/km) | 171 | 274 | 417 |
| Horsepower (hp) | 206 | 215 | 356 |
| Displacement(cu.in/cm3) | 167/2733 | 193/3159 | 366/5998 |
| Type | Average Mid-size Diesel car | Average Large Diesel car | Average Diesel Truck |

*Hybrid Cars*: A hybrid car features a small fuel-efficient gas engine combined with an electric motor that assists the engine when accelerating. The electric motor is powered by batteries that recharge automatically while you drive. There are two types of gasoline-electric hybrid cars: the parallel hybrid and the series hybrid. In a parallel hybrid car, a gasoline engine and an electric motor work together to move the car forward, while in a series hybrid the gasoline engine either directly powers an electric motor that powers the vehicle or charges batteries that will power the motor. Table15 describes a Hybrid Cars in the US in 2009.

TABLE 15 Example of hybrid vehicle characteristics

| Hybrid cars | SUMMARY | | |
|---|---|---|---|
| Consumption city/highway/average (MPG) | 33.4/35.4/34.4 | 25.65/25.18/25.18 | 20.5/21/20.5 |
| Price MSRP ($) | 36130.5 | 42411.8 | 39190 |
| Curb Weight (lb/kg) | 3533.8/1602.9 | 4850.18/2200 | 5533.5/2509.95 |
| Dimensions Overall Height/Width/Length (in/m) | 57.3/71.3/187.1 / 1.46/1.81/4.75 | 71.1/77.3/190.1 / 1.81/1.96/4.83 | 73.8/80/230.1 / 1.87/2.03/5.84 |
| Seating Capacity | 5 | 6.5 | 6 |
| Passenger Volume (cu ft/m3) | 98.1/2.78 | 122.7/3.47 | 110.5/3.13 |
| Luggage capacity (cu ft/m3) | 13.1/0.37 | 25.5/0.72 | 34.3/0.97 |
| Fuel tank (gal/L) | 16.2/61.4 | 20.85/78.9 | 26/98.4 |
| Acceleration | 0->60 mph in 8.6s | 0->60 mph in 9.2s | 0->60 mph in 8.7s |
| Max speed or Top speed(mph) | 115 | 105.5 | 98.5 |
| CO2 Emissions (g/km) | 137.6 | 225 | 254 |
| Horsepower Engineering/Electric Motor(hp) | 200 | 274 | 332 |
| Displacement(cu.in/cm3) | 153/2501 | 254/4156 | 364/5967 |
| Type | Average Mid-size Hybrid car | Average Large Hybrid car | Average Hybrid Truck |

*Electric Cars:* An electric car is a car powered by an electric motor rather than a gasoline engine.

The differences between gasoline and electric cars are:

- The gasoline engine is replaced by an electric motor.
- The electric motor gets its power from a controller.
- The controller gets its power from an array of rechargeable batteries.

The reasons for the growing interest in these vehicles are:

- Electric cars create less pollution than gasoline-powered cars, so they are an environmentally friendly alternative to gasoline-powered vehicles (especially in cities).
- Hybrid cars development is strictly related to the progress of electric cars.
- Vehicles powered by fuel cells are electric cars, and fuel cells are getting a lot of attention right now.

### 5.3.2 Survey Phase 2: Fuel choice

The second phase of the survey aims at understanding fuel related factors that affect vehicle choice selection. The second phase of the survey is divided into three parts

(Figure16): (a) respondent's socioeconomic information, (b) questions on the vehicles currently owned with emphasis on fuel related issues, and (c) the SP vehicle choice with fuel related attributes. Three attributes characterize alternatives: (1) Fuel price ($), (2) Fuel tax (as percentage of fuel price), and (3) Average distance between refueling station (mile).

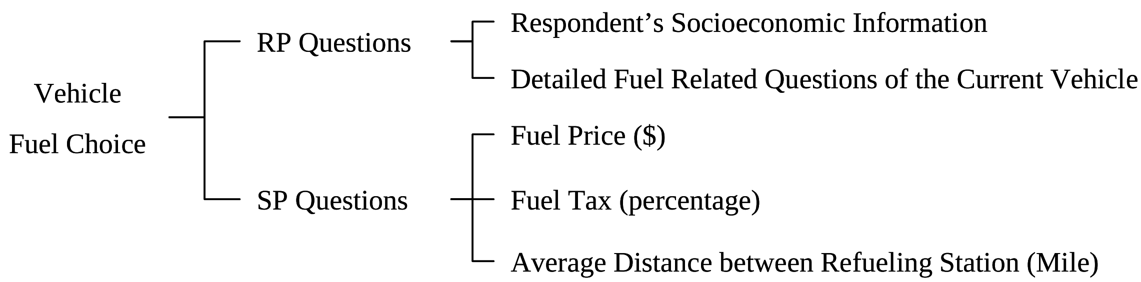



FIGURE 16 Game 2: Fuel Choice

Each respondent has the choice between conventional fuel or alternative fuel. Conventional fuels include Gasoline and Diesel while alternative fuels include E85, natural gas, Propane, LPG, and electric car. The detailed description of these types of fuel is given below.

- *Gasoline fuel*

Gasoline is produced in oil refineries. This Material is separated from crude oil via distillation. Gasoline is made up of molecules composed of hydrogen and carbon arranged in chains. Gasoline molecules have from 7 to 11 carbons in each chain. When gasoline is burned under ideal conditions, with plenty of oxygen, carbon dioxide, water and lots of heat is developed. A gallon of gasoline contains about $132*10^6$ joules of energy, which is equivalent to 125,000 BTU or 36,650 watt-hours. In the United States, most cars are gasoline vehicles. This is the reason why gasoline is cheaper than diesel. The Gasoline sales prices from 2009 to 2015 used in the survey design are obtained from Energy Information Administration (EIA).

- *Diesel fuel*

Although most of the cars in the US have gasoline engines, since 2004, demand for diesel has risen for several reasons, including increased industrialization and construction. Diesel fuel has a higher energy density than gasoline. On average, 1 gallon (3.8 L) of diesel fuel contains approximately $155 \times 10^6$ joules (147,000 BTU). This, combined with the improved efficiency of diesel engines, explains why diesel engines get better mileage than equivalent gasoline engines.

As of 2006, almost all of the petroleum-based diesel fuel available in Europe and North America is of an Ultra Low Sulfur Diesel (ULSD) type. The move to lower sulfur content is expected to allow the application of newer emissions control technologies that should substantially lower emissions of particulate matter from diesel engines. This change occurred first in the European Union and is now happening in North America. New emissions standards, dependent on the cleaner fuel, have been in effect for automobiles in the United States since model year 2007. As the difference between ULSD and Low Sulfur Diesel (LSD) is small, we have chosen to keep the Diesel all type value which is an average. The Diesel sales prices from 2009 to 2015 used in the survey design are obtained from Energy Information Administration (EIA).

- *E85 fuel*

E85 is a blend of 85 percent ethanol and 15 percent gasoline. E85 is an alternative fuel as defined by the U.S. Department of Energy. Besides its superior performance characteristics due to the high compression used with it, ethanol burns cleaner than gasoline. It is a completely renewable, domestic, environmentally friendly fuel.

It can reduce global warming gas releases by up to 80% as compared to today's conventional technology gasoline vehicle (E85 vehicles reduce harmful hydrocarbon, benzene and $CO_2$ emissions). Moreover ethanol also degrades quickly in water and, therefore, poses much less risk to the environment than an oil or gasoline spill. However, E85 ethanol is used only in engines modified to accept higher concentrations of ethanol: flex-fuel vehicles (FFVs).

As of December 31, 2008, there were about 1921 public E85 fueling stations available in the United States. Prices vary by location, some prices over 30% less than regular gasoline. In other places it has been more expensive.

E85 sales price used in the survey design are averaged from the data among Energy Information Administration (EIA) and the Maryland gas station websites. The Gasoline Gallon Equivalent (GGE) is used to compare the E85 price with other fuel types by using the equivalent Btu/ gallon factor.

The use of ethanol fuel is promoted by several tax incentives. The Volumetric Ethanol Excise Tax Credit, also known as VEETC, is a Federal tax credit that went into effect on January 1, 2005. This is a credit of $.51 for every gallon of pure ethanol blended into gasoline. For example, an E10 blend will have a credit available of $.051/gallon, and E85 will have a credit available of $.4335/gallon. This credit is identical for both E10 and E85, as are the forms to file for it.

- *Natural gas*

Natural gas is a naturally occurring mixture of hydrocarbon and non-hydrocarbon gases found in porous geological formations (reservoirs) beneath the earth's surface. It is colorless and odorless; odorants are added for safety purposes. It is one of the world's leading alternative fuels and has been in use for over 70 years. Natural gas is made up of mostly methane (typically over 90%), but also contains some ethane, propane, isobutane and a few other gases in very small quantities. As a gas, it does not pool when refueling but dissipates in air. Natural gas is the most inexpensive alt fuel and can save users significantly over a year (up to 40% in some areas)

There are 2 forms of natural gases as followed:

*Compressed Natural Gas (CNG)*

CNG is, as its name suggests, the close relative of LNG and as a natural gas it has the same basic characteristics even if it is basically composed of methane. However, because it is not liquefied it has a lower energy density (25% compared to diesel and 42%

compared to LNG). Moreover, it is stored at very high pressures, about 200 bar. These two factors are a big disadvantage for CNG. Storage and vehicle tanks have to be robust and heavy because of the high pressure requirement. The space taken up on the vehicles by the tanks is significantly more than twice that for LNG tanks (or the range is much less than half) because of the lower energy density. LNG is much more portable because CNG depots need to be supplied by pipeline and need compressors on site. LNG sites require much less capital investment and are more expensive to run. Although vehicles can use natural gas as either a liquid or a gas, most vehicles use the gaseous form compressed to pressures above 3,100 pounds per square inch($6{,}45*10^{-5}m^2$).

*Liquefied Natural Gas (LNG)*

LNG is produced from a mixture of raw components but is predominantly methane and is compatible with diesel technology subjected to necessary modifications. The LNG must be stored and transported permanently approximately at this temperature and the fuel is only suited to large, heavy diesel vehicles such as trucks, buses and HGVs. Although the energy density is about 60% compared to diesel the fuel costs are much lower and LNG should provide lower running costs. Because of LNG's increased driving range, it is used in heavy-duty vehicles, typically vehicles that are classified as "Class 8" (33,000 - 80,000 pounds, gross vehicle weight).

The Natural gas sales price used in the survey design before 2009 are obtained from the Maryland natural gas price prediction website while the price after 2009 are obtained from the Central Atlantic natural gas price predictions website.

- *Propane, LPG (liquefied petroleum gas)*

Propane has been used as a transportation fuel since 1912 and is the third most commonly used fuel in the United States, after gasoline and diesel. More than four million vehicles fueled by propane are in use around the world in light-, medium-, and heavy-duty applications. Our estimate of energy density is 65% compared to diesel and about 75% compared to petrol (gasoline) and so LPG requires more storage volume to drive a range equivalent to gasoline, but it is price-competitive on a cents-per-mile-driven basis.

Typically the gas is composed of propane with some butane derived mainly from oil refineries. The ratio of carbon to hydrogen is important. In fact, the smaller is the better for the environment.

The most notable difference between LPG and petrol or diesel, for cars and vans, is the cost of fuel. From a local environmental point of view LPG is cleaner than petrol and diesel, although it is still a fossil fuel and thus its use, as a whole, contributes to global pollution and climate change.

Many governments impose less tax on LPG than on petrol or diesel, which helps offset the greater consumption of LPG than of petrol or diesel. Propane is the third most widely used motor fuel in the world. 2008 estimates are that over 13 million vehicles are fueled by propane gas worldwide. Over 20 million tones (over 7 billion US Gallons) are used annual as a vehicle fuel.

Currently, a $0.50 motor fuels excise tax credit per gasoline gallon equivalent (GGE) of CNG, LNG or LPG exists for fuel purchases between October 1, 2006 and September 30, 2009. The credit is applied/paid to eligible recipients *without regard to the amount of excise tax paid*, and may be taken as excise tax credit, income tax credit, or direct payment, depending on circumstances. In other words tax exempt entities are entitled to a direct cash payment after registering with IRS. The sales price data are found from Central Atlantic prediction values in the U.S. department of energy report.

- *Electric car*

An electric car is an alternative fuel car that uses electric motors and motor controllers instead of an internal combustion engine (ICE). Currently, in most cases, electrical power is derived from battery packs carried on board the vehicle.

The term electric vehicle is often used, implying, in context, an electric road vehicle, though in its broader sense it covers all vehicles with electrical propulsion including trains and trams.

Vehicles that make use of both electric motors and other types of engine are known as hybrid electric vehicles and are not considered pure electric vehicles (EVs) because they operate in a charge-sustaining mode. Hybrid vehicles with batteries that can be charged externally from an external source are called plug-in hybrid electric vehicles (PHEV), and become pure battery electric vehicles (BEVs) during their charge-depleting mode. Other types of electric vehicles besides cars include light trucks and neighborhood electric vehicles.

The fuel cost of driving an electric vehicle depends on the cost of electricity per kilowatt-hour (kWh) and the energy efficiency of the vehicle.

**Cost of Charging Formula:**

Price= Price of electricity from power utility.

Energy = Amount of energy your battery charging system uses (in Kilowatt hours)

Energy **x** Price Per KWh = Total cost to charge batteries.

**Cost Per Mile:**

Cost = Total Cost of a full charge of your EV's batteries. (from the formula above)

Range = Total Range of your EV from a full charge, in Miles, Kilometers or any other distance measurement.

$$\text{Cost Per Mile} = \frac{\text{Cost}}{\text{Range}} \quad \text{or} \quad \text{Cost Per Mile} = \text{Cost} \div \text{Range}$$

5.3.3 Survey Game 3: Vehicle taxes and tolls incentive

The third Game of the survey aims at understanding how vehicle taxes and tolls affect vehicle choice selection. The third phase of the survey is divided into three parts (Figure17): (a) respondent’s socioeconomic information, (b) details on taxes and tolls actually paid by the respondent, and (c) the SP vehicle choice with alternative attributes describing taxes and tolls in the future. Three attributes are considered to describe the alternatives: (1) Vehicle registration fee ($), (2) Vehicle title fee ($), (3) Toll price ($), (4) Vehicle sales tax ($), and (5) Vehicle tax deduction ($).

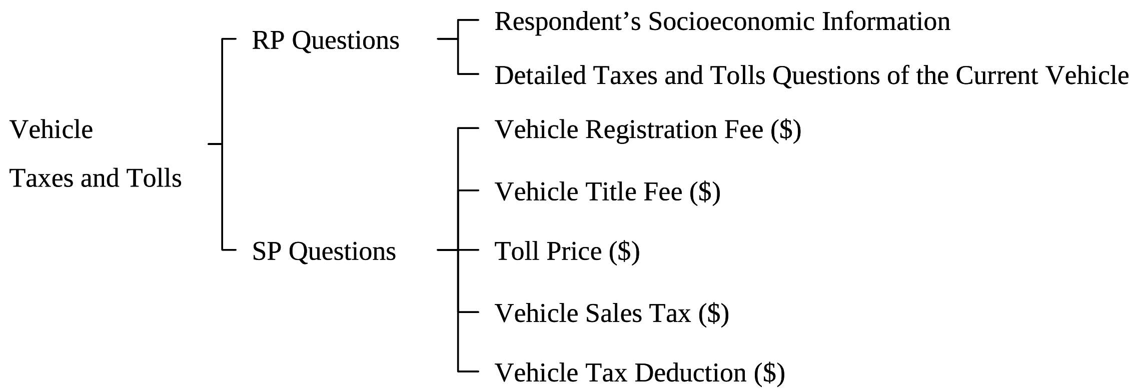



FIGURE 17 Game 3: Vehicle Taxes and Tolls

Taxes charged to vehicles depend on vehicle type. These taxes include sales taxes, dealer fees, registration fees, titles fee, tax deduction and tolls. The US government offers some tax deductions (e.g. tax credit) for environmental friendly vehicles such as vehicle with alternative fuels and electric cars. In 2007, the vehicle excise tax rate raised from 5% to 6%. Moreover, all motor vehicles, trailers, and related transportation equipment domiciled within the State must register with MVA. Most vehicles are registered biannually.

- *Vehicle Registration fee*

Vehicle registration fee depends on the car weight. Vehicles under 3,700 lbs of weight are considered to be small and mid size car. Vehicle over 3,700 lbs of weight are considered to be large cars.

- *Title fee*

Maryland title fee is reported in Figure18:

**Vehicle Registration**

| | |
|---|---|
| Additional/Duplicate Registration Card/Sticker | $5.00 |
| Farm Area Temporary Registration - 30 Day | $20.00 |
| - 60 Day | $40.00 |
| - 90 Day | $60.00 |
| Individual' s w/Disability Placards | No Fee |
| IRP Duplicate/Replacement Cab Card | $5.00 |
| IRP New Cab Card | $5.00 |
| IRP Temporary Authorization | $2.00 |
| IRP Trip Permit | $15.00 |
| Medevac Surcharge – per year | $13.50 |
| Non-Resident Permit | $27.00 |
| Organization Tags – without logo | $15.00 |
| Organization Tags – with logo | $25.00 |
| Restoration Fee | $30.00 |
| Registration / Tag Transfer | $10.00 |
| Salvage Certificate | $20.00 |
| Salvage Certificate – Duplicate | $20.00 |
| Security Interest Filing | $20.00 |
| Security Interest Filing – Duplicate | $20.00 |
| Substitute Tags | $20.00 |
| Temporary Registration | $20.00 |
| Title Certificate – Corrected | $50.00 |
| Title Certificate – Duplicate | $20.00 |
| Title Certificate – New / Used | $50.00 |
| Titling Tax – Based on Fair Market Value | 6% |
| - minimum tax | ($38.40) |
| Vanity Plates – per year | $25.00 |
| Commemorative Tags – Chesapeake Bay* | $20.00 |
| Commemorative Tags – Agricultural* | $20.00 |
| Amateur Radio Operator' s Tags* | $5.00 |

*indicates $5 additional per year fee

FIGURE 18 Title fee in Maryland

Source:http://www.marylandmva.com/AboutMVA/FEE/default.htm#VehicleRegistration

From figure18, we can see that there are several title fees which vary according to customers' necessity. We will include in our questionnaire the title certificate (e.g. title fee) and the Security Interest Filing into account. The amount of these to fees is $70.

- *Tax deductions*

*Electric car:*

Tax deduction for electric car is fully deducted for tax credit of $7,500 for the first 250,000 vehicles sold.

Source: http://www.ushuaia.com/ushuaia-terre/info-planete/actu-en-continu/transport/0,,4311509,00-les-usa-veulent-rouler-a-l-electrique-.html

*Hybrid car:*

The new clean vehicle tax credit allows a tax credit which ranges between $500 and $3400, depending on the vehicle, and no state sales taxes are due. Thus, tax credits for many hybrid cars have already expired, or are close to expiring. Table16 describes tax deductions for Hybrid car until April 1st 2009.

TABLE 16 Tax deduction for hybrid vehicle

| | |
|---|---|
| Chevy Malibu Hybrid = $1,300.00<br>Chevy Tahoe Hybrid = $2,200.00<br>Chrysler Aspen Hybrid = $2,200<br>Dodge Durango Hybrid =$2,200<br>Ford Escape Hybrid = (2009) 2wd=$1,500; 4wd=$975.00<br>(2008) 2wd=$1500.00; 4wd=$1100.00<br>Ford Fusion Hybrid = $3,400.00<br>GMC Yukon Hybrid = $2,200.00<br>Honda Accord Hybrid = No longer sold<br>Honda Civic Hybrid = Expired.<br>Honda Insight Hybrid = Expired. | Lexus RX400h Hybrid = ExpiredMazda Tribute Hybrid = (2008) 2wd=$1500.00; 4wd=$975.00<br>Mercury Mariner Hybrid = (2009) 2wd=$1500.00; 4wd=$9750.00<br>(2008) 2wd=$1500.00; 4wd=$1100.00<br>Ford Fusion Hybrid = $3,400.00<br>Nissan Altima Hybrid = $2350.00<br>Saturn Aura Hybrid = $1,300.00<br>Saturn Vue Hybrid = $1,550.00<br>Toyota Camry Hybrid = Expired<br>Toyota Highlander Hybrid = Expired<br>Toyota Prius Hybrid = Expired |

Source: http://www.hybridcars.com/federal-incentives.html

### *5.4 Survey Interface*

The car ownership survey is computer assisted with WinMint 2.1 (HCG, 2000). The interface is shown as Figure 19 to 24.

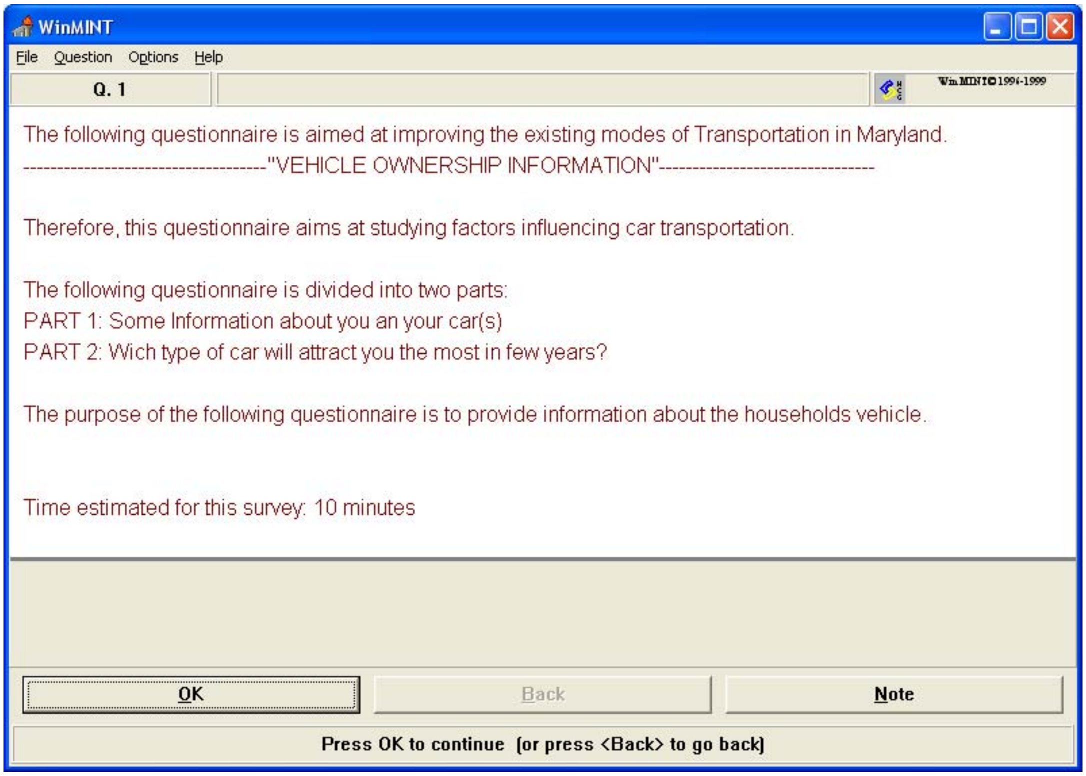



FIGURE 19 Interface of WinMint 2.1

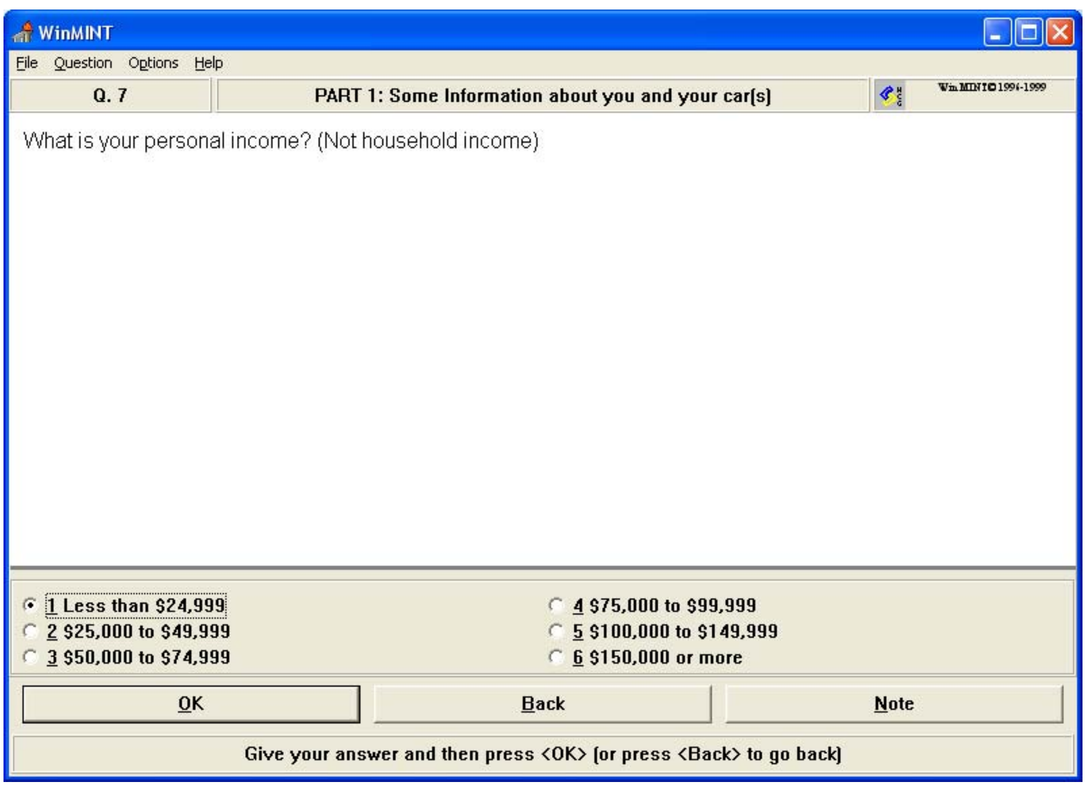



FIGURE 20 RP Questions

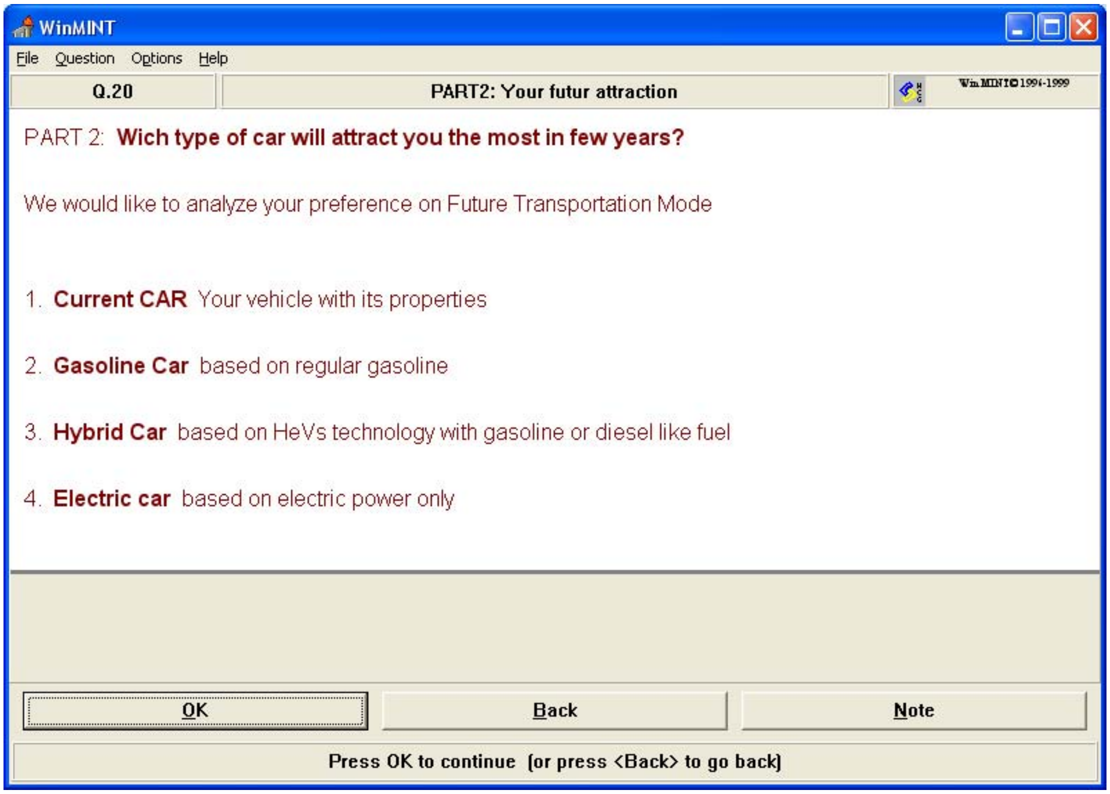



FIGURE 21 SP Choices

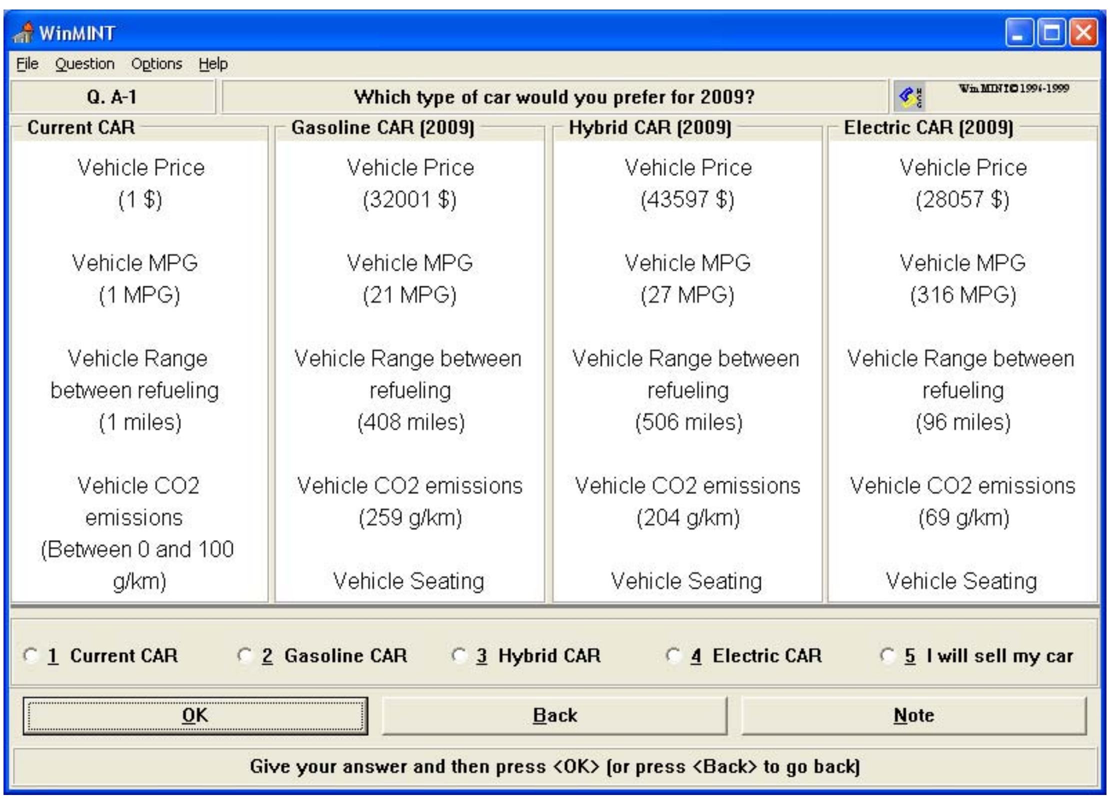



FIGURE 22 SP Scenarios phase1

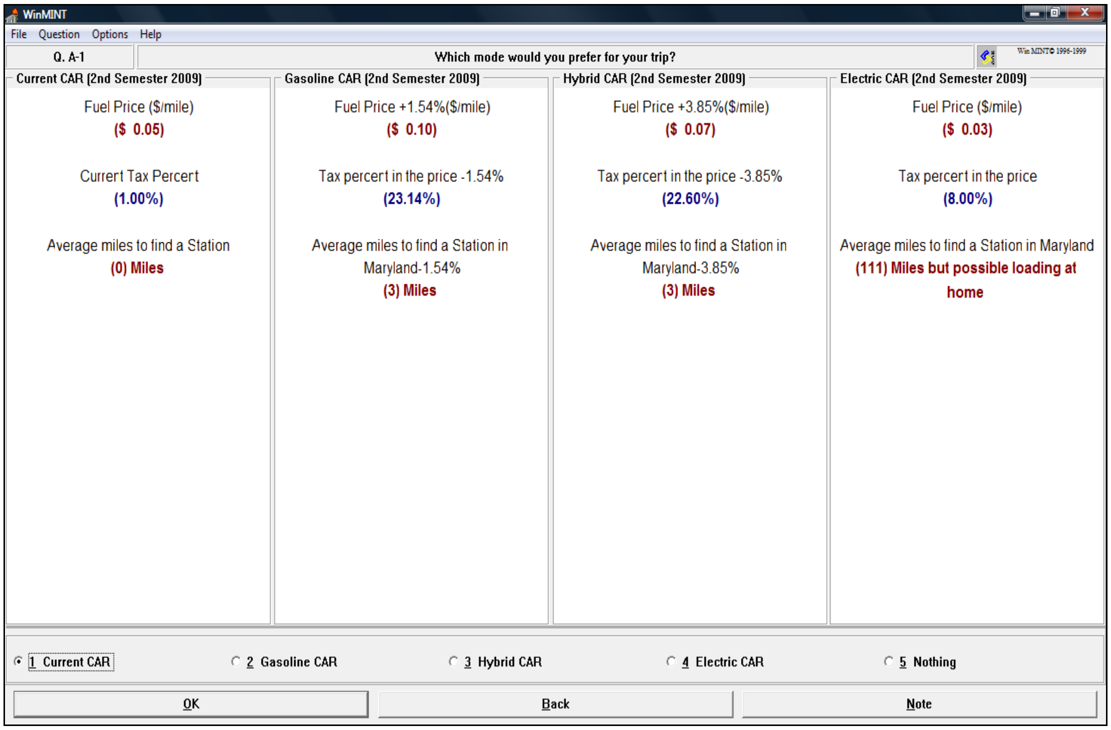


FIGURE 23 SP Scenarios phase2

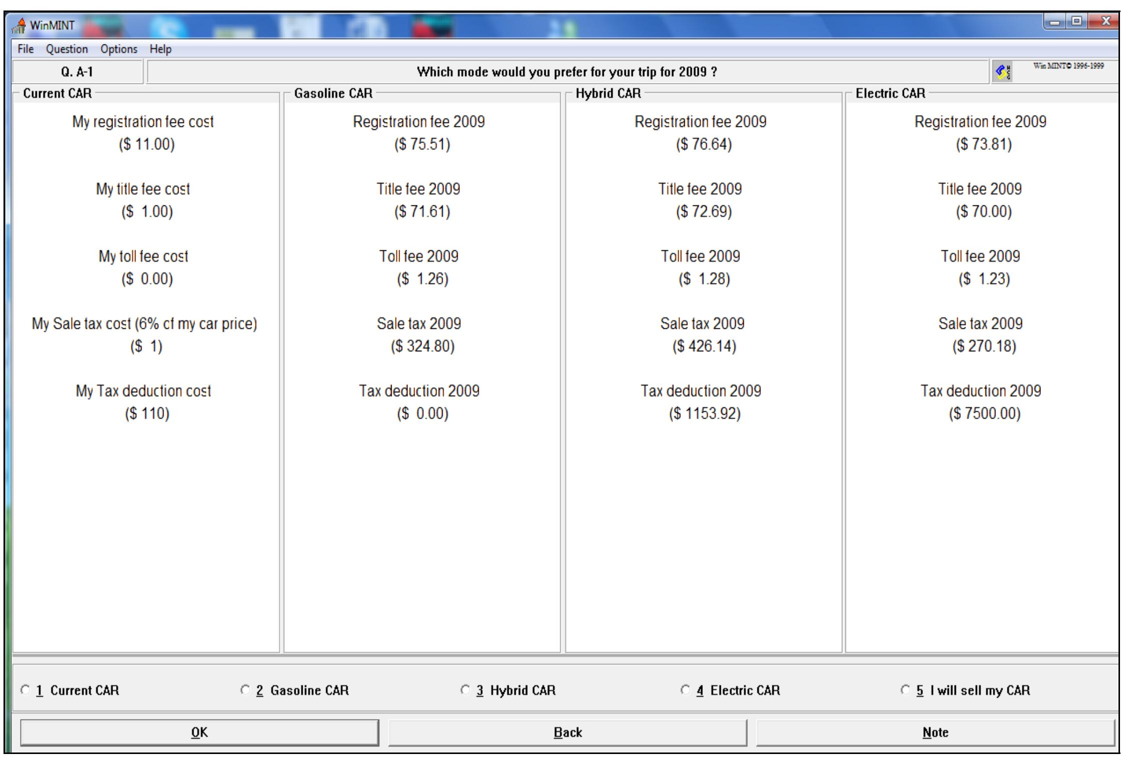


FIGURE 24 SP Scenarios phase 3

## 6. Future Tasks

1. **Finalize the model specification**
   - Include in the model specification all the socio-economic attributes and the vehicle characteristics that are expected to be statistically significant.
   - Add attributes on land use and transit availability

2. **Estimate the model on 2008 NHTS data**
   - The data set on household and vehicle characteristics for Washington and Baltimore area are expected to be available by fall 2009.
   - Finalize the model estimation and test the predictive power of the model.

3. **Migrate the survey from WinMint 2.1 format to the new software under development**
   - The three SP games have been coded using WinMint 2.1. However, this software has several limitations, (i.e. limited number of alternatives and variables in SP games). The software under development is designed to be much more flexible and will allow the respondents to fill on line the questionnaire.

4. **Survey administration**
   - Selection of sampling procedure.
   - Data collection

5. **Policy analysis**
   - Estimate the joint RP and SP model.
   - Test different policy scenarios.

6. **Reporting**

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