**Title**

A Personal Vehicle Transactions Choice Model for Use in Forecasting Demand for Future Alternative-Fuel Vehicles



**Authors**

Ren, Weiping
Brownstone, David
Bunch, David S.
et al.

**Publication Date**

1994-08-01

UCI-ITS-WP-94-7

# A Personal Vehicle Transactions Choice Model for Use in Forecasting Demand for Future Alternative-Fuel Vehicles

UCI-ITS-WP-94-7

Weiping Ren [1]
David Brownstone [2]
David S. Bunch [3]
Thomas F. Golob [1]

[1] Institute of Transportation Studies
University of California, Irvine

[2] Department of Economics and Institute of Transportation Studies
University of California, Irvine

[3] Graduate School of Management, University of California, Davis

August 1994

Institute of Transportation Studies
University of California, Irvine
Irvine, CA 92697-3600, U.S.A.
http://www.its.uci.edu

# A Personal Vehicle Transactions Choice Model for Use in Forecasting Demand for Future Alternative-Fuel Vehicles

Weiping Ren
David Brownstone
David S. Bunch
Thomas F. Golob

*University of California, Irvine and Davis*

### *ABSTRACT*

A discrete choice model has been developed in which the choice alternative consist of vehicle transactions rather than portfolios of vehicle holdings. The model is based on responses to customized stated preference questions involving both hypothetical future vehicles and the household's current vehicle holdings. The stated choices were collected from 4747 survey respondents located throughout most of the urbanized portions of the state of California. Respondents were asked what their next vehicle transaction would most likely be (replace a current vehicle, add another vehicle, or dispose of a current vehicle), and respondents who wanted to replace or add vehicles were asked to indicate their most preferred vehicle from a set of six hypothetical vehicles. The hypothetical vehicles were described in terms of fourteen attributes, manipulated according to an experimental design.

The transactions model is a multinomial logit model of the choice of the hypothetical vehicles and whether or not the hypothetical vehicle will be a replacement or addition to the household fleet. The model is conditioned on the household's current vehicle stock, and the characteristics of the current vehicles are important explanators of the stated preference choices. In addition to the model estimates, forecasts are given for a base case scenario in 1998.

This model is one component in a micro-simulation demand forecasting system being designed to produce annual forecasts of new and used vehicle demand by type of vehicle and geographic area. The system will also forecast annual vehicle miles traveled for all vehicles and recharging demand by time of day for electric vehicles. These results are potentially useful to utility companies in their demand-side management planning, to public agencies in their evaluation incentive schemes, and to manufacturers faced with designing and marketing alternative-fuel vehicles.

## Research Context

### *Background*

Manufacturers and government agencies interested in promoting alternative-fuel vehicles, and public utilities who must provide adequate refueling infrastructure, need to know how demand is affected by attributes that distinguish these vehicles from conventional gasoline or diesel vehicles. Such attributes include: range between refueling, overnight recharging requirements (electric and compressed natural gas), the potential availability of at-home refueling (compressed natural gas), the availability of refueling and opportunity recharging stations, vehicle performance levels, cargo carrying capacity, and capital and operating cost differences compared to conventional-fuel vehicles. It is also important to establish the extent to which consumers are attracted to vehicles that have reduced tailpipe emissions, as well as the effectiveness of various proposed incentives designed to promote sales and use of alternative-fuel vehicles. This is especially important in states like California, where stringent vehicle emission standards have been adopted or proposed. All new cars sold in the state will be required to emit 80 percent less hydrocarbons by the year 2000, and 50 to 75 percent less carbon monoxide and nitrogen oxide. The California Air Resources Board (CARB) has also mandated the production and sale of zero-emission (electric) vehicles, beginning with 2 percent of annual sales in 1998 and increasing to 10 percent in 2003.

In this paper we describe a model that has been developed to provide the personal vehicle choice component of an integrated microsimulation forecasting system. A major goal is to improve the quality of forecasts by focusing on vehicle transactions rather than vehicle holdings. The source of the data is a multi-year panel study, and another goal of the research program is to produce state-of-the-art dynamic transactions models that combine data from discrete choice stated preference questions with actual vehicle transactions behavior observed over the life of the panel.

## *Overview of the Forecasting Model System*

The system is being designed to forecast demand for all types of vehicles subject to clean air mandates for each of 79 geographic areas, called districts, within the urbanized regions in California, excluding San Diego County. The districts are defined to be consistent with utility company service planning areas. The types of vehicles include all cars and light-duty trucks (pickup trucks, vans, and sport utility vehicles), as well as medium duty trucks up to 14,000 pounds gross vehicle weight. There will be two separate components for personal vehicles and commercial fleet vehicles, respectively, that will be linked through a third component that takes into account price effects associated with the used vehicle market.

The system will provide forecasts for aggregated "vehicle classes," and is being designed to support the definition of a variety of conventional-fuel and alternative-fuel classes that might become available during future forecast periods. Thus, vehicle classes for today's existing vehicles are formed by clustering together all makes and models with similar attributes (e.g., body type and size) into relatively homogeneous groups. We are currently using 14 classes (7 car classes and 7 light truck classes) for conventional-fuel personal vehicles, with each class further subdivided into 10 model-year vintage subclasses. The commercial fleet model will contain a medium-duty truck class in addition to all of these light truck and car classes, all broken down into similar model-year vintage subclasses.

The system will also forecast fuel usage for each type of vehicle in each district. To determine the impact of electric vehicle recharging on the electric transmission and distribution system, it will also forecast recharge demand for electric vehicles by time of day. Currently, peak electricity demand in California occurs during summer afternoons, and minimum demands occur between midnight and 6:00 A.M. Therefore, electric vehicle recharging will be much cheaper and less polluting if it takes place during late night hours when electricity is generated by relatively clean baseline plants.

The model system must be able to simulate the dynamics of the new vehicle adoption process. Thus, the system is designed to produce a separate forecast for each period, and the next period's forecast must depend on all the previous forecasts. For this reason, it is desirable to focus on vehicle transactions, and to calibrate dynamic behavioral models that use panel data. Previous efforts ( e.g., Train 1986) have focused on vehicle holdings, and were estimated using those cross-sectional data sets that were available.

The system uses microsimulation: it starts with a database of representative households and commercial fleets for the base year, and then simulates vehicle transactions at the level of the individual decision-making unit. Forecasts are reported for the current period by aggregating the results to the district level. However, dynamic effects are preserved by maintaining individual disaggregated histories as required by the behavioral models. This structure is similar to the system of Hensher, et al. (1992), where the population is represented by a relatively small number of "synthetic" households. We use a large sample of actual households and fleets obtained from our surveys. Such a microsimulation approach requires more computation, but it should be more accurate.

The inputs to our transaction models are the current characteristics of the household (or fleet) and the current vehicle inventory and utilization. Since vehicle type decisions are discrete, the models can only provide probabilities that a particular household or firm will purchase a particular type of vehicle. Forecasting a particular choice from these models requires simulating an actual choice, which introduces some random noise into the forecasting process. Fortunately, the effect of this randomness disappears when forecasts for individual households or fleets are aggregated to predict market demand. The predicted changes in vehicle holdings and utilization are then combined with initial holdings to forecast vehicle stocks for the next period.

The effects of estimation errors on the resulting forecasts will be measured by a "bootstrapping" process (Efron and Tibshirani, 1993). A number of different forecasts will be generated using different parameter values chosen to represent the parameter estimation uncertainty. The resulting spread of forecasts will generate confidence regions for our forecasts.

The model system will internally set used car prices so that the demands for used cars forecast by the submodels equals the predicted number of used cars sold by the submodels. This price equilibration will be performed separately for small groups of vehicle type-vintage classes. Therefore, one important feature of our model system is that it will provide estimates of used prices for alternative-fuel vehicles. Our approach requires that the used vehicle market in California is closed, or that used-vehicle price differences do not cause people to move vehicles in or out of the state. This assumption is reasonable given California's geography: the main urban areas are far away from urban areas in neighboring states.

Although our personal vehicle and fleet demand submodels exclude rental and state and federal fleets, these fleets are an important source of vehicles entering the used market. At this time, it appears that rental fleets will be excluded from all alternative-fuel vehicle mandates, so we will model their behavior as fixed throughout the forecast period. Specifically we will assume that rental fleets purchase and sell the same type and number of vehicles as they did in 1993-1994.

For political reasons, state and federal fleets will need to meet alternative-fuel vehicle mandates. We will therefore assume that they purchase enough vehicles to meet these mandates in the lowest-cost fashion. We will also assume that these fleets continue to follow the same vehicle sales and scrappage policies as in 1993-1994. Clearly our rental and government fleets "models" could be considerably improved. Unfortunately, the required data collection is beyond the scope of the current project.

### *Exogenous Inputs*

The key inputs to our forecasting system are vehicle technology, fuel prices, fuel infrastructure, and incentives. Vehicle technology includes all attributes of vehicles which will become available in the future, including fuel type, refueling or recharging range, price, operating costs, vehicle tailpipe emissions, payload, and performance. Although it is relatively easy to forecast these attributes two to three years ahead, it is very difficult to predict the state of new technology ten or more years ahead. Forecasts from the model system crucially depend on future vehicle technology, and users of the model system will need to continually update this information as time progresses. Since the model produces forecasts for each year, it is also important to forecast when new technology vehicles will be introduced. Finally, the model system assumes that manufacturers are willing to provide as many vehicles as demanded at the forecast vehicle price.

Fuel prices are another exogenous input to the model system. Although these are typically very difficult to forecast, we only need accurate forecasts of relative fuel prices. The prices of three of the fuels considered in our model -- gasoline, compressed natural gas, and electricity -- have tended to move together with the price of crude oil during the past decade. However, if crude oil prices start to rise substantially, then the off-peak electricity price may diverge from recent patterns since in California off-peak electricity is primarily generated by hydroelectric power.

Fuel infrastructure describes the availability of alternative fuels. For compressed natural gas and methanol this is described in comparison to the availability of gasoline (e.g., "one methanol station for every 10 gasoline stations"). The electricity fuel infrastructure also includes the types of places (e.g. shopping centers, airports, etc.) where "opportunity charging" is available.

The final set of exogenous inputs are incentives for purchasing alternative-fuel vehicles. Many proposed incentives (such as, sales tax and vehicle registration fee subsidies) simply lower the capital and/or operating costs of these vehicles, so the effects of these incentives can be modeled by changing the appropriate cost variables in the vehicle technology section. Other proposed incentives, such as free parking, solo driver access to high-occupancy vehicle (carpool) lanes, or extended vehicle warranties, do not directly affect vehicle technology. The surveys are being designed so that both the personal and fleet demand submodels can be sensitive to such incentives.

### *Personal Vehicle Submodel*

Our framework for forecasting personal vehicle demand is summarized by the model in Figure 1, which consists of a number of linked sub-models. The initial current vehicle holdings and household structure are taken from the personal vehicle survey described below. Box A in Figure 1 represents a series of models which age each household, and simulate births, deaths, divorces, children leaving home, etc. Once the new household structure is determined, other models in Box A determine the household's income and employment status. The dotted line leaving Box A shows that this updated household is used as the starting point for aging the household in the next period. The models in Box A are mostly calibrated from the Panel Study of Income Dynamics (Hill, 1992).

Ellipse B in Figure 1 takes the updated household and current (aged) vehicle holdings as inputs. It then decides whether or not a vehicle transaction takes place during this period. The period length is set at six months, in order to limit the number of transactions per period to one, but model system outputs are given annually. A vehicle transaction is defined to include: disposing of an existing vehicle, replacing an existing vehicle with another one, or adding a new vehicle to the household's fleet.

If the simulation from the transactions model in Ellipse B predicts that a vehicle transaction has taken place, the transaction type model in Box C determines exactly what type of transaction takes place. The household's vehicle holdings are updated accordingly, and these are used as inputs to the vehicle utilization model in Box D as well as starting values for the next period's forecast. The model outputs for each year accumulate the probabilities of all actions to the total numbers of vehicles owned or leased by type and vintage. For new vehicles, this represents market penetration.

Another important component is utilization (sub-model D.). It takes the updated vehicle holdings and household structure as inputs. It then predicts the annual vehicle miles traveled for each household vehicle. The usage forecasts are then converted to fuel demand by using average miles per gallon for liquid fuels and miles per equivalent gallons for non-liquid fuels. For electric vehicles, the utilization model also predicts the frequency of recharging at different times of day.

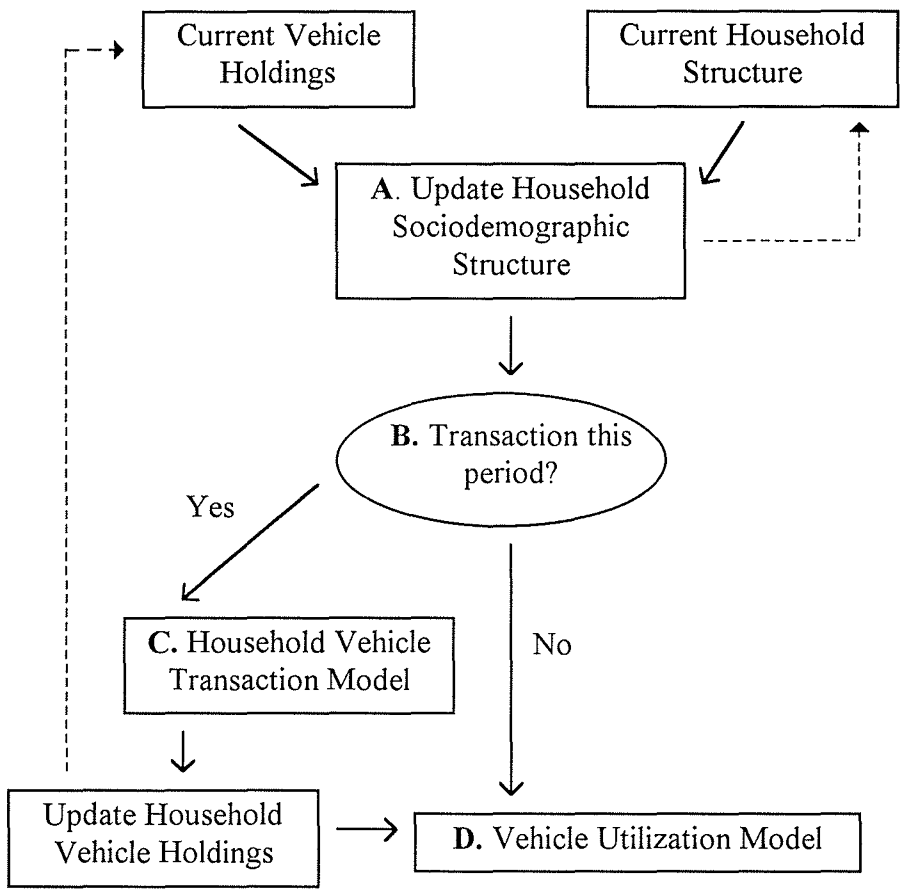
The focus in this paper is on the model represented by Box C in Figure 1.

## Literature Review

### *Alternative-fuel Vehicle Demand*

Most of the earlier studies on alternative fuel vehicle demand focused on demand for electric vehicles (EV's). One of the earliest relevant studies was SRI (1978), which used the model of Crow and Ratchford's (1977) to forecast total sales of electric vehicles in the United States. Crow and Ratchford's model forecasts the market shares based on vehicles' characteristics. SRI's forecast over-estimated electric vehicle demand by ignoring some important explanatory variables, particularly the limited range of electric vehicles and key vehicle ownership variables.

***Figure 1: Personal Vehicle Submodel***




Mathtech (Karfisi, Upton, and Agnew, 1978) forecasted electric vehicle demand by adapting a model in Wharton (1977). Their version of the Wharton model computes market shares for vehicle classes using an extended set of attributes designed to include features relevant to electric cars. It partially captures the dynamics of auto demand by adjusting to changes in key economic factors. However, only one household socioeconomic variable, household income, is included as an explanatory variable.

Beggs, Cardell and Hausman (1980) study the potential demand for EVs by applying an ordered logit model to stated preference data in which individuals provide rank orderings for hypothetical vehicle descriptions. Logit model coefficients are estimated for each individual rather than at the aggregated level, as is usual with most logit applications. They used 193 respondents from nine cities with warm climatic conditions who were primary drivers in multi-car households. Respondents are balanced by gender, trip purpose, age, income, and residence location. Drivers who exceed 50 miles per day were excluded. This study shows that because of limited range and long refueling time, there will be a very low potential demand for electric cars. Their findings also indicate that the average multi-vehicle household would pay from $2,000 to $6,000 to avoid the typical limitations of electric vehicles, with the exact amount depending on the characteristics of the electric car. Although an electric car has lower operating costs, their results show a high discount rate for the average consumer. They conclude that people are so concerned about limited vehicle range that EVs may not have a market unless the technology greatly improves.

Train (1980) uses a vehicle-type choice model (multinomial logit model), which was developed by Lave and Train (1978), to forecast the market share for several specific non-gasoline-powered automobiles: three types of battery-powered vehicles (nickel-zinc, high-temperature #1, and high-temperature #2), a hybrid gas and battery vehicle, a hydrogen vehicle, and a vehicle run by the reaction of aluminum into energy and oxidation products. Train develops a "most likely case" scenario, and concludes that, for this scenario, 2.3% of passenger autos will be battery-powered by the year 2000. These results are similar to Dickson and Walton's (1977): they estimated that 3.4 million electric vehicles would be sold from 1990 to 2000, or about 2.4 percent of all vehicles sales during that period.

Hensher (1982) focuses on the demand elasticities for electrical cars in Sydney, Australia. Individuals choose cars based on three attributes: gasoline price ($2, $3,

$4), the purchase price of an EV compared to a gasoline vehicle (30% lower, 20% lower, same, 20% higher, 30% higher), and the range of the EV (150km, 300km, 450km). Following the principles of factorial design (Hahn and Shapiro), 27 out of 45 combinations are remained. Respondents are required to rank order of the 27 combinations. Forty-five valid surveys received, giving 1215 valid cases. The result shows that when gasoline price is above $3 households will shift to EV's. His result also shows that multi-vehicle households are more likely than one-vehicle households to replace their holding vehicle by an electric vehicle.

Calfee (1985) studies only the potential private demand for electric autos (i.e., no trucks or vans), using discrete-choice SP data and a fully disaggregated logit model; that is, he applies the logit model for each individual, rather than pooling them together as is usually done. He can do this because each respondent was given 30 choices; in each choice the respondent chooses a gas vehicle or one of two different electric vehicles. The vehicles are characterized by price, operating cost, capacity in adult passengers, plus range and top speed for electric cars. He believes that using a fully disaggregated logit model can disclose "dirt" covered by the aggregate logit model. His sample is 51 church members in Berkeley, California who are multi-car owners. He claims that this sample, similar to Beggs et al's, is biased toward purchasing EVs. Calfee defines the utility function as a linear combination of EV dummy and other attributes. He estimates a positive coefficient for the electric vehicle dummy variable, which implies that respondents "tended to choose electric cars even when, according to their own revealed evaluations of attributes, the conventional car was more desirable" (p. 195). He also states that "[t]here remain at least three other possible reasons for a positive EV dummy. They are: (a) worries about gasoline, its price and, especially, its availability; (b) worries about the environment, along with a willingness to spend money to help preserve it; and (c) a simple 'bias' toward the new and, perhaps, trendy electric vehicles" (p. 196). He concludes that the market share is very limited, only about 2%.

The work described here was preceded by a study described in Bunch et al.

(1992). Bunch et al. (1992) employs nested multinomial logit models and multinomial probit models for vehicle choice and the binary logit model for fuel choice. However, they only present the result from the nested multinomial logit model. The number of observations is 3460, which is produced by five SP responses and 692 respondents. In this study, they use some squared and interaction terms. They present three vehicle-choice results: the SP choice model using vehicle fuel-specific attributes exclusively; the SP choice model with socioeconomic segmentation variables, and the SP choice model with vehicle-type and socioeconomic segmentation variables. They focus on interpreting the estimated attribute coefficients, so there is no EV demand forecasting. The coefficient values are as expected.

We see that these studies are characterized by small, potentially biased samples, or very limited information on household or vehicle attributes. Furthermore, due to the limitation of households' information, all the studies are based purely on respondents' stated preferences to alternative fuel vehicles, without considering their current vehicle holdings at all. This restriction is inappropriate since people make their future vehicle purchases based on their current holdings. Therefore, a larger detailed survey and a better forecasting model is needed. The model should combine SP data and RP data and also forecast SP vehicle choices conditioned on RP vehicle holdings.

### *Vehicle Holdings and Transaction Models*

There are many studies on vehicle holding and transactions: Farrell (1954), Janosi (1959), Kreini (1959), Huang (1964, 1966), Golob and Burns (1976), Johnson (1975, 1978), Lave and Train (1979), Lave and Bradley (1980), Train (1980a), Hocherman, Prashker, and Ben-Akiva (1982), Booz, Allen, and Hamilton, Inc. (1983), Hensher and Le Plastirer (1983), Mannering and Winston (1983), Winston and Mannering (1985), Berkovec and Rust (1985), Train (1986), Hensher, Barnard, Simith, and Milthorpe (1990), and Smith, Hensher, and Wrigley (1991). Mannering and Train

(1985) and Train (1986) have discussed and compared in detail most of the studies before 1986, so here we confine the review to Train (1986) and Hensher, et al. (1992).

Train (1986) develops a nested structure to model auto ownership and use. This model has several submodels: vehicle quantity submodel, class/vintage submodel for one-vehicle households, class/vintage submodel for two-vehicle households, annual VMT submodel for one-vehicle households, annual VMT submodel for each vehicle for two-vehicle households, submodel for the proportion of VMT in each category for one-vehicle households, and submodel for the proportion of VMT in each category for each vehicle for two-vehicle households.

Train's model has much in common with previous models: (1) it captures, by conditioning households' choices, the behavioral factors by estimating from a sample of households; (2) each household's choices depend on both the vehicle characteristics of each class/vintage (such as vehicle purchase price) and the household characteristics (such as household annual income); and (3) the model can be incorporated with 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 vehicles owned and the annual VMT for each vehicle class/vintage; (2) it explicitly shows the interdependence of a household's choice of how many vehicles to own and of which vehicle class/vintage to own; (3) it explicitly indicates that a household's choice of how many and what vehicle 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 for each make/model.

Although there is a transaction dummy in Train's vehicle type submodel, the model only explains which class/vintage vehicle a household owns at some points in time, without considering what the transaction is. The estimation is not conducted from both purchase and holding information but from holding information only. In the VMT submodel for two-vehicle households, Train's model treats independently the usage of the two vehicles in the same household; however, their usage is likely not independent.

Hensher, et al. (1992) and his colleagues (Hensher, Barnard, Simith, and Milthorpe, 1990, and Smith, Hensher, and Wrigley, 1991) extend the static discrete-choice model to incorporate temporal elements and develop a dynamic discrete choice sequence model. They apply this model to automobile transactions for households which had one vehicle in each of the four study periods. In each period, two choices are available for each household: replace a vehicle (R) or keep a vehicle (K). In this study, they illustrate their dynamic discrete choice model by assuming outcome sequences through time of the beta-logistic form and by using a four wave panel data set of household automobile transactions.

The static discrete choice model is developed by assuming a distribution on the unobserved component. The unobserved components are probably correlated over time for each individual, and there are time invariant individual effects. To reach a closed form solution for a static discrete choice model, the random component must be removed, and to circumvent the cumbersome integration of multivariate joint probability distribution, they develop a relatively tractable specification by decomposing the unobserved component into three additive elements. The transaction model only deals with households which have one vehicle in each of the four periods; that is, there are no adding and disposing transactions. It is also difficult to apply this model to multi-vehicle households, since probability has to be specified for the decision of which vehicle to keep and which vehicle to replace.

### *Combined Revealed Preference and Stated Preference*

Several studies have been conducted on the issue of stated preference (SP) and revealed preference (RP): Kroes and Sheldon (1988), Fowkes and Wardman (1988), Hensher, Barnard, and Truong (1988), Wardmand (1988), Louviere (1988), Ben-Akiva and Morikawa (1990), Hensher (1992), Bradley and Daly (1993), and Morikawa (1993).

The major contribution of Morikawa (1993) is correcting the state dependence and correlation in the RP/SP by linking error components of separate SP and RP equations. Fully jointly estimated SP/RP models are not generally available. The present model represents an attempt to link SP and RP choice information within a single choice model structure.

Although we will use both RP and SP information, we will not estimate RP and SP choices jointly, but estimate SP vehicle choices conditioned on current RP holdings. Since the model we build will be used for one-step dynamic forecasting, using a conditional model is appropriate. Also forecasting SP vehicle choices by conditioning on RP vehicle holdings can capture some heterogeneity existing in a household and also can avoid some possible bias problems.

## The Survey Data

The first wave of our personal vehicle panel survey was carried out in June and July, 1993. The sample was identified using pure random digit dialing and was geographically stratified into 79 areas covering most of the urbanized area of California. 7,387 households completed the initial computer-aided telephone interview (CATI). This initial CATI interview collected information on: household structure, vehicle inventory, housing characteristics, basic employment and commuting for all adults, and the next vehicle transaction.

The data from the initial CATI interview were used to produce a customized mail-out questionnaire for each sampled household. This questionnaire asked more detailed questions about each household member's commuting and vehicle usage, including information about sharing vehicles in multiple-vehicle and multiple-driver households. The mail-out questionnaire also contained two "stated preference" experiments for each household. Each of these experiments described three hypothetical vehicles, from which the households were asked to choose their preferred vehicle. These hypothetical vehicles included both alternative-fuel and gasoline vehicles, and the body types and prices were customized to be similar (but not identical) to the household's description of their next intended vehicle purchase.

After the households received the mail-out questionnaires, they were again contacted for a final CATI interview. This interview collected all the responses to the mail-out questions. Additional questions about the household's attitudes towards alternative-fuel vehicles were also included in this interview.

The 4747 households that successfully completed the mail-out portion of wave one of the personal vehicle survey in 1993 represent a 66% response rate among the households that completed the initial CATI survey. A comparison with Census data reveals that the sample is slightly biased toward home-owning larger households with higher incomes, and weights are being applied to balance the sample to the known population. Importantly, 18% of the surveyed households had more than one phone number, and 7% of the households shared a phone with at least one other household. These are important statistics in weighting the households to account for their probability of being selected in a random-digit-dialing sample.

Regarding vehicle ownership and use, 80% of the households in the sample had exactly one driver per vehicle, proving that, in California, the number of drivers is the most important determinant of the vehicle ownership level. For two vehicle households, a little over one-third of the vehicles are driven 10,000 miles per year or less, a third are driven 10,000 - 15,000 miles per year, and almost a third are driven more than 15,000 miles per year. Regarding long trips, 54% of these vehicles are driven on trips of 100 miles or more six or fewer times per year.

Another potential problem is whether households can accommodate a limited-range alternative-fuel vehicle that requires home recharging. Our survey results show that 16% of all households commute less than 30 miles per day round trip and also have a private garage or carport with electric service. 20% of all households commute less than 60 miles per day round trip and also have a private garage or carport with electric service. Finally, 21% commute less than 120 miles per day round trip and also have a private garage or carport with natural gas service nearby.

An example of the SP task on the questionnaire is given in Appendix A. There are four fuel-type vehicles: gasoline, compressed natural gas (CNG), methanol, and electric (EV). In the SP survey questions, each household is given three out of the four fuel-type vehicles. SP purchase prices and SP vehicle types are designed based on households intended spending and vehicle types. "The specific experimental design was chosen as a compromise among various competing objectives. The framework of three vehicles per choice set retained the possibility of estimating models which do not necessarily rely on the assumption of independence from irrelevant alternatives. This format required that levels be chosen for six or seven attributes per vehicle per choice set. In most cases four levels per attribute were used to cover the range of interest and to provide for estimation of nonlinear effects. The basic design used to produce the variation in attribute levels was an orthogonal main effects plan for a $4^{21}$ factorial in 64 runs" (Golob et al., 1993).

## Model Specification: SP Vehicle Choices Conditioned On RP Holdings

### *Dependent Variables*

We are modeling the future demand for vehicles of four fuel-types: gasoline, EV, CNG, and methanol. Each household may have three actions: adding, replacing, or disposing. For adding or replacing, a household must decide which vehicle to add; for replacing or disposing, a household must decide which vehicle to dispose of. In our survey design each household faces six vehicle choices with different fuel types, vehicle types, vehicle sizes, and other attributes. A household could have 13, 20, or 27 alternatives when its number of vehicles is 1, 2, or 3, respectively. For the present, zero-vehicle households are excluded, since there are only 53 households in the sample which own no vehicles.

We use the conditional logit model. McFadden (1974) defines the logit model above as a conditional logit model. "The main difference between the conditional logit model and the multinomial logit model is that the conditional logit model considers the effects of choice characteristics and the determinants of choice probabilities as well, whereas the MNL model makes the choice probabilities dependent on individual characteristics only" (Maddala, 1983, p. 42).

Figures 2, 3, and 4 depict the choice specification in the model. These tree structures suggest that the transactions should be modeled with a nested logit specification. Nested logit specifications were estimated for one-vehicle households and we found that the coefficient for each inclusive value is insignificantly different from one. Thus, the conditional multinomial logit model was used for both one- and two-vehicle households. We applied the Hausman test to verify the IIA property for both one- and two-vehicle households.

The specifications of the dependent variables for the one-, two-, and three-vehicle households are provided in Tables 1 through 3, respectively. The order of the 1st, 2nd, and 3rd vehicles corresponds to the order in which respondents entered their vehicles. The other of the 1st to 6th SP vehicles corresponds to the order on the survey form.

The estimates and forecasts described here do not distinguish between new and used SP vehicles. In the initial CATI interview we asked respondents whether they intended to purchase a new or used vehicle at their next transaction, and we also asked the price range for the vehicle purchased as part of the next transaction.

*Figure 2. One-Vehicle Household Transaction Tree*

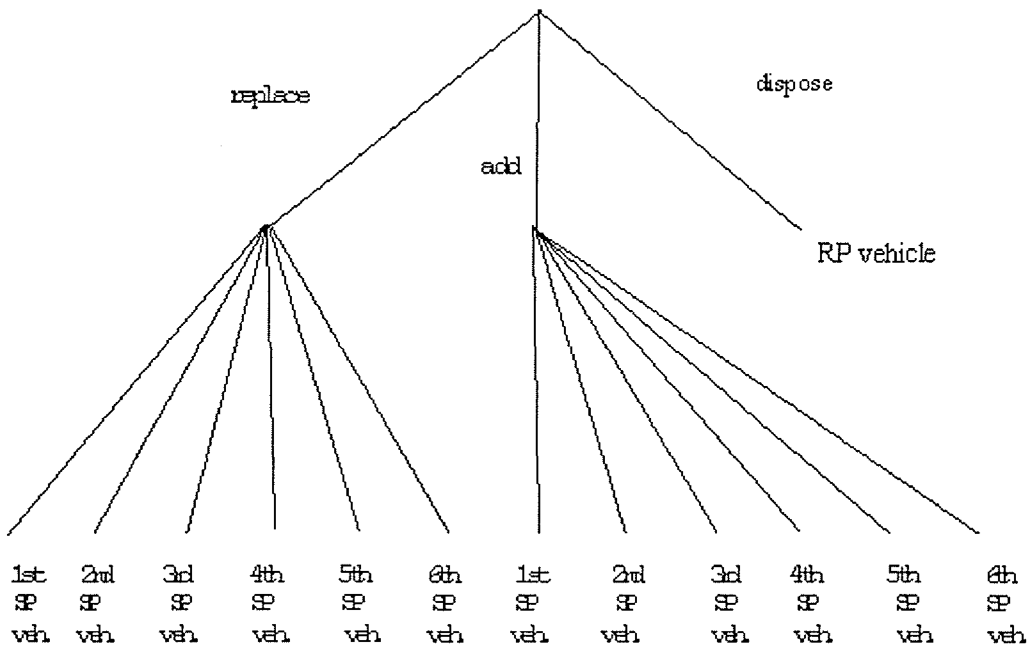


*Figure 3. Two-Vehicle Household Transaction Tree*

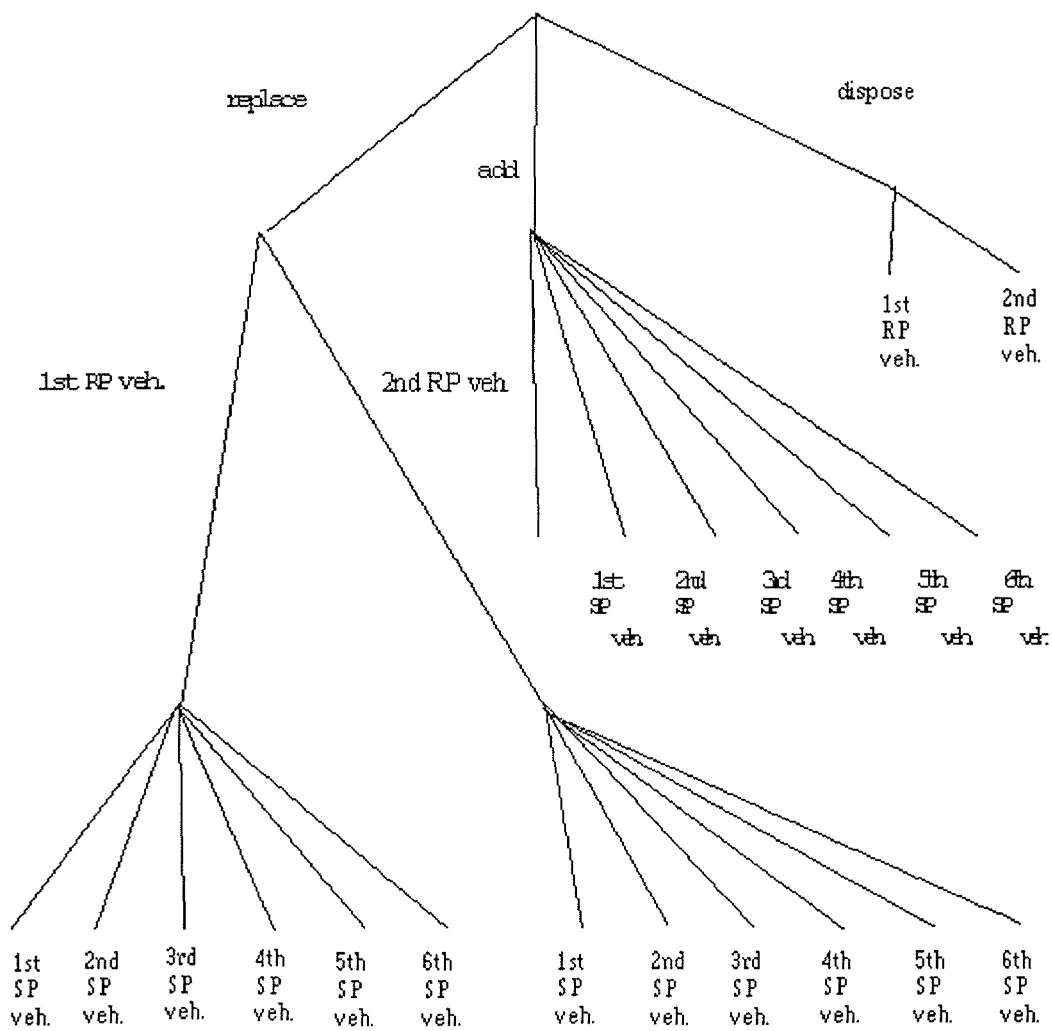
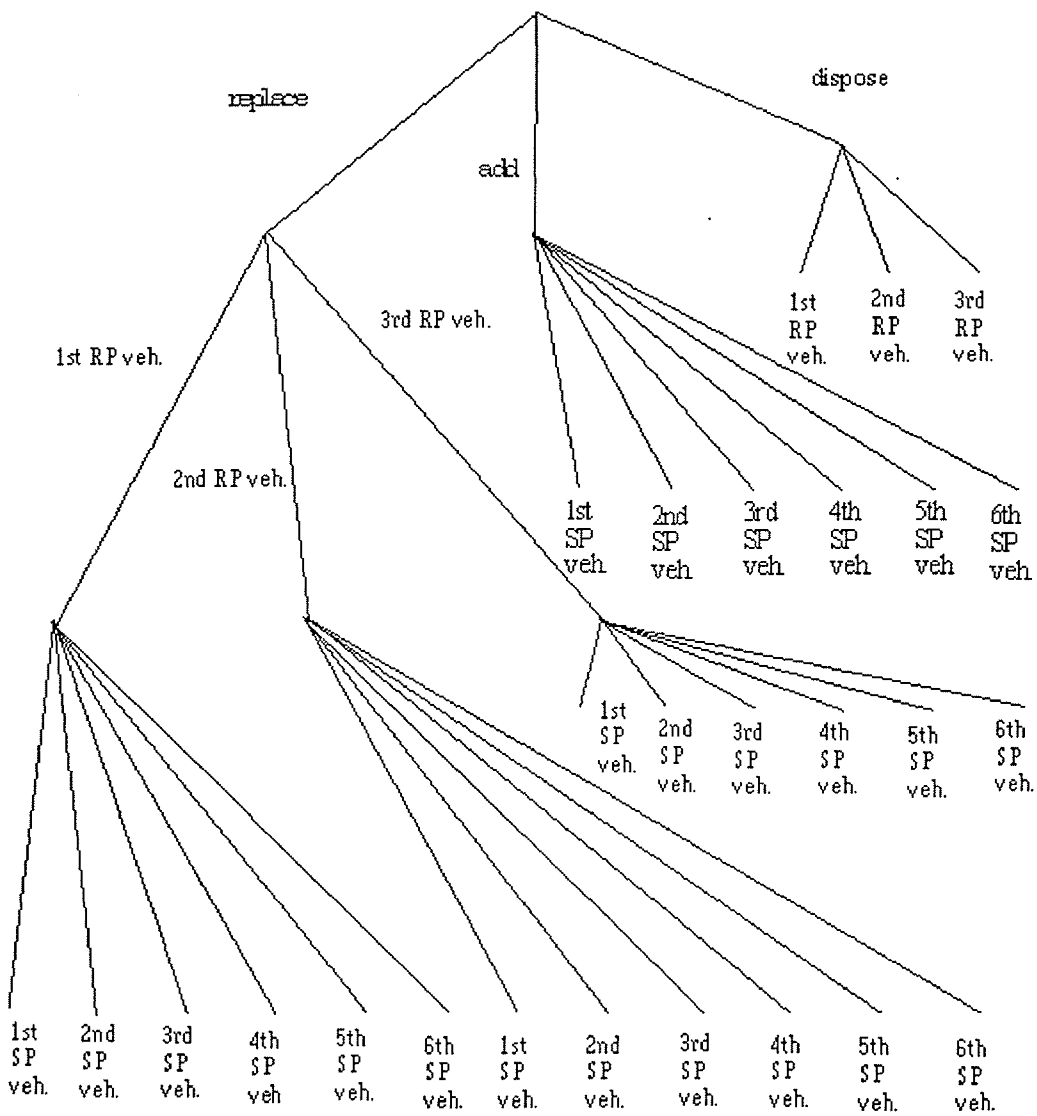


*Figure 4. Three-Vehicle Household Transaction Tree*



Future work will use these data to model the choice of new/used vehicles as well as the vintage of the used vehicles. However, preliminary tests did not find any significant differences in preferences between new and used vehicle purchasers.

**Table 1: The Dependent Variable for One-Vehicle Households**

| Value | Description |
|---|---|
| 1 | choose 1st SP vehicle to replace the holding vehicle |
| 2 | choose 2nd SP vehicle to replace the holding vehicle |
| 3 | choose 3rd SP vehicle to replace the holding vehicle |
| 4 | choose 4th SP vehicle to replace the holding vehicle |
| 5 | choose 5th SP vehicle to replace the holding vehicle |
| 6 | choose 6th SP vehicle to replace the holding vehicle |
| 7 | add 1st SP vehicle |
| 8 | add 2nd SP vehicle |
| 9 | add 3rd SP vehicle |
| 10 | add 4th SP vehicle |
| 11 | add 5th SP vehicle |
| 12 | add 6th SP vehicle |
| 13 | dispose of the holding vehicle |

### *The Independent Variables*

Since we are modeling the SP vehicle choices conditioned on current vehicle holdings, we, therefore, can decompose $X_{ij}$ in equation (2) into five parts

$$X_{ij} = X^{SP\text{-}RP}{}_{ij} + X^{RRP}{}_{ij} + X^{SP}{}_{ij} + X^{SPRP}{}_{ij} + X^{OT}{}_{ij}, \qquad (1)$$

where $X^{SP\text{-}RP}{}_{ij}$ are the variables indicating the differences between the SP data and RP data; $X^{RRP}{}_{ij}$ are the variables representing the attributes of the remaining holding vehicle; $X^{SP}{}_{ij}$ are the attributes of SP vehicles; $X^{SPRP}{}_{ij}$ are the variables interacting with SP data and RP data; and $X^{OT}{}_{ij}$ are other attributes. The above specification shows the idea of estimating SP vehicle choices conditioned on vehicle holdings. The computation of the independent variables is demonstrated by example.

**Table 2: Dependent Variable for Two-Vehicle Households**

| Value | Description |
|---|---|
| 1 | choose 1st SP vehicle to replace the 1st holding vehicle |
| 2 | choose 2nd SP vehicle to replace the 1st holding vehicle |
| 3 | choose 3rd SP vehicle to replace the 1st holding vehicle |
| 4 | choose 4th SP vehicle to replace the 1st holding vehicle |
| 5 | choose 5th SP vehicle to replace the 1st holding vehicle |
| 6 | choose 6th SP vehicle to replace the 1st holding vehicle |
| 7 | choose 1st SP vehicle to replace the 2nd holding vehicle |
| 8 | choose 2nd SP vehicle to replace the 2nd holding vehicle |
| 9 | choose 3rd SP vehicle to replace the 2nd holding vehicle |
| 10 | choose 4th SP vehicle to replace the 2nd holding vehicle |
| 11 | choose 5th SP vehicle to replace the 2nd holding vehicle |
| 12 | choose 6th SP vehicle to replace the 2nd holding vehicle |
| 13 | add 1st SP vehicle |
| 14 | add 2nd SP vehicle |
| 15 | add 3rd SP vehicle |
| 16 | add 4th SP vehicle |
| 17 | add 5th SP vehicle |
| 18 | add 6th SP vehicle |
| 19 | dispose of the 1st vehicle |
| 20 | dispose of the 2nd vehicle |

Table 3: Dependent Variable for Three-Vehicle Household

| Value | Description |
|---|---|
| 1 | choose 1st SP vehicle to replace the 1st holding vehicle |
| 2 | choose 2nd SP vehicle to replace the 1st holding vehicle |
| 3 | choose 3rd SP vehicle to replace the 1st holding vehicle |
| 4 | choose 4th SP vehicle to replace the 1st holding vehicle |
| 5 | choose 5th SP vehicle to replace the 1st holding vehicle |
| 6 | choose 6th SP vehicle to replace the 1st holding vehicle |
| 7 | choose 1st SP vehicle to replace the 2nd holding vehicle |
| 8 | choose 2nd SP vehicle to replace the 2nd holding vehicle |
| 9 | choose 3rd SP vehicle to replace the 2nd holding vehicle |
| 10 | choose 4th SP vehicle to replace the 2nd holding vehicle |
| 11 | choose 5th SP vehicle to replace the 2nd holding vehicle |
| 12 | choose 6th SP vehicle to replace the 2nd holding vehicle |
| 13 | choose 1st SP vehicle to replace the 3rd holding vehicle |
| 14 | choose 2nd SP vehicle to replace the 3rd holding vehicle |
| 15 | choose 3rd SP vehicle to replace the 3rd holding vehicle |
| 16 | choose 4th SP vehicle to replace the 3rd holding vehicle |
| 17 | choose 5th SP vehicle to replace the 3rd holding vehicle |
| 18 | choose 6th SP vehicle to replace the 3rd holding vehicle |
| 19 | add 1st SP vehicle |
| 20 | add 2nd SP vehicle |
| 21 | add 3rd SP vehicle |
| 22 | add 4th SP vehicle |
| 23 | add 5th SP vehicle |
| 24 | add 6th SP vehicle |
| 25 | dispose of the 1st vehicle |
| 26 | dispose of the 2nd vehicle |
| 27 | dispose of the 3rd vehicle |

**Example 1. One vehicle household**

*a. Net capital cost ($X^{SP\text{-}RP}_{ij}$)*

i. For replacing: alternatives 1 - 6;

= SP vehicle price - current market value of the holding vehicle

ii. For adding: alternatives 7 - 12;

= SP vehicle price

iii. For disposing: alternative 13;

= - current market value of the holding vehicle

*b. Value of the remaining vehicle* ($X^{RRP}{}_{ij}$)

i. For replacing: alternatives 1 - 6

= 0

ii. For adding: alternatives 7 - 12

= current market value of the holding vehicle

iii. For disposing: alternative 13

= 0

**Example 2. Two-vehicle household**

*a. Net capital cost* ($X^{SP\text{-}RP}{}_{ij}$)

i. For replacing: alternatives 1 - 6

= SP vehicle price - current market value of the *1st* holding vehicle

ii. For replacing: alternatives 7 - 12

= SP vehicle price - current market value of the *2nd* holding vehicle.

iii. For adding: alternatives 13 - 18

= SP vehicle price

iv. For disposing: alternative 19

= - current market value of the *1st* holding vehicle

v. For disposing: alternative 20

= - current market value of the *2nd* holding vehicle

*b. Value of the remaining vehicle* ($X^{RRP}{}_{ij}$)

i. For replacing: alternatives 1 - 6

= current market value of the *2nd* holding vehicle

ii. For replacing: alternatives 7 - 12

= current market value of the *1st* holding vehicle

iii. For adding: alternatives 13 - 18

= sum of current market values of the *1st* and the *2nd* vehicles

iv. For disposing: alternatives 19

= current market value of the *2nd* holding vehicle

v. For disposing: alternative 20

= current market value of the *1st* holding vehicle

Net capital cost and value of the remaining holding vehicles is generated in the same way for three-vehicle households.

The same procedure applies to the calculation of operating costs. The only difference, say for a one-vehicle household, is that for alternative 13 the difference is set to zero since after disposing of the holding vehicle, a household bears zero operating costs. The same procedure can also apply to top-speed and acceleration time.

The rationale for using these net benefit/cost variables is that a household not only compares the net gain or loss of a transaction, but also takes the benefit/cost left over from former holdings into account since this value does contribute to their utility. In other words, different remaining vehicles have different values to a household, so the utility function has to include this factor.

The independent variables are listed in Table 4. These variables are either used directly or in interaction terms.

**Table 4: The Independent Variables**

| Household attributes | Vehicle Attributes |
|---|---|
| 1. Household size | 24. Model Year of holding vehicles |
| 2. Number of drivers | 25. Body type of holding vehicles |
| 3. Number of vehicles | 26. Class of holding vehicles |
| 4. Age of all household members | 27. VMT of holding vehicles |
| 5. Sex of all household members | 28. Market value of holding vehicles |
| 6. Household income | 29. MPG of holding vehicles |
| 7. Number of workers | 30. Top-speed of holding vehicles |
| 8. Number of part-time workers | 31. Acceleration time of holding vehicles |
| 9. Number of full-time workers | 32. Acceleration time of SP vehicles |
| 10. HH type: couple only | 33. Dual-fuel possibility of SP vehicles |
| 11. HH type: couple + kid(s) (1 - 5) | 34. Fuel-type of SP vehicles |
| 12. HH type: couple + kid(s) (6 - 15) | 35. Home-fuel cost of SP vehicles |
| 13. HH type: couple + kid(s) (16 - 20) | 36. Home-fuel time of SP vehicles |
| 14. HH type: couple + kid(s) + other adult | 37. Home-fuel availability of SP vehicles |
| 15. HH type: single parents | 38. Luggage space of SP vehicles |
| 16. HH type: couple + other adult (no kids) | 39. Pollution level of SP vehicles |
| 17. HH type: single person | 40. Price of SP vehicles |
| 18. HH type: multi-adult | 41. Range of SP vehicles |
| 19. Household weight | 42. Service station fuel cost of SP vehicles |
| 20. Residence location, LA area | 43. Service station refueling time: SP vehicles |
| 21. Residence location, SF area | 44. Service station availability of SP vehicles |
| 22. Residential location, north non-San Francisco (Bay) Area | 45. Top speed of SP vehicles |
| 23. Residence location, south non-Los Angeles Area | 46. Vehicle size of SP vehicles |
| | 47. Vehicle type of SP vehicles |

### *Testing the Independence of Irrelevant Alternatives*

Using the MNL specification to model the transaction above, the basic assumption is that the disturbances are independent. To test the validity of the assumption versus the nested logit specification, Hausman and McFadden (1984) show that if a subset of the choices is irrelevant, eliminating it from the model will not systematically affect the estimates. However, excluding these choices will be inefficient. The irrelevancy is the basis for Hausman's specification test. The test is constructed as follows:

$$\chi^2 = (\hat{\beta}_r - \hat{\beta}_u)'[\hat{V}_r - \hat{V}_u]^{-1}(\hat{\beta}_r - \hat{\beta}_u), \tag{2}$$

where $r$ represents the estimators for the restricted subset, $u$ represents the estimators for the full set of choices, $\beta$ is the coefficient estimate, and $V$ is the estimate of the asymptotic covariance matrix. The statistic is asymptotically distributed as chi-squared with $K$ degrees of freedom, where *K is the rank of the weight matrix in the above expression.*

Note that in this test after the choices are eliminated, some explanatory variables which are interacted with the eliminated alternatives are always zero. So, we can only use the remaining variables to do the test.

## *Forecasting Methodology*

Forecasts are generated using sample enumeration, and confidence bands for the forecasts are generated by parametric bootstrapping as described below:

Step 1. Estimate the coefficients ($\beta$) by using the sample.

Step 2. Set up the scenarios for the year to be forecast.

Step 3. Apply the results from step 1 to scenarios from step2, then calculate the probability of individual $i$ choosing alternative $j$.

Step 4. Use the equation below to get a consistent estimate of the average probability of choosing alternative $j$ in the population:

$$\hat{P}_{ij} = \frac{1}{N_p}\sum_{i=1}^{N} w_i P_{ij}, \tag{3}$$

where $\hat{P}_{ij}$ is the forecast or the average probability of choosing alternative $j$ in the population; $N_p$ is the population size; $N$ is the sample size; $w$ is the individual weight; and $P_{ij}$ is the probability of individual $i$ choosing alternative $j$.

Step 5. Apply the bootstrapping technique to the result from step 4; that is, based on initial $\beta$ and variance and covariance matrix of $\beta$, randomly draw $\beta$ hundreds or thousands of times to recalculate $\hat{P}_{ij}$. Then the median and the 90% confidence bounds of $\hat{P}_{ij}$ can be calculated.

Step 6. Forecast a particular fuel-type vehicle. As we know, choice in the model is for a transaction: replacing, adding, and disposing. So, to calculate the probability of demand for a particular fuel-type vehicle, we should add the probability of adding to the probability of replacing.

## Estimation Results

Of 1607 one-vehicle households, 2220 two-vehicle households and 624 three-vehicle households, 1153, 1156, and 169 valid observations remain. The reduction in size of the sample is due to missing or incorrect data, primarily household income and vehicle year/make/model. Due to the small valid sample size for three-vehicle households, in this paper we estimate and forecast for only one- and two-vehicle households. The model year of the vehicles goes back to 1979. Estimation results are obtained by using the first set of SP data.

For easy comparison, we will first list the results of one- and two-vehicle households, and then analyze and compare the results. Since this model is used for forecasting, more explanatory variables than usual are included.

In the tables below, HH stands for household; K stands for $1,000; # stands for number; and a dummy takes the value 1 when the condition is met, otherwise it is zero.

The estimation results for the sample of one-vehicle households are listed in Table 5. The Hausman test was conducted for one-vehicle households by excluding the replacement alternatives. At 95% significance level, we cannot reject $H_0$ of IIA; that is, the MNL specification is correct.

The two-vehicle household estimation results are listed in Table 6. The Hausman test was also conducted for two-vehicle households by excluding the replacement alternatives. At 95% significance level, we cannot reject $H_0$ of IIA; that is, the MNL specification is correct.

## *Interpretation of Results*

### Net capital cost

The net capital cost is the difference between the price of the SP vehicle and the current market value of the holding vehicle. As implied by the formulae discussed in the model specification, the net capital cost shows the net amount of money people have to spend for their transaction.

Table 5 shows that the net capital cost for one-vehicle households with annual income less than $75,000 has, as we expect, a negative sign. For households with annual income greater than $76,000 the coefficient for net capital cost is insignificant.

## Table 5: Estimation Results for One-Vehicle Households

| Explanatory variables | coefficient | t-value |
|---|---|---|
| Net capital cost (HH income<=30K, HH has a child of age<21) [*] | -0.00003290 | -1.1 |
| Net capital cost (HH income<=30K, HH has no child of age<21) [*] | -0.00006952 | -3.8 |
| Value of the remaining vehicle (HH income<=30K) [*] | 0.00008264 | 2.4 |
| Net capital cost (31K<=HH income<=75K, HH has no children<21) [*] | -0.00003925 | -2.5 |
| Value of the remaining vehicle (31K<=HH income<=75K) [*] | 0.00003080 | 1.3 |
| Net capital cost (76K<=HH income, HH has a child of age<21) [*] | -0.00005253 | -1.5 |
| Net capital cost (76K<=HH income, HH has no child of age<21) [*] | 0.00002766 | 1.3 |
| Net operating cost(HH income<=30K, HH has a child of age<21) [**] | -0.008119 | -0.2 |
| Net operating cost (HH income<=30K, HH has no child of age<21 [**] | -0.08003 | -3.3 |
| Operating cost of the remaining vehicle (HH income<=30K) [**] | -0.03190 | -0.6 |
| Net operating cost (31K<=HH income <=75K, HH has a child of age<21) [**] | -0.1137 | -3.1 |
| Net operating cost (31K<=HH income <=75K, HH has no child of age<21) [**] | -0.07709 | -3.4 |
| Net operating cost (76K<= HH income, HH has no child of age<21) [**] | -0.1252 | -2.4 |
| Top-speed difference between the SP vehicle and the holding vehicle | 0.0008844 | 0.5 |
| Acceleration time diff. between the SP vehicle and the holding vehicle [***] | -0.03713 | -1.6 |
| Refueling time of the SP vehicle | -0.0005721 | -0.9 |
| Range of the SP vehicle | 0.006191 | 2.7 |
| Range$^2$ of the SP vehicle | -0.000005299 | -1.0 |
| Service station availability for EV [†] | 0.5736 | 1.2 |
| Service station availability for dedicated CNG vehicle [†] | 1.004 | 2.3 |
| Service station availability for methanol vehicle and dual fuel CNG vehicle | 0.2995 | 1.3 |
| Luggage space of SP vehicle [††] | 0.6246 | 1.8 |
| Dual fuel (dummy) | 0.2780 | 1.3 |
| Pollution level of SP vehicle, for HH *with* child of age<21 [†††] | -0.5397 | -1.8 |
| Pollution level of SP vehicle, for HH *without* child of age<21 [†††] | -0.4637 | -2.1 |
| Van (HH size<=3) (dummy) | -0.7891 | -3.4 |
| Van (HH size>=4) (dummy) | 0.7851 | 2.4 |
| EV (Northern Calif. w/o SF, Oakland, San Jose) (dummy) | -0.1714 | -0.6 |
| EV*Subcompact (dummy) | 0.2307 | 0.8 |
| EV*Compact car (dummy) | 0.2501 | 1.1 |
| EV*Large (dummy) | 0.4355 | 1.8 |
| EV*Station Wagon (dummy) | -0.4104 | -1.3 |
| EV*Sport car (dummy) | 0.3840 | 0.9 |
| EV*Van (dummy) | -0.3092 | -0.9 |
| EV*Truck (dummy) | -1.042 | -3.3 |
| EV*Utility vehicle (dummy) | 0.3604 | 0.8 |
| CNG*Mid-size car (dummy) | 0.05368 | 0.3 |
| CNG*Large car (dummy) | -0.2283 | -1.1 |
| CNG*Station Wagon (dummy) | -0.8535 | -3.0 |
| CNG*Van (dummy) | 0.6419 | 2.2 |

| | | |
|---|---|---|
| CNG*Utility (dummy) | 2.004 | 6.0 |
| CNG*Sport car (dummy) | 1.011 | 3.0 |
| Methanol*Mid-size car (dummy) | 0.1497 | 0.9 |
| Gasoline (dummy) | 0.5947 | 2.0 |
| Gasoline*Subcompact (dummy) | -0.1309 | -0.5 |
| Gasoline*Mini (dummy) | -1.180 | -2.0 |
| .Gasoline*Compact (dummy) | -0.3851 | -1.5 |
| Gasoline*Mid-size car (dummy) | -0.3255 | -1.3 |
| Gasoline*Station Wagon (dummy) | -0.4900 | -0.6 |
| Gasoline*Van (dummy) | 0.05017 | 0.2 |
| Gasoline*Sport (dummy) | 1.553 | 4.6 |
| Gasoline*Utility (dummy) | 0.5034 | 1.4 |
| Gasoline*Truck (dummy) | -1.063 | -4.5 |
| New holding--two vans (dummy) | -0.9030 | -1.2 |
| New holding--two trucks (dummy) | 0.7444 | 1.3 |
| New holding--two utility vehicles (dummy) | -0.4545 | -0.4 |
| New holding--two station wagons (dummy) | -0.4900 | -0.6 |
| New holding--two cars (dummy) | 0.1738 | 0.4 |
| Alternative-add constant for HH with # cars < # drivers (dummy) | 1.183 | 3.1 |
| Alternative-add constant for HH, with children 15 or 16 years old (dummy) | 0.7204 | 1.7 |
| Alternative-add constant for HH with holding vehicle's type different from the SP vehicle's type | -0.1999 | -0.5 |
| Alternative-replace constant for HHs with # cars >= # drivers (dummy) | 0.2207 | 0.6 |
| Alternative-replace constant (replacing station wagon by van) (dummy) | 0.6097 | 1.3 |
| Alternative-replace constant for HHs with holding vehicle's type the same as SP vehicle's (dummy) | 1.453 | 14.6 |
| Alternative-dispose constant for Hhs with at least one member's age>=60 | 1.359 | 3.8 |
| Number of observations | 1153 | |
| Initial Likelihood | -2957.3866 | |
| Final Likelihood | -2349.0719 | |
| "Rho-Squared" w.r.t. Zero | 0.2057 | |

* 1993 U.S. dollar.
** For EV, using home-refueling cost and home-refueling time. The unit for cost is cent/mile and the unit for refueling time is minute. The gasoline price is assumed 120 cents/gallon.
*** The time from 0 to 30 mph.
† It is the proportion of service stations which carry the fuel.
†† It takes the value of 1 (same size as RP vehicle) or .7 (30% smaller than RP vehicle).
††† It takes the value of 1 (1993 gasoline vehicle), or 0.4, 0.25, or 0 (for other alternative-fuel vehicles).

## Table 6: Estimation Results for Two-Vehicle Households

| Explanatory variables | Coefficient | t-value |
|---|---|---|
| Net capital cost (HH income<=30K, HH has a child of age<21) [*] | -0.0000706 | -1.5 |
| Net capital cost*(HH income<=30K, HH has no child of age<21) [*] | -0.0000288 | -0.7 |
| Value of the remaining vehicle (HH income<=30K) [*] | 0.0001215 | 2.2 |
| Net capital cost (31K<=HH income,HH has a luxury vehicle and a child of age<21) [*] | 0.0000220 | 1.4 |
| Net capital cost (31K<=HH income, HH has a luxury vehicle and no child of age<21) [*] | 0.0000211 | 1.8 |
| Net capital cost (31K<=HH income, HH has no luxury vehicle, but a child of age<21) [*] | -0.0000174 | -1.0 |
| Net capital cost (31K<=HH income, HH has no luxury vehicle and no child of age<21) [*] | -0.0000411 | -2.7 |
| Value of the remaining vehicle (31K<=HH income, HH has no luxury vehicle) [*] | 0.0001512 | 5.8 |
| Net operating cost (HH income<=30K, HH has a child of age<21) [**] | -0.01004 | -0.2 |
| Net operating cost (HH income<=30K, HH has no child of age<21) [**] | -0.03318 | -0.8 |
| Net operating cost (31K<HH income, HH has a luxury vehicle and a child of age<21) [**] | -0.08157 | -1.5 |
| Net operating cost (31K<=HH income, HH has a luxury vehicle and no child of age<21) [**] | -0.08467 | -1.9 |
| Operating cost of the remaining vehicle (31K <=HH income, HH has a luxury vehicle) [**] | 0.1963 | 3.1 |
| Net operating cost (31K<=HH income, HH has no luxury vehicle, but a child of age<21) [**] | -0.08214 | -3.3 |
| Net operating cost (31K<=HH income, HH has no luxury vehicle and no child of age<21) [**] | -0.08404 | -3.5 |
| Operating cost of the remaining vehicle (31K<=HH income, HH has no luxury vehicle) [**] | -0.01627 | -0.4 |
| Top-speed difference between the SP vehicle and the holding vehicle | 0.002398 | 1.6 |
| Acceleration time difference between the SP vehicle and the holding vehicle (HH income<=30K) [***] | 0.08322 | 1.6 |
| Acceleration time of the remaining vehicle (HH income<=30K) [***] | -0.2512 | -1.4 |
| Acceleration time difference between the SP vehicle and the holding vehicle (HH income>=31K) [***] | -0.08143 | -3.4 |
| Acceleration time of the remaining vehicle (HH income>=31) [***] | -0.1905 | -1.8 |
| Refueling time of the SP vehicle | -0.0004997 | -0.8 |
| Range of the SP vehicle | 0.005088 | 2.2 |
| $Range^2$ of the SP vehicle | -0.00000127 | -0.2 |
| Service station availability for EV [†] | 0.5846 | 1.3 |

| | | |
|---|---|---|
| Service station availability for dedicated CNG vehicle w/o home-refueling † | 0.7408 | 1.5 |
| Service station availablity for dedicated CNG vehicle w/ home-refueling† | 0.6312 | 1.2 |
| Luggage space of SP vehicle †† | 0.4897 | 1.4 |
| Dual fuel (dummy) | 0.1136 | 0.8 |
| Pollution level of SP vehicle for HH *with* child of age<21 ††† | -0.2453 | -1.1 |
| Pollution level of SP vehicle for HH *without* child of age<21 ††† | -0.02630 | -0.1 |
| Van (HH size<=3) (dummy) | -0.07966 | -0.4 |
| Van (HH size>=4) (dummy) | 0.9119 | 4.7 |
| EV*(LA & Orange Counties) (dummy) | -0.4391 | -1.9 |
| EV*(S.F., Oakland, San Jose) (dummy) | -0.2549 | -1.1 |
| EV*(Northern Calif. w/o SF, Oakland, and San Jose (dummy) | -0.1064 | -0.4 |
| EV*(Subcompact, Mini, Compact Cars) (dummy) | 0.3935 | 1.7 |
| EV*Mid-size car (dummy) | 0.6481 | 2.6 |
| EV*Sport car (dummy) | 0.4521 | 1.0 |
| EV*Van (dummy) | -0.4435 | -1.7 |
| EV*Truck (dummy) | -0.7238 | -2.8 |
| EV*Utility vehicle (dummy) | 0.3357 | 0.8 |
| CNG*Station Wagon (dummy) | -0.9945 | -3.3 |
| CNG*Van (dummy) | -0.2642 | -1.1 |
| CNG*Truck (dummy) | -0.6307 | -2.6 |
| CNG*Utility (dummy) | 0.8466 | 2.7 |
| CNG*Sport car (dummy) | 0.8092 | 2.0 |
| Methenol*Subcompact car (dummy) | -0.1107 | -0.5 |
| Gasoline*Subcompact (dummy) | -0.2140 | -0.9 |
| Gasoline*Mini (dummy) | 0.7479 | 1.2 |
| Gasoline*Compact (dummy) | -0.1091 | -0.6 |
| Gasoline*Large car (dummy) | -0.2788 | -1.3 |
| Gasoline*Station Wagon (dummy) | -0.9993 | -3.3 |
| Gasoline*Van (dummy) | -0.3276 | -1.4 |
| Gasoline*Sport (dummy) | 0.1597 | 0.4 |
| Gasoline*Utility (dummy) | 0.7747 | 2.6 |
| Gasoline*Truck (dummy) | -0.3948 | -2.1 |
| New holding--two or more vans (dummy) | -0.5580 | -1.9 |
| New holding--two or more trucks (dummy) | -0.07972 | -0.3 |
| New holding--two or more utility vehicles (dummy) | -0.2514 | -0.5 |
| New holding--two or more station wagons (dummy) | -0.3542 | -0.7 |
| New holding--two or more cars (dummy) | 0.2489 | 2.5 |
| Alternative-add constant for Hhs with # cars < # drivers (dummy) | 0.3763 | 1.1 |
| Alternative-add constant for Hhs with a child 15 or 16 years old (dummy) | 0.8745 | 2.6 |
| Alternative-add constant for Hhs with holding vehicle's type different from the SP vehicle's type | -0.4368 | -2.6 |
| Alternative-replace constant for HHs with # cars >= # drivers (dummy) | 1.037 | 3.9 |
| Alternative-replace constant * (Lower value vehicle) (dummy) | 0.3618 | 3.7 |

| | | |
|---|---|---|
| Alternative-replace constant * (Replacing Station wagon by van) (dummy) | 0.6508 | 2.0 |
| Alternative-replace constant for HHs with holding vehicle's type the same as SP vehicle's (dummy) | 1.001 | 12.5 |
| Alternative-dispose constant for Hhs with at least one member's age>=60 | 1.447 | 3.7 |
| Number of observations<br>Initial Likelihood<br>Final Likelihood<br>"Rho-Squared" w.r.t. Zero | 1156<br>-3463.0665<br>2880.1143<br>0.1683 | |

* 1993 U.S. dollar.
** For EV, using home-refueling cost and home-refueling time. The unit for cost is cent/mile and the unit for refueling time is minute. The gasoline price is assumed 120 cents/gallon.
*** The time from 0 to 30 mph.
† It is the proportion of service stations which carry the fuel.
†† It takes the value of 1 (same size as RP vehicle) or .7 (30% smaller than RP vehicle).
††† It takes the value of 1 (1993 gasoline vehicle), or 0.4, 0.25, or 0 (for other alternative-fuel vehicles).

For the two-vehicle households with annual income less than $30,000, the results are very similar to the one-vehicle results in that both have a negative sign. However, for the two-vehicle households with income greater than $31,000, the result varies significantly between households with and without luxury cars. The households without luxury cars behave more like "rational" people in that they demand less when the price is high. The households with luxury cars, however, prefer high-priced vehicles as reflected in the positive and significant coefficient. This result implies that there is a "name-plate" effect; that is, some people not only buy a vehicle but also buy status. This specification--with and/or without luxury vehicles--does capture some unobservable characteristics existing in the households.

Both results also show the big variation in coefficients for households with and without children under 21. This variation captures the difference for households with and without children under 21, although it is not clear in which direction the coefficient should vary.

**Net operating cost**

The net operating cost is the difference between the operating cost of the SP vehicle and the operating cost of the holding vehicles. As indicated by the formulae, which were discussed in the model specification, the net operating cost shows the net amount of money that people have to spend when they use the chosen vehicle.

Except the two-vehicle households with luxury cars, the coefficients of net operating costs for both one- and two-vehicle households have the expected negative sign. For two-vehicle households with luxury cars and with income greater than $31,000, the coefficient for net operating cost is positive and significant, as it was for net capital cost; that is, those high-income households with luxury cars behave "irrationally". Coefficients vary according to household income and with/without children under 21. Still, the direction of variation cannot be explained.

**Value and operating cost of the vehicles in the resulting household fleet**

The remaining vehicles are the remaining holding vehicles after a household's transaction. Since the value of the remaining vehicles is an asset to a household, the coefficient should have a positive sign. The estimation does support this expectation.

However, the operating cost of the remaining vehicle is still a cost or negative value to a household, so the sign of the coefficient should be negative. The estimation also supports this expectation. The coefficient of the value and the coefficient of operating cost of the remaining vehicle each varies with households' income and with/without children under 21. However, we can not foretell in which direction the coefficient should vary.

### Top speed and acceleration time

The coefficients of the difference in top-speed have expected positive signs for both one- and two-vehicle households. However, the coefficient does not show significance for the one-vehicle household, and has a t-statistic of 1.6 for the two-vehicle household.

For the one-vehicle households, the coefficient of the difference in acceleration has a t-statistic of -1.6 and an expected sign, negative.

For the two-vehicle households, the coefficient for a household with income of $30,000 or less has a positive sign, and the coefficient for income of $31,000 or higher has an expected negative sign and is significant. Although it is not clear why the coefficient for a low-income household is positive, this does show that a low-income household, in contrast to a high-income household, does not care too much about acceleration time.

For a two-vehicle household, acceleration time of the remaining vehicle for low- and high-income households is specified. Acceleration time and operating cost of the remaining vehicle are similar in that they both have a negative value to a household. So, the negative and significant coefficients are expected.

### Refueling time

Refueling time is service station refueling time for a non-EV and home-refueling time for an EV. For both one- and two-vehicle households the coefficients of refueling time have the expected signs, but are not significant. The reason is that people can recharge an EV at home, so the refueling time does not matter too much.

### Vehicle Range

As expected, the coefficient of range for both one- and two-vehicle households has a positive sign and is significant. This implies that the range is a very important factor when households buy an alternative-fuel vehicle. The coefficient for $(\text{range})^2$ has a negative sign and is not significant. Although the coefficients of $(\text{range})^2$ are not significant for both one- and two-vehicle households, the implication is important: the increase in value from increasing vehicle range declines.

**Service station availability**

For both one-vehicle and two-vehicle households, the service station availability coefficients have the expected positive signs and their *t*-statistics range from 1.2 to 2.3. For two-vehicle households the coefficient for dedicated CNG vehicles without home-refueling is, as expected, the largest. For one-vehicle households service station availability for dedicated CNG vehicles with and without home-refueling have the same value, so they are combined. For two-vehicle households, this coefficient is significant and relatively large in magnitude.

**Emissions level**

For both one- and two-vehicle households, these two coefficients have expected negative signs and are significant. Also, as expected, the coefficient for households with children has a larger negative value than that of households without children. Especially, for two-vehicle households, the coefficient for households with children under 21 years of age is almost 10 times greater than that of households without children.

**Vehicle and fuel-type interactions**

There are many interaction variables between vehicle type and fuel type in both one- and two-vehicle models. To summarize, the results show that for the alternative-fuel vehicles, people are generally more likely to buy electric cars, as opposed to electric light-duty trucks and vans, and they are more likely to buy CNG utility and sport utility vehicles.

One-vehicle households generally prefer a gasoline vehicle to other alternative-fuel vehicles. For two-vehicle households this coefficient is zero; that is, for two-vehicle households a gasoline vehicle has no special advantage over other alternative-fuel vehicles.

**Vehicle type = vans**

For both one- and two-vehicle households, the coefficients of van dummies for household size greater than 3 are significant and have expected positive signs. This result implies that households with 4 or more people will more likely buy a van.

For one-vehicle households with size less than 4, the coefficient has an expected negative sign and is significant. For two-vehicle households the coefficient has an expected negative sign, but is not significant. This difference between one- and two-vehicle households implies that for households with 3 or fewer people the value of a van is much less for a one-vehicle household than for a two-vehicle household.

**Holdings of two or more vehicles of the same type**

When a household decides to add a vehicle, a one-vehicle household will become a two-vehicle household and a two-vehicle household will become a three-vehicle household. We generally expect a household to have two or more cars, but not two or more special vehicles, such as two vans. For one-vehicle households, these coefficients are not significant, but it is hard to understand why the coefficient for new-holding-two-trucks has a positive sign. For two-vehicle households, all the signs of the coefficients are expected. The coefficients for new-holding-two-or-more-vans and for new-holding-two-or-more-cars are significant.

**Households adding vehicles**

For both one- and two-vehicle households, coefficients associated with adding vehicles in households with numbers of vehicles less than the number of drivers, and in households with children 15 or 16 years old, have the expected positive signs and have t-statistics ranging from 1.1 to 3.1. Obviously, when a household has more drivers than cars, or has a child 15 or 16 years old, close to or in the legal driving age, the household will more likely plan to add a car.

The coefficient associated with households in which the holding vehicle's type is different from the SP vehicle's type variable is designed to determine if a household would like to add a vehicle which is different in type from the holding vehicle. For one-vehicle households the coefficient is negative and not significant, which implies that one-vehicle households may or may not add a new vehicle that is different in type from the holding vehicle; that is, any combination of two types of vehicle is possible.

For two-vehicle households the coefficient is negative and significant, which implies that it is unlikely for a two-vehicle household to add a new vehicle that is different in type from both holding vehicles; that is, a three-vehicle household is unlikely to have, for example, a car, a truck, and a van.

**Households disposing of vehicles**

For both one- and two-vehicle households, the alternative-replace constant for the variable defining households with more vehicles than drivers has an expected positive sign. That is, if a household has more vehicles than drivers, it is unlikely to add a new car. This coefficient is significant for two-vehicle households.

For both one- and two-vehicle households, the alternative-dispose constant for households with a member over 60 years old is, as expected, positive and significant. This obvious result shows that older people are more likely to get rid of their vehicles.

**Other vehicle type effects**

This coefficient associated with replacing a station wagon by a van has an expected positive sign for both one- and two-vehicle households; that is, people are more likely to replace a holding station wagon by a van.

Also, for both one- and two-vehicle households, the alternative-replace constant for households in which the holding vehicle's type is the same as the SP vehicle's type, is positive and significant. This implies that most households just replace their old vehicle by a new vehicle with the same type.

**Alternative-replace constant of replacing a cheaper vehicle**

This variable is designed only for two-vehicle households. When a household decides to replace one of their holding vehicles, the one that is more likely to be replaced is not the older one but the one which has lower market value. The estimation supports this idea with a positive and significant coefficient.

**Electric vehicle interactions with geographic variables**

For two-vehicle households, the fuel type electric (EV) interacts with three geographic dummies: Los Angeles metropolitan area; San Francisco, Oakland, and San Jose; and Northern California excluding San Francisco, Oakland, and San Jose. All three coefficients are negative. The coefficient of EV fuel-type interacting with Los Angeles has the largest negative value, and is the only significant one. This implies that households in the Los Angeles Metropolitan Area are less inclined to purchase EV's than households in other urban areas in California, *ceteris paribus*. This is consistent with the fact that commuters in the Los Angeles area drive long distances.

## Forecasts

### *Forecasting Scenarios*

The main source of the data for these scenarios is the 1993/94 Draft Energy Analysis Report from the California Energy Commission (February, 1994, P300-94-002). This report provides data on price, operating costs, shoulder room luggage space, horsepower, and range for 36 body type/size classes of vehicles. Unfortunately, our model also requires information on acceleration time and top speed for these vehicles. As part of our model estimation we collected this information for all existing vehicles between 1978 and 1992. These data were then to fit regression models which were in turn used to predict acceleration and top speed for each vehicle type/size class in 1998.

These models fit very well: the adjusted $R^2$ values for acceleration and top speed are .98 and .96 respectively. One problem with this procedure is that it assumes that the relationship between acceleration, top speed, vehicle class, horsepower, efficiency, shoulder room, and luggage space are the same for each fuel type. Although this is probably true for gasoline, methanol, and CNG, it may not be true for EVs. Nevertheless, this method appears to give reasonable values for EVs as well.

The prices for Electric Vehicles (EVs) are set at $10,000 higher than a comparable gasoline vehicle. These numbers were suggested by discussion with SCE and CEC staff on an earlier draft of the report.

All prices are in 1993 dollars. We give values for horsepower in each class, although they are not currently being used in the choice models. If any of the 14 body type/size classes are missing for a particular fuel type, then that type/size class is assumed to not be available for that fuel type in 1998. Operating cost is given as cents/mile, and acceleration is in seconds to reach 30 miles per hour.

### Gasoline Vehicles

The range for all gasoline vehicles is assumed to be 400 miles, the price of gasoline is $1.42 per gallon, and it takes 7 minutes to refuel an empty fuel tank. The fuel availability index is 1.0 (all service stations have gasoline) and the pollution index is .90 (indicating that 1998 gasoline vehicles are slightly cleaner than comparable 1994 models. The gasoline vehicle details for the scenario is described in Table 7.

**Table 7: Forecast Scenario for Gasoline Vehicles**

| Class Number | Vehicle Class | Price | MPG | Horse-power | Accel. time | Top speed | Oper. Cost |
|---|---|---|---|---|---|---|---|
| 1 | Car - Mini | 12908 | 33 | 109 | 3.2 | 124 | 4.35 |
| 2 | Car - Subcompact | 12162 | 30 | 103 | 3.8 | 114 | 4.78 |
| 3 | Car - Compact | 16684 | 25 | 131 | 3.2 | 125 | 5.75 |
| 4 | Car - Midsize | 18742 | 23 | 155 | 3.0 | 129 | 6.12 |
| 5 | Car - Large | 20322 | 21 | 173 | 3.3 | 124 | 6.79 |
| 6 | Car - Luxury | 36536 | 20 | 206 | 2.8 | 133 | 7.24 |
| 7 | Car - Sport | 17105 | 23 | 159 | 2.7 | 136 | 6.26 |
| 8 | Pickup - Compact | 13430 | 21 | 132 | 3.3 | 124 | 6.67 |
| 9 | Pickup - Standard | 17068 | 15 | 185 | 3.5 | 120 | 9.42 |
| 10 | Van - Compact | 19699 | 20 | 148 | 3.2 | 125 | 7.17 |
| 11 | Van - Standard | 17433 | 15 | 182 | 3.8 | 113 | 9.52 |
| 12 | Sport Utility - Compact | 21417 | 19 | 161 | 3.1 | 127 | 7.65 |
| 13 | Sport Utility - Standard | 23266 | 14 | 205 | 3.5 | 118 | 10.27 |
| 14 | Sport Utility - Mini | 14377 | 26 | 87 | 4.4 | 100 | 5.43 |

## Methanol (M85)

The scenario for methanol vehicles is detailed in Table 8. The fuel availability index for methanol is .10 and the pollution index is .70. The fuel price is assumed to be $1.21 per gallon, and it takes 7 minutes to refuel an empty fuel tank. All vehicles are assumed to have "flex-fuel" capability, but the range and operating costs in the table assume M85 operation.

### Table 8: Forecast Scenario for Methanol Vehicles

| Class Number | ]Vehicle Class | Price | MPG | Horse-power | Accel. time | Top speed | Range | Oper. Cost |
|---|---|---|---|---|---|---|---|---|
| 15 | Car - Subcompact | 12350 | 32 | 109 | 3.7 | 115 | 244 | 3.81 |
| 16 | Car - Compact | 16872 | 26 | 139 | 3.1 | 128 | 242 | 4.58 |
| 17 | Car - Midsize | 18965 | 25 | 164 | 2.9 | 132 | 267 | 4.87 |
| 18 | Car - Large | 20585 | 22 | 183 | 3.1 | 126 | 261 | 5.40 |
| 19 | Car - Luxury | 36589 | 21 | 218 | 2.7 | 135 | 264 | 5.76 |
| 20 | Pickup - Compact | 13653 | 23 | 140 | 3.1 | 127 | 262 | 5.31 |
| 21 | Pickup - Standard | 17329 | 16 | 196 | 3.3 | 123 | 300 | 7.50 |
| 22 | Van - Standard | 17694 | 16 | 193 | 3.7 | 116 | 300 | 7.58 |

## Compressed Natural Gas (CNG)

The scenario for CNG vehicles is described in Table 9. The service station fuel availability index for CNG is .10 and the pollution index is .30. The fuel price is assumed to be equivalent to $1.00 per gallon, and it takes 7 minutes to refuel an empty fuel tank. All vehicles are assumed to be dedicated, except for Vehicle Class 30 which is dual fuel, and home refueling is available for those households with natural gas service.

### Table 9: forecast Scenario for CNG Vehicles

| Class Number | Vehicle Class | Price | MPG | Horse-power | Accel. time | Top speed | Range | Oper. Cost |
|---|---|---|---|---|---|---|---|---|
| 23 | Car - Subcompact | 14405 | 30 | 91 | 4.2 | 106 | 180 | 3.30 |
| 24 | Car - Compact | 18926 | 25 | 119 | 3.6 | 119 | 180 | 3.98 |
| 25 | Car - Midsize | 20984 | 24 | 143 | 3.3 | 124 | 180 | 4.23 |
| 26 | Car - Large | 22367 | 21 | 159 | 3.6 | 119 | 180 | 4.69 |
| 27 | Car - Luxury | 19831 | 15 | 170 | 2.7 | 138 | 180 | 6.51 |
| 28 | Pickup - Compact | 22489 | 21 | 145 | 2.8 | 135 | 180 | 4.85 |
| 29 | Pickup - Standard | 20200 | 15 | 167 | 3.8 | 114 | 180 | 6.58 |
| 30 | Sport Utility - Standard | 20740 | 14 | 160 | 4.2 | 105 | 160 | 7.01 |

## Electric Vehicles

Finally, the scenario for electric vehicles is given in Table 10. The service station fuel availability index for EVs is .10 and the tailpipe pollution index is 0.00. The operating costs are calculated by adding 7 cents per mile to the operating costs given in the CEC fuels report (which are also consistent with the figures provided in SCE Report Number U 338-E on "Emissions Reductions"). The 7 cents per mile figure accounts for battery replacement costing $2000 every 3 years and driving 10,000 miles per year. All vehicles are assumed to be dedicated EVs, and home recharging is available for all households. It takes 4 hours to recharge a discharged EV at home.

**Table 10: Forecast Scenario for Electric Vehicles**

| Class Number | Vehicle Class | Price | MPG | Horse power | Accel. time | Top speed | Range | Oper. Cost |
|---|---|---|---|---|---|---|---|---|
| 31 | Car - Mini | 2290 8 | 168 | 45 | 5.2 | 78 | 80 | 8.57 |
| 32 | Car - Subcompact | 2216 2 | 106 | 60 | 5.1 | 78 | 100 | 9.48 |
| 33 | Car - Compact | 2668 4 | 71 | 75 | 5.1 | 79 | 100 | 10.71 |
| 34 | Car - Sport | 2710 5 | 86 | 100 | 4.4 | 92 | 100 | 10.06 |
| 35 | Pickup - Compact | 2343 0 | 66 | 62 | 5.7 | 66 | 120 | 10.98 |
| 36 | Van - Compact | 2969 9 | 49 | 70 | 5.8 | 64 | 120 | 12.40 |

### *Preliminary Forecasts*

We only computed forecasts for those households that intend to purchase a new vehicle as part of their next transaction. The model predicts the probability that the household will purchase one of the 36 vehicles described in the above scenario tables as well as whether this purchase will be an addition to the household vehicle fleet or a replacement for an existing vehicle. These probabilities can be interpreted as the proportions chosen by all people in the population who are observationally identical to the sample household. The sampling weights estimate the number of these observationally identical households, so forecasts for the entire population are therefore derived by multiplying the choice probabilities by the sample weights.

The one-vehicle household model predicts choice probabilities for 73 discrete alternatives: replacing the existing vehicle with one of the 36 hypothetical vehicles (described in the scenario tables), adding one of the 36 hypothetical vehicles, and disposing of the current vehicle. The two-vehicle household model predicts choice probabilities for 110 alternatives: replacing the existing first vehicle with one of the 36 hypothetical vehicles, replacing the second, adding one of the 36 hypothetical vehicles, disposing of the first existing vehicle, and disposing of the second vehicle.

The transaction models do not predict the timing of the transaction, just the type of transaction. We give forecasts only for those households (605 one-vehicle and 691 two-vehicle, representing 46 and 52 percent of all one and two-vehicle households, respectively) who indicated that their next vehicle transaction would involve purchasing a new vehicle. Since this choice rules out disposing of a vehicle and not purchasing a new one, we only produce forecasts for the alternatives that include a new vehicle purchase. The resulting forecasts can be interpreted as the results of 4-5 years of new car purchasing with only the 36 hypothetical vehicle types available.

Since we have not carefully analyzed the changes in the sampling weights caused by excluding households with missing data, we only present forecasts in terms of purchase shares. These shares should be more reliable than the underlying forecasts of absolute numbers of vehicle sales.

All of the forecasts are given in terms of 90% confidence bands. These bands incorporate the uncertainty in the estimates from the two models. The true purchase shares should fall inside these bands 90% of the time if the entire survey and estimation process were independently replicated many times.

The following tables give purchase shares for one and two-vehicle households. These are given by transaction type (replace or add) and also combined. The "median" shares do not always add up to 100% because of rounding errors and the fact that the confidence bands are not perfectly symmetric.

**Table 11: Two-Vehicle Household Forecast Shares by Transaction**

| Transaction Type | Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|---|
| Replace | Gasoline | 45.8 | 53.5 | 62.3 |
| | Methanol | 11.9 | 17.8 | 22.5 |
| | CNG | 8.6 | 12.5 | 16.9 |
| | Electric | 1.9 | 2.8 | 3.6 |
| Add | Gasoline | 6.3 | 8.1 | 10.1 |
| | Methanol | 1.9 | 2.6 | 3.3 |
| | CNG | 1.3 | 1.9 | 2.4 |
| | Electric | 0.3 | 0.5 | 0.6 |

**Table 12: Two-Vehicle Household Forecast Shares**

| Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|
| Gasoline | 52.5 | 61.9 | 72.0 |
| Methanol | 13.5 | 20.3 | 25.5 |
| CNG | 9.8 | 14.4 | 19.2 |
| Electric | 2.2 | 3.3 | 4.3 |

**Table 13: One-Vehicle Household Forecast Shares by Transaction**

| Transaction Type | Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|---|
| Replace | Gasoline | 36.7 | 45.1 | 52.2 |
| | Methanol | 8.6 | 13.0 | 16.9 |
| | CNG | 11.3 | 15.0 | 19.4 |
| | Electric | 2.2 | 3.1 | 4.1 |
| Add | Gasoline | 11.7 | 14.7 | 18.6 |
| | Methanol | 2.2 | 3.5 | 4.9 |
| | CNG | 3.4 | 4.6 | 5.9 |
| | Electric | 0.6 | 0.9 | 1.3 |

**Table 14: One-Vehicle Household Forecast Shares**

| Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|
| Gasoline | 49.0 | 59.5 | 70.8 |
| Methanol | 10.7 | 16.5 | 21.9 |
| CNG | 14.5 | 19.5 | 25.3 |
| Electric | 2.7 | 3.9 | 5.4 |

**Table 15: Combined Household Forecast Shares by Transaction**

| Transaction Type | Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|---|
| Replace | Gasoline | 43.2 | 49.2 | 55.2 |
| | Methanol | 11.3 | 15.1 | 18.5 |
| | CNG | 11.2 | 13.8 | 16.5 |
| | Electric | 2.2 | 2.9 | 3.5 |
| Add | Gasoline | 9.9 | 11.5 | 13.6 |
| | Methanol | 2.3 | 3.0 | 3.8 |
| | CNG | 2.6 | 3.3 | 3.9 |
| | Electric | 0.5 | 0.7 | 0.9 |

**Table 16: Combined Household Forecast Shares**

| Fuel Type | Lower Bound | Median | Upper Bound |
|---|---|---|---|
| Gasoline | 53.2 | 60.9 | 68.1 |
| Methanol | 13.6 | 18.3 | 22.3 |
| CNG | 13.8 | 17.2 | 20.4 |
| Electric | 2.6 | 3.6 | 4.4 |

### *Sensitivity Analysis*

Since the forecasting models are quite complex, it is difficult to judge the sensitivity of the forecasts to changes in key exogenous variables. To help understand these sensitivities, we present the results of four different changes from the baseline scenario.

One problem with the pollution variable is that it doesn't represent a private cost to any of the respondents, so they may choose a low-pollution hypothetical vehicle to indicate a preference for public policies designed to reduce pollution. To test for this effect, we set the pollution level for all vehicles equal to .9 and run the forecasts again. The results are given in the first row of the following table. We also consider the effects of changing Electric Vehicle purchase price, operating costs, and range.

**Table 17: Change in Purchase Share by Fuel Type**

| Change from Base Scenario | Electric | CNG | Methanol | Gasoline |
|---|---|---|---|---|
| No Pollution | -0.8 | -2.2 | -0.1 | 3.1 |
| EV Price Reduced by $10,000 | 1.4 | -0.3 | -0.2 | -0.9 |
| EV operating cost increased 25% | -0.6 | 0.1 | 0.1 | 0.4 |
| EV range increased 25% | 0.4 | -0.1 | -0.1 | -0.2 |

The confidence bands for the changes in the above table are also shifted by the same amount. Due to the highly non-linear nature of the forecasting models, it is dangerous to extrapolate these sensitivity results beyond the figures given in the above table.

## Conclusions

The modeling system described in this paper will be capable of analyzing most of the proposed policies for stimulating the demand for alternative-fuel vehicles. The system can also be used by vehicle manufacturers to help gauge the demand for various types and configurations of alternative-fuel vehicles. Although the key models in the system will be calibrated from new surveys, it will be necessary to undertake additional survey work to validate and extend these models. Our preliminary work suggests that consumers' responses to our hypothetical vehicle choice experiments are realistic, but the only proof of this assertion will come when alternative-fuel vehicles similar to these hypothetical vehicles are actually offered in the marketplace.

The actual implementation of our modeling system is focused on California since it is the first state to mandate the introduction and sale of alternative-fuel vehicles. Other states and countries are also interested in promoting the sale and use of alternative-fuel vehicles, and our modeling system should be relatively straightforward to adapt to other regions.

The model forecasts the demand for future vehicles conditioned on the current holdings of the household. The estimation results shows that: high-income households or households currently holding luxury vehicles are likely to buy high-priced vehicles; households with children are more sensitive to air pollution than households without children; vehicle range is a very important concern to households when they buy alternative-fuel vehicles; acceleration time is important only for high income households; refueling time seems not too important since most alternative-fuel vehicles can either refuel at home or use gasoline; households with number of cars greater than number of drivers are more likely to replace their holding vehicles; households with number of drivers greater than number of cars are likely to add a vehicle; households with a child of age 15 or 16 are also likely to add a vehicle; and households with one member's age over 60 are more likely to scrap a vehicle.

Based on this model, a preliminary forecast has been done for households that have stated they would purchase new vehicles. Forecast shares for gasoline, methanol, CNG, and electric vehicles are: lower bounds 53.2, 13.6, 13.8, 2.6 percent; medians 60.9, 18.3, 17.2, 3.6 percent; and upper bounds 68.1, 22.3, 20.4, 4.4 percent.

The forecast implies that if the scenarios presented in Tables 7 - 10 are accurate, then the model forecasts indicate that manufacturers will be able to sell more than enough electric and other alternative-fuel vehicles to meet the current California mandates. The models used in this paper can only be sensitive to features of these new vehicles that were included in our Wave 1 questionnaire. Therefore we are unable to include other potentially important vehicle attributes such as safety, reliability, and maintenance costs (including battery replacement). Data currently being collected as part of our Wave 2 survey will allow us to assess the importance of these other attributes. The main reason for promoting alternative-fuel vehicles is to reduce urban air pollution. A full evaluation of any policy promoting alternative-fuel vehicles for reducing pollution must also consider other competing policies such as promoting mass transit use and policies designed to reduce the use of conventional vehicles. This full analysis is beyond the scope of our current efforts, although we hope to extend our model system in the future to make it more useful for evaluating a broader range of pollution and congestion-reducing policies.

Although the conditional transaction model is used here for forecasting alternative alternative-fuel vehicles' demand, it can be easily applied to forecast the demand for gasoline vehicles alone simply by deleting all the explanatory variables related to non-gasoline fuels. Future work will be building a model for three-vehicle households and re-estimating the models and re-forecasting the demand for one-, two-, and three-vehicle households. we will also try to use this model to forecast the demand for gasoline vehicles alone and compare these forecasts to wave-2 actual transactions. we will also build a new/used model to forecast the model year split for the used-car market.


## Acknowledgments

In addition to our project managers - Ernest Morales and Richard Rice (Southern California Edison Co.) and Dan Fitzgerald (Pacific Gas and Electric Co.) - the authors wish to thank their colleagues - Ryuichi Kitamura, Mark Bradley, Stuart Hardy, Seyoung Kim, Jane Torous, Soheila Crane and Camilla Kazimi - who have all contributed enormously to the work described in this paper. In addition, Gary Occhiuzzo, Mike Jaske, and Tim Tutt of the California Energy Commission, Debbie Brodt of Southern California Edison, and Lisa Cooper of Pacific Gas and Electric have worked diligently on behalf of the project. None of these kind people or their organizations are responsible for any errors or for the specific views expressed here.

## References


Bates, J. (1988). Econometric issues in stated preference analysis, *Journal of Transport Economics and Policy.*

Beggs, S. D. and N. S. Cardell (1980). Choice of smallest car by multi-vehicle households and the demand for electric vehicles. *Transportation Research*, 14A: 389-404.

Beggs, S., S. Cardell and J. Hausman (1981). Assessing the potential demand for electric cars. *Journal of Econometrics*, 16: 1-19.

en-Akiva, M. and S.R. Lerman (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand.* MIT Press, Cambridge, MA.

Ben-Akiva, M. and T. Morikawa (1990). Estimation of travel demand models from multiple data sources. *Transportation and Traffic Theory.*

Berkovec, J. and J. Rust (1985). A Nested logit model of automobile holdings for one vehicle households. *Transportation Research*, 19B: 275-285.

Booz, Allen, and Hamilton, Inc. (1983). Forecasting household demand for light duty motor vehicles. Report prepared for Oak Ridge National Laboratories, Contract No. 40X-40485C.

Bradley, M. and A. Daly (1983). Estimation of logit choice models using information from both stated preferences and revealed preferences. Discussion paper for the Duke International Symposium on Choice Modeling and Behavior, July.

Bunch, D.S., M. Bradley, T.F. Golob, R. Kitamura, and G.P. Occhiuzzo (1993). Demand for alternative-fuel vehicles in California: A discrete-choice stated preference pilot project. *Transportation Research,* 27A: 237-253.

Calfee, J.E. (1985). Estimating the demand for electric automobiles using fully disaggregated probabilistic choice analysis. *Transportation Research*, 19B: 287-302.

Crow R. and Ratchford B. (1977) Classical qualitative choice and new goods: An application to electric automobiles. Unpublished paper, Electric Power Research Institute, Palo Alto, California.

Dickson E. and B. Walton (1977). A scenario of battery/electric vehicle market evaluation. Unpublished Stanford Research Institute Report, SRI, Menlo Park, CA.

Efron, B. and R. Tibshirani (1993). *An Introduction to the Bootstrap.* Chapman and Hall, New York.

Fowkers, T. and M. Wardman (1988). The Design of stated preference travel choice experiments, with special reference to inter-personal taste variations. *Journal of Transport Economics and Policy*, 22.

Giuliano, G., K. Hwang, D. Perrine, and M. Wachs (1991). Preliminary evaluation of Regulation XV of the South Coast Air Quality Management District. Presented at Annual Meeting of Transportation Research Board, Washington DC, January 13-17.

Golob, T.F. and L.D. burns (1978). Effects of transportation levels of service on automobile ownership. *Transportation Research Record No. 673*: 137-144.

Golob, T.F., R. Kitamura, M. Bradley and D.S. Bunch (1993). Predicting the market penetration of electric and alternative-fuel vehicles. *The Science of the Total Environment,* 134: 371-381.

Gourieroux, C., A. Holly, and A. Monfort (1982). Likelihood ratio test, Wald test, and Kuhn-Tucker test in linear models with inequality constraints on the regression parameters, *Econometrica*, 50, No. 1.

Greene, D.L. (1989). Motor fuel choice: An econometric analysis. *Transportation Research,* 23A: 243-254.

Greene, D.L. (1990). Fuel choice for multi-fuel vehicles. *Contemporary Policy Issues,* 8: 118-137.

Greene, W. H. (1990). *Econometric Analysis.* New York: Macmillan.

Farrell, M.J. (1954). Demand for passenger cars in the United States. *Royal Statistical Society Journal,* 117A.

Hausman, J., B. Hall and Z. Griliches (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica,* 52: 909 - 938, 1984.

Hensher, D.A. (1982). Functional measurements, individual preferences and discrete choice modeling: Theory and application. *Journal of Econometric Psychology,* 2: 323-335.

Hensher, D.A., N.C. Smith, F.W. Milthorpe and P.O. Barnard (1992). *Dimensions of Automobile Demand.* Elsevier, Amsterdam.

Hensher, D.A., (19XX). Dimensions of Automobiles Demand and Overview of a Large Australian Research Project. *Environment and Planning*, 18: 1339-74.

Hensher, D.A., P.O. Barnard, and T.P. Truong (1988). The Role of Stated Preference Methods in Studies of Travel Choice, *Journal of Transport Economics and Policy*, 22: .

Hensher, D.A., P.O. Barnard, and F.W. Milthorpe (1990). An Empirical Model of Household Automobile Holdings. *Applied Economics*,.

Hensher, D.A. (1992). Integrating revealed preference and stated response data into a jointly estimated hierarchical mode choice model. Presented at the Seventeenth Australasian Transport Research Forum Conference, Canberra, 7-9 October.

Hill, M. (1992). *The Panel Study of Income Dynamics: A Users Guide.* Sage Publications, Newberry Park, CA.

Hocherman, I., J. Prashker, and M. Ben-Akiva (1983). Estimation and use of dynamic transaction models of automobile ownership, *Transportation Research Record No. 944:* 134-141.

Huang, D.S. (1964). A Microanalytic model of automobile purchase, *Research Monograph*, *No. 29.* Bureau of Business Research, Graduate School of Business, University of Texas at Austin.

Huang, D.S. (1966). A multi-cross-section investigation of demand for automobiles, *Research Monograph*, *No. 31.* Bureau of Business Research, Graduate School of Business, University of Texas at Austin.

Janosi, P.E. de, (1959). Factors influencing the demand for new automobiles, *Journal of Marketing*, Vol. 23.

Johnson, T. (1975). The Structure of markets for new and used automobiles. Unpublished doctoral thesis, Department of Economics, University of Washington.

Johnson, T. 1978). A Cross-section analysis of the demand for new and used automobiles in the United States, *Economics Inquiry*, 16: 531-548.

Kain, J., and M. Beeseley (1965). Forecasting car ownership and use, *Urban Studies*.

Kain, J., and G. Fauth (1977). Forecasting auto ownership and mode choice for U.S. metropolitan areas. Department of City and Regional Planning, Harvard University, Cambridge, MA.

Karfisi E., C. Upton, and C. Agnew (1978). The Impact of electric passenger automobiles on utility system loads, 1985 - 2000. Report EA-623 to Electric Power Research Institute, research project 751-1.

Kroes, Eric P., and Robert J. Sheldon (1988). Stated preference methods: An introduction. *Journal of Transport Economics and Policy*, 22.

Lave, C. and J. Bradley (1980). Market share of imported cars: a model of geographic and demographic determinants, *Transportation Research,* 14A: 379-388.

Lave, C., and K. Train (1979). A Disaggregate model of auto-type choice, *Transportation Research*, 13A: 1-9.

Lerman, S. and M. Ben-Akiva. A behavioral analysis of automobile ownership and modes of travel. Report No. DOT-05-3005603, prepared by Cambridge Systematics, Inc., for the U.S. Department of Transportation, Office of the Secretary, and the Federal Highway Administration.

Louviere, J. (1988). Conjoint analysis modeling of stated preferences: A review of theory, methods, recent developments and external validity. *Journal of Transport Economics and Policy*, 12: 93-120.

Louviere, Jordan J., Conjoint analysis modelling of stated preferences. *Journal of Transport Economics and Policy*, pp. 93-119, January 1988.

Maddala, G.S. Limited dependent variable models using panel data. *The Journal of Human Resources*, XXII.3, pp. 307-338.

Mannering, F. L. and K. Train, Recent Direction in Automobile Demand and Modelling, *Transportation Research,* Vol. 19B, No.4, pp.215-236, 1985.

Mannering, F. L. and C. Winston (1985). Dynamic empirical analysis of household vehicle ownership and utilization. *Rand Journal of Economics*, 16: 215-236.

Mogridge, M. (1978). The Effect of the oil crisis on the growth in the ownership and use of cars. *Transportation*, 7: 45-68.

Morikawa, T. (1993). Estimation of discrete choice models from serially correlated RP and SP data. Discussion paper for the Duke International Symposium on Choice Modeling and Behavior, July.

Smith, N.C., D.A. Hensher, and N. Wrigley (1991). A discrete choice sequence model: method and an illustrative application to automobile transactions. *International Journal of Transport Economics*, 28, No. 2.

SRI (1978). *Electric Vehicle News*, May.

Train, K. (1980a). A Structured logit model of auto ownership and mode choice. *Review of Economic Studies*, :357-370.

Train, K. (1980). The potential market for non-gasoline-powered vehicles. *Transportation Research*, 14A: 405-414.

Train, K. (1986). *Qualitative Choice Analysis: Econometrics and an Application to Automobile Demand*. MIT Press, Cambridge, MA.

Wardon, M. (1988). A Comparison of revealed preference and stated preference models of travel behaviour. *Journal of Transport Economics and Policy*, 22:.

Wharton Econometric Forecasting Associates, Inc. (1977). An Analysis of the automobile market: modeling the long-run determinants of the demand for automobiles, Vol. 1-3. Prepared for the U.S. Department of Transportation, Transportation Systems Center, Cambridge, MA.

Winston, C. and F. Mannering (1984). Consumer demand for automobile safety. *American Economic Review*, 74: 316-319.

## APPENDIX A

# Vehicle Choice Survey Question

Suppose that you were considering purchasing a vehicle and the following three vehicles were available: (assume that gasoline costs $1.20 per gallon)

| | Vehicle A | Vehicle B | Vehicle C |
|---|---|---|---|
| Fuel Type | Electric<br>Runs on electricity only. | Natural Gas (CNG)<br>Runs on CNG only. | Methanol<br>Can also run on gasoline. |
| Vehicle Range | 80 miles | 120 miles on CNG | 300 miles on methanol |
| Purchase Price | $21,000 (includes home charge unit) | $19,000 (includes home refueling unit) | $23,000 |
| Home Refueling Time | 8 hrs for full charge (80 miles) | 2 hrs to fill empty tank (120 miles) | Not Available |
| Home Refueling Fuel Cost | 2 cents per mile (50 MPG gasoline equiv.) for recharging between 6 pm and 10 am<br>10 cents per mile (10 MPG gasoline equiv.) for recharging between 10 am and 6 pm | 4 cents per mile (25 MPG gasoline equiv.) | |
| Service Station Refueling Time | 10 min. for full charge (80 mi.) | 10 min. to fill empty CNG tank (120 mi.) | 6 min. to fill empty tank (300 mi.) |
| Service Station Fuel Cost | 10 cents per mile (10 MPG gasoline equiv.) | 4 cents per mile (25 MPG gasoline equiv.) | 4 cents per mile (25 MPG gasoline equiv.) |
| Service Station Availability | 1 recharge station for every 10 gasoline stations | 1 CNG station for every 10 gasoline stations | Gasoline available at current stations |
| Acceleration Time to 30 mph | 6 seconds | 2.5 seconds | 4 seconds |
| Top Speed | 65 miles per hour | 80 miles per hour | 80 miles per hour |
| Tailpipe Emissions | 'Zero' tailpipe emissions | 25% of new1993 gasoline car emissions when run on CNG | Like new 1993 gasoline cars when run on methanol |
| Vehicle Size | Like a compact car | Like a sub-compact car | Like a mid-size car |
| Body Types | Car or Truck | Car or Van | Car or Truck |
| Luggage Space | Like a comparable gasoline vehicle | Like a comparable gasoline vehicle | Like a comparable gasoline vehicle |

1. Given these choices, which vehicle would you purchase? (please circle one choice)
    1) Vehicle "A" (car)
    2) Vehicle "A" (truck)
    3) Vehicle "B" (car)
    4) Vehicle "B" (van)
    5) Vehicle "C" (car)
    6) Vehicle "C" (truck)

2. Would this vehicle most likely be purchased as a replacement vehicle for your household, or as an additional vehicle?

    1) Replacement    2) Additional

3. If you choose "Replacement" in Question 2, please cross off the household vehicle that would be replaced from the following list:

    1) 1990 Ford Bronco    2) 1989 Toyota Camry
    3) ...