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**Publication Date**
1996-04-01

UCI-ITS-WP-96-6

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April 1996

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*Research in Transportation Economics*, forthcoming.

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***ABSTRACT***

The vehicle choice model developed here is one component in a micro-simulation demand forecasting system being designed to produce annual forecasts of new and used vehicle demand by vehicle type and geographic area in California. The system will also forecast annual vehicle miles traveled for all vehicles and recharging demand by time of day for electric vehicles. The choice model specification differs from past studies by directly modeling vehicle transactions rather than vehicle holdings. The model is calibrated using stated preference data from a new study of 4747 urban California households. These results are potentially useful to public transportation and energy agencies in their evaluation of alternatives to current gasoline-powered vehicles. The findings are also useful to manufacturers faced with designing and marketing alternative-fuel vehicles as well as to utility companies who need to develop long-run demand-side management planning strategies.

## I. BACKGROUND

Manufacturers and government agencies are increasingly interested in promoting 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 California will be required to emit 80 percent fewer hydrocarbons and 50 to 75 percent fewer carbon monoxides and nitrogen oxides by the year 2000. At one time, the California Air Resources Board (CARB) 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.

Since alternative-fuel vehicles, particularly electric vehicles, do not yet exist in the market, we need to use stated preference techniques to predict the demand for these vehicles. Previous studies have either ignored households' current vehicles and just modeled their choices over hypothetical vehicles, or they have tried to jointly model the choice of current and hypothetical vehicles (see the following literature review section for references) in a static framework. Since our primary interest here is forecasting, we will model the choice among hypothetical vehicles conditional on the vehicles currently held by the households. This approach captures the common-sense notion that households do consider their current vehicle holdings when purchasing new vehicles. A major goal is to improve the quality of forecasts by focusing on vehicle transactions rather than vehicle holdings. By directly modeling transactions, we are able to forecast the diffusion of new alternative-fuel vehicles. In particular, we can predict what type and vintage of vehicles will be replaced by these new vehicles, which is a critical component in predicting the air pollution consequences from introducing alternative-fuel vehicles (see Kazimi, 1995).

## II. LITERATURE REVIEW

### A. Alternative-Fuel Vehicle Demand Models

Most of the earlier studies on alternative-fuel vehicle demand focused on demand for electric vehicles (EV's). The SRI (1978) study uses the model of Crow and Ratchford (1977) to forecast total sales of electric vehicles in the United States. Mathtech (Karfisi, Upton, and Agnew, 1978) forecasted electric vehicle demand by adapting a model in a Wharton Econometrics (1977) report. Beggs, Cardell and Hausman (1981) 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. Train (1980a) uses a vehicle-type choice model (multinomial logit model developed by Lave and Train (1979) to estimate the potential demand for EVs. Hensher (1982) focuses on the demand elasticities for electric cars in Sydney, Australia. 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. Bunch *et al.* (1993) employ nested multinomial logit models and multinomial probit models for vehicle choice, and binary logit models for fuel choice.

Probably the most comprehensive forecasting work performed to date is that of Train (1986), which we describe here and in the next section. This work extends Train (1980b) and Lave and Train (1979) 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 those of Dickson and Walton (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.

## B. Vehicle Holdings and Transaction Models

There are many studies on vehicle holdings and transactions: see, e.g., the books by Train (1986) and Hensher *et al.* (1992) and references contained therein. The studies that are closest to our work are similar to Train (1986), so we summarize Train's model below.

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

Train's model has much in common with previous models: (1) it is a behavioral model that is estimated using choices from a household survey; (2) each household's choices depend on both vehicle class/vintage characteristics (such as vehicle purchase price) and household characteristics (such as household annual income); and (3) the model can be incorporated into a simulation framework to forecast the demand for and use of vehicles.

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

Although there is a transaction dummy variable in Train's vehicle type submodel to take into account the generalized transaction costs associated with switching to a new vehicle portfolio, the model only predicts which class/vintage(s) a household will own at some point in time, without considering the transaction(s) leading to this portfolio. The model described in this paper is a dynamic model of household vehicle transactions. Since households change their vehicle holdings slowly, an explicit transactions model is necessary to accurately forecast households' responses to new alternative-fuel vehicles over the 10-15 year horizon most relevant to policy makers.

### C. Combined Revealed Preference and Stated Preference Models

Since we need to measure households' preferences for alternative-fuel vehicles which are not currently available, we need to use responses to stated preference choice tasks in which households choose among hypothetical vehicle descriptions. Economists have been skeptical of stated preference data since they do not represent real choices in a market, and there have been few published attempts to compare forecasts from models calibrated using stated preference data to actual market behavior. Wardman (1988) reviews a number of studies comparing the forecasting ability of stated preference (SP) and revealed preference (RP) models of travel mode choice. He concludes that neither models generate good forecasts, but in some cases SP models were more accurate than RP models.

Many researchers have attempted to combine stated preference (SP) and revealed preference (RP) information to mitigate concerns about reliability of SP responses: Kroes and Sheldon (1988), Fowkes and Wardman (1988), Hensher, Barnard, and Truong (1988), Wardman (1988), Louviere (1988), Ben-Akiva and Morikawa (1990), and Bradley and Daly (1993). The most recent work by Morikawa (1994) and Hensher (1994) propose joint estimation of SP and RP choices allowing for the variances of the error term to differ.

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 incorporating all current information is appropriate. Forecasting SP vehicle choices by conditioning on RP vehicle holdings can also serve to capture some heterogeneity between households, therefore avoiding some possible bias problems.

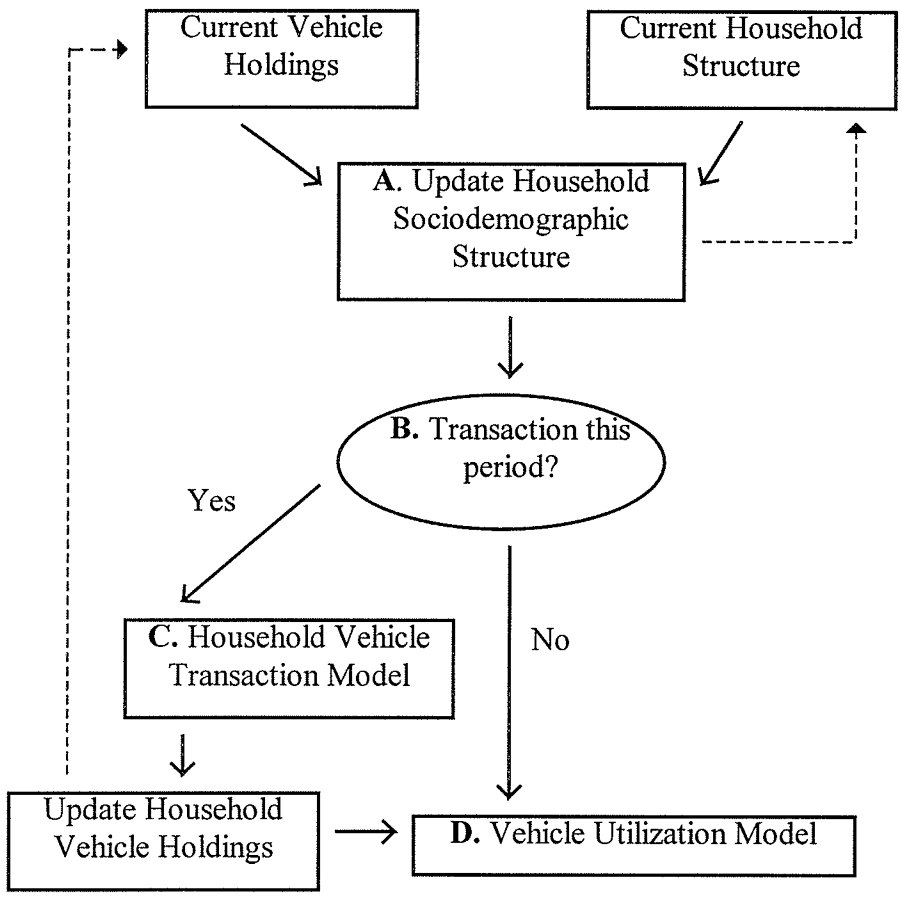
## III. THE PERSONAL VEHICLE DEMAND MODEL

The framework for forecasting personal vehicle demand is summarized by the system diagram in Figure 1, which consists of a number of linked 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 by simulating 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 calibrated from the Panel Study of Income Dynamics (Hill, 1992), and their detailed specification is given in Kazimi (1995).

Ellipse B in Figure 1 takes the updated (aged) household and current vehicle holdings as inputs. It then decides whether or not a vehicle transaction takes place during this period. The simulation period length is set at six months so that the number of transactions occurring per period can be reasonably limited to one. However, model system outputs are reported 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 starting values for the next period's simulation. The model outputs reported at the end of each year include estimates of vehicle totals by type and vintage. These are computed using choice probabilities taken over all possible actions to get weighted estimates. For new vehicles, this represents market penetration. The focus of this paper is on the model represented by Box C in Figure 1.

**Figure 1: Personal Vehicle Submodel**




Another important component is utilization (model D). At the end of each year, it takes the updated vehicle holdings and household structure as inputs and then predicts the annual vehicle miles traveled for each household vehicle. For a more detailed discussion of this model, see Golob, Bunch, and Brownstone (1996). 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.

## IV. THE SURVEY DATA

The survey used to calibrate the model in the next section 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 urbanized California. An initial computer-aided telephone interview (CATI) was completed for each of 7,387 households. This initial CATI collected information on: household structure, vehicle inventory, housing characteristics, basic employment and commuting for all adults, and the household's intended next vehicle transaction.

The data from the initial CATI 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 discrete-choice 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 include vehicles that were 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. 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 at the end of this interview.

The 4747 households that successfully completed the mail-out portion of the survey in 1993 represent a 66% response rate among the households that completed the initial CATI. A comparison with Census data reveals that the sample is slightly biased toward home-owning larger households with higher incomes, and weights have been developed to balance the sample to the known population. Eighty percent of the households in the sample had exactly one driver per vehicle, showing 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 to 15,000 miles per year, and almost a third are driven more than 15,000 miles per year.

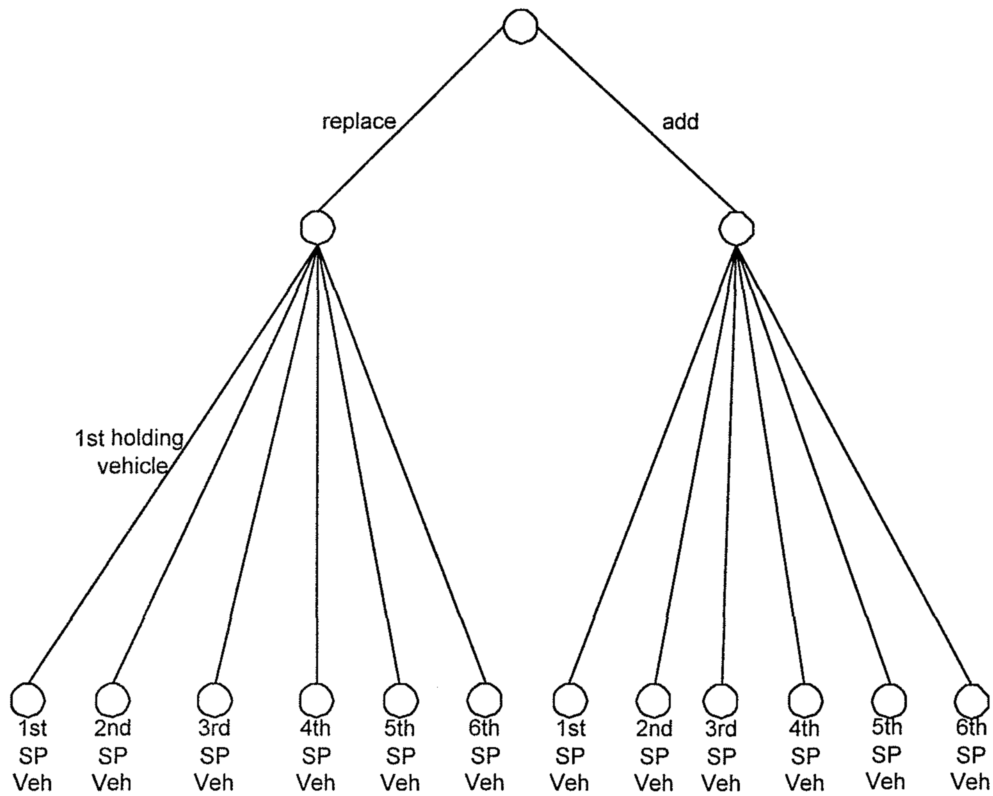
An example SP task from the questionnaire is given in the Appendix. There are four fuel-types for vehicles: gasoline, compressed natural gas (CNG), methanol, and electric (EV). Three of the four fuel-types appear in each SP question. For each fuel-type, two different body type versions are available. There were six (or seven) attributes per vehicle per choice set (depending upon the fuel type of the vehicle). Four levels were used to cover the range of most attributes, allowing for estimation of nonlinear effects. The basic experimental design used for producing variation in the attribute levels was an orthogonal main effects plan for a $4^{21}$ factorial in 64 runs (Golob *et al.*, 1995). Respondents were specifically instructed to treat all non-listed attributes (e.g., maintenance costs and safety) as identical for all vehicles in the choice set.

## V. MODEL SPECIFICATION

### A. Variable Definitions

Any household vehicle transaction must fall into one of three categories: 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 containing a variety of fuel types, vehicle types, vehicle sizes, and other attributes. A household completing the stated preference survey in the Appendix could have 13, 20, or 27 transaction alternatives depending on whether its current number of vehicles is 1, 2, or 3, respectively. Figures 2 and 3 depict these alternatives for our models and they show all possible transactions each household type can carry out. For the present, zero-vehicle households are excluded, since there are only 53 households in the sample that own no vehicles.

**Figure 2. One-Vehicle Household Transaction Tree**




The dependent variable specifications for the one- and two-vehicle households are provided in Tables 1 and 2, respectively. The order of the 1st and 2nd vehicles corresponds to the order in which respondents listed their vehicles. The order of SP vehicles one through six 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. Future work will use these data to model the choice of new/used vehicles as well as the vintage of the used vehicles, but more accurate models require explicitly incorporating the choice of new or used vehicles into the stated preference design. Preliminary tests did not find any significant differences in preferences between new and used vehicle purchasers.

**Figure 3. Two-Vehicle Household Transaction Tree**

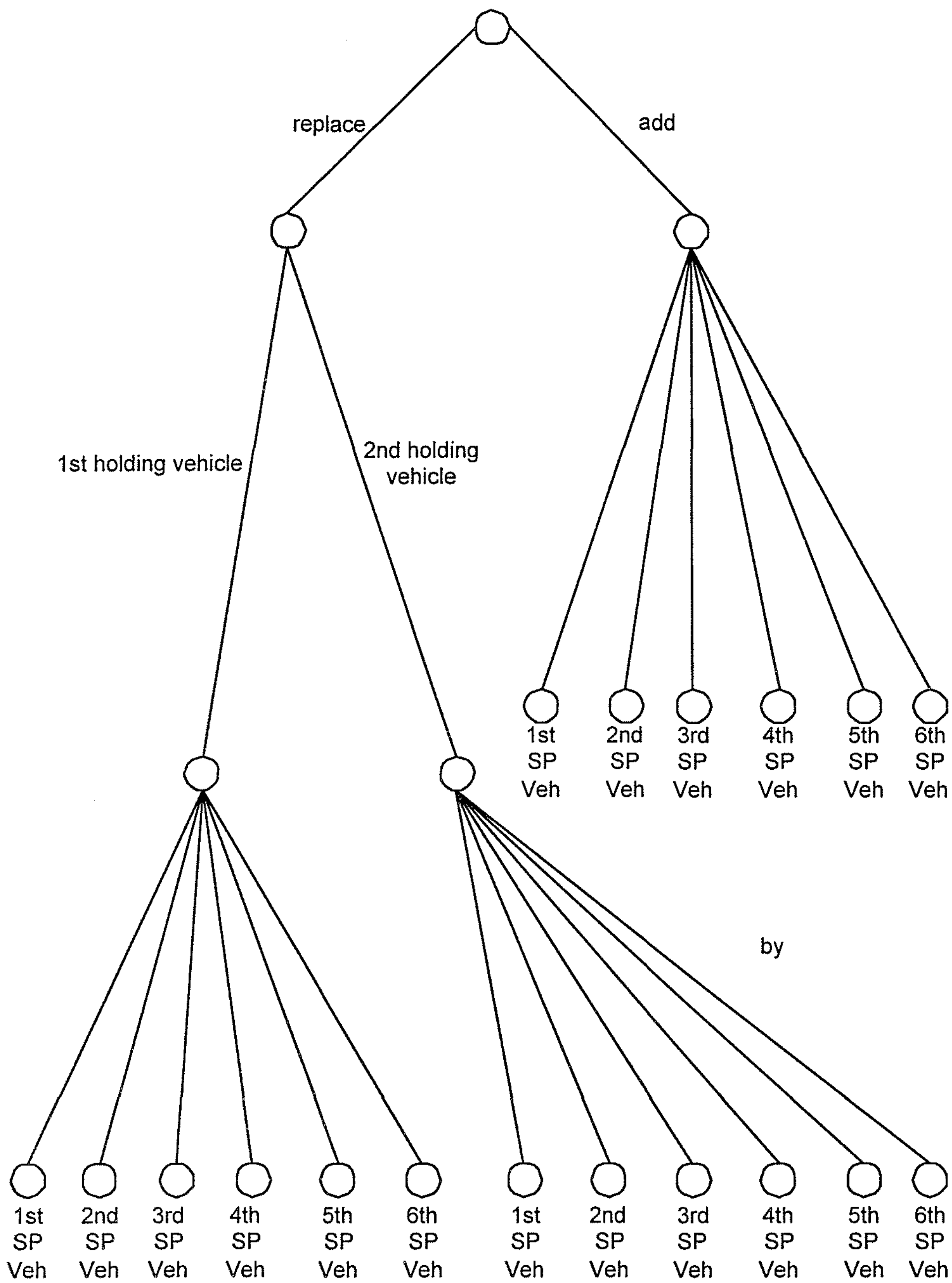


**Table 1: The Dependent Variable for One-Vehicle Households**

| Value | Description |
|---|---|
| 1 | choose 1st SP vehicle to replace the held vehicle |
| 2 | choose 2nd SP vehicle to replace the held vehicle |
| 3 | choose 3rd SP vehicle to replace the held vehicle |
| 4 | choose 4th SP vehicle to replace the held vehicle |
| 5 | choose 5th SP vehicle to replace the held vehicle |
| 6 | choose 6th SP vehicle to replace the held 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 held vehicle |

The model is intended to be used in a forecasting system, so all of the independent variables must either be exogenous to the forecasting system (e.g. vehicle attributes and fuel cost) or be an output from some other part of the forecasting system (e.g. household characteristics). This restriction eliminates potential variables such as home or work location, job classification, or commute distance. To avoid over-fitting (or "data mining") biases we did not repeatedly re-estimate models in an attempt to eliminate all insignificant coefficient estimates. Our primary interests are in the models' forecasts, not in the individual coefficient estimates.

We use the standard multinomial logit model to explain the discrete choices given in Tables 1 and 2, although we did carry out specification tests which are described in the next section. Since we are modeling the SP vehicle transaction choices conditioned on current vehicle holdings, attributes describing currently held vehicles enter the variables defining the utility scales corresponding to the discrete choices. For example, instead of entering the SP vehicle purchase price as an attribute, we enter the net capital cost associated with the entire transaction. This is defined as the SP vehicle purchase price minus the current market value of the held vehicle(s) for alternatives corresponding to replacing a vehicle; the SP vehicle purchase price for alternatives corresponding to adding a vehicle; and minus the current market value of the held vehicle for alternatives corresponding to disposing a vehicle. We use the same procedure to calculate net operating costs, top-speed and acceleration time.

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

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

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 must include these factors.

Although these variables are formulated based on transactions rather than on more traditional applications involving simple choices, they still retain the usual expected signs and interpretations. For example, since the net capital cost variable measures the capital cost associated with a vehicle transaction, all else equal households prefer to pay less for any transaction. Therefore we expect that this variable will have a negative coefficient in the utility function. For similar reasons, we expect that the coefficient of net operating costs will be negative, and the coefficient of the differences in top speeds will be positive.

## B. Testing the Independence of Irrelevant Alternatives

The multinomial logit specification used above assumes independently distributed Weibull disturbances in a random utility model. To test the validity of this specification, Hausman and McFadden (1984) show that if a subset of the choices is irrelevant, then eliminating it from the model will not systematically affect the underlying parameter estimates. However, excluding these choices will be inefficient. This is the basis for Hausman's specification test:

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

where $\beta$ is the vector of coefficient estimates, matrix $V$ is the estimate of the asymptotic covariance matrix, subscript $r$ denotes estimators for the restricted subset, and $u$ denotes estimators for the full set of choices. This statistic is asymptotically distributed as chi-squared with $K$ degrees of freedom, where $K$ is the rank of the weight matrix. In applying this test, a specific nominal choice alternative associated with an alternative-specific dummy variable might be eliminated from all choice sets. In this case, the coefficients for the alternative-specific dummy variable and any other variables that interact with this variable will not be identified in the restricted $\beta$ vector. In this case only the remaining identified coefficients can be used to perform the test.

## C. Forecasting Methodology

Forecasts are generated using sample enumeration. Confidence bands for the forecasts are generated by parametric bootstrapping (see Efron and Tibshirani, 1993) as described below. In the most general case different models could be estimated for individual "market segments" in the population. Our forecasts are obtained using two models: one for one-vehicle households, and one for multiple-vehicle households. The following steps (with some notational details suppressed) summarize the procedure:

Step 1. Establish a scenario for the forecast year, e.g., establish vehicle types and attributes for a hypothetical new vehicle market.

Step 2. Establish the $\hat{\beta}$ to be used.

Step 3. Using the scenario from step 1, establish transaction alternatives for each household in the sample. Using the $\hat{\beta}$ from step 2, compute choice probabilities for all transaction alternatives.

Step 4. Use equation 2 below to compute a consistent estimate of the population's average probability of choosing transaction alternative $j$:

$$\hat{S}_j = \frac{1}{N_p}\sum_{i=1}^{N} w_i P_{ij}(\hat{\beta}), \qquad (2)$$

where $\hat{S}_j$ is the forecast average probability of choosing alternative $j$ in the population; $N_p$ is the population size; $N$ is the sample size; $w_i$ is the household weight; and $P_{ij}$ is the probability that household $i$ chooses transaction alternative $j$.

Step 5. Compute a sales forecast for vehicles of a particular fuel-type. A transaction alternative is characterized by a transaction type (add, replace, dispose), and for adds or replaces the type of vehicle that has been purchased is also specified. So, to calculate the demand probability for a particular fuel-type, one should combine the appropriate transaction choice probabilities.

Step 6. Apply bootstrapping using steps 2 to 5; that is, based on the initial estimates of $\hat{\beta}$ and its covariance matrix, randomly draw $\hat{\beta}$ in step 2 and repeat the remaining steps. Do this hundreds or thousands of times. Relevant statistics such as the median and the 90% confidence bounds of $\hat{S}_j$ are then calculated using these bootstrapped values.

## VI. PERSONAL VEHICLE DEMAND ESTIMATION RESULTS

Of 1607 one-vehicle households and 2220 two-vehicle households, 1153 and 1156 valid observations remained after excluding those with missing or incorrect data, primarily household income and vehicle year/make/model. Although the model specification could be extended to three or more vehicle households, they are excluded from this paper due to their small sample sizes. Due to lack of data on vehicle attributes, we excluded all vehicles with model years before 1979. Estimation results are obtained using data from the first SP task for each sample household.

For easy comparison, the results for one- and two-vehicle households are listed first and then the results are analyzed and compared. Standard likelihood ratio tests show that the coefficients from these two models are significantly different, although preliminary tests cannot reject the hypothesis that the two-vehicle household model holds for three-vehicle households as well.

The estimation results for the sample of one-vehicle households are listed in Table 3. The Hausman test described in the previous section was computed for one-vehicle households by excluding the replacement alternatives. At the 95% significance level, we cannot reject the hypothesis that the multinomial logit specification is correct.

The two-vehicle household estimation results are listed in Table 4. The Hausman test was also computed for two-vehicle households by excluding the replacement alternatives. At the 95% significance level, we cannot reject the hypothesis that the multinomial logit specification is correct.

## Table 3: 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 (\$30k < HH income ≤ \$75K, HH has no children<21) [*] | -0.00003925 | -2.5 |
| Value of the remaining vehicle (\$30k < HH income ≤ \$75K) [*] | 0.00003080 | 1.3 |
| Net capital cost (HH income > \$75k, HH has a child of age<21) [*] | -0.00005253 | -1.5 |
| Net capital cost (HH income>\$75K, 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 (HH income>=\$76K, HH has no child of age<21) [**] | -0.1252 | -2.4 |
| Top-speed difference between the SP vehicle and the held vehicle | 0.0008844 | 0.5 |
| Acceleration time difference between the SP vehicle and the held 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 held vehicle type different from SP veh. type | -0.1999 | -0.5 |
| Alternative-replace constant for HH with # cars >= # drivers (dummy) | 0.2207 | 0.6 |
| Alternative-replace constant (replacing station wagon by van) (dummy) | 0.6097 | 1.3 |
| Alternative-replace constant: HH with held veh. type same as SP veh. (dummy) | 1.453 | 14.6 |
| Alternative-dispose constant for HH 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" with respect to Zero | 0.2057 | |

Notes: 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.

* 1993 U.S. dollars.

** For EV, using home-refueling cost and home-refueling time. The unit for cost is cent/mile and the unit for refueling time is minutes. 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 4: 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) * | -0.00002882 | -0.7 |
| Value of the remaining vehicle (HH income ≤ $30K) * | 0.0001215 | 2.2 |
| Net capital cost (HH income ≤$30K,HH has a luxury vehicle and a child of age<21) * | 0.00002205 | 1.4 |
| Net capital cost (HH income≤$30K,HH has a luxury vehicle and no child of age<21) * | 0.00002118 | 1.8 |
| Net capital cost(HH income≤$30K,HH has no luxury vehicle, but a child of age<21) * | -0.00001741 | -1.0 |
| Net capital cost (HH income≤$30K,HH has no luxury vehicle & no child of age<21) * | -0.00004112 | -2.7 |
| Value of the remaining vehicle (HH income <= $30k, 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(HH income>=$31K, has luxury vehicles & a child of age<21) ** | -0.08157 | -1.5 |
| Net operating cost (HH income>=$30K, has a luxury vehicle & no child of age<21) ** | -0.08467 | -1.9 |
| Operating cost of the remaining vehicle(HH income≤$30K, has a luxury vehicle) ** | 0.1963 | 3.1 |
| Net operating cost (HH income≤$30k, has no luxury vehicle, but a child of age<21) ** | -0.08214 | -3.3 |
| Net operating cost (HH income≤$30k, has no luxury vehicle & no child of age<21) ** | -0.08404 | -3.5 |
| Operating cost of the remaining vehicle (HH income≤ $30k, has no luxury vehicle) ** | -0.01627 | -0.4 |
| Top-speed difference between the SP vehicle and the held vehicle | 0.002398 | 1.6 |
| Acceleration time difference between the SP veh. and the held veh. (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 veh. and the held veh. (HH income > $30K) *** | -0.08143 | -3.4 |
| Acceleration time of the remaining vehicle (HH income > $30k) *** | -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 availability 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*(Los Angeles & Orange Counties) (dummy) | -0.4391 | -1.9 |
| EV*(San Francisco, 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 HH with # cars < # drivers (dummy) | 0.3763 | 1.1 |
| Alternative-add constant for HH with a child 15 or 16 years old (dummy) | 0.8745 | 2.6 |
| Alternative-add constant for HH with held vehicle type different from the SP vehicle type | -0.4368 | -2.6 |
| Alternative-replace constant for HH 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 HH with held vehicle type the same as SP veh. (dummy) | 1.001 | 12.5 |
| Alternative-dispose constant for HH with at least one member's age>=60 | 1.447 | 3.7 |
| Number of observations | 1156 | |
| Initial Likelihood | -3463.0665 | |
| Final Likelihood | 2880.1143 | |
| "Rho-Squared" with respect to Zero | 0.1683 | |

Notes: 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.

* 1993 U.S. dollars.

** For EV, using home-refueling cost and home-refueling time. The unit for cost is cent/mile and the unit for refueling time is minutes. 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).

## 1. Net capital cost

Net capital cost is defined as the difference between the price of the SP vehicle and the current market value of the held vehicle. Since this is just the capital cost of carrying out the transaction, we expect that the coefficient will be negative. Table 3 shows that net capital cost for one-vehicle households with annual income less than $75,000 has a coefficient with the expected negative sign. For households with annual income greater than $76,000 the coefficient for net capital cost is insignificant. Note that there are large differences (for both one and two-vehicle households) between households with and without children living at home.

For 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 $30,000, the result varies significantly between households with and without luxury cars. The households without luxury cars behave more like "rational" people in that their demand is a negative function of price. 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.

2. Net operating cost

Net operating cost is defined as the difference between the operating cost of the SP vehicle and the operating cost of the held vehicle(s). Net operating cost reflects the net amount of money that must be spent when a household uses the chosen vehicle. Except for two-vehicle households holding luxury cars, the coefficients of net operating costs for both one- and two-vehicle households have the expected negative sign. For two-vehicle households holding 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. Coefficients also vary according to household income and the presence of children under twenty-one years of age.

3. Value and operating cost of the vehicles in the resulting household fleet

The value of the vehicles left in the household fleet after a particular transaction takes place represents an asset. Thus, we expect that the coefficients of "Value of remaining vehicle" should have a positive sign, and they do.

However, operating costs of all remaining vehicles still represent expenses, so the signs of the coefficients of "Operating cost of the remaining vehicle" should be negative. The results also support this expectation. The value and operating cost coefficients also varied with households' income and the presence of children under twenty-one years of age.

4. Top speed and acceleration time

The coefficients of the difference in top-speed have expected positive signs for both one- and two-vehicle households, which confirms that households prefer higher top speeds. However, the coefficient is insignificant for one-vehicle households, and is only marginally significant for two-vehicle households.

For the one-vehicle households, the coefficient of the difference in acceleration is marginally significant with the expected negative sign. For 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 low-income households, in contrast to a high-income households, do not care too much about acceleration time. Acceleration time of the remaining vehicle for low- and high-income two-vehicle households have the expected negative coefficients.

5. Refueling time

Refueling time is defined as the service station refueling time for a non-EV and home-refueling time for an EV. For both one- and two-vehicle households the refueling time coefficients have the expected negative signs, but are not significant. Although EVs take much more time to refuel than do non-EVs, EV recharging occurs overnight at home so that the time requirement is not significant.

### 6. 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 range is an 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.

### 7. 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. Service station availability for dedicated CNG vehicles with and without home-refueling have the same value for one-vehicle households, so they are combined. For two-vehicle households, this coefficient is significant and relatively large in magnitude.

### 8. 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 for households without children. This is especially so for two-vehicle households, where the coefficient for households with children under 21 years of age is almost 10 times greater than that of households without children. These results indicate that households with children are willing to pay for less-polluting vehicles regardless of fuel type.

### 9. Vehicle and fuel-type interactions

There are many significant interactions between vehicle type and fuel type in both the one- and two-vehicle models. These interaction terms imply preferences for particular vehicle fuel and body type combinations that cannot otherwise be explained by capital costs, operating costs, and range. To summarize, the results show that people are 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 alternative-fuel vehicles.

## 10. Vans

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

For one-vehicle households of 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.

## 11. 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 the coefficient associated with holding two trucks has an (unexpected) positive sign. For two-vehicle households, all the signs of the coefficients are as expected. The coefficients for new-holding-two-or-more-vans and for new-holding-two-or-more-cars are negative and significant.

## 12. Households adding vehicles

For both one- and two-vehicle households, coefficients associated with adding vehicles in households with fewer vehicles than 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 at legal driving age), the household will be more likely to add a car.

The coefficient associated with households where the held vehicle type is different from the SP vehicle type variable is designed to determine if a household would like to add a vehicle which is different from their held 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 held 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 held vehicles; that is, a three-vehicle household is unlikely to have, for example, a car, a truck, and a van.

### 13. Households replacing or disposing of vehicles

The estimates imply that both one- and two-vehicle households with more vehicles than drivers are more likely to replace than add an additional vehicle. 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 shows that older people are more likely to dispose of their vehicles.

### 14. Other vehicle type effects

The coefficient associated with replacing a station wagon with a van has an expected positive sign for both one- and two-vehicle households; that is, people are more likely to replace a station wagon with a van. Also, for both one- and two-vehicle households, the alternative-replace constant for households in which the held vehicle's type is the same as the SP vehicle's type, is positive and significant. This implies that many households decide to replace their old vehicle with a new vehicle of the same type.

15. Alternative-replace constant for replacing a cheaper vehicle

This variable is only applicable for two-vehicle households. When a household decides to replace one of their held vehicles, the one that is more likely to be replaced is not necessarily the older one, but the one which has lower market value. The results support this idea through the positive and significant coefficient for "Alternative-replace constant * Lower value vehicle".

16. Electric vehicle interactions with geographic variables

For two-vehicle households, the fuel-type electric (EV) dummy variable interacts with three geographic dummy variables: 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 for 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 hypothesis that those choosing to live in the Los Angeles area have demonstrated a higher tolerance for air pollution.

## VII. FORECASTS

Although the models' coefficients can be used to see how households trade off various vehicle characteristics, these tradeoffs cannot be easily translated into market demand estimates for specific vehicles. This section describes some simple forecasting exercises which use the models specified in the previous section to produce market demand forecasts for some specific future scenarios.

### A. 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). The report provides data on price, operating costs, shoulder room, luggage space, horsepower, and range for 36 body type/size classes of vehicles expected to be available in 1998. Unfortunately, our model also requires information on acceleration time and top speed for these vehicles. To support our model estimation, this information was collected for all existing vehicles between 1978 and 1992. These data were then used to estimate regression models which were in turn used to predict acceleration and top speed for each vehicle type/size class in 1998.

These models had a very high goodness-of-fit: 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 is 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) were set at $10,000 higher than a comparable gasoline vehicle. These numbers were suggested in discussions with Southern California Edison (SCE) and California Energy Commission (CEC) staff. All prices are in 1993 dollars. Values are given 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 was assumed to not be available for that fuel type in 1998. Operating cost is cents/mile, and acceleration is seconds needed to reach 30 miles per hour.

## 1. Gasoline Vehicles

The range for all gasoline vehicles is assumed to be 400 miles, the price of gasoline $1.42 per gallon, and it was assumed to take 7 minutes to refuel an empty fuel tank. A fuel availability index of 1.0 (gasoline available at all current stations) and a pollution index of .90 (indicating that 1998 gasoline vehicles are slightly cleaner than comparable 1994 models) were used. The gasoline vehicle details for the scenario are described in Table 5.

**Table 5: Forecast Scenario for Gasoline Vehicles**

| Class Code | 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 |

2. Methanol (M85)

Scenario data for methanol vehicles is detailed in Table 6. The fuel availability index for methanol is .10 and the pollution index is .70. The fuel price is $1.21 per gallon, and it takes 7 minutes to refuel an empty fuel tank. All vehicles have "flex-fuel" capability, but the range and operating costs in the table assume M85 operation.

3. Compressed Natural Gas (CNG)

Scenario data for CNG vehicles are in Table 7. 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.

Home refueling is assumed to be available for those households with natural gas service.

**Table 6: Forecast Scenario for Methanol Vehicles**

| Class Code | 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 |

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

| Class Code | 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 - Std. | 20740 | 14 | 160 | 4.2 | 105 | 160 | 7.01 |

## 4. Electric Vehicles

Finally, scenario data for electric vehicles is given in Table 8. 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 8: Forecast Scenario for Electric Vehicles**

| Class Code | Vehicle Class | Price | MPG | Horse-power | Accel. time | Top speed | Range | Oper. Cost |
|---|---|---|---|---|---|---|---|---|
| 31 | Car - Mini | 22908 | 168 | 45 | 5.2 | 78 | 80 | 8.57 |
| 32 | Car - Subcompact | 22162 | 106 | 60 | 5.1 | 78 | 100 | 9.48 |
| 33 | Car - Compact | 26684 | 71 | 75 | 5.1 | 79 | 100 | 10.71 |
| 34 | Car - Sport | 27105 | 86 | 100 | 4.4 | 92 | 100 | 10.06 |
| 35 | Pickup - Compact | 23430 | 66 | 62 | 5.7 | 66 | 120 | 10.98 |
| 36 | Van - Compact | 29699 | 49 | 70 | 5.8 | 64 | 120 | 12.40 |

## B. Forecast Results

Forecasts were computed using only those households in our sample that intended to purchase a new vehicle as part of their next transaction. The choice models give transaction probabilities for the households, where each choice alternative involves either an addition or a replacement transaction in which one of the 36 vehicles from the scenario tables is purchased. For a given sample household, these probabilities can be interpreted as the predicted proportions associated with the much larger group of households in the general population that are observationally identical to the "representative" sample household. The sampling weights are used to estimate the number of these observationally identical households, so that forecasts for the entire population may be 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 parameter 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.

Tables 9 and 10 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 9: 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 10: 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 |

## C. 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 produce an estimate of the upper bound for this effect, we set the pollution level for all vehicles equal to 0.9 and run the forecasts again. The results are given in the first row of the following table. We also consider the effects of changing EV purchase price, operating costs, and range.

Not surprisingly, the main effect of removing the pollution variable is to reduce the demand for electric vehicles by almost 25%. Neutralizing this demand reduction would require reducing EV purchase prices by approximately $6000 and/or increasing EV range substantially more than 25%. The sensitivity results broadly show that changing EV vehicle characteristics has a proportionately larger effect on CNG vehicle demand. This is as expected since CNG vehicles also have limited range and refueling options.

Although all of the scenarios represented in Table 11 still show EV purchase shares meeting the 1998 California 2 percent mandate, the results also show the difficulty of increasing EV penetration much past 5 percent. Even if EV purchase price and range are substantially improved, significant market penetration will require the availability of EVs in a broader range of body types than those given in Table 8.

**Table 11: 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 inadvisable to extrapolate these sensitivity results beyond the figures given in the above table.

## VIII. CONCLUSIONS

The modeling system described in this paper is 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. This 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 model forecasts the demand for future vehicles conditioned on the current holdings of the household. The estimation results show 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 more cars than drivers are more likely to replace their held vehicles, households with more drivers than 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, we have computed forecasts for households who intend to purchase new vehicles. Median forecast shares for gasoline, methanol, CNG, and electric vehicles are 60.9, 18.3, 17.2, and 3.6 percent. These forecast electric vehicle shares are slightly higher than those found in previous work discussed in Section II, but each of these studies made different assumptions about vehicle technology. If the scenarios presented in Tables 5- 8 are accurate predictions of the vehicles offered in 1998, then manufacturers will be able to sell enough electric and other alternative-fuel vehicles to meet the current 1998 California mandates.

The models used in this paper can only be sensitive to features of new vehicles that were included in the questionnaire. Therefore we are unable to include other potentially important vehicle attributes such as reliability and maintenance costs (including battery replacement) which may be different from existing gasoline vehicles. Data currently being collected as part of a follow-up survey of the same households 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.

## IX. ACKNOWLEDGMENTS

Funding for the work reported in this paper has been provided by the Southern California Edison Co. and Pacific Gas and Electric Co. 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.

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## APPENDIX: 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 hr. for full charge (80 miles) | 2 hr. 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 new 1993 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