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DISCLAIMER

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by

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Abstract

A study was conducted to determine how demand for clean-fuel vehicles and their fuels is likely to vary as a function of attributes that distinguish these vehicles from conventional gasoline vehicles. For the purposes of the study, clean-fuel vehicles are defined to encompass both electric vehicles, and unspecified (methanol, ethanol, compressed natural gas or propane) liquid and gaseous fuel vehicles, in both dedicated or multiple-fuel versions. The attributes include vehicle purchase price, fuel operating cost, vehicle range between refueling, availability of fuel, dedicated versus multiple-fuel capability, and the level of reduction in emissions (compared to current vehicles). In a mail-back stated preference survey, approximately 700 respondents in the California South Coast Air Basin gave their choices among sets of hypothetical future vehicles, as well as their choices between alternative fuel versus gasoline for hypothetical multiple-fuel vehicles. Estimates of attribute importance and segment differences are made using discrete-choice nested multinomial logit models for vehicle choice, and binomial logit models for fuel choice. These estimates can be used to modify present vehicle-type choice and utilization models to accommodate clean-fuel vehicles; they can also be used to evaluate scenarios for alternative clean-fuel vehicle and fuel supply configurations. Results indicate that range between refueling is an important attribute, particularly if range for an alternative fuel is substantially less than that for gasoline. For fuel choice, the most important attribute is fuel cost, but the predicted probability of choosing alternative fuel is also affected by emissions levels, which can compensate for differences in fuel prices.

1. INTRODUCTION

1.1. Research setting

Air quality is an important concern in California, and particularly in the South Coast Air Basin of California, which includes the densely populated parts of the Los Angeles, Riverside, San Bernardino and Anaheim-Santa Ana (Orange County) metropolitan areas. Cars, trucks, and buses are estimated to contribute 88 percent of carbon monoxide emissions and about 50 percent of the ozone precursors (oxides of nitrogen and reactive organic gases) in the Air Basin. The 1990 amendments to the Federal Clean Air Act and the 1990 Regulations by the California Air Resources Board require that vehicle emissions be reduced substantially.

The California regulations treat a vehicle and its fuel as a system subject to emissions standards. Compliance with these regulations, scheduled to begin in 1994, can be achieved by using advanced emission control technology, clean-burning fuels (including reformulated gasoline), or a combination of both. Four new categories of cars and light-duty trucks are created by the regulations, where each category is defined by its level of tailpipe emissions. Standards for the average emissions of new car fleets for the years 1994 to 2003 are established, along with guidelines for achieving these standards through introduction of clean vehicles. By 1996, 10 to 20% of the new-car fleet should be "transitional low-emission" vehicles (TLEV). By 2003, 25 to 75% of the fleet should be "low-emission" (LEV), and 2 to 15 % should be "ultra low-emission" (ULEV). A full 10% of the fleet is required to be "zero emission" (ZEV, presumably electric) by the year 2003. Details are provided in Air Resources Board (1991).

Clean-fuel vehicles are likely to differ from conventional-fuel vehicles in terms of fuel costs and vehicle prices, but more importantly in non-monetary attributes: availability of the fuel, range between refueling or recharging, vehicle performance, refueling time and convenience, and interior space in the vehicle, for example. Estimating consumer preferences regarding such attributes is critical to the evaluation of policy options, design of the vehicle and fuel subsystems, and their marketing and promotion. However, it is not possible to estimate such preferences by "revealed preference" (RP) methods of observing the acts of buying and not buying clean-fuel vehicles, or by eliciting reactions to currently available cars and trucks, as can be accomplished in the case of conventional-fuel vehicles. Clean-fuel vehicles are currently in limited, even isolated supply, often as parts of demonstration projects, or in the hands of inventors, promoters, and enthusiasts. There is no realistic hope of monitoring revealed preferences for representative future clean-fuel vehicles and fuels.

Preferences for clean-fuel vehicles are also complicated because a major benefit from use of such vehicles, improved air quality, is a "social good." An individual consumer cannot directly receive this benefit by purchasing a clean-fuel vehicle, nor is purchase of a clean-fuel vehicle required for a person to receive the benefit. The benefit of improved air quality only accrues when a substantial number of clean vehicles are in use. However, there is increasing evidence of "green" segments of consumers, who place personal value on the environmental characteristics of the products they buy. These monetary, non-monetary, and environmental attributes combine to distinguish the problem of modeling demand for clean-fuel vehicles from previous modeling of the demand for car ownership and use.

1.2. Objectives and Scope

The present research results are extracted from a study that addresses the potential large-scale introduction of clean-fuel vehicles. The absence of market data has led to the use of a stated preference approach in model development. In such an approach respondents are asked to express preferences for hypothetical products described in terms of their attributes. Statistical models are then applied to estimate the relative values of the attributes to consumers. The immediate goals of the study are (1) to demonstrate the feasibility of using stated preference (SP) methods to identify the characteristics of demand for clean vehicles and fuels, and (2) to construct quantitative choice models for clean vehicles and fuels.

For the purposes of the study, clean-fuels are assumed to encompass electricity, and liquid and gaseous fuels such as methanol, ethanol, compressed natural gas (CNG) and propane. Extensive efforts were made in the early stages of this study to determine those factors that critically affect consumers' preferences for clean vehicles and fuels. Focus group interviews were held, expert opinions sought, and a pre-survey conducted with several hundred households (Golob, et al., 1991). It was found that consumers are likely to distinguish clean-fuel vehicles from present conventional (gasoline and diesel) vehicles on the basis of many generic attributes, but seven of attributes were the most important to consumers: (1) vehicle purchase price, (2) fuel operating cost, (3) vehicle range between refueling, (4) availability of fuel, (5) vehicle performance (potentially in the case of electric vehicles), (6) dedicated versus multiple-fuel capability, and (7) the level of reduction in emissions compared to (current) gasoline vehicles.

1.3. Background

The stated preference (SP) models developed in the current study complement previous work on revealed preference (RP) models for ownership and usage of conventional-fuel vehicles. For a review of RP vehicle choice models, see Mannering and Train (1985). A specific example is the disaggregate model system described in Train (1986) for vehicle demand and utilization at the household level. It consists of a hierarchy of submodels which include: (1) number of vehicles owned by the household, (2) vehicle holdings by class/vintage, (3) vehicle miles traveled (VMT). Discrete choices are modeled as functions of both household characteristics and vehicle attributes, e.g., household income, vehicle operating cost, purchase price, internal space, etc. Relationships between discrete and continuous choices are accounted for using a method due to Dubin and McFadden (1984).

This model system is used by the California Energy Commission to conduct scenario simulations for assessing the impact of policies and programs directed toward reducing gasoline consumption by personal-use vehicles. These concerns arose primarily in response to oil supply disruptions in the late 1970's, but are now also considered important for environmental reasons. The new SP models developed here can be used to modify this and other systems to better incorporate preferences for clean vehicles and fuels, the attributes of which are beyond the range of current conventional vehicles. Ways of accomplishing this are discussed in Section 6.

Multi-year simulations involving the introduction of new classes of alternatively-fueled vehicles have been conducted by Train (1986) using the previously available RP models. Scenarios are defined by projecting the likely attributes for these new classes of vehicles, as well as existing classes of vehicles. However, the RP model system omits the potentially important attributes which are likely to differ between clean-fuel and conventional-fuel classes, as previously discussed. Moreover, for practical reasons the required alternative-specific constants for the new classes were approximated by matching them with those vehicle classes deemed to be most similar in any missing variables. Unfortunately, these factors are likely to be extremely important, and their effects on the "forecasts" are impossible to fathom. The present SP approach is intended to provide both an alternative scenario simulation capability and a source of data for modifying and extending RP models.

1.4. Organization of the paper

In Section 2 there is a brief review of SP methodology. The survey is described in Section 3. Section 4 presents modeling results based on SP choices for vehicles; these include a simple model based on fuel-related attributes only, as well as more detailed models that include relevant market segmentation variables based on, e.g., household characteristics. Section 5 presents fuel-choice modeling results for multiple-fuel vehicles that can be powered by either gasoline or an alternative fuel such as methanol or CNG. Section 6 outlines possible approaches for using the present results in analyzing clean-fuel vehicle demand. Finally, conclusions are drawn in Section 7.

2. STATED PREFERENCE MODELING

The advantage of using RP data is that models are based on observation of actual behavior, not on consumers' responses to questions regarding their intentions. Unfortunately, as with many issues involving introduction of radically new products, models estimated for existing products and their attributes are generally not adequate.

There is little alternative in these cases but to directly solicit preferences from consumers, as is often done in many marketing research contexts.

Stated preference approaches involve asking respondents to express preferences for hypothetical products that have been characterized in terms of their attributes. Responses can be elicited through judgmental rating or ranking tasks, or through choices made from hypothetical choice sets (Louviere, 1988). There have been a few SP studies of the demand for electric vehicles by Beggs, Cardell, and Hausman (1981), Hensher (1982), and Calfee (1985). The former study elicited rank orderings, whereas the latter two studies used discrete choice approaches. SP discrete choice data sets may be analyzed in a manner similar to RP data, but the range of models that may be estimated depends on the experimental design used to generate the hypothetical alternatives and the choice sets (Louviere and Hensher, 1983; Bunch, Louviere, and Anderson, 1991).

The present study extends previous research in several ways. First, there is a much wider range of clean-fuel vehicles. Second, RP data are collected in conjunction with the SP data to facilitate merging results with existing RP models, and to allow other types of joint RP-SP analyses. Third, a sophisticated discrete-choice experimental design is used, in which it is assumed that the correct discrete-choice model form might be more complex than the standard multinomial logit model. Fourth, in addition to vehicle choices, respondents are also asked about the choice of fuel they might make when using multiple-fuel vehicles. Finally, a much larger sample size is used than in previous studies.

3. THE STATED PREFERENCE SURVEY

3.1. Overview of the three-phase survey

The first stage of survey development involved identifying the attributes and fuel-types to be used for defining hypothetical vehicles. Information was collected through focus group interviews and a pre-survey (Golob, et al., 1991), as well as through a literature review and solicitation of expert opinions from the staff of the

California Energy Commission. The final fuel-related vehicle attributes can be divided into two types: generic, and those specific to fuel type. The generic attributes and their measurement units are: (1) vehicle purchase price (dollars), (2) fuel operating cost (cents per mile), (3) range between refueling or recharging (miles), (4) emissions levels (as a fraction of 1991 gasoline cars), and (5) fuel availability (fraction of stations having fuel). Vehicle and fuel costs for clean-fuel vehicles might be higher or lower than for comparable gasoline vehicles, depending on potential subsidies, incentives, and unknown production and distribution costs.

Pollutant emissions by clean-fuel vehicles are expected to be below the levels for current gasoline vehicles, and future conventional-fuel vehicles could have lower emissions levels due to reformulated gasoline. More importantly, focus group interviews and pre-survey results from the target population in the California South Coast Air Basin indicate that many potential buyers perceive vehicle cleanliness to be an important factor affecting their future vehicle purchase behavior. Thus, the emissions level attribute provides important personal utility for these consumers and is included in the survey. However, this attribute is unique in that it can be associated with the "social good" of improved air quality, and special care should be taken in interpreting the numerical results for the emissions level attribute.

Three basic fuel types were defined in the survey: (1) gasoline, (2) alternative, and (3) electric. The term "alternative" was chosen to represent any of the possible gaseous or liquid fuels now being considered (e.g., methanol, ethanol, CNG, etc.). For alternative-fuel vehicles, an additional attribute indicated whether the vehicle was (a) dedicated (i.e., could run on alternative fuel only), or (b) had multiple-fuel capability (i.e., could run on gasoline and/or the alternative fuel). Multiple-fuel vehicles allow the use of gasoline, but emission reductions are compromised when gasoline is used. Multiple-fuel methanol- and ethanol-powered vehicles are typically known as "flexible-fuel" vehicles; gasoline and the alternative fuel can be mixed in any proportion in a single tank, and emissions levels are nonlinearly related to the proportion of gasoline in the mixture. Multiple-fuel CNG- and propane-powered vehicles are typically referred to as "dual-fuel" vehicles. They have separate tanks for gasoline and the (pressurized) alternative fuel, and the engine is readily switched to run on either fuel. LPG (propane) dual-fuel vehicles are common in Europe, particularly the Netherlands, and CNG dual-fuel vehicles can be found in Canada and New Zealand (Sperling, 1988).

For historical reasons, many consumers have developed a perception of electric cars as small vehicles with very slow acceleration and limited range. However, technological breakthroughs could result in electric cars that have performance characteristics comparable to gasoline vehicles. The issue of how electric cars might be refueled is also uncertain. Accordingly, to reflect this uncertainty in levels of performance and recharging, electric vehicles were assigned two performance levels and two recharging scenarios. The performance levels were: (1) high performance (i.e., "acceleration like today's gasoline cars"), and (2) low performance (i.e., "acceleration slower than today's cars"); and the recharging scenarios were: (1) recharge at home (presumably overnight), and (2) recharge at both home and the work location. Different configurations of electric vehicles were also included. Electric vehicles were characterized as either dedicated or "hybrid" (i.e., able to run on electricity and/or gasoline). Choice sets were used which included three vehicles per choice set. This is described in more detail in Section 3.3.

The complexity of considering vehicles defined using these attributes made a telephone survey impractical for meeting the objectives of this study. The other alternatives were face-to-face interviews and mail surveys. Face-to-face interviews, either at homes or central locations, were judged to be too costly given the resource constraints, yielding unacceptably small sample sizes. The vast land area of the South Coast Air Basin was a major impediment, since the desired spatial distribution of the sample would require extensive interviewer travel. Survey pretesting revealed that an SP mail survey was feasible, especially if the SP choice tasks could be customized to approximate the choice sets that might actually be considered by the each respondent. Pretesting also indicated that, in order to avoid confusion and respondent fatigue, it was important to separate the vehicle choice SP and fuel choice SP for multiple-fuel vehicles. These considerations led to the three-phase survey design described in the next three sections.

3.2. Survey Phase 1: Background Information

The first phase of the survey involved a recruitment letter, an incentive prize announcement, and the business-reply postcard questionnaire. It was mailed to a random sample of households in the California South Coast Air Basin. The attempt was to introduce respondents to the multi-phase survey with a compelling, short recruitment letter and a simple initial survey task.

The postcard questionnaire elicited information on household size, home ownership status, number of drivers, number of vehicles owned or leased, and three characteristics of the respondent's anticipated next vehicle purchase: whether the vehicle would likely be new or used, vehicle type (in eight categories), vehicle price range (in six categories), and fuel economy range (in four categories). The household information will be used to develop sampling weights (income was not asked because of its effect on response), and to perform some limited testing on non-response bias. The particulars concerning the respondent's anticipated next vehicle purchase were used to customize the subsequent vehicle choice phase of the survey.

3.3. Survey Phase 2: Vehicle Choice

The second phase of the survey was divided into three parts: (1) household socioeconomic information, (2) detailed questions about the vehicles presently owned or leased by the household, and (3) the SP vehicle-choice tasks on customized choice sets. The household information included such standard variables as income, household size and composition, and number of workers; these may be used as market segmentation criteria or as choice model explanatory variables. They can also be used to develop weights for expanding model results to the sample universe of South Coast Air Basin households.

Five SP choice sets such as the one shown in Figure 1 are contained in each Phase 2 questionnaire. Each choice set consists of three vehicles: one gasoline vehicle and two clean-fuel vehicles, the vehicles being described on the basis of the attributes outlined above. Respondents indicate which one of the three hypothetical vehicles they prefer, and then answer additional questions concerning whether or not they would actually replace an existing vehicle if their first choice were available.The respondents were randomly divided into two groups. The first group considered choice sets that always contained one gasoline vehicle, one alternative fuel vehicle, and one electric vehicle. The second group considered choice sets that always contained one gasoline vehicle, one dedicated alternative fuel vehicle, and one multiple-fuel alternative fuel vehicle. Since attributes of electric vehicles exhibit a greater deviation from existing vehicles than do fossil-fuel-based alternatives, the different choice contexts could potentially affect the nature of the responses. This feature of the survey design allows testing for such effects.

The procedure for creating the choice sets was chosen as a compromise among various competing objectives. The framework of three vehicles per choice set (along with the final experimental design) 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 6 or 7 attributes per vehicle per choice set, or a maximum of 21 attributes per choice set. For most attributes, four levels 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.

Establishing the range of interest for each attribute, as well as the actual attribute levels, required balancing competing concerns of potential forecasting flexibility versus statistical efficiency. Wider ranges would allow more scenarios to be considered, but might result in unrealistic situations for respondents. Final ranges and levels were selected in close consultation with the staff of the CEC.

The attribute ranges covered by the survey are: (1) fuel cost (2 to 10 cents per mile), (2) range between refueling or recharging (75 to 300 miles), (3) emissions levels (10% to 100% of levels for 1991 cars), and (4) fuel availability (10% to 100% of stations have fuel). The overall range of vehicle purchase prices covered by the study was quite broad, but for any given individual the range of levels was customized.

Figure 1: Example of a Vehicle-Choice Question

On this and the following four pages, we are asking you to choose from among three hypothetical new vehicles.

Suppose that you were considering purchasing a
new four-door sedan and the following three vehicles were available:

	Vehicle "A"	Vehicle "B"	Vehicle "C"
Fuel type	Gasoline only	Alternative fuel only	Electric only
Fuel availability	Gasoline available at all stations	1 out of 3 stations have alternative fuel	Recharge at home
Range in miles between refueling	300 miles	150 miles	75 miles
Purchase price	$13,000	$12,000	$15,000
Fuel cost	8 cents/mile	10 cents/mile	6 cents/mile
Level of pollution relative to 1991 cars	85% of today's levels	25% of today's levels	10% of today's levels
Performance	Like today's cars	Like today's cars	Like today's cars

1. **Given these choices, which vehicle would you choose?**

☐ 1 **Vehicle "A"** ☐ 2 **Vehicle "B"** ☐ 3 **Vehicle "C"**

Software was written to produce customized Phase 2 questionnaires. Each respondent received five of the 64 different experimental design treatments. The design levels for the vehicle purchase price and fuel cost attributes were centered about the midpoints of the category values reported by the respondents in Phase 1, and all hypothetical vehicles were described to be the type that the respondent indicated he or she would next purchase. The order of the attributes in the questionnaire was randomized across individuals to eliminate possible bias, but the order was kept the same for each individual to minimize survey difficulty.

3.4. Survey Phase 3: Fuel Choice

The third and last phase of the survey had two main parts: (1) detailed descriptions of usage for each of (up to three of) the household's present vehicles, and (2) the fuel-choice SP task. The questions about the present vehicles can be used to estimate inferred shifts in usage between household vehicles, if a limited range vehicle (such as today's electrically powered vehicle) is forecasted as replacing an existing vehicle. The underlying relationships between vehicle characteristics and usage patterns are yet to be developed.

In the fuel choice SP task, shown in Figure 2, respondents are told: "Some future vehicles might be able to run on both gasoline and an alternative fuel, such as methanol, ethanol, propane, or compressed natural gas. Owners of these vehicles could decide which fuel to use each time they refueled. Fuels might differ in price and in their emissions levels. They might also differ in how far you can drive on a tankful because some fuels are less dense. The alternative fuels might not be available at all service stations."

For each of four hypothetical situations, respondents are then asked to choose which fuel they would most likely choose on a regular basis. In each of the four situations, the alternative fuel and gasoline choices are each described in terms of four attributes manipulated according to an experimental design similar to that used in the vehicle choice SP. The four attributes are: price per (equivalent) gallon, availability, range on a tankful, and emissions. The attribute ranges and levels were similar to those used in the vehicle choice survey.

Figure 2: Example of a Fuel-Choice Question for Multiple-Fuel Vehicles

10. **Some future vehicles might be able to run on *both* gasoline and an alternative fuel, such as methanol, ethanol, propane, or compressed natural gas. Owners of these vehicles could decide which fuel to use each time they refueled. Fuels might differ in price and in their emissions levels. They might also differ in how far you can drive on a tankful because some fuels are less dense. The alternative fuels might not be available at all service stations.**

Suppose you owned a multiple-fuel minivan that ran on both gasoline and an alternative fuel. For each of the four hypothetical situations below, please indicate which fuel you would most likely choose on a regular basis. Assume that you get 27 miles per gallon with both fuels.

SITUATION 1:

	The alternative fuel:	Gasoline:
Price per gallon	$1.75	$1.25
Range on a full tank	75 miles	375 miles
Pollution relative to 1991 cars	40% of today's levels	85% of today's levels
Availability	2 out of every 3 stations have the alternative fuel	All stations have gasoline
I would regularly refuel with:	☐ The alternative fuel	☒ Gasoline

SITUATION 2:

	The alternative fuel:	Gasoline:
Price per gallon	$1.25	$1.75
Range on a full tank	150 miles	375 miles
Pollution relative to 1991 cars	25% of today's levels	40% of today's levels
Availability	1 out of every 10 stations has the alternative fuel	All stations have gasoline
I would regularly refuel with:	☒ The alternative fuel	☐ Gasoline

There are 64 experimental design treatments; four SP task replications per survey, resulted in 16 survey versions (prior to customizing the surveys). The order of the attributes is once again randomized for each respondent, and the vehicle type and fuel economy of each respondent's anticipated next purchase (from the Phase 1 data) are reproduced on this Phase 3 survey to keep the choices in perspective.

3.5. Survey Implementation

The survey was administered during the months of May through August 1991. The target was 2,750 households. Phase 1 postcard responses were obtained from 1,096 of these households. Phase 2 (vehicle choice) surveys were sent to these 1,096 Phase 1 households, and 717 Phase 2 responses were returned. Each Phase 2 household was sent a Phase 3 survey, and 562 Phase 3 (fuel choice) surveys were returned. The effective response rates were: 40% for Phase 1, 26% for Phase 2, and 20% for Phase 3. The attrition rate of only 35% between phases 1 and 2 (a drop off from 1096 to 717) indicates that the SP vehicle-choice tasks were comprehended by the majority of persons who responded to the simple Phase 1 postcard questionnaire.

4. VEHICLE-CHOICE MODEL RESULTS

Only a handful of respondents supplied incomplete choice information, indicating that the vast majority of respondents experienced no difficulty in answering the survey questions. A data set was assembled using all five SP responses from 692 respondents with no missing choice data, yielding 5 x 692 = 3460 observations. All results reported here were obtained from this pooled data set; examination of issues related to ordering of questions, response fatigue, pooling and/or other repeated measures effects, etc., are outside the scope of this paper.

Analyses were performed using a variety of discrete choice models, including the standard multinomial logit (MNL) model, the nested multinomial logit (NMNL) model, and the multinomial probit (MNP) model. (For a general discussion of these models, see McFadden, 1981 or Ben-Akiva and Lerman, 1985.) The NMNL and MNP models are more general than the MNL model in that they do not rely on the independence of irrelevant alternatives (IIA) assumption, and provide the capability for examining the importance of various types of non-IIA behavior in clean-fuel vehicle choice models. For example, if important vehicle and/or household attributes have been omitted from the vehicle choice model, then the sample population's perceptions or preferences for various fuel-types might be correlated. In this case multinomial logit would be an unacceptable model, and parameter estimates would be biased.

The results reported here were obtained using the NMNL model, although similar results were obtained using the MNP model. The theoretical properties of the NMNL model are outlined in McFadden (1981). Full-information maximum likelihood estimates for all models were obtained using the program ALOGIT developed by Daly (1987). The primary focus is on interpreting the estimated attribute coefficients, together with a general discussion of the sample population's preferences for clean vehicles and fuels. NMNL model coefficients for "log-sum" quantities (or "inclusive values") are also reported below; log-sum coefficients are related to the correlation of unobserved utilities among various choice alternatives, and are useful for capturing specific types of non-IIA behavior. Specifically, the correlation of unobserved utilities is given by one minus the log-sum coefficient. Hence, a NMNL model with all log-sum coefficients equal to unity is equivalent to the standard MNL model, which assumes uncorrelated random utilities.

4.1. SP Choice Model Using Vehicle Fuel-Specific Attributes Exclusively

The first vehicle-choice model, presented in Table 1, uses only the SP design variables, represented by the vehicle attributes. In Table 1 and subsequent tables, log-likelihood statistics are denoted as follows: "Log-Likelihood *initial(0)*" for the naive model (i.e., all parameters constrained to zero, giving equally-likely choices); "Log-likelihood *constant terms only*" for the MNL model using only alternative-specific constants; and "Log-likelihood *model*" for the model using all variables shown in the table.

The model in Table 1, and those in the subsequent Tables, are NMNL models with log-sum coefficients for non-electric vehicles. These models are hierarchical (or nested) with respect to the sequential addition of parameters: the relative explanatory power of any pair of models can therefore be compared using a likelihood ratio test. (The likelihood ratio statistic, computed as -2 times the difference in Log-likelihood values for two models, is Chi-square distributed with degrees-of-freedom equal to the difference in the number of parameters for the two models.) Based on this test, the NMNL model in Table 1 represents an improvement over the constants-only MNL model that is significant at $p < .01$.

The log-likelihood statistic for a simpler MNL logit using the same variables as the NMNL model in Table 1, minus the log-sum coefficient, is -3102.8. Comparing this to the log-likelihood of -3097.9 for the NMNL model in Table 1, the NMNL model represents an improvement over the basic MNL model that is also significant at $p < .01$ ($\chi^2 = 4.9$ with 1 degree of freedom). Moreover, the t-statistic for the log-sum coefficient is significantly different from one with $p < 0.01$. This indicates that independence from irrelevant alternatives is rejected for this preference function.

This NMNL model is consistent with a parsimonious covariance structure in which random utilities for vehicles in the non-electric group are correlated with each other, but are uncorrelated with utilities for electric vehicles. The extent of the correlation is given by one minus the log-sum coefficient, and choices involving both non-electric and electric vehicles do not satisfy IIA. However, a choice from a restricted set that includes only non-electric vehicles would satisfy IIA for this model. Finally, if the estimated log-sum coefficient is not statistically different from unity, then the NMNL model is equivalent to the MNL model, and IIA is satisfied for choices among all vehicle types. The source of the correlation in NMNL models is usually attributed to explanatory variables that have been omitted from the model, or that are otherwise not observable. Of course, many correlation structures could be hypothesized for this problem; a more complete discussion of NMNL model structures and selection of functional forms is beyond the scope of this paper.

The asymptotic t-statistics for the linear main effects in the NMNL model (Table 1) are highly significant for all five generic variables, and the signs are theoretically supportable. For example, the linear main effects for purchase price, fuel cost, and pollution are all negative, indicating that these factors have a significant negative effect on vehicle demand. The effects for range and fuel availability, on the other hand, have the theoretically anticipated positive effects on demand. With respect to the nonlinear terms, the t-statistic for the quadratic component of vehicle range is highly significant, followed by those for fuel availability and pollution level.

Table 1: Vehicle-Choice Nested Multinomial Logit Model 1
Fuel-Specific Attributes (SP Design Variables) Exclusively

VARIABLE	COEFFICIENT	t-STATISTIC
Purchase price ($1,000)	-.134	10.1
Fuel cost (cents/mile)	-.190	16.4
Range (100 miles)	2.52	11.4
Range^2 $(100\text{ miles})^2$	-.408	7.4
Emissions level (fraction of current)	-2.45	7.0
Emissions level^2 $(\text{fraction of current})^2$	0.855	2.7
Fuel availability (fraction of stations)	2.96	5.7
$\text{Fuel availability}^2$ $(\text{fraction of stations})^2$	-1.63	3.5
Alternative fuel (constant term relative to gasoline veh.)	0.0979	0.9
Multiple fuel (constant term relative to gasoline)	0.693	6.7
Electric vehicle (constant term relative to gasoline)	-.0240	0.1
Hybrid electric vehicle (constant term relative to gasoline)	-.257	1.5
Electric: charge at work as well as home (dummy var.)	-.126	1.1
Electric: low performance (dummy variable)	-1.04	6.2
Electric: low performance *with* hybrid (dummy variable)	0.544	2.3
Non-electric vehicles (log-sum coefficient)	0.805	3.2 w/r/t unity
Sample size	3460 (692 respondents)	
Log-likelihood *initial(0)*	-3801.2	
Log-likelihood *constant terms only*	-3739.2	
Log-likelihood *model*	-3097.9	

The t-statistics might be biased because no correction is made for repeated measurements. However, analyses using subsets of the data with no repetition (one choice observation per respondent) revealed similar results regarding significance levels of the coefficients.

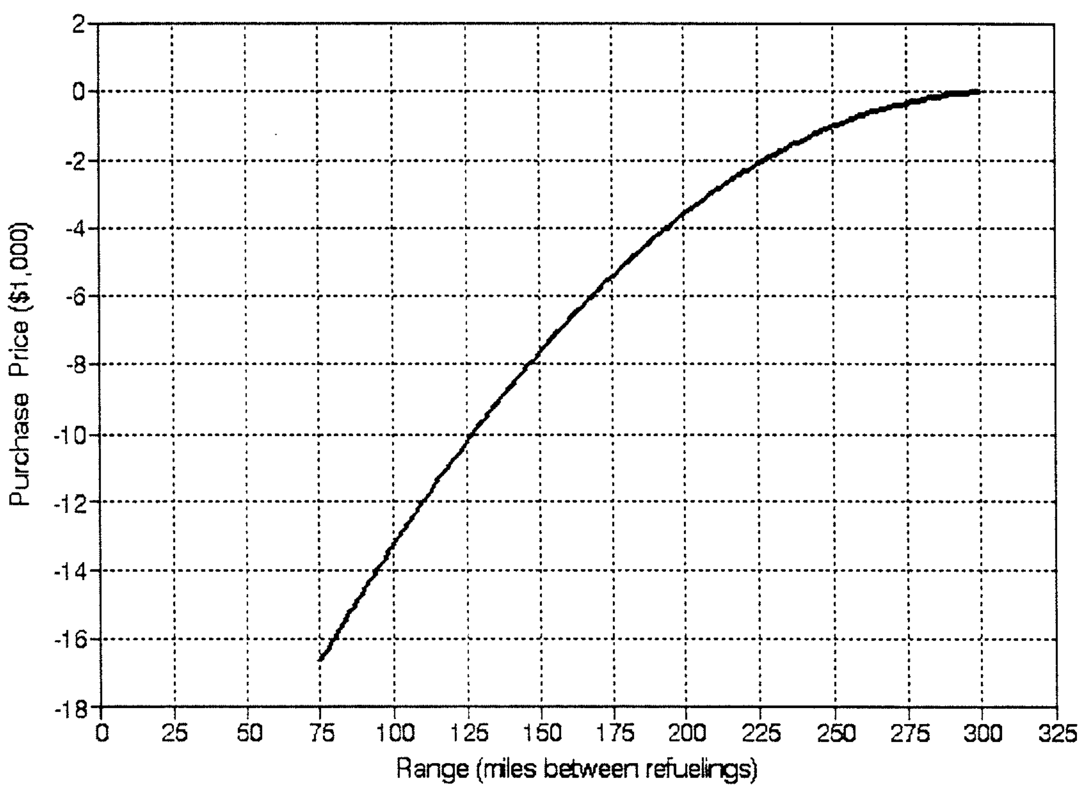
With regard to fuel-specific attribute coefficients, neither the (dedicated) alternative fuel constant nor the electric vehicle constant is significantly different from zero. Hence, when effects from all other model variables are taken into account, no important differences in vehicle preferences can be explained based on the "nominal" fuel type. This indicates that it is unlikely that any critical fuel-related variables were omitted from the survey design.

There were no detectable systematic biases for or against particular types of new vehicle fuel technologies, all other things being equal. On the other hand, fuel flexibility adds to the attractiveness of vehicles. The multiple fuel constant is positive with a t-statistic of 6.7. But the coefficient for hybrid electric vehicles is not significantly different from zero at the $p = .05$ level. The low performance ("slow acceleration") coefficient for electric vehicles is negative and significant, as expected. The "low performance *with* hybrid" coefficient is positive and significant, indicating that fuel flexibility mitigates the low performance concern. There were no detectable differences in preferences for electric vehicles under the two different recharging scenarios, because the "charge at work as well as home" coefficient is insignificantly different from zero (with a t-statistic of only 1.1).

Preferences are linear in purchase price and fuel price; however, it is worth recalling that surveys were customized based on the stated purchase price range and mpg range for the next vehicle the respondent intends to buy, as well as the class (body type) of vehicle. Hence, these coefficients relate primarily to tradeoffs among fuel-related attributes once the general class of vehicle has already been taken into account.

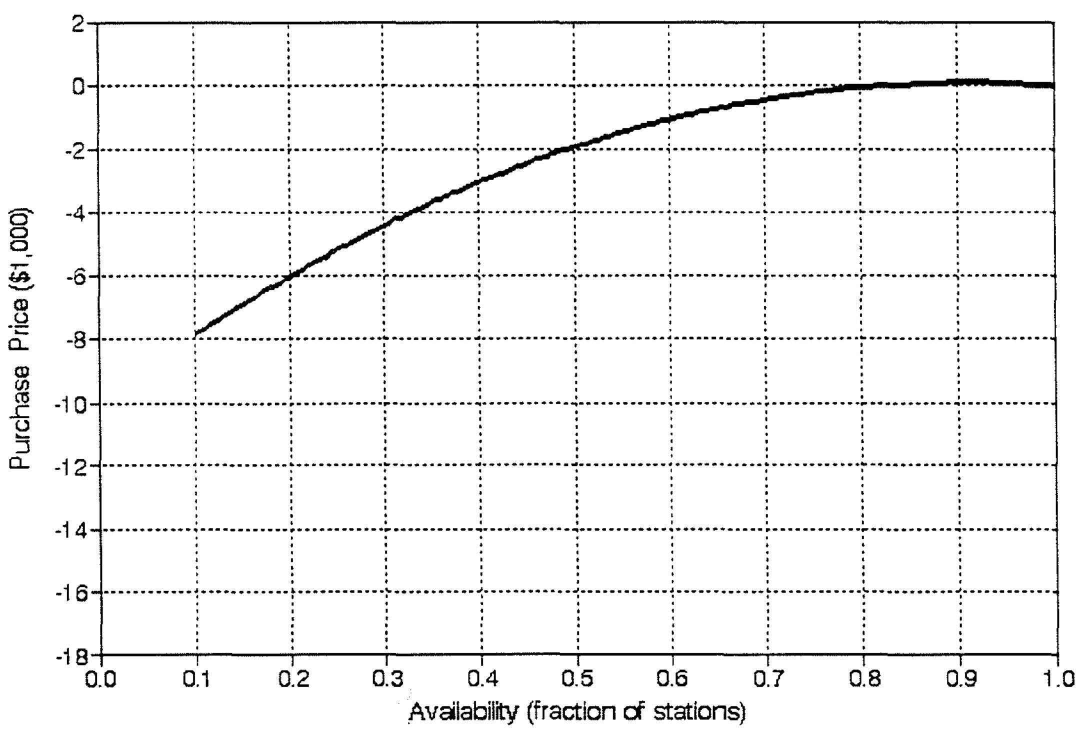
Examining tradeoffs for the remaining generic attributes (range, pollution, fuel availability) is more complex because preferences for these are nonlinear. The tradeoff between vehicle range and purchase price implied by the Model 1 coefficients is graphed in Figure 3. A reference point from which to measure changes in purchase price was arbitrarily set to zero for range equal 300, a typical value for gasoline cars. A decrease in range from 300 to 225 miles must be compensated by a decrease in vehicle purchase price of $2,000 for the choice probability to remain unchanged. Figure 3 shows that range displays diminishing marginal utility, which is a theoretically satisfying result. An increase of 50 miles in range from 100 to 150 miles is equivalent to a change in purchase price of more than $5,000, whereas a 50 mile increase from 250 to 300 is equivalent to a change of $1,000. The curve becomes flat at approximately 310 miles.

Figure 3: Iso-Probability Tradeoffs
Range versus Purchase Price



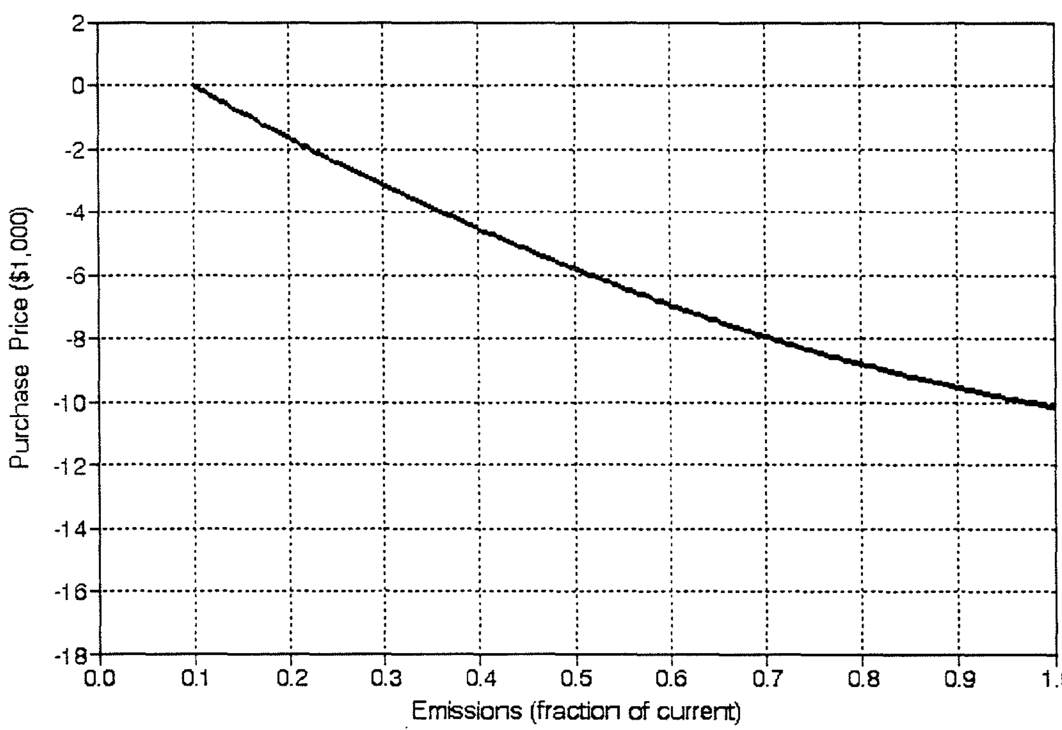
The implied tradeoff between fuel availability and purchase price is graphed in Figure 4. As in the case of range, there is diminishing marginal utility as fuel availability approaches that of gasoline (the fraction of stations having gasoline equals one). The slope of the curve becomes very flat if the fraction of stations having the fuel exceeds 0.75. (Theoretically, the slope of the nonlinear curve might be expected to approach zero as availability approaches 1. However, our quadratic approximation actually peaks earlier than this, and the computed slope, although very flat, is actually slightly negative in the 90 to 100% range; this can be regarded to be a statistical artifact.) Approximate purchase price equivalents for equal-interval increases in fuel availability are: \$1,700 for an increase of 10% to 20%, \$1,500 for 20% to 30%, \$1,300 for 30% to 40%, \$1,000 for 40% to 50%, and so forth, down to \$300 for an increase of 70% to 80%.

Figure 4: Iso-Probability Tradeoffs
Fuel Availability versus Purchase Price



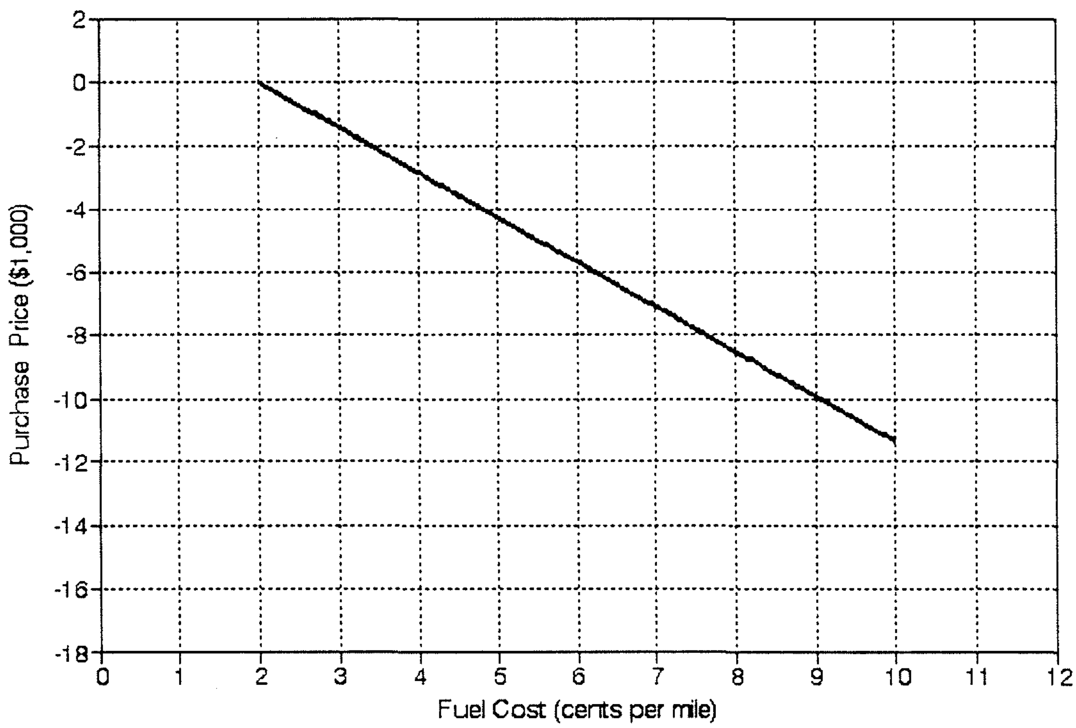
The model-implied tradeoff between emissions level and purchase price is shown in Figure 5. In contrast to the nonlinear relationships for range and availability, the tradeoff for pollution is concave to the origin, indicating an increasing marginal utility for emissions reductions as vehicles depart from current emissions levels. This is consistent with attitudes expressed by consumers in our focus groups: participants indicated that they would seriously consider paying extra for a cleaner vehicle, but only if they were convinced that the vehicle was substantially cleaner than today's conventional vehicles. Vehicle cleanliness might be valued higher by residents of the South Coast Air Basin because of the Basin's chronic air quality problem and the recent extensive media coverage of emissions-reduction efforts. It would be necessary to repeat the survey outside of the South Coast Air Basin to test this hypothesis.

Figure 5: Iso-Probability Tradeoffs
Emissions Level versus Purchase Price



Finally, the implied linear iso-probability trade-off between fuel cost and vehicle cost is graphed in Figure 6. This relationship indicates that a reduction in fuel cost by one cent per mile is equivalent to a reduction in vehicle purchase price of approximately $1,400, where the term "equivalent" means that either reduction would have the same effect on the predicted SP choice probability. Assuming no discount rate, this could be interpreted to mean that an "average" respondent estimates the lifetime use of a vehicle to be 140,000 miles (for the original purchaser *and* all subsequent owners), which is judged to be a reasonable value for a new vehicle.

Figure 6: Iso-Probability Tradeoffs
Fuel Cost versus Purchase Price



4.2. *SP Choice Model with Socio-economic Segmentation Variables*

It is quite possible that some differences in preferences across respondents can be described by differences in respondents' personal and household characteristics, such as gender, age, number of workers in the household, or income. Disaggregate prediction tables (Ben-Akiva and Lerman, 1985, pp. 208-215) were used to identify potential market segmentation variables that might be related to the under- or over-prediction of choice probabilities in the data set. The parameter estimates and log-likelihood statistics for Model 2, in which person- and household-specific segmentation variables are added to Model 1, are shown in Table 2.

The likelihood ratio statistic for Model 2 versus Model 1 is 31.9 with 7 degrees of freedom, indicating a highly significant improvement in goodness-of-fit. The t-statistics are also significant, and the coefficients provide information about differences in preferences among persons and households. For example, households with higher incomes have a stronger preference for gasoline cars, and respondents with a college education have a stronger preference for electric cars. Households where the respondent was at least 55 years of age have lower preference for electric cars. Persons with longer commuting distances exhibit a greater sensitivity to fuel cost, as measured by the negative coefficient on the interaction term between commuting distance and the generic fuel cost attribute, although this interaction term is significant only at the $p = .08$ level for one-tailed tests. Other significant interaction terms reveal that females are less sensitive to limited range, but respondents from households with greater numbers of workers per vehicle are more sensitive to range. These results provide potentially useful market research information.

As in Model 1, the log-sum coefficient for Model 2 is significantly different from unity, and the log-likelihood ratio statistic comparing the exhibited NMNL model (log-likelihood = -3066.0) to a MNL model with the same variables minus the log-sum term (log-likelihood = -3071.6) is 11.2 with 1 degree of freedom. This indicates that statistically important explanatory variables that might explain differences in preferences for electric versus non-electric vehicles are still likely to be omitted.

Table 2: Vehicle-Choice Nested Multinomial Logit Model 2
Fuel-Specific Attributes (SP design vars.) and Person/Household Segmentation Variables

VARIABLE	COEFFICIENT	t-STATISTIC
Purchase price ($1,000)	-.139	10.4
Fuel cost (cents/mile)	-.177	11.6
Range (100 miles)	2.50	11.1
Range^2 $(100\text{ miles})^2$	-.414	7.5
Emissions level (fraction of current)	-2.50	7.0
Emissions level^2 $(\text{fraction of current})^2$	0.862	2.7
Fuel availability (fraction of stations)	3.06	5.8
$\text{Fuel availability}^2$ $(\text{fraction of stations})^2$	-1.71	3.7
Alternative fuel (constant term relative to gasoline veh.)	0.385	3.1
Multiple fuel (constant term relative to gasoline)	0.979	7.9
Electric vehicle (constant term relative to gasoline)	-.070	0.3
Hybrid electric vehicle (constant term relative to gasoline)	-.329	0.6
Electric: charge at work as well as home (dummy var.)	-.143	1.2
Electric: low performance (dummy variable)	-1.06	6.2
Electric: low performance *with* hybrid (dummy variable)	0.575	2.4
Fuel cost (cents/mile) * Commuting distance (100 miles)	-.130	1.4
Range (100 miles) * Female gender (dummy variable)	-.311	3.6
Range (100 miles) * Household workers per vehicle	0.152	2.3
Gasoline vehicle (constant) * Income ($100,000/year)	0.330	4.3
Electric vehicle (constant) * College education (dummy)	0.619	4.3
Electric vehicle (constant) * Age 55+ (dummy variable)	-.354	2.9
Electric vehicle (constant) * 1-vehicle household (dummy)	-.218	1.4
Non-electric vehicles (log-sum coefficient)	0.7946	3.4 w/r/t unity
Sample size	3460 (692 respondents)	
Log-likelihood *initial(0)*	-3801.2	
Log-likelihood *constant terms only*	-3739.2	
Log-likelihood *model*	-3066.0	

4.3. SP Choice Model with Vehicle-type and Socio-economic Segmentation Variables

In addition to differences among socio-economic segments, preferences are likely to vary according to the type of vehicle that the respondent has in mind when choosing among the hypothetical future vehicles. In the Phase 1 survey, respondents were asked to indicate which of eight vehicle types would best categorize the household's next purchase: (1) four-door sedan, (2) two-door coupe, (3) sports car, (4) station wagon, (5) compact pickup, (6) minivan, (7) full-size pickup or van, or (8) sport utility vehicle. In addition, the expected fuel economy of the households' next purchase was elicited in four categories: (1) less than 20 MPG, (2) 20-24 MPG, (3) 25-30 MPG, and (4) over 30 MPG. It was determined through exploratory prediction-table analyses that preferences were related to segmentation involving combinations of several of these vehicle type and fuel economy variables.

Six vehicle-type segmentation variables were added to Model 2, yielding Model 3 (Table 3). The log-likelihood ratio statistic for Model 3 versus Model 2 is 80.4 with 6 degrees of freedom, once again indicating that the added variables have significant power in explaining sample differences in preference; the t-statistics for the segmentation variables are also significant.

Respondents intending to purchase compact pickups or sports cars, and respondents who do not intend to buy soon, are less sensitive to range restrictions than the general sample population. In contrast, purchasers of full-size vans/pickups have greater sensitivity to range. Purchasers of sport utility vehicles have lower preference for electric cars. This might be due to the electric car's current reputation for poor performance, or, perhaps users of sport utility vehicles require greater refueling flexibility than electricity would allow (camping trips, etc). Respondents who seek fuel economies of at least 25 mpg in their next vehicle have relatively lower preferences for gasoline cars, all else held equal. This might be an indication of a "green" segment of consumers who might become innovators in demand for clean-fuel vehicles.

The t-statistic for the log-sum coefficient in Model 3 is approximately 1.9, and the likelihood ratio statistic for Model 3 versus the corresponding MNL model is 3.4, with

Table 3: Vehicle-Choice Nested Multinomial Logit Model 3 Fuel-Specific Attributes, Person/Household Segmentation Variables, and Segmentation Variables Based on Type of Vehicle to be Purchased

VARIABLE	COEFFICIENT	t-STATISTIC
Purchase price ($1,000)	-.141	10.3
Fuel cost (cents/mile)	-.173	11.2
Range (100 miles)	2.70	11.9
Range^2 (100 miles)^2	-.431	7.7
Emissions level (fraction of current)	-2.49	7.0
Emissions level^2 (fraction of current)^2	0.854	2.7
Fuel availability (fraction of stations)	3.02	5.7
Fuel availability^2 (fraction of stations)^2	-1.68	3.6
Alternative fuel (constant term relative to gasoline veh.)	0.332	2.4
Multiple fuel (constant term relative to gasoline veh.)	0.927	6.7
Electric vehicle (constant term relative to gasoline veh.)	0.160	0.7
Hybrid electric vehicle (constant term relative to gasoline veh.)	-.144	0.6
Electric: charge at work as well as home (dummy variable)	-.137	1.1
Electric: low performance (dummy variable)	-1.08	6.3
Electric: low performance *with* hybrid (dummy variable)	0.613	2.5
Fuel cost (cents/mile) * Commuting distance (100 miles)	-.178	1.9
Range (100 miles) * Female gender (dummy variable)	-.319	3.7
Range (100 miles) * Household workers per vehicle	0.056	2.5
Gasoline vehicle (constant) * Income ($100,000/year)	0.276	3.6
Electric vehicle (constant) * College education (dummy var.)	0.539	3.7
Electric vehicle (constant) * Age 55+ (dummy variable)	-.407	3.3
Electric vehicle (constant) * 1-vehicle household (dummy var.)	-.168	1.1
Range (100 miles) * Full-size pickup or Van (dummy variable)	0.841	4.1
Range (100 miles) * Compact pickup (dummy variable)	-.515	3.9
Range (100 miles) * Sports car (dummy variable)	-.336	3.0
Range (100 miles) * Not intending to buy (dummy variable)	-.300	3.7
Electric vehicle (constant) * Sport utility vehicle (dummy)	-.750	2.5
Gasoline vehicle (constant) * Fuel economy 25+ MPG (dummy)	-.286	3.5
Non-electric vehicles (log-sum coefficient)	0.900	1.9 w/r/t unity
Sample size	3460 (692 respondents)	
Log-likelihood *initial(0)*	-3801.2	
Log-likelihood *constant terms only*	-3739.2	
Log-likelihood *model*	-3025.8	

one degree of freedom. Both of these statistics indicate that the NMNL model is only a marginal improvement over a simpler MNL model. Inclusion of segmentation variables related to the type of vehicle the household intends to purchase next apparently reduces the correlation of unobserved errors among non-electric vehicles.

Models 2 and 3 (Tables 2 and 3) illustrate the additional explanatory power of market segmentation variables, but the coefficients and t-scores for the original fuel-related attributes are quite stable across all three models. Thus, models which rely on a smaller set of variables may still prove useful for many types of market penetration analyses which cannot support the high level of detail included in Models 2 and 3.

In further exploring the relationships between type of vehicle and preferences for clean-fuel attributes, separate MNL choice models were estimated for each of six intended-vehicle-type segments, where segments were grouped according to similarity in preference structures. These MNL models were estimated with linear attribute coefficients to simplify comparisons among the segments. The coefficients for the six models are listed together with their t-statistics in Table 4.

The segment of "intended purchasers of sedans, coupes, and station wagons with average fuel economies of at least 25 miles per gallon" (column 1) exhibits a relatively high preference for alternative fuel vehicles and for electric vehicles, but also is sensitive to low performance in electric vehicles. The corresponding segment with fuel economies below 25 mpg (column 2) is also sensitive to low performance in electric cars, but is relatively less sensitive to changes in purchase price, as might be expected of a segment that is less concerned about fuel economy. The third segment (intended buyers of compact pickups or minivans) is more sensitive to fuel cost, but is less sensitive to limitations on range. Intended buyers of full-size pickups, vans, and sport utility vehicles (column 4) have a lower preference for alternative fuel vehicles (both dedicated and multiple-fuel), and are more sensitive to range. The fifth segment (intended sports car buyers) is extremely sensitive to low performance in electric cars, has a higher preference than the general sample for multiple-fuel vehicles, and is less sensitive to range. Finally, those not planning to by a car at the present time (column 6) are more sensitive to a number of attributes, including purchase price, fuel cost, and fuel availability; however, they have higher preferences for both types of alternative fuel vehicles (dedicated and multiple-fuel).

Table 4: Vehicle-Choice Multinomial Logit Models for Six Vehicle-Type Segments
Fuel-Specific Attributes (SP Design Variables) Exclusively
(Shown are Coefficient estimates with t-statistics in parentheses)

VARIABLE	SEGMENT: 4-door or 2-door or sta. wag. 25+ mpg	4-door or 2-door or sta. wag. <25 mpg	Compact pickup or van	Full size pickup or van or sports util	Sports-car	Not planning to buy
Purchase price ($1,000)	-.143 (6.2)	-.070 (2.7)	-.184 (4.6)	-.181 (4.4)	-.148 (2.6)	-.200 (3.3)
Fuel cost (cents/mile)	-.175 (8.9)	-.162 (6.9)	-.240 (7.4)	-.209 (5.8)	-.225 (4.5)	-.227 (5.9)
Range (100 miles)	2.06 (5.7)	3.25 (6.7)	2.55 (4.4)	2.94 (3.9)	3.44 (3.8)	1.51 (2.2)
Range^2 $(100 \text{ miles})^2$	-.303 (3.3)	-.561 (4.8)	-.414 (2.6)	-.462 (2.5)	-.678 (2.9)	-.168 (1.0)
Emissions level (fraction of current)	-3.08 (5.0)	-2.81 (4.0)	-2.33 (2.4)	-2.36 (2.1)	-1.96 (0.1)	-1.81 (1.5)
Emissions level^2 $(\text{fraction of current})^2$	1.53 (2.8)	1.14 (1.9)	0.730 (0.8)	0.857 (0.9)	-1.85 (1.4)	0.443 (0.4)
Fuel availability (fraction of stations)	2.24 (2.4)	3.73 (3.6)	3.72 (2.6)	2.96 (1.9)	2.69 (1.2)	1.83 (1.0)
Fuel availability^2 $(\text{fraction of stations})^2$	-.956 (1.2)	-2.29 (2.5)	-2.64 (2.1)	-2.07 (1.5)	-1.22 (0.6)	-.087 (0.1)
Alternative fuel (constant relative to gasoline veh.)	0.340 (1.8)	-.097 (0.5)	0.054 (0.2)	-.310 (1.0)	-.470 (1.1)	0.908 (2.5)
Multiple fuel (constant relative to gasoline veh.)	0.902 (5.0)	0.426 (2.1)	0.513 (1.8)	0.264 (0.8)	0.966 (2.2)	1.40 (3.2)
Electric vehicle (constant relative to gasoline veh.)	0.541 (2.0)	-.133 (0.2)	0.241 (0.6)	-.179 (0.4)	0.703 (1.0)	0.536 (1.0)
Hybrid electric veh. (constant relative to gasoline veh.)	-.013 (0.0)	-.367 (0.6)	0.401 (1.0)	-.413 (0.8)	0.266 (0.4)	0.469 (0.8)
Electric: charge at work as well as home (dummy var.)	0.195 (1.1)	-.251 (1.0)	0.037 (0.1)	-1.05 (2.0)	-.931 (1.5)	-.449 (1.0)
Electric: low performance (dummy variable)	-.846 (3.4)	-1.13 (3.1)	-1.11 (2.3)	-2.57 (2.3)	-2.92 (2.4)	-1.34 (2.2)
Electric: low performance *with* hybrid (dummy variable)	0.287 (0.8)	0.773 (1.5)	0.723 (1.0)	2.25 (1.7)	2.35 (1.6)	1.28 (1.5)
Non-electric vehicles (log-sum coefficient) (t-statistic w/r/t 1.0)	0.795 (2.1)	1.01 (0.1)	1.02 (0.1)	1.06 (0.3)	0.784 (0.8)	1.17 (0.8)
Sample size (# respondents)	1170 (224)	840 (168)	470 (94)	390 (78)	235 (47)	305 (61)
Log-likelihood *initial(0)*	-1285.4	-977.8	-516.4	-428.5	-258.2	-335.1
Log-likelihood *constants only*	-1274.3	-945.6	-513.8	-398.3	-240.8	-330.0
Log-likelihood *model*	-1072.6	-772.1	-409.4	-314.1	-183.7	-266.3

5. FUEL-CHOICE MODEL RESULTS

For each of four hypothetical fuel choice situations, respondents were asked to (1) assume they own a multiple-fuel vehicle, and (2) indicate which fuel they would choose (gasoline or alternative). Because these choices are binary, there are no potentially complicating issues of non-IIA as with vehicle choice, and the logit model is appropriate. A sequence of logit models, similar to that described for vehicle choice, has been developed for assessing the roles of various attributes in explaining SP fuel-choice behavior. The sample size for these models is 2208, representing 552 respondents, each with four replicated choices.

The first fuel-type choice model uses fuel-specific (SP design) attributes only, and the coefficient estimates and log-likelihood statistics for this model are listed in Table 5. Fuel-choice Model 1 exhibits strongly significant likelihood ratio statistics and asymptotic t-statistics. These goodness-of-fit indicators are greater than those for the comparable vehicle-choice Model 1, indicating that vehicle choice is an inherently more complex decision than is fuel choice for multiple-fuel vehicles.

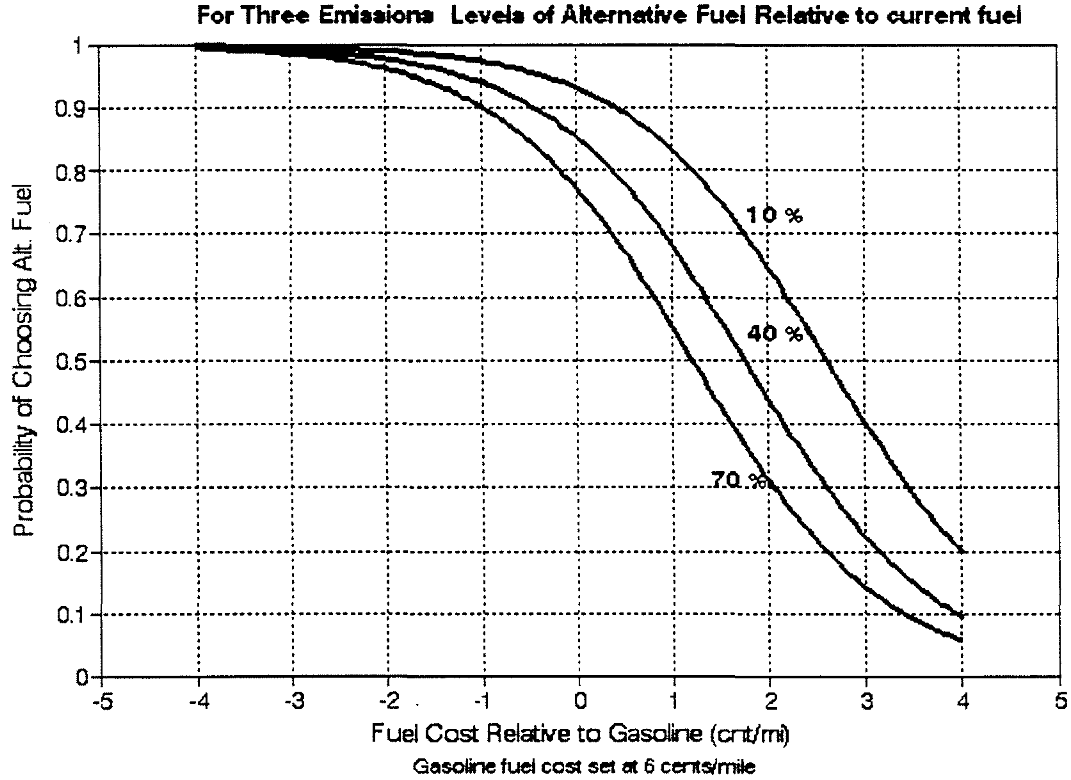
Table 5: Fuel-Choice Binomial Logit Model
Fuel-Specific Attributes (SP Design Variables) Only

VARIABLE	COEFFICIENT	t-STATISTIC
Fuel cost (cents/mile)	-1.010	10.0
Fuel cost^2 (cents/mile^2)	0.0309	4.4
Range (100 miles)	2.27	8.5
Range^2 (100 miles)^2	-2.59	4.4
Emissions level (fraction of current)	-3.15	4.9
Emissions level^2 (fraction of current^2)	1.16	2.2
Fuel availability (fraction of stations)	1.55	7.3
Alternative fuel (constant)	0.975	6.6
Sample size	2208 (552 respondents)	
Log-likelihood *initial*	-1530.5	
Log-likelihood *constant terms only*	-1519.1	
Log-likelihood *model*	-905.0	

Fuel-choice Model 1 captures significant nonlinear (quadratic) effects for all the fuel attributes except fuel availability. For each of fuel cost, range, and pollution, the quadratic term tends to offset the linear term at high levels, which indicates a decreasing marginal effect on preference for these three attributes.

Figure 7 illustrates the effect of the fuel cost attribute on the SP choice probability for alternative fuel versus gasoline. In Figure 7 both fuels are assumed to be available at all stations, the vehicle is assumed to have the same range for either fuel, and the fuel cost for gasoline is set at an intermediate value of 6 cents per mile. The predicted probability of choosing the alternative fuel is graphed as a function of alternative fuel cost, over the range of (decreasing cost) from 10 to 2 cents per mile. Because the major advantage of using alternative fuel is reduced emission levels, curves are plotted for three levels of emissions, where the level is measured as the percentage of emissions relative to 1990 cars (levels: 10%, 40%, 70%). The 10% level is much

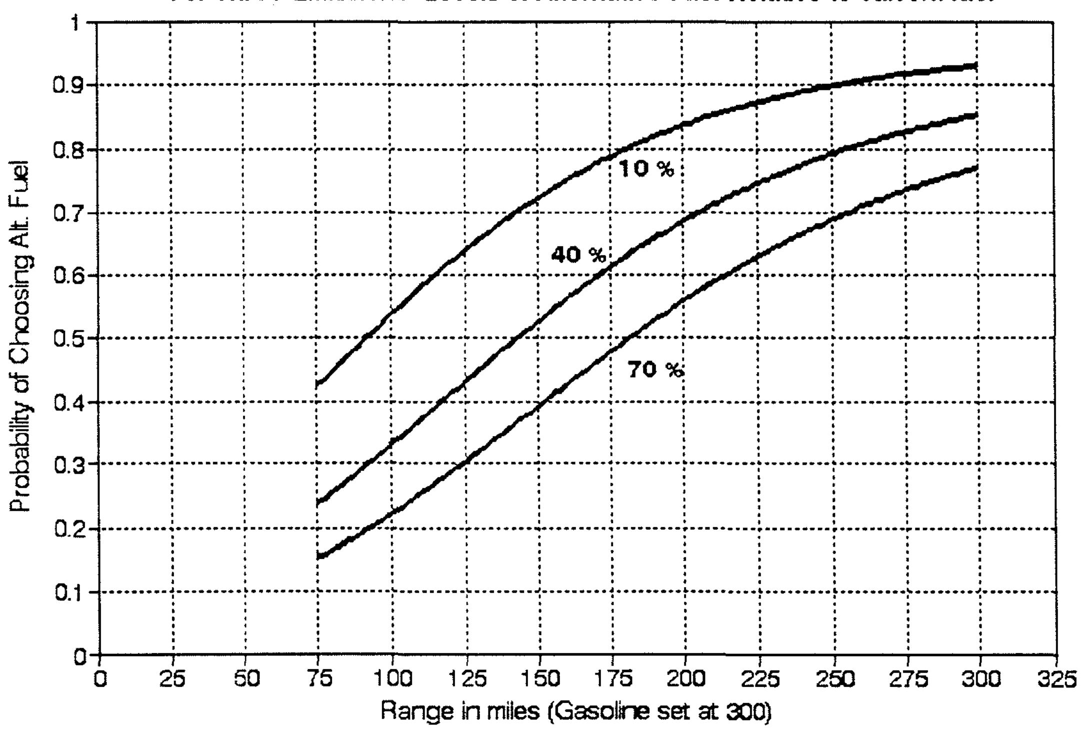
Figure 7: Alt Fuel Choice Probabilities
By Difference in Alt and Gas Fuel Costs
For Three Emissions Levels of Alternative Fuel Relative to current fuel



cleaner than current vehicles, and seems readily attainable with the new technologies currently being developed. The 70% level could correspond to a short-term version of reformulated gasoline.

When alternative fuel and gasoline cost the same (i.e., 6 cents per mile) in addition to having the same range and availability, the probability of choosing alternative fuel is 0.94, 0.87, and 0.79 for 10%, 40%, and 70% emissions, respectively. As fuel cost decreases below 6 cent per mile, the choice probability rapidly approaches unity for all three emission levels. As fuel cost increases above 6 cents per mile, the choice probabilities begin dropping quickly, and they diverge for the three emissions levels. However, even at a cost of 10 cents per mile, the choice probability is 0.39 for 10% emissions. The corresponding probability for 70% emissions is 0.14, giving an indication of how choice of fuel might be affected by its cleanliness.

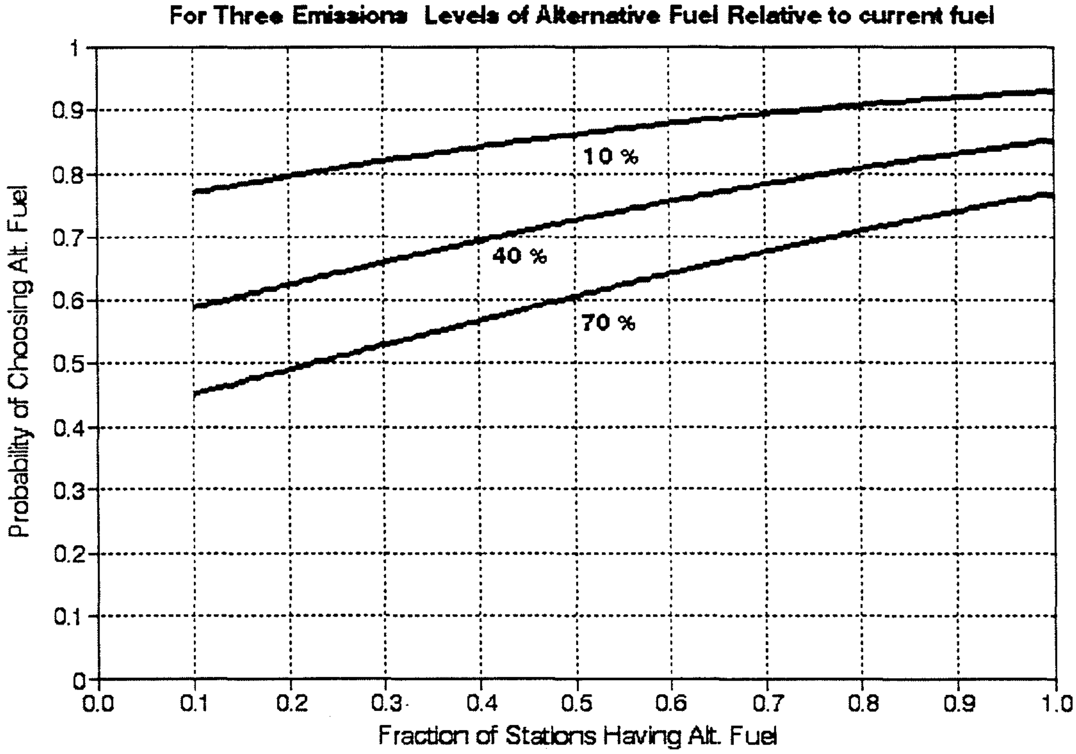
Figure 8: Alt Fuel Choice Probabilities
By Alt Fuel Range Between Refuelings
For Three Emissions Levels of Alternative Fuel Relative to current fuel



A choice probability plot for vehicle range between refueling is given in Figure 8. Conventional-fuel cars are assumed to have a range of 300 miles, and fuel costs and availabilities are assumed to be the same for the two fuels. Under these conditions, vehicle range with alternative fuel has a marked effect on fuel choice over the range of attribute levels included in the SP survey (75 to 300 miles). When the range is the same for both fuels, the alternative fuel choice probabilities are (as previously shown), 0.94, 0.87, and 0.79 for the three emission levels. For 10% emission levels the choice probability exceeds 0.84 until range falls below 200 miles; however, below 200 miles the choice probabilities diminish quickly for all emissions levels.

The effects of fuel availability are graphed in Figure 9. These effects appear to be less pronounced over the range of values in the survey. Choice probabilities remain relatively high for the full range of fuel availabilities, assuming that the fuel is relatively clean (10% emissions) and other attributes (range and fuel cost) are comparable for both fuels.

Figure 9: Alt Fuel Choice Probabilities
By Alternative Fuel Availability
For Three Emissions Levels of Alternative Fuel Relative to current fuel



A variety of segmentation variables were found to have statistically significant interactions with the fuel attributes, yielding a second model with improved prediction of fuel choice. The log-likelihood statistics, coefficient estimates, and their t-statistics for fuel-type choice Model 2 are listed in Table 6. As in the case of vehicle choice, these results provide potentially useful market research information. Respondents greater than 55 years of age are more sensitive to limited fuel availability, and respondents with no college education are more likely to choose gasoline. The coefficient for the interaction between commuting distance and fuel cost has the theoretically anticipated sign (negative); respondents with commuting distance less than 15 miles are less sensitive to limited range. Respondents who intend to purchase a full-size pickup/van are more sensitive to limited range, whereas those intending to purchase a compact pickup or two-door car are less sensitive to limited range. Respondents who typically refuel while on a shopping trip are less sensitive to limited range, but those who refuel more than one time per week are more sensitive to limited range.

As in the case of vehicle choice, the estimated coefficients for the fuel-specific attributes remain stable across fuel-type Models 1 and 2 (Tables 5 and 6). This indicates that either model can be used to evaluate fuel-choice scenarios for multiple-fuel vehicles. Use of Model 2 (Table 6) requires forecasts of population segments, while Model 1 (Table 5) requires only forecasts of vehicle and fuel supply attributes.

**Table 6: Fuel-Choice Binomial Logit Model
Fuel-Specific Attributes, Person/Household Segmentation Variables, and
Segmentation Variables Based on Type of Vehicle to be Purchased**

VARIABLE	COEFFICIENT	t-STATISTIC
Fuel cost (cents/mile)	-.992	9.3
Fuel cost^2 (cents/mile)^2	.0330	4.5
Range (100 miles)	2.54	8.6
Range^2 (100 miles)^2	-.270	4.5
Emissions level (fraction of current)	-3.31	5.0
Emissions level^2 (fraction of current)^2	1.24	2.2
Fuel availability (fraction of stations)	1.43	6.7
Alternative fuel (constant)	1.03	6.7
Fuel availability (frac. of sta.) * Age 55+ years (dummy)	0.546	2.4
Gasoline (constant) * No college education (dummy var.)	0.592	2.2
Fuel cost (cents/mile) * Commuting distance (100 miles)	-.779	2.9
Range (100 miles) * Commuting distance < 15 miles (dummy)	-.272	2.4
Range (100 miles) * Full-size pickup or Van (dummy var.)	0.884	3.1
Range (100 miles) * Compact pickup (dummy var.)	-.944	4.2
Range (100 miles) * Usually refuel on shopping trip (dummy)	-.450	3.4
Range (100 miles) * Usually refuel > 1 per week (dummy)	0.308	3.1
Sample size	2208 (552 respondents)	
Log-likelihood *initial*	-1530.5	
Log-likelihood *constant terms only*	-1519.1	
Log-likelihood *model*	-867.8	

6. ESTIMATING MARKET PENETRATION

6.1. Sample Enumeration Using SP Choice Models

SP choice models can be used in conjunction with the survey database to provide a useful form of scenario testing. In this approach, a market scenario is developed by defining hypothetical vehicles based on the four generic fuel-technology types (gasoline, dedicated alternative, multiple, and electric). The existence of particular vehicles, as well as their attributes levels, could be specified separately for each vehicle class (four-door sedan, minivan, etc.). Using the survey sample of households to represent a vehicle-buying market, SP choice models could be directly applied by using a sample enumeration approach. Choice sets are established and choice probabilities are computed for each household. Changes in specific household-level choice probabilities and/or average probabilities for the entire sample could be examined under various policy scenarios (e.g., subsidies for clean-fuels or vehicles, increased taxes on gasoline, etc.). In addition, the sample could be re-weighted with respect to such variables as vehicle class, household income, age, sex, etc., to reflect different types of markets.

The disadvantage of this approach is that it is based solely on the stated intentions of survey respondents, and has not been adjusted to incorporate available information on actual market-based behavior. In addition, the approach only examines how choice probabilities might shift as fuel-related attributes are changed. The level and distribution of purchases by vehicle class is assumed to remain fixed (unless the sample is re-weighted). Furthermore, the choice sets available for use in sample enumeration, consisting of just a few vehicles with different fuel types, do not represent choice sets that are actually considered by buyers. Thus, although this approach provides a useful tool for policy analysis, it is not capable of simulating shifts in actual demand. The extent of these potential difficulties have yet to be evaluated, and could be overcome by approaches which combine SP and RP information. This is a clear direction for further research.

6.2. Extensions of Existing RP Vehicle Holdings and Utilization Models

A different approach to forecasting demand for clean-fuel vehicles would be to extend the current RP models by adding fuel-related variables to their submodels. Coefficients would be obtained by estimating appropriate SP models, and re-scaling the coefficients for use in the RP models. Linkage can be achieved through the vehicle attributes common to both models, namely, vehicle purchase price and fuel (operating) cost. For example, vehicle-type choice alternatives in the Train (1986) model system are described in terms of vehicle holdings defined at the class/vintage level. Class/vintage choices for the one-vehicle holdings submodel are characterized by such explanatory variables as luggage space and horsepower in addition to purchase price and fuel cost. For the two-vehicle submodel each choice alternative is defined by summing the attributes from a pair of class/vintages. Class/vintage definitions would be expanded to include fuel-related attributes such as range, fuel availability, etc.

The simplest application of this approach would be to re-scale each parameter from Model 1 by a factor equal to the purchase price coefficient from the one-vehicle submodel in the Train (1986) system, divided by the purchase price coefficient from Model 1. This simple approach is valid as long as the tradeoff between purchase price and fuel cost in the two models is similar. This seems to be the case: the coefficient ratio for fuel cost to purchase price from Model 1 was 1420, and the corresponding ratio for the PVM one-vehicle submodel (for households earning more than $12K in 1978 dollars) is 1134, a difference of approximately 25 percent.

It is also necessary for the preference function specifications to be similar. SP models have been re-estimated using income categories which match those in the vehicle holdings model of Train (1986), so that their coefficient estimates can be consistently introduced. Extension of the two-vehicle holdings submodel would follow a similar approach, but will require SP modeling results different from those of section 3.

The advantage of this approach is that much of the data and programming needed to produce demand simulations is already in place. The only requirement would be that the models be modified to include the additional attribute coefficients, and the new attributes be appended to all vehicle types defined in the relevant files. A disadvantage of this approach is that it relies on a model system that contains vehicle type choice models formulated for one-, and two-vehicle households only. Although this may have been acceptable at the time the model was developed, a substantial number of households in California now hold three or more vehicles. This deficiency will be addressed in future research. Although a direct extension of vehicle holdings models to include more vehicles is possible, more promising approaches involve models based on household vehicle transactions, rather than vehicle holdings. In addition, new models should incorporate both SP and RP data to take full advantage of all available information.

7. CONCLUSIONS

The statistical significance, ease of interpretation, and stability of the SP choice modeling results are very encouraging. This indicates that our survey provides a useful database for estimating preferences for clean-fuel vehicles in the California South Coast Air Basin.

Estimates of attribute importance and segment differences are made using discrete-choice nested multinomial logit models for vehicle choice, and binomial logit models for fuel choice. These estimates can be used to modify present vehicle-type choice and utilization models to accommodate clean-fuel vehicles; but they can also be used to evaluate scenarios for alternative clean-fuel vehicle and fuel supply configurations. Results indicate that range between refueling is a particularly important attribute in cases where a clean-fuel vehicle has a range that is considerably less than that of existing gasoline vehicles. Vehicle preferences are relatively less sensitive to fuel availability when range and fuel costs are comparable to gasoline, although sensitivity increases nonlinearly as fuel availability approaches lower levels. For fuel choice, the most important attribute is fuel cost. However, the predicted probability of choosing alternative fuel is also affected by emissions levels, which can compensate for differences in fuel prices.

The differences in preferences captured by the person and household segmentation variables are readily interpretable and provide a strong foundation for future studies of the demand for alternative-fuel vehicles. The coefficient estimates for the fuel-specific attributes are stable across all choice models, an indication that the population has a measurable preference structure.

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