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Predicting the market penetration of electric and clean-fuel vehicles

Prévision du degré de pénétration du marché par les véhicules électriques et à carburant propre

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ABSTRACT

Air quality in Southern California and elsewhere could be substantially improved if some gasoline-powered personal vehicles were replaced by vehicles powered by electricity or alternative fuels, such as methanol, ethanol, propane, or compressed natural gas. Quantitative market research information about how consumers are likely to respond to alternative-fuel vehicles is critical to the development of policies aimed at encouraging such technological change.

In 1991, a three-phase stated preference (SP) survey was implemented in the South Coast Air Basin of California to predict the effect on personal vehicle purchases of attributes that potentially differentiate clean-fuel vehicles from conventional gasoline (or diesel) vehicles. These attributes included: limited availability of refueling stations, limited range between refueling or recharging, vehicle prices, fuel operating costs, emissions levels, multiple-fuel capability, and performance. Respondents were asked to choose one vehicle from each of five sets of hypothetical clean-fuel and conventional gasoline vehicles, each vehicle defined in terms of attributes manipulated according to a specific experimental design. Discrete choice models, such as the multinomial logit model, are then used to estimate how the values of the attribute levels influence purchase decisions. The SP survey choice sets were customized to each respondent's situation, as determined in the preceding Phase of the survey. The final Phase of the survey involved fuel-choice SP tasks for multi-fuel vehicles that can run on either clean fuels or gasoline. Preliminary results from a pilot sample indicate that the survey responses are plausible and will indeed be useful for forecasting.

RESUMÉ ANALYTIQUE

La qualité de l'air en California du Sud serait nettement améliorée si l'on pouvait remplacer une partie des véhicules à essence par des véhicules électriques ou encore des véhicules propulsés par *des combustibles propres tel le gaz propane, le méthanol, l'éthonal ou encore le gaz naturel comprimé. Il est essentiel d'effecturer une évaluation quantitative du marché et des réactions de le clientèle à ces véhicules "propres" avant d'élaborer les politiques qui permettraient un tel développement technilogique.*

Un sondage tri-phasé de préférence (SP) a été effectué en 1991 dans la région de South Coast Air Basin. On visait à déterminer le rôle potentiel des facteurs qui distinguent les véhicules à combustible propre des véhicules à essence, dans la décision d'achat d'un véhicule par le consommateur. Ces facteurs incluent: nombre limité de postes d'alimentation, coût dbpération, niveau d'émission, adaptabilité du véhicule à plusieurs types de carburant, indépendance limitée entre les pleins de carburant, prix d'achat, performances techniques. Nous avons établi cinq groupes de véhicules conventionnels et "propres", chaque véhicule étant défini en terme de facteur manipulés selon les critères spécifiques de conception du sondage. Les répondants devaient choisir un véhicules dans chacun des cinq groupes. À l'aide de modèle de choix discrets tels le modèle multinomial logit on détermine ensuite l'influence des facteurs citès plus haut sur la decision d'achat. Les groupes de véhicules ont été adaptes à la situation particulière de chaque répondant tel que déterminé dans une phase précédente de l'enquête.

La phase finale du sondage visait à déterminer les préférences de carburant applicables aux véhicules multi-carburant qui fonctionnent à base d'essence ou de carburant propre. Les résultats prélininaires d'un échantillon pilote indiquent que les données du sondage sont plausibles et peuvent donc servir à effectuer des prévisions.

1. Overview

Objectives

Reducing vehicle emissions levels is particularly important in the South Coast Air Basin of California, which includes the Los Angeles Metropolitan Area and the adjacent and interdependent Orange County, Riverside, and San Bernardino Metropolitan Areas. The climate and topography create ideal conditions for the area's infamous smog; and cars, trucks and buses contribute 88 percent of carbon monoxide emissions and about 50 percent of the ozone components: oxides of nitrogen and reactive organic gases. It is apparent that air quality can be greatly improved if gasoline-powered personal vehicles can be replaced in substantial numbers by vehicles powered by electricity or alternative fuels, such as methanol, ethanol, propane, or compressed natural gas (CNG) (see Sperling, 1988 and National Research Council, 1990, for discussions of the environmental factors associated with specific alternative fuels). While none of these alternative fuels has zero-level emissions (even electricity, if generation is taken into account), they all have lower overall emissions levels than currently available gasoline and diesel fuels; they are considered "clean" fuels for the purposes of this market research study. Personal vehicles are defined for the purposes of the study to be cars or light trucks owned or leased by private individuals.

The objective of this study is to determine the effect on personal vehicle purchase and fuel use of a few important attributes that potentially differentiate clean-fuel vehicles from conventional gasoline or diesel vehicles. By concentrating on quantitative estimation, it is intended that this study complement others aimed at qualitative assessments of the roles of information and uncertainty in consumer acceptance of clean-fuel vehicles (e.g., Turrentine and Sperling, 1991).

A stated preference (SP) survey and demand modeling method is used to accomplish the study objective: Survey respondents are asked to choose one vehicle from each of five sets of hypothetical clean-fuel and conventional gasoline vehicles, each vehicle defined in terms of five generic attributes and several vehicle type-specific attributes manipulated according to a specific experimental design. Discrete choice models, such as multinomial logit, are then used to estimate the values of the attribute levels in the consumers' utility functions.

Vehicle and fueling attributes studied

Clean-fuel vehicles are likely to differ from conventional-fuel vehicles in a number of important aspects involving their costs and operation. Focus group interviews were conducted and expert opinions were sought to define a set of attributes to be included as explanatory variables in the demand models developed in the study. These attributes can be divided into two subsets: generic attributes, and attributes specific to a certain type of vehicle. The generic attributes are: (1) limited availability of refueling stations, (2) limited range between refueling or recharging, (3) prices of the vehicles, (4) fuel operating costs, and (5) perceived emissions levels. Vehicle and fuel costs might be higher or lower than for comparable gasoline vehicles, depending on potential subsidies, incentives, and unknown production and distribution costs. Pollutant emissions by alternative-fuel vehicles are expected to be below the levels for gasoline vehicles, but the postulated emissions levels need to take into account potentially lower emissions from future reformulated gasoline.

In addition to being described by the five main generic attributes, there were vehicle-specific attributes for the classes of gaseous and liquid alternative-fuel vehicles and electric vehicles. For gaseous and liquid alternative fuels, an attribute distinguished (a) dedicated (alternative fuel only) vehicles and (b) multiple-fuel (gasoline and/or the alternative fuel). Multiple-fuel vehicles allow the use of gasoline when alternative fuel is unavailable, but obviously emissions reductions are compromised when gasoline is used. Multiple-fuel methanol- and ethanol-powered vehicles are 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 known 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.

Different configurations of electric vehicles also were studied. One electric-vehicle attribute distinguished two performance levels: (a) future high performance electric vehicles with essentially the same performance (acceleration) as gasoline cars, and (b) low performance electric vehicles with unspecified reduced acceleration. A second vehicle-specific attribute distinguished two recharging scenarios: (a) recharge available only at home, presumably overnight, and (b) recharge available at both home and the work location.

Organization

The survey is being conducted as a multi-phase self-administered mail-back (postal) questionnaire mailed to a random sample of more than 3,000 households in the California South Coast Air Basin. The survey is comprised of three phases: (1) an initial contact and short questionnaire to recruit respondents and obtain basic information to customize the subsequent survey Phases, (2) a vehicle-choice stated-preference (SP) survey, and (3) a vehicle usage questionnaire and fuel-choice SP survey for multiple-fuel vehicles.

The development of the entire survey is reported here. The SP methodology is discussed in Section 2. Each of these survey Phases is described in detail in Sections 3-5. Some preliminary results from a pilot survey of Phases 1 and 2 are presented in Section 6 to illustrate the information that is being obtained in these first two Phases. Conclusions are drawn in Section 6, together with an outline of further research.

2. Application of the stated preference (SP) method

Previous efforts to forecast demand for clean-fuel vehicles have relied on models estimated from existing market choices, or so-called "revealed preference" (SP) data (e.g., Train, 1980, 1986). Unfortunately, the variation of attributes for existing vehicles is not adequate for providing the necessary sensitivity required for forecasting and policy evaluation. In particular, attributes such as limited fuel availability, limited range, and improved (reduced) vehicle emissions for clean-fuel vehicles are likely to deviate substantially from presently existing situations (Beggs and Cardell, 1980). Predicting the influences of such attributes on choice is the principal goal of the present research. These limitations of traditional SP data motivate a stated preference (SP) approach, in which respondents are asked to express preferences for hypothetical products described in terms of their attributes. Stated preference responses can be elicited in terms of judgmental ratings or ranking tasks, or through choices made from hypothetical choice sets (Louviere, 1988). In this study, choices are made by respondents who are presented with hypothetical choice sets that contain a gasoline vehicle and clean-fuel vehicles, and discrete choice models are estimated on these data. In this way, SP data are used in a similar manner as revealed-preference (RP) data on actual market choices (Louviere and Hensher, 1983; Bates, 1988).

There have been a few SP studies involving clean-fuel vehicles, examples of which are studies of the demand for electric vehicles by Beggs, Cardell and Hausman (1981) and Calfee (1985). The present study extends the previous research in several ways. Among other things, in the present study there is a wider range of clean-fuel vehicles, a sophisticated discrete-choice experimental design is used, fuel choice is introduced for multiple-fuel vehicles, a joint SP-RP analysis is attempted to merge results concerning existing and extended attribute ranges, and there is a much larger sample size than in previous studies.

The complex SP survey tasks required to meet the objectives of this study cannot, in general, be administered as a telephone interview. The remaining alternatives are face-to-face interviews and mail surveys. Resource constraints dictated that the costs of face-to-face interviews, either at homes or central locations, would limit the attainable sample size. The vast land area of the South Coast Air Basin was a contributing factor to the high costs of face-to-face interviews, since the desired spatial distribution of the sample implied 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 SP implementation via the three-phase survey described in the three subsequent Sections.

3. Survey Phase 1: Background information

The first Phase of the survey involved a recruitment letter, an incentive prize announcement, and a 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 test non-response bias and develop sampling weights (income was not asked because of its negative affect on response). The particulars concerning the respondent's anticipated next vehicle purchase were used to customize the subsequent vehicle choice phase (Phase 3 of the survey).

The pilot sample was comprised of approximately 900 households; and size of the main sample is expected to exceed 3,000 households.

4. Survey Phase 2: the vehicle choice SP

The second Phase of the survey was divided into three parts: household socio-economic information, detailed questions about the vehicles presently owned or leased by the household, and the SP vehicle-choice tasks. The household information obtained was of the type generally used in revealed preference (RP) vehicle choice models: such as, income, household size and composition, and number of workers. These variables will be tested as segmentation criteria and as explanatory variables in the SP choice models. Some of these data can also serve in developing weights for expanding model results to the sample universe of South Coast Air Basin households.

Five SP choice sets are contained in each Phase 2 questionnaire. Each choice set consisted of three vehicles: one gasoline vehicle and two alternative-fuel vehicles, the vehicles being described on the basis of the attributes outlined in Section 1. Respondents are asked which one of the three hypothetical vehicles they prefer, then answer additional questions concerning whether or not they would replace an existing vehicle if their first choice was available. The respondents were randomly divided into two groups; one was presented with choice sets that contained one electric vehicle, and the other with choice sets without an electric vehicle. This design allows testing of the effects on choices of including or excluding hypothetical vehicles with greater attribute differences compared to existing vehicles.

The specific experimental design was chosen as a compromise among various competing objectives. The framework of three vehicles per choice set retained the possibility of estimating models which do not necessarily rely on the assumption of independence from irrelevant alternatives. This format required that levels be chosen for 6 or 7 attributes per vehicle per choice set. In most cases four levels per attribute were used to cover the range of interest, and to provide for estimation of nonlinear effects. The basic design used to produce the variation in attribute levels was an orthogonal main effects plan for a 4^{21} factorial in 64 runs.

The SP survey tasks were completely personalized, being individually printed using a specifically designed software package that read the experimental design file and the data from an the Phase 1 survey. Each respondent received five of the 64 different experimental design treatments. The design levels of the vehicle 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 during printing to eliminate possible bias.

5. Survey Phase 3: the fuel choice SP

The third and last Phase of the survey had two main parts: detailed descriptions of usage for each of (up to three of) the household's present vehicles, and 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 an electrically powered vehicle) is forecasted as replacing an existing vehicle. The underlying relationships between vehicle characteristics and usage patterns are yet to be developed and are beyond the scope of the research reported here.

In the fuel choice SP, 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 (four levels for both fuels), availability (where gasoline is always defined to be available at all stations, and the alternative fuel has four levels of limited availability), range on a tankful (four different levels for each of the two fuels), and pollution (four different levels for each of the two fuels).

There are 64 experimental design treatments; with four SP task replications per survey, resulting in 16 survey versions on the basis of attribute values. 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) is reproduced on this Phase 3 survey to keep the choices in perspective.

6. Preliminary vehicle choice results

The response rate for the Phase 1 pilot sample was approximately 34 percent. More than 67 percent of Phase 1 respondents successfully returned Phase 2 surveys as well, yielding an effective Phase 2 response rate of about 22 percent. This is similar to response rates experienced in many other mail surveys, indicating that the complexity of the Phase 2 survey did not have an adverse effect on the response rate.

An initial analysis was accomplished using the Phase 2 pilot data. These data represent the choices of 173 individuals, 88 of whom responded to the survey version containing an electric vehicle in each choice set, and 85 of whom responded to the version containing only gasoline and alternative-fuel vehicles. The repeated choices indicated by each respondent are treated initially as independent choices, leading to a sample size of 343 for the first group and 367 for the second.

Results from multinomial logit models estimated on the pilot data are displayed in Table 1. Two models were estimated, one for each of the two groups of respondents. Given in Table 1 for each model are the coefficient estimates and associated t-values, and the log-likelihood statistics: lnL(0) denotes the natural logarithm of the initial likelihood; lnL(C) denotes the log of the likelihood for a model with only constants (accounting for marginal choice frequencies); and lnL(B) denotes the log of the likelihood for the final model (accounting for all the explanatory attributes).

Attribute	Version 1		Version 2	
	coeff.	t-value	coeff.	t-value
Alt-fuel/gasoline multi-fuel dummy	0.207	0.78		
Alt-fuel/gasoline multi-fuel dummy	-.102	-.30		
Alt-fuel/gasoline multi-fuel dummy	-.036	-.10		
Purchase price	-.161	-3.48	-.200	-4.76
Electric veh. at-work recharge dummy	-.224	-.83		
Alt-fuel availability: "all stations"	1.045	2.83	1.194	3.75
Alt-fuel availability: "2 out of 3 sta."	1.129	3.01	1.206	3.79
Alt-fuel availability: "1 out of 3 sta."	0.080	0.19	0.900	2.74
Fuel price	-.225	-5.82	-.233	-.617
Range (in miles * 100)	0.962	7.37	1.105	8.62
Electric veh. lower performance dummy	-.872	-3.14		
Pollution level (% of 1991 gasoline cars)	-2.373	-5.26	-1.750	-4.25
Alt-fuel vehicle dummy	.210	0.63		
Electric vehicle dummy	1.081	2.18		
Dedicated alt-fuel veh. dummy			0.396	1.33
Dual-fuel dummy			1.134	3.83
SAMPLE SIZE	343		367	
Log-likelihood ratio: lnL(0)	-376.8		-403.2	
Log-likelihood ratio: lnL(C)	-372.7		-396.5	
Log-likelihood ratio: lnL(B)	-303.4		-311.5	
Model chi-square: -2[lnL(0)-lnL(B)]	146.9	(df=14)	183.5	(df=9)
Model chi-square: -2[lnL(C)-lnL(B)]	138.7	(df=12)	170.1	(df=9)

Table 1: Multinomial logit vehicle-choice model results for the pilot sample

Table 1: Les résultats de les modèles multinomial logit d'un énchantillon pilote

For each group, the overall model represents a significant explanation of choice, as indicated by the likelihood-ratio chi-square statistics. The coefficient estimates for the attribute levels in each model are generally significant and theoretically supportable. For example, purchase price, fuel price, a dummy variable for slower acceleration, and vehicle emission levels all have negative coefficients, indicating that higher levels of these factors have negative influences on vehicle demand. Range and fuel availability, on the other hand, have anticipated positive coefficients. The results are very encouraging as they lend strong support to the survey design, particularly the selection of the levels of vehicle attributes used in designing the choice sets.

The model results for the two groups are similar in terms of the estimates of the common coefficients. The coefficients of fuel price are practically the same, while those of range, and those of the first two availability dummy variables are respectively within 15% of each other. Similarly, the two coefficients estimates of purchase price are within 25% of each other. The two groups of respondents exhibit very similar preferences regarding these vehicle attributes, despite the fact that electric vehicles are included in the choice sets of only one of the groups.

A notable discrepancy between the two groups concerns the estimated coefficient for the dummy variable representing the level of alternative-fuel availability: "1 out of 3 stations" (the lowest level of fuel availability, "1 out of 10 stations" is the base level of comparison in each model). The estimated coefficient for the first group with electric vehicles is insignificantly different from zero, while that for the second group is significant. When electric vehicles are in the choice set, levels of fuel availability as low as "1 out of 3 stations" are viewed as being just as inconvenient as the base availability level of "1 out of 10 stations". However, this same level of availability is viewed as a positive in the second model where electric vehicles are not included in the choice set. These results indicate the presence of tradeoff between electric and alternative-fuel vehicles.

The estimated choice-specific constants are positive for both the alternative-fuel vehicle and the electric vehicle. This reveals that the respondents exhibit strong preferences toward clean-fuel vehicles if they are otherwise identical to the gasoline vehicle. The model for the second group indicates that dual-fuel vehicles are preferred over dedicated alternative-fuel vehicles.

Regarding dedicated versus hybrid electric vehicles, the initial choice model results for the first group provide no indication that hybrid electric/gasoline vehicles or electric/alternative-fuel vehicles are preferred over dedicated electric vehicles. Neither is the ability to recharge at the work location viewed as an added advantage. It is possible that more sophisticated choice models applied to the larger, main survey sample will establish positive values for these electric vehicle enhancements, but the respondents in the pilot sample prefer electric vehicles *ceteris paribus*, and this preference is not amplified by dual-fuel capabilities or non-home recharging capabilities.

7. Conclusions and Directions for Further Research

The SP survey has generated data that are likely to prove valuable in forecasting demand for clean-fuel vehicles. The survey response rates are acceptable, and the initial vehicle choice models are yielding statistically significant and theoretically supportable coefficient estimates. These results allow estimation of the relative effects on demand of: purchase price, fuel price, fuel availability, vehicle range, and pollutant emission on vehicle demand, as well as the influences of many vehicle type-specific attributes, such as the multiple-fuel option. The results are very encouraging as they lend strong support to the survey design. In particular, the results indicate that the levels of vehicle attributes used in designing the choice sets are comparable in that they .

The reported results are preliminary, based on the simplest multinomial discrete choice models applied to a small pilot sample. Models for the Phase 3 fuel-choice data are yet to be developed. Results of detailed analyses of the full data set will not be available until late 1991.

Future research is underway or anticipated along several lines. First, competing choice-model assumptions will be tested by applying several different choice models to the main sample data;

the models to be examined include multinomial probit and nested logit. Second, the Phase 2 and 3 surveys elicited repeated choices from each respondent, and error component models will be used to account for differences in preference across individuals. Third, joint estimation of vehicle choice and fuel choice data (from survey Phases 2 and 3) will be pursued. Finally, the results of this SP analysis will be used to generate a more comprehensive model for car ownership and usage forecasting. This is done by combining coefficients from both the SP model and an RP model estimated from vehicle make-model-vintage market choice and annual usage data. The coefficients for clean-fuel vehicle attributes, that are only available from the SP model, will be combined with those of conventional vehicle attributes, such as trunk space and vehicle-class choice-specific constants. The latter attributes had to excluded from the SP data collection effort to maintain comprehensible SP survey choice tasks.

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