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# Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-fuel Vehicles

by

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August, 1997

ABSTRACT: We compare multinomial logit and mixed logit models for data on California households' revealed and stated preferences for automobiles. The stated preference data elicited households' preferences among gas, electric, methanol, and CNG vehicles with various attributes. The mixed logit models provide a much better fit to these data, and forecasting exercises demonstrate substantial differences between logit and mixed logit model forecasts.

ACKNOWLEDGEMENTS: Tom Golob helped collect the data and conducted preliminary analyses upon which our analysis relies. We are grateful to him for allowing us to use these data. Hongyan Sheng provided invaluable assistance with preparing the data for analysis. Collection of the data used in this paper was financed by Southern California Edison Co,. Pacific Gas and Electric Co., and the California Energy Commission. Of course, none of these people or agencies are responsible for any errors or representations that we make in this paper.

## 1. INTRODUCTION

Forecasting the demand for new products or transportation innovations requires information about consumers' preferences for products or services that don't exist in the current marketplace. Researchers have overcome this problem by designing stated preference (SP) experiments to measure consumers' preferences over hypothetical alternatives including new products. SP data have been subject to considerable criticism by economists and other researchers because many times consumers react differently to hypothetical experiments than they would facing the same alternatives in a real market. This problem is particularly severe when the new products incorporate "politically correct" public good attributes such as "zero-pollution" electric vehicles. Respondents may misrepresent their choices in SP experiments to strategically signal their preference for provision of the public good (less pollution), although in reality they would not spend extra money on purchasing an electric vehicle (possibly because of the obvious free-rider problem).

One partial method to detect biases in SP responses is to design the SP experiment so that at least some of the measured preferences can be validated against observed, or revealed preference (RP) data. This paper describes preliminary investigations of combining SP and RP vehicle choice data where the SP alternatives include electric, compressed natural gas (CNG), and methanol fueled vehicles that aren't yet widely available in the marketplace. These data were collected as part of a larger project to build a microsimulation model of the California vehicle market. The SP data come from the first wave of the study collected in mid-1993. Approximately 2800 of the 4747 households from this study were re-interviewed approximately 15 months later, and the RP data consist of the vehicle purchases made by this subset during these 15 months.

These SP data have already been used to build a large multinomial logit (MNL) model of alternative-fuel vehicle choice (Brownstone et. al. , 1996) which is incorporated in a microsimulation model of the vehicle market for the greater Los Angeles area (roughly 10% of the U.S. vehicle market). More recently, Brownstone and Train (1996) used these SP data to compare MNL and "mixed logit" models where random error components are added to the MNL specification. They found strong evidence that the MNL specification is not appropriate for these data, and they demonstrated that there are large differences between forecasts based on the different specifications.

This paper extends the analysis in Brownstone and Train (1996) to jointly model SP and RP vehicle choices. Previous methodological work on combining SP and RP data have focused on the problems caused by scaling differences and the correlation in unobserved attributes across repeated choices by the same decision makers. We develop simple mixed logit specifications that easily incorporate unobserved correlation and scaling differences. These mixed logit specifications are statistically superior to the "standard" joint scaled logit models previously used for these applications. The mixed logit models also yield very different, but not necessarily more credible, forecasts. These incredible forecasts are caused by the failure of our maintained hypothesis that, apart from scaling, the SP and RP preferences are identical. Future work will concentrate on identifying the particular attributes where SP and RP preferences are substantially different.

Neither Brownstone and Train (1996) nor this paper attempt to build a complete model of alternative-fuel vehicle choice. This paper only models choices for those households that actually purchased vehicles during the 15 month survey period, and clearly this group is not representative of the overall population. We also do not attempt to condition on the households' current vehicle holdings or type of transaction (replace versus add) as in Brownstone et. al. (1996). While this would clearly improve the accuracy and realism of our models, we did not have the time or resources to collect these data for the RP transactions. What this paper does do is show that mixed logit models are a useful and computationally feasible class for joint modeling of SP and RP choice data.

The next section reviews the data sources and SP experimental design. The third section reviews general mixed logit model, and the following section gives estimation results for SP, RP and joint mixed logit models for vehicle choice. We next give results of some forecasting experiments which highlight the different substitution patters between the MNL and mixed logit specifications.

## 2. DATA

The survey used to collect the SP data used in the next sections was carried out in June and July, 1993. The sample was identified using pure random digit dialing and was geographically stratified into 79 areas covering most of urbanized California. An initial computer-aided telephone interview (CATI) was completed for each of 7,387 households. This initial CATI collected information on: household structure, vehicle inventory, housing characteristics, basic employment, and commuting for all adults. The survey also asked for the body type, size, and approximate purchase price (including whether new or used) for the household's intended next vehicle transaction. These data were used to center the SP hypothetical vehicles, and we also tried to model these data as stated intentions from each household. Unfortunately almost one half of the respondents gave inconsistent responses which could not clearly be matched to any vehicle available in the market. For example, some respondents stated that they intended to purchase a new mid-size car for less than $10,000.

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

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

The 4747 households that successfully completed the mail-out portion of the survey in 1993 represent a 66% response rate among the households that completed the initial CATI. A comparison with Census data reveals that the sample is slightly biased toward home-owning larger households with higher incomes. Eighty percent of the households in the sample had exactly one driver per vehicle, showing that, in California, the number of drivers is the most important determinant of the vehicle ownership level. For two-vehicle households, a little over one-third of the vehicles are driven 10,000 miles per year or less, a third are driven 10,000 to 15,000 miles per year, and almost a third are driven more than 15,000 miles per year.

An example SP task from the questionnaire is given in Figure 1. There are four fuel-types for vehicles: gasoline, compressed natural gas (CNG), methanol, and electric (EV). Three of the four fuel-types appear in each SP question. For each fuel-type, two different body type versions are available so the respondent faced a choice among six alternatives. There were six (or seven) attributes per vehicle per choice set (depending upon the fuel type of the vehicle). Four levels were used to cover the range of most attributes, allowing for estimation of nonlinear effects. The basic experimental design used for producing variation in the attribute levels was an orthogonal main effects plan for a $4^{21}$ factorial in 64 runs. Respondents were specifically instructed to treat all non-listed attributes (e.g., maintenance costs and safety) as identical for all vehicles in the choice set.

To avoid problems with unobserved error correlations across repeated choices, all previous analyses of these data have only used the first set of SP tasks given to each respondent. Even though our mixed logit specifications can easily accommodate repeated choices, we did not use the second SP task data since resource constraints precluded cleaning and coding these data.

Approximately 15 months after the first survey, a geographically stratified of the approximately 7300 households who completed the first telephone interview were recontacted for a second wave of interviewing. After excluding motor homes, motorcycles, and heavy trucks, 874 out of the 2857 households surveyed for this reinterview reported at least one vehicle purchase since the first interview. 706 of these 874 also completed the SP experiments as part of the wave one interviews, and we use this group to fit joint SP/RP models in the following sections of this paper.

For each vehicle transaction, respondents reported the make, model year, and body type of the purchased vehicle. These vehicles were then matched to a vehicle classification scheme developed as part of the microsimulation system described in Brownstone et. al. (1996). For each model year beginning usually in 1974, all vehicles are classified according to 13 body type/size categories (see Table 5 for definitions), and each of these categories is further subdivided into a high and low purchase price group and finally subdivided into a domestic and import group. Due to hopefully temporary data processing problems, we were unable to recover

## Figure 1: SP Vehicle Choice Survey Question

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

| | Vehicle A | Vehicle B | Vehicle C |
|---|---|---|---|
| Fuel Type | Electric<br>Runs on electricity only | Natural Gas (CNG)<br>Runs on CNG only | Methanol<br>Can also run on gasoline |
| Vehicle Range | 80 miles | 120 miles | 300 miles on methanol |
| Purchase Price | $21,000 (includes home charge unit) | $19,000 (includes home refueling unit) | $23,000 |
| Home refueling time | 8 hrs for full charge (80 miles) | 2 hrs to fill empty tank (120 miles) | Not available |
| Home refueling cost | 2 cents per mile (50 mpg gasoline equivalent) | 4 cents per mile (25 mpg gasoline equivalent) | |
| Service station refueling time | 10 min. for full charge (80 mi.) | 10 min. to fill empty CNG tank (120 mi.) | 6 min. to fill empty tank (300 mi.) |
| Service station fuel cost | 10 cents per mile (10 mpg gasoline equivalent) | 4 cents per mile (25 mpg gasoline equivalent) | 4 cents per mile (25 mpg gasoline equivalent) |
| Service station availability | 1 recharge station for every 10 gasoline stations | 1 CNG station for every 10 gasoline stations | Gasoline available at current stations |
| Acceleration Time to 30 mph | 6 seconds | 2.5 seconds | 4 seconds |
| Top speed | 65 miles per hour | 80 miles per hour | 80 miles per hour |
| Tailpipe emissions | 'Zero' tailpipe emissions | 25% of new 1993 gasoline car emissions when run on CNG | Like new 1993 gasoline cars when run on methanol |
| Vehicle size | Like a compact car | like a sub-compact car | Like a mid-size car |
| Body types | Car or truck | Car or van | Car or truck |
| Luggage space | Like a comparable gasoline vehicle | Like a comparable gasoline vehicle | Like a comparable gasoline vehicle |

Given these choices, which vehicle would you purchase? (please circle one choice)

1) Vehicle "A" (car)
2) Vehicle "A" (truck)
3) Vehicle "B" (car)
4) Vehicle "B" (van)
5) Vehicle "C" (car)
6) Vehicle "C" (truck)

the domestic/import attributes for this study so we averaged all attributes across domestic and import categories. We therefore have 488 categories approximating the universe of new and used vehicles from which respondents made their RP choices. For each of these categories we have: new and current used price, fuel economy, range, top speed, acceleration time (0-30 miles per hour), luggage volume, emissions index (proportion relative to new 1996 gasoline vehicles of same body/size class), and maintenance costs.

In addition to the data described above, additional SP tasks were given to the 2857 Wave 2 respondents. These tasks have more attributes than the Wave 1 SP design analyzed in this paper, and they have 17 vehicles per experiment instead of 6 in the Wave 1 design. Future work will add these data to the models described in the following sections.

The data used in this paper are a hopefully improved version of the data used in Brownstone and Train (1996). The improvements come from implementing editing and consistency checks across the Wave 1 and Wave 2 data. As a result, the models in Brownstone and Train (1996) do not exactly replicate with our current data, although there are few significant differences.

## 3. MIXED LOGIT MODELS

A person faces a choice among J alternatives. Without loss of generality, the person's utility from any alternative can be decomposed into a nonstochastic, linear-in-parameters part that depends on observed data, a stochastic part that is perhaps correlated over alternatives and heteroskedastic, and another stochastic part that is independently, identically distributed over alternatives and people. In particular, the utility from alternative i is denoted $U_i = \beta' x_i + [\eta_i + \varepsilon_i]$ where $x_i$ is a vector of observed variables relating to alternative i and the person; $\beta$ is a vector of parameters to be estimated which are fixed over people and alternatives; $\eta_i$ is a random term with zero mean whose distribution over people and alternatives depends in general on underlying parameters and observed data relating to alternative i; and $\varepsilon_i$ is a random term with zero mean that is iid over alternatives, does not depend on underlying parameters or data, and is normalized to set the scale of utility. Stacking the utilities, we have: $U=\beta' X+[\eta+\varepsilon]$ where $V(\varepsilon)=\alpha I$ with known (i.e., normalized) $\alpha$ and $V(\eta)$ is general and can depend on underlying parameters and data. For standard logit, each element of $\varepsilon$ is iid extreme value, and, more importantly, $\eta$ is zero, such that the unobserved portion of utility (i.e., the term in brackets) is independent over alternatives. This independence gives rise to the Independence from Irrelevant Alternatives (IIA) property and its restrictive substitution patterns

The Mixed Logit class of models assume a general distribution for $\eta$ and extreme value for $\varepsilon$. Denote the density of $\eta$ as $f(\eta|\Omega)$ where $\Omega$ are the fixed parameters of the distribution. Given the value of $\eta$, the conditional choice probability is simply logit, since the remaining error term is iid extreme value:

$$L_i(\eta) = \exp(\beta' x_i + \eta_i) / \textstyle\sum_j \exp(\beta' x_j + \eta_j).$$

Since $\eta$ is not given, the (unconditional) choice probability is this logit formula integrated over all values of $\eta$ weighted by the density of $\eta$:

$$P_i=\int L_i(\eta)\, f(\eta|\Omega)d\eta$$

Models of this form are called "mixed logit" since the choice probability is a mixture of logits with f as the mixing distribution. The probabilities do not exhibit iia and different substitution patterns are attained by appropriate specification of f.

The choice probability cannot be calculated exactly because the integral does not have a closed form in general. The integral is approximated through simulation. For a given value of the parameters $\Omega$, a value of $\eta$ is drawn from its distribution. Using this draw, the logit formula $L_i(\eta)$ is calculated. This process is repeated for many draws, and the average of the resulting $L_i(\eta)$'s is taken as the approximate choice probability:

$$SP_i = (1/R) \sum_{r=1,\ldots,R} L_i(\eta^r)$$

where R is the number of replications (i.e., draws of $\eta$), $\eta$ is the r-th draw, and $SP_i$ is the simulated probability that the person chooses alternative i. By construction, $SP_i$ is an unbiased estimate of $P_i$ for any R; its variance decreases as R increases. It is strictly positive for any R, such that $\ln(SP_i)$ is always defined, which is important when using $SP_i$ in a log-likelihood function (as below). It is smooth (i.e., twice differentiable) in parameters and variables, which helps in the calculation of elasticities and especially in the numerical search for the maximum of the likelihood function. The simulated probabilities sum to one over alternatives, which is useful in forecasting.

The choice probabilities depend on parameters $\beta$ and $\Omega$, which are to be estimated. Adding subscript n to index sampled individuals and denoting the chosen alternative for each person by i, the log-likelihood function $\sum_n \ln(P_{ni})$ is approximated by the simulated log-likelihood function $\sum_n \ln(SP_{ni})$ and the estimated parameters are those that maximize the simulated log-likelihood function. Lee (1992) derives the asymptotic distribution of the maximum simulated likelihood estimator based on smooth probability simulators with the number of replications increasing with sample size. Under regularity conditions, the estimator is consistent and asymptotically normal. When the number of replications rises faster than the square root of the number of observations, the estimator is asymptotically equivalent to the maximum likelihood estimator.

The gradient of the simulated log-likelihood function is simple to calculate, which speeds the search for the maximum:

$$G(\beta) \equiv \delta \sum_n \ln(SP_{ni}) / \delta\beta = \sum_n [1/SP_{ni}](1/R) \sum_r L_{ni}(\eta_n^r)[\sum_j (d_{nj} - L_{nj}(\eta_n^r)) x_{nj}]$$

$$G(\Omega) \equiv \delta \sum_n \ln(SP_{ni}) / \delta\Omega = \sum_n [1/SP_{ni}](1/R) \sum_r L_{ni}(\eta_n^r)[\sum_j (d_{nj} - L_{nj}(\eta_n^r))(\delta\eta_n^r/\delta\Omega)]$$

where $d_{nj} = 1$ for $j=i$ and zero otherwise. The derivative $\delta\eta_n^r/\delta\Omega$ depends on the specification of $\eta$ and f. Also, if the same parameters enter $\beta$ and $\Omega$ (as in the third model in section III), the gradient is adjusted accordingly. Analytic second derivatives can also be calculated. However, Revelt and Train (1996) found that calculating the Hessian from formulas for the second derivatives resulted in computationally slower estimation than using the BHHH or other approximate-Hessian procedures.

Different types of mixed logit models have been used in empirical work; they differ in the type of structure that is placed on the model, or, more precisely, in the specification of f. In section 4 below, as in Train (1995) and Ben-Akiva and Bolduc (1996), we specify an error-components structure: $U_i = \beta' x_i + \mu' z_i + \varepsilon_i$ where $\mu$ is a random vector with zero mean that does not vary over alternatives and has density $g(\mu|\Omega)$ with parameters $\Omega$; $z_i$ is a vector of observed data related to alternative i; and $\varepsilon_i$ is iid extreme value. This is a mixed logit with a particular structure for $\eta$, namely, $\eta_i=\mu' z_i$. The terms in $\mu' z_i$ are interpreted as error components that induce heteroskedasticity and correlation over alternatives in the unobserved portion of utility: $E([\mu' z_i + \varepsilon_i] \ [\mu' z_j + \varepsilon_j]) = z_i' V(\mu) z_j$. Even if the elements of $\mu$ are uncorrelated such that $V(\mu)$ is diagonal, the unobserved portion of utility is still correlated over alternatives.

In this specification, the choice probabilities are simulated by drawing values of $\mu$ from its distribution and calculating $\eta_i=\mu' x_i$. Insofar as the number of error components (i.e., the dimension of $\mu$) is smaller than the number of alternatives (the dimension of $\eta$), placing an error-components structure on a mixed logit reduces the dimension of integration and hence simulation that is required for calculating the choice probabilities.

Different patterns of correlation, and hence different substitution patterns, are obtained through appropriate specification of $z_i$ and g. For example, an analog to nested logit is obtained by specifying $z_i$ as a vector of dummy variables -- one for each nest taking the value of 1 if i is in the nest and zero otherwise -- with $V(\mu)$ being diagonal (thereby providing an independent error component associated with each nest, such that there is correlation in unobserved utility within each nest but not across nests). Restricting $V(\mu)=\sigma I$ is analogous to restricting the log-sum coefficients in a nested logit model to be the same for all nests. Importantly, McFadden and Train (1997) has shown that any random utility model can be approximated by a mixed logit with an error-components structure and appropriate choice of the $z_i$'s and g. McFadden and Train (1997) also gives Lagrange Multiplier tests for the presence of significant random error components in MNL models. Our experience with these tests for the specifications in section 4 below shows that they are easy to calculate and appear to be quite powerful omnibus tests. However, they are not as good for identifying which error components to include in a more general mixed logit specification.

Most recent empirical work with mixed logits has been motivated by a random-parameters, or random-coefficients, specification (Bhat, 1996a and b; Mehndiratti, 1996; Revelt and Train, 1996; Train 1996). The difference between a random-parameters and an error-components specification is entirely interpretation. In the random-parameters specification, the utility from alternative i is $U_i = b' x_i + \varepsilon_i$ where coefficients b are random with mean $\beta$ and deviations $\mu$. Then $U_i = \beta' x_i + [\mu' x_i + \varepsilon_i]$, which is an error-components structure with z=x. Elements of x that do not enter z can be considered variables whose coefficients do not vary in the population. And elements of z that do not enter x can be considered variables whose coefficients vary in the population but with zero means. In different contexts one or the other interpretation will seem more natural.

The random-coefficients interpretation is useful when considering models of repeated choices by the same decision maker. The simplest model is generated by assuming that the same draw of the random coefficient vector is used for all repeated choices, and we use this specification in or work with joint RP/SP models below. This specification does not lead to perfect error correlations because the independent extreme value term $\varepsilon_i$ still enters the utilities for each choice. The error correlation across repeated choices therefore increases as the variance of the random coefficients increases. A feasible (but computationally more demanding) model which might be more appropriate for panel data would be to specify a first-order autoregressive process for the random coefficients. This more general model would permit the error correlation to decrease over time.

## 4. MODEL SPECIFICATION

This section compares MNL and mixed logit specifications for separate SP, RP and joint SP/RP models of vehicle choice. All of the specifications use a subset of the variables defined in Table 1. We began with the specification in Brownstone and Train (1996), but we eventually dropped some variables which were insignificant in all of our models.

Most of our models are estimated using the 706 cases with both SP and RP data, while Brownstone and Train (1996) used approximately 4654 cases with complete SP data. Note that the Station Availability, Station Wagon, EV, CNG, and Methanol constants are only identified in the SP data, and Used is only identified in the RP data.

### 4.1 Stated Preference Models

Table 2 gives the results of our pure stated preference models. The first three columns replicate the MNL model in Brownstone and Train (1996) for the current version of the data. Although there are only two additional observations, there are some significant differences caused by the changes in the data. The coefficient of “Big Enough” is much smaller and no longer significant, and variables capturing short commute distance interacted with EV and college interacted with methanol are also insignificant. The EV constant has also dropped by an order of magnitude and is no longer significant. These changes highlight the sensitivity of discrete choice models to small changes in the data.

The next three columns give the results of the best MNL model on the 706 observations with both SP and RP data. This group is not a random sample of the survey respondents, so it is not surprising to see differences in the model estimates. The coefficients of Top Speed, Big Enough, and Sports Car are completely insignificant and are dropped from the model, and the coefficient of Luggage Space increases significantly. In the SP design, Luggage Space is only reduced for some CNG and Electric vehicles in choice sets with dual-fuel CNG vehicles. However, the dual-fuel attribute is insignificant in all the models we tried. The coefficient for the Pollution variable also decreases substantially and becomes insignificant.

**Table 1: Variable Definitions**

| Variable names: | Definitions: |
|---|---|
| Price / ln(income) | Purchase price in thousands of dollars, divided by the natural log of household income in thousands. Range: .2 - 27, Mean: 2.8 |
| Range | Hundreds of miles that the vehicle can travel between refuelings/rechargings. Range: .5-5.6, Mean: 3.7 |
| Acceleration | Seconds required to reach 30mph from stop. Range: 2.1-6.2, Mean: 3.8 |
| Top speed | Highest speed that the vehicle can attain, in hundreds of miles per hour (e.g., 80mph is entered as .80). Range: .55-1.4, Mean: 1.0 |
| Pollution | Tailpipe emissions as fraction of comparable 1995 new gas vehicle. Range: 0-6.1, Mean 1.5 |
| Pollution x Used | Tailpipe emissions for used vehicles. Range: 1-6.1, Mean: 2.0 |
| Size | 0=mini, 1=subcompact, 2=compact, 3=mid-size or large. Mean: 2.1 |
| "Big enough" | 1 if household size is over 2 and vehicle size is 3; 0 otherwise. Mean .18 |
| Luggage space | Luggage space as fraction of comparable new gas vehicle. Range: .48 - 2, Mean: 1 |
| Operating cost | Fuel cost per mile of travel, in cents per mile. For electric vehicles, cost is for home recharging. For other vehicles, cost is for station refueling. Range: 1-12, Mean: 6 |
| Station availability | Fraction of stations that have capability to refuel/recharge the vehicle. Range: .1 - 1, Mean: .85 |
| Sports utility vehicle | 1 for sports utility vehicle, zero otherwise |
| Sports car | 1 for sports car, zero otherwise |
| Station wagon | 1 for station wagon, zero otherwise |
| Truck | 1 for truck, zero otherwise |
| Van | 1 for van, zero otherwise |
| Constant for EV | 1 for electric vehicle, zero otherwise |
| College x EV | 1 if respondent had some college education and vehicle is electric; zero otherwise. 40% of sample have college education |
| Constant for CNG | 1 for compressed natural gas vehicle, zero otherwise |
| Constant for methanol | 1 for methanol vehicle, zero otherwise |
| Used | 1 if vehicle is used; zero otherwise. |

The last four columns of Table 2 give the estimates for the best fitting Mixed Logit specification. The normally distributed random coefficients were determined by testing exclusion restrictions against a larger model with all coefficients allowed to vary. We find significant error components for the Price, EV, CNG, and Methanol variables. To be precise, the stochastic portion of utility for alternative i is defined as $[\sum_{k=1\text{-}4}\sigma_k(\varsigma_k z_{ki})] + \varepsilon_i$ where $\varsigma_k$ is iid standard normal, $z_{ki}$ are the four variables described above, and $\varepsilon_i$ is iid extreme value. The parameters $\sigma_k$ for k=1-4 are estimated (see the column “Std. Dev.”); each denotes the standard deviation of the normal deviate that generates that error component. In simulating the choice probability for a respondent, four numbers are drawn from a random-number generator for the standard normal distribution; the four "variables" $\varsigma_1 z_{1i}$ - $\varsigma_4 z_{4i}$ are created; and the conditional probability is evaluated with coefficients $\sigma_k$ k=1-4 for the four "variables." This process is repeated for numerous draws and the conditional probabilities are averaged to obtain the simulated probability. We used 250 draws in estimation of the mixed logit models.

Brownstone and Train (1996) used a different specification for the random components. They had components for Size, Luggage Space, Non-EV, and Non-CNG. The specification in the last columns of Table 2 obtains a lower Log Likelihood value with the same degrees of freedom. However, the relatively large error component for the Price variable implies that the model will generate an implausible positive price effect approximately 30% of the time. This problem could be circumvented by specifying a log-normal distribution for the Price random component, but this restriction would substantially reduce the goodness of fit of the model.

Since the stochastic portion of the utilities have different variances in the MNL and Mixed Logit specifications, the coefficients must be normalized before they can be meaningfully compared. The columns denoted “Normalized Coefficients” normalize by dividing by the Price coefficient times the natural log of median income in thousands (which is approximately $50,000). The normalized coefficients can then be interpreted as the average amount that a respondent with median income would be willing to pay for an additional unit of a particular attribute. For example, the results in Table 2 indicate that the typical respondent would pay either $1000 or $492 (MNL or Mixed Logit) to purchase a Sports Utility Vehicle with all other attributes held constant. As in previous studies, these average willingness to pay figures are quite similar for MNL and Mixed Logit. However, the following section will demonstrate that the implied substitution patterns and forecasts from the two models are quite different.

### 4.2 Revealed Preference Models

Table 3 gives the estimates from the best fitting MNL and Mixed Logit models for the respondents’ actually choice of vehicles observed between panel waves. These models are estimated using all 874 households which reported vehicle transactions, but there are no significant differences when using only the 706 households which also have Wave 1 SP data.

The universe of all new and used vehicles is given by a 488-level classification scheme according to vintage, body type, size, and price level. The first vehicle purchased by each household was matched to this classification scheme to identify the chosen alternative. Therefore each respondent’s RP choice is modeled as a discrete choice from 488 alternatives. Unfortunately our current software and hardware are incapable of estimating models of this size in a reasonable amount of time. One solution, which works well for the MNL model, is to randomly sample

**Table 2: Stated Preference Models**

| Variable | MNL, 4656 Obs. Log Like. = -7404.66 | | | MNL, 706 Obs. Log Like. = -1122.46 | | | Normalized Coefficients | | Mixed Logit, 706 Obs. Log Likelihood= -1113.99 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | t-stat | Coef. | Std. Err. | t-stat | MNL | ML | Coef. | Std. Err. | Std. Dev. | Std. Err. |
| Price / ln(income) | -0.185 | 0.027 | -6.796 | -0.183 | 0.074 | -2.479 | -0.256 | -0.256 | -0.445 | 0.229 | 1.178 | 0.752 |
| Range | 0.349 | 0.027 | 13.039 | 0.351 | 0.068 | 5.137 | 0.492 | 0.503 | 0.873 | 0.351 | | |
| Acceleration | -0.068 | 0.011 | -6.192 | -0.117 | 0.029 | -4.038 | -0.164 | -0.157 | -0.273 | 0.107 | | |
| Top Speed | 0.262 | 0.081 | 3.244 | | | | | | | | | |
| Pollution | -0.442 | 0.102 | -4.350 | -0.105 | 0.256 | -0.411 | -0.148 | -0.097 | -0.169 | 0.538 | | |
| Size | 0.107 | 0.033 | 3.212 | 0.071 | 0.076 | 0.943 | 0.100 | 0.109 | 0.190 | 0.174 | | |
| Big Enough | 0.025 | 0.064 | 0.384 | | | | | | | | | |
| Luggage Space | 0.460 | 0.190 | 2.420 | 1.428 | 0.501 | 2.848 | 2.000 | 2.214 | 3.845 | 1.805 | | |
| Operating Cost | -0.077 | 0.008 | -10.159 | -0.070 | 0.020 | -3.547 | -0.098 | -0.079 | -0.138 | 0.060 | | |
| Station Availability | 0.315 | 0.084 | 3.737 | 0.498 | 0.224 | 2.228 | 0.698 | 0.872 | 1.514 | 0.781 | | |
| Sports Utility Vehicle | 0.820 | 0.141 | 5.831 | 0.750 | 0.260 | 2.881 | 1.050 | 0.492 | 0.855 | 0.318 | | |
| Sports Car | 0.639 | 0.148 | 4.308 | | | | | | | | | |
| Station Wagon | -1.435 | 0.062 | -23.117 | -1.199 | 0.144 | -8.310 | -1.680 | -0.741 | -1.287 | 0.167 | | |
| Truck | -1.016 | 0.049 | -20.751 | -0.919 | 0.123 | -7.458 | -1.288 | -0.613 | -1.064 | 0.137 | | |
| Van | -0.800 | 0.047 | -16.871 | -0.735 | 0.120 | -6.116 | -1.029 | -0.459 | -0.797 | 0.145 | | |
| Electric Vehicle (EV) | -0.046 | 0.123 | -0.371 | 0.021 | 0.314 | 0.066 | 0.029 | 0.251 | 0.436 | 0.859 | 2.665 | 1.340 |
| College x EV | 0.271 | 0.084 | 3.238 | 0.387 | 0.231 | 1.673 | 0.541 | 0.551 | 0.958 | 0.585 | | |
| CNG | 0.277 | 0.086 | 3.202 | 0.543 | 0.223 | 2.437 | 0.761 | 0.625 | 1.085 | 0.635 | 3.800 | 1.718 |
| Methanol | 0.422 | 0.070 | 6.000 | 0.430 | 0.184 | 2.334 | 0.603 | 0.671 | 1.165 | 0.577 | 2.132 | 1.145 |

from the full choice set and treat the respondent’s choice as having come from the reduced choice set.

While it is straightforward to show that this sampling procedure leads to consistent inference with the MNL model, it is not clear that this sampling procedure works with Mixed Logit models. We conjecture that the biases caused by sampling may asymptotically cancel out in similar fashion to the biases caused by simulating the Mixed Logit choice probabilities. Some limited experiments with smaller models suggests that this may be true, but much more work is needed to verify our conjecture. For the moment we assume that our conjecture is true and construct RP choice sets by sampling 15 alternatives (including the chosen one) from the set of 488 alternatives.

The first three columns of Table 3 give results for the best fitting MNL model using the variables described in Table 1. Generally the coefficients are larger in magnitude than the MNL estimates for the SP data given in Table 2. This indicates that the variance of the stochastic portion of the utility indices are lower for the RP data. The coefficients on “Big Enough” and Acceleration are also significant but have unexpected signs. The Pollution variable is also significant with a positive sign, indicating a preference for more polluting vehicles, which for these data means older vehicles and trucks. This model could clearly be improved by a richer set of explanatory variables, but this work is beyond the scope of the current paper.

The last four columns of Table 3 give the best fitting Mixed Logit model for these data. As before, the two significant error components on Price and Operating Cost were discovered by comparison with a larger model where all coefficients were allowed to vary. While these estimates show substantial variation across the sample, the standard deviations are not so large as to lead to a significant number of cases with positive price and cost effects. The normalized coefficients (computed as in Table 2) show no significant differences in average effects between the models. The normalized coefficients for Used vehicles indicate that respondents are willing to purchase a used vehicle with identical attributes to a new one if the used vehicle costs $2200 less.

There are a number of important differences between the SP and RP results which can be easily seen by comparing the normalized coefficients. The RP models show much higher sensitivity to operating costs and much less sensitivity to luggage space. In contrast to the SP results, the RP estimates indicate that respondents prefer vans and trucks.

### 4.3 Joint Models

Given the substantial differences between the separate SP and RP models described above, there are a number of strategies for specifying joint models. Given the common suspicion of SP data, we could specify a model where the SP data only contributed to identifying the attributes uniquely present in the SP data. The other extreme is to ignore the differences and try to find the best compromise model. The more common middle ground is to pool data from some attributes

**Table 3: Revealed Preference Models**

| | MNL, 874 Observations Log Likelihood = -1705.35 | | | Normalized Coefficients | | Mixed Logit, Log Likelihood=-1692.97 | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Coef. | Std. Err. | t-stat | MNL | ML | Coef. | Std. Err. | Std. Dev. | Std. Err. |
| Price / ln(income) | -0.441 | 0.044 | -9.922 | -0.256 | -0.256 | -0.508 | 0.075 | 0.171 | 0.066 |
| Range | 0.414 | 0.121 | 3.417 | 0.241 | 0.195 | 0.387 | 0.155 | | |
| Acceleration | 0.613 | 0.255 | 2.407 | 0.356 | 0.319 | 0.633 | 0.280 | | |
| Top Speed (MPH) | 0.103 | 0.017 | 5.967 | 0.060 | 0.059 | 0.117 | 0.022 | | |
| Pollution | 0.559 | 0.063 | 8.874 | 0.325 | 0.310 | 0.615 | 0.071 | | |
| Big Enough | -0.407 | 0.158 | -2.572 | -0.237 | -0.250 | -0.495 | 0.180 | | |
| Size | 0.678 | 0.079 | 8.634 | 0.394 | 0.439 | 0.871 | 0.100 | | |
| Luggage Space | 0.293 | 0.262 | 1.119 | 0.170 | 0.226 | 0.449 | 0.337 | | |
| Operating Cost | -0.687 | 0.064 | -10.668 | -0.400 | -0.462 | -0.915 | 0.095 | 0.423 | 0.072 |
| Sports Utility Vehicle | 1.630 | 0.302 | 5.399 | 0.947 | 0.996 | 1.974 | 0.352 | | |
| Van | 1.247 | 0.258 | 4.831 | 0.725 | 0.825 | 1.635 | 0.323 | | |
| Truck | 1.055 | 0.280 | 3.765 | 0.613 | 0.684 | 1.356 | 0.323 | | |
| Sports Car | -0.687 | 0.166 | -4.138 | -0.399 | -0.347 | -0.687 | 0.185 | | |
| Used | -3.976 | 0.161 | -24.701 | -2.311 | -2.148 | -4.259 | 0.236 | | |

**Table 4: Joint Revealed/Stated Preference Models**

| | Joint Scaled Logit Log Likelihood=-2572.6612 | | | Normalized Coefficients | | Mixed Logit Log Likelihood = -2528.4857 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coef. | Std. Err. | t-stat | MNL | ML | Coef. | Std. Err. | Std. Dev. | Std. Err. |
| Price / ln(income) | -0.351 | 0.036 | -9.80 | -0.26 | -0.26 | -0.492 | 0.073 | 0.187 | 0.071 |
| Range | 0.742 | 0.117 | 6.34 | 0.54 | 0.47 | 0.901 | 0.164 | | |
| Acceleration | -0.402 | 0.078 | -5.18 | -0.29 | -0.52 | -0.994 | 0.177 | 0.316 | 0.357 |
| Top Speed | 0.705 | 0.441 | 1.60 | 0.52 | 0.45 | 0.870 | 1.057 | | |
| Pollution | -0.392 | 0.540 | -0.73 | -0.29 | -0.63 | -1.215 | 1.580 | | |
| Pollution x Used | 0.759 | 0.549 | 1.38 | 0.55 | 0.95 | 1.823 | 1.589 | | |
| Big Enough | -0.541 | 0.165 | -3.27 | -0.39 | -0.30 | -0.569 | 0.201 | | |
| Size | 0.371 | 0.072 | 5.17 | 0.27 | 0.36 | 0.695 | 0.102 | | |
| Luggage Space | -0.073 | 0.321 | -0.23 | -0.05 | 0.16 | 0.310 | 0.367 | | |
| Operating Cost | -0.261 | 0.042 | -6.18 | -0.19 | -0.33 | -0.627 | 0.085 | 0.347 | 0.074 |
| Sports Utility Vehicle | -0.165 | 0.167 | -0.99 | -0.12 | 0.09 | 0.172 | 0.183 | | |
| Van | -0.560 | 0.137 | -4.10 | -0.41 | -0.41 | -0.782 | 0.194 | 1.473 | 0.302 |
| Truck | -0.766 | 0.136 | -5.62 | -0.56 | -0.61 | -1.166 | 0.197 | 1.418 | 0.262 |
| Sports Car | -0.522 | 0.176 | -2.97 | -0.38 | -0.30 | -0.567 | 0.179 | | |
| Station Wagon | -2.356 | 0.433 | -5.44 | -1.72 | -0.64 | -1.231 | 0.178 | | |
| Station Availability | 0.752 | 0.559 | 1.34 | 0.55 | 2.96 | 5.665 | 2.395 | 10.593 | 4.028 |
| Electric Vehicle (EV) | -0.852 | 0.682 | -1.25 | -0.62 | -11.68 | -22.387 | 14.795 | 33.626 | 17.315 |
| College x EV | 1.007 | 0.519 | 1.94 | 0.74 | 2.01 | 3.861 | 5.501 | 16.795 | 12.599 |
| CNG | 0.393 | 0.480 | 0.82 | 0.29 | 0.17 | 0.324 | 1.774 | 12.731 | 3.526 |
| Methanol | 0.753 | 0.455 | 1.66 | 0.55 | 2.27 | 4.352 | 1.717 | 6.639 | 1.992 |
| Used | -4.672 | 0.582 | -8.03 | -3.41 | -3.29 | -6.299 | 1.625 | | |
| SP Scale Std. Dev. | 3.326 | 0.575 | 5.78 | | | | | | |

but not others. The problem with this approach is the difficulty of choosing the attributes to be pooled. Since the main purpose of this paper is to explore the use of Mixed Logit models for pooling SP and RP data, we take the simplest approach and attempt to pool all attributes. It is important to realize that this pooling is rejected by standard statistical tests, and much more work is needed to develop a realistic joint SP/RP model for these data.

One issue which has generated some controversy is caused by the different variances in the stochastic portions of the utility indices in the SP and RP data. The "low-tech" solution to this problem is to scale the SP data so that the magnitude of key coefficients are similar before fitting joint MNL models. More recent work (see Ben-Akiva and Morikawa, 1997 and Hensher and Bradley, 1993) estimates the scaling parameter jointly with the model coefficients. It is simple to specify a Mixed Logit model which jointly estimates the scaling parameter jointly with the logit coefficients. A set of alternative-specific constants are added to each SP alternative, and the mean coefficients of these constants are constrained to equal zero while their standard deviations are constrained to be equal.

The first three columns of Table 4 give the results of estimating this joint scaled logit model on the combined SP and RP data for the 706 survey respondents. The only change in the specification is the inclusion of an interaction between Pollution and Used vehicles. This interaction is included to help explain the different signs of the Pollution coefficient between the SP and RP data. The large and significant estimated standard deviation for the SP error components is consistent with our earlier observation that the stochastic variation is greater in the SP data. The normalized coefficients indicate that these estimates lie between the separate SP and RP MNL models. For these data, the "low-tech" approach of scaling to match the price and operating cost coefficients implies dividing the SP data by 4. The resulting MNL joint model is essentially identical to the joint scaled model in Table 4.

The last four columns in Table 4 show the best fit Mixed Logit model for the joint data. As before, the important error components are identified by comparison with a larger model where all coefficients are allowed to vary. Notice that the SP scaling coefficient has disappeared from the model. When the 10 significant error components are added, the estimated scaling standard error becomes very small (0.02) and insignificant. Relative to the Mixed Logit models for the separate SP and RP data, this joint Mixed Logit model has many more error components with large standard deviations. These large error components are reflecting increased heterogeneity caused by our forced pooling of the SP and RP preferences. There is also a much larger improvement in the Log Likelihood values from adding random effects than we saw in the separate SP and RP models.

The joint mixed logit model specification also allows for correlation between the SP and RP utilities for each respondent by using the same error components for both choices. We compared this to a specification where these error components were drawn independently and we got essentially identical results. It is likely that there would be more differences between these specifications in situations with more similar repetitions such as commonly found in repeated SP tasks. Ben-Akiva and Morikawa, 1997, and Morikawa (1994) specify models with state dependence (between the SP and RP choices) and serial correlation in the stochastic terms.

Mixed logit versions of their models would be easy to specify and estimate, but this is beyond the scope of the current paper.

Comparisons between the normalized coefficients show that the biggest differences between the Scaled Logit and Mixed Logit models are for the Station Availability and alternative fuel constants. The Mixed Logit model shows much higher sensitivity to these attributes. These differences are probably not due to problems with pooling the SP and RP data since these attributes are only identified in the SP data. Even though there are large differences in the average effects, it is important to note that the large error component standard deviations for these attributes indicate huge variability over the sample.

## 5. SCENARIO FORECASTS

Although there are some differences in the normalized coefficients between the MNL and Mixed Logit models described in the previous section, the main differences between these models are due to the different substitution patterns caused by the different error specifications. The easiest way to see these differences is to compare forecasts for new alternatives for the various models. This sections presents the results of some forecasting experiments using a more realistic description of available vehicles than in Brownstone and Train (1996). The full set of vehicles we consider is given in Table 5, and is taken from a comprehensive set of vehicle technology forecasts prepared by the California Energy Commission as an input to the microsimulation model described in Brownstone et. al. (1996). We chose the year 1998 since that was originally the year that California would begin to mandate the sale of a substantial number of alternative-fuel vehicles. The operating fuel costs are derived assuming that gasoline costs \$1.20/gallon and electricity costs 6 cents/KWH. The "MPG" column in Table 5 gives mileage in gasoline equivalents for CNG and methanol.

The vehicle classes described in Table 5 present a very optimistic view of electric vehicle technology since they exclude battery replacement costs. Some estimates of these costs indicate that they might exceed the fuel costs (listed in the "cents/mile" column) if averaged over 10,000 annual miles per year. Measuring acceleration as time to reach 30 miles per hour also paints a rosy picture of electric vehicles, since their acceleration capabilities dramatically reduce as speed increases. Of course, this bias towards electric vehicles should not affect the comparison between the different models' forecasts since they are all based on the same data given in Table 5.

Table 6 gives the results of some forecasting experiments for the SP and Joint models described in the previous section. Note that these are unweighted forecasts over the 706 respondents with both SP and RP data, so they do not represent overall population or vehicle market forecasts. The first column of Table 6 for each model gives the market share forecasts for a scenario only including the gasoline vehicles in Table 5. The second column shows the forecasts when the non-electric (CNG and methanol) vehicles are added, and the third shows the forecasts when all vehicles in Table 5 are available.

**Table 5: "1998" Scenario Definition**

| alt. no. | class | cost | Body Type | fuel | price | cents /mile | mpg | range | 0-30 Acc | topspeed | pollut | ssav | lugg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | low | mini | electric | 17518 | 1.33 | | 75 | 3.87 | 92 | 0 | 0.1 | 1 |
| 2 | 1 | high | mini | gasoline | 19986 | 4.90 | 24.5 | 281 | 3.01 | 120 | 0.8 | 1 | 1 |
| 3 | 2 | low | sub compact | electric | 19562 | 1.47 | | 75 | 3.55 | 98 | 0 | 0.1 | 1 |
| 4 | 2 | low | sub compact | gasoline | 13524 | 4.53 | 26.5 | 344 | 3.46 | 110 | 0.8 | 1 | 1 |
| 5 | 2 | high | sub compact | gasoline | 31415 | 5.48 | 21.9 | 277 | 2.94 | 122 | 0.8 | 1 | 1 |
| 6 | 3 | low | compact | gasoline | 14814 | 4.63 | 25.9 | 389 | 3.4 | 111 | 0.8 | 1 | 1 |
| 7 | 3 | high | compact | gasoline | 35689 | 5.77 | 20.8 | 306 | 2.97 | 121 | 0.8 | 1 | 1 |
| 8 | 3 | low | compact | cng | 21057 | 4.14 | 29 | 147 | 3.72 | 105 | 0.4 | 0.1 | 0.75 |
| 9 | 4 | low | midsize | gasoline | 18695 | 5.73 | 20.9 | 345 | 3.29 | 114 | 0.8 | 1 | 1 |
| 10 | 4 | low | midsize | methanol | 18985 | 5.38 | 22.3 | 215 | 3.23 | 115 | 0.6 | 0.7 | 0.9 |
| 11 | 4 | high | midsize | gasoline | 36127 | 6.39 | 18.8 | 310 | 2.57 | 133 | 0.8 | 1 | 1 |
| 12 | 4 | high | midsize | gasoline | 39382 | 5.92 | 20.3 | 334 | 2.79 | 126 | 0.8 | 1 | 1 |
| 13 | 4 | high | midsize | methanol | 36504 | 6.00 | 20 | 193 | 2.53 | 134 | 0.6 | 0.7 | 1 |
| 14 | 5 | low | large | cng | 26561 | 5.24 | 22.9 | 150 | 3.35 | 112 | 0.4 | 0.1 | 0.75 |
| 15 | 5 | low | large | gasoline | 23083 | 5.88 | 20.4 | 398 | 3.13 | 117 | 0.8 | 1 | 1 |
| 16 | 5 | high | large | gasoline | 50000 | 6.70 | 17.9 | 390 | 2.93 | 122 | 0.8 | 1 | 1 |
| 17 | 6 | low | sports | electric | 26414 | 1.96 | 3.06 | 75 | 2.99 | 109 | 0 | 0.1 | 1 |
| 18 | 6 | low | sports | gasoline | 19641 | 5.41 | 22.2 | 344 | 2.99 | 121 | 0.8 | 1 | 1 |
| 19 | 6 | high | sports | gasoline | 38999 | 6.78 | 17.7 | 247 | 2.04 | 154 | 0.8 | 1 | 1 |
| 20 | 6 | high | sports | gasoline | 53309 | 6.18 | 19.4 | 270 | 2.62 | 132 | 0.8 | 1 | 1 |
| 21 | 7 | low | compact p.u. | electric | 21669 | 2.05 | | 75 | 3.22 | 84 | 0 | 0.1 | 1 |
| 22 | 7 | low | compact p.u. | gasoline | 15000 | 5.61 | 21.4 | 362 | 3.19 | 94 | 0.8 | 1 | 1 |
| 23 | 7 | high | compact p.u. | gasoline | 20401 | 7.23 | 16.6 | 299 | 3.1 | 95 | 0.8 | 1 | 1 |
| 24 | 8 | low | standard p.u. | gasoline | 18839 | 8.34 | 14.4 | 324 | 3.18 | 94 | 0.8 | 1 | 1 |
| 25 | 8 | low | standard p.u. | methanol | 19129 | 7.84 | 15.3 | 202 | 3.13 | 95 | 0.6 | 0.7 | 0.9 |
| 26 | 8 | high | standard p.u. | gasoline | 24175 | 7.96 | 15.1 | 336 | 3.82 | 84 | 0.9 | 1 | 1 |
| 27 | 9 | low | compact van | electric | 29785 | 2.36 | | 75 | 3.33 | 82 | 0 | 0.1 | 1 |
| 28 | 9 | low | compact van | gasoline | 22000 | 6.49 | 18.5 | 370 | 3.33 | 91 | 0.8 | 1 | 1 |
| 29 | 9 | high | compact van | gasoline | 27533 | 6.96 | 17.3 | 354 | 3.41 | 90 | 0.8 | 1 | 1 |
| 30 | 10 | low | standard van | gasoline | 19741 | 8.40 | 14.3 | 357 | 3.2 | 94 | 0.8 | 1 | 1 |
| 31 | 10 | low | standard van | methanol | 20031 | 7.89 | 15.2 | 223 | 3.15 | 95 | 0.6 | 0.7 | 0.9 |
| 32 | 10 | high | standard van | gasoline | 24820 | 9.43 | 12.7 | 326 | 3.43 | 90 | 0.8 | 1 | 1 |
| 33 | 11 | low | compact SUV | gasoline | 23100 | 7.16 | 16.8 | 338 | 3.15 | 91 | 0.8 | 1 | 1 |
| 34 | 11 | high | compact SUV | gasoline | 30000 | 8.28 | 14.5 | 299 | 3 | 95 | 0.8 | 1 | 1 |
| 35 | 12 | low | standard SUV | gasoline | 25651 | 9.08 | 13.2 | 396 | 3.37 | 91 | 0.9 | 1 | 1 |
| 36 | 12 | high | standard SUV | gasoline | 27629 | 9.41 | 12.8 | 385 | 3.42 | 90 | 0.9 | 1 | 1 |
| 37 | 13 | low | mini SUV | gasoline | 15223 | 5.28 | 22.7 | 261 | 3.65 | 86 | 0.8 | 1 | 1 |

**Table 6: Scenario Forecast Market Shares (%)**

| Alt No. | SP MNL Gas. | SP MNL Non EV | SP MNL Full | SP Mixed Logit Gas. | SP Mixed Logit Non EV | SP Mixed Logit Full | Joint Scaled Logit Gas. | Joint Scaled Logit Non EV | Joint Scaled Logit Full | Joint Mixed logit Gas. | Joint Mixed logit Non EV | Joint Mixed logit Full |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | 1.70 | | | 1.99 | | | 0.55 | | | 2.97 |
| 2 | 3.81 | 3.37 | 3.17 | 1.25 | 0.98 | 0.91 | 3.25 | 2.81 | 2.74 | 1.81 | 0.70 | 0.57 |
| 3 | | | 1.69 | | | 1.58 | | | 0.76 | | | 5.82 |
| 4 | 6.87 | 6.07 | 5.71 | 14.68 | 12.52 | 11.78 | 11.93 | 10.31 | 10.08 | 11.82 | 4.58 | 3.74 |
| 5 | 2.23 | 1.97 | 1.86 | 0.60 | 0.47 | 0.44 | 1.43 | 1.23 | 1.20 | 0.72 | 0.27 | 0.22 |
| 6 | 8.10 | 7.16 | 6.74 | 16.02 | 13.35 | 12.47 | 21.43 | 18.53 | 18.11 | 29.39 | 11.35 | 9.27 |
| 7 | 2.11 | 1.87 | 1.76 | 1.00 | 0.79 | 0.74 | 1.59 | 1.38 | 1.34 | 1.00 | 0.38 | 0.31 |
| 8 | | 1.79 | 1.69 | | 3.54 | 3.39 | | 1.46 | 1.43 | | 14.34 | 11.68 |
| 9 | 5.75 | 5.09 | 4.79 | 4.07 | 3.24 | 2.98 | 10.22 | 8.79 | 8.59 | 10.52 | 4.02 | 3.29 |
| 10 | | 3.84 | 3.61 | | 4.95 | 4.68 | | 6.76 | 6.61 | | 25.37 | 20.72 |
| 11 | 2.26 | 2.00 | 1.88 | 1.31 | 1.04 | 0.98 | 2.04 | 1.75 | 1.71 | 1.90 | 0.72 | 0.58 |
| 12 | 2.12 | 1.87 | 1.76 | 2.02 | 1.63 | 1.55 | 1.79 | 1.54 | 1.51 | 1.74 | 0.66 | 0.53 |
| 13 | | 1.81 | 1.71 | | 2.95 | 2.83 | | 1.47 | 1.43 | | 4.75 | 3.87 |
| 14 | | 1.44 | 1.35 | | 2.22 | 2.13 | | 0.97 | 0.95 | | 9.09 | 7.42 |
| 15 | 5.63 | 4.97 | 4.68 | 3.38 | 2.62 | 2.41 | 10.51 | 9.04 | 8.83 | 10.78 | 4.10 | 3.35 |
| 16 | 1.45 | 1.29 | 1.21 | 13.34 | 11.96 | 11.71 | 0.80 | 0.69 | 0.67 | 0.72 | 0.27 | 0.22 |
| 17 | | | 1.34 | | | 0.96 | | | 0.41 | | | 3.90 |
| 18 | 5.40 | 4.77 | 4.49 | 3.15 | 2.49 | 2.29 | 5.92 | 5.12 | 5.00 | 5.58 | 2.14 | 1.75 |
| 19 | 1.52 | 1.35 | 1.27 | 0.83 | 0.67 | 0.63 | 0.64 | 0.55 | 0.54 | 0.51 | 0.19 | 0.16 |
| 20 | 0.82 | 0.72 | 0.68 | 11.18 | 10.44 | 10.32 | 0.17 | 0.15 | 0.14 | 0.14 | 0.05 | 0.04 |
| 21 | | | 0.65 | | | 0.46 | | | 0.37 | | | 3.74 |
| 22 | 2.79 | 2.46 | 2.32 | 3.79 | 3.15 | 2.94 | 5.98 | 5.17 | 5.05 | 7.60 | 2.97 | 2.43 |
| 23 | 1.54 | 1.36 | 1.28 | 0.49 | 0.38 | 0.35 | 1.53 | 1.33 | 1.30 | 0.96 | 0.37 | 0.30 |
| 24 | 1.78 | 1.57 | 1.48 | 0.81 | 0.65 | 0.59 | 1.82 | 1.57 | 1.53 | 1.37 | 0.53 | 0.43 |
| 25 | | 1.24 | 1.16 | | 1.08 | 1.02 | | 1.34 | 1.31 | | 3.30 | 2.72 |
| 26 | 1.34 | 1.19 | 1.12 | 0.37 | 0.29 | 0.26 | 0.92 | 0.79 | 0.77 | 0.38 | 0.15 | 0.12 |
| 27 | | | 0.51 | | | 0.36 | | | 0.19 | | | 1.88 |
| 28 | 2.25 | 1.99 | 1.87 | 0.98 | 0.76 | 0.70 | 2.96 | 2.56 | 2.50 | 2.74 | 1.04 | 0.85 |
| 29 | 1.55 | 1.37 | 1.29 | 0.50 | 0.38 | 0.35 | 1.34 | 1.16 | 1.13 | 0.89 | 0.34 | 0.27 |
| 30 | 2.29 | 2.02 | 1.90 | 1.18 | 0.93 | 0.85 | 2.57 | 2.21 | 2.16 | 2.52 | 0.95 | 0.77 |
| 31 | | 1.52 | 1.43 | | 1.39 | 1.31 | | 1.73 | 1.69 | | 4.76 | 3.92 |
| 32 | 1.45 | 1.28 | 1.20 | 0.39 | 0.30 | 0.28 | 0.86 | 0.74 | 0.72 | 0.56 | 0.21 | 0.17 |
| 33 | 8.16 | 7.21 | 6.79 | 3.22 | 2.50 | 2.29 | 2.79 | 2.41 | 2.35 | 1.76 | 0.67 | 0.55 |
| 34 | 4.78 | 4.23 | 3.98 | 1.39 | 1.08 | 1.00 | 0.91 | 0.78 | 0.76 | 0.44 | 0.17 | 0.14 |
| 35 | 7.97 | 7.04 | 6.63 | 3.67 | 2.83 | 2.60 | 2.13 | 1.84 | 1.79 | 1.24 | 0.47 | 0.39 |
| 36 | 6.77 | 5.98 | 5.63 | 2.83 | 2.18 | 2.01 | 1.47 | 1.26 | 1.23 | 0.78 | 0.30 | 0.24 |
| 37 | 9.25 | 8.18 | 7.70 | 7.56 | 6.26 | 5.84 | 2.98 | 2.58 | 2.52 | 2.10 | 0.81 | 0.66 |

Generally the mixed logit models show much higher market shares for the alternative-fuel vehicles than the independent logit models. This is due to the large error components associated with the fuel constants in the mixed logit models. The IIA property of the independent logit models guarantees that a proportionate share of each new vehicle's market share must come from all other vehicles. Thus the market share for the mini electric vehicle (alternative number 1) draws a proportionate share from all vehicles in the Non-EV scenario. The mixed logit specifications generate the more reasonable prediction that the market share for the mini electric vehicle comes disproportionately from other mini and subcompact vehicles.

The joint mixed logit model gives very high forecasts for CNG and methanol vehicles - their total share for the full scenario is 50%. In contrast, the joint logit model gives a CNG and methanol vehicles a combined 13% share. The joint mixed logit model also gives electric vehicles 18% market share as compared to the 2 - 5% shares for the other models. Even though mixed logit models can fit very general substitution patterns, the results in Table 6 show that they do not necessarily generate better forecasts.

## 6. CONCLUSIONS

Mixed logit models are a general and feasible class of models for joint RP/SP choice data. They can easily account for the scaling and unobserved error correlations typically found in these applications. Although the mixed logit models presented in this paper took an average of 5 hours to estimate on a 200Mhz Pentium Pro workstation, we encountered no numerical or convergence problems. We expect that software optimization can reduce these estimation times by an order of magnitude.

The mixed logit specifications used here are particularly helpful in applications with a large number of alternatives. The order of integration or simulation is just given by the number of error components, not the number of discrete alternatives. More work is needed to justify our use of sampled choice sets here, but the only impediment to estimating models with large numbers of discrete alternatives is computer size and speed.

The alternative-fuel vehicle models presented here also highlight problems in merging SP and RP data that can't be solved by using more general choice models. Some attributes, such as pollution, acceleration, and truck and van constants, are evaluated differently in the different choice settings. Much more work with a richer set of explanatory variables is needed before a satisfactory joint model can be specified. We expect that the mixed logit model class will be useful in the search for these better models.

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