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A Nested Logit Model of Vehicle Fuel Efficiency and Make-Model Choice

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Abstract

Using data from a 1989 household survey of new vehicle buyers, this paper develops and estimates a nested logit model of new vehicle demands where the make-models in the lower nest are partitioned by their fuel efficiencies in the upper nest. In comparison with the more restrictive multinomial logit model, the results support a nested structure of vehicle choice. Among the findings, improvements in vehicle size, safety and quality increase a make-model's demand. Females, lower income households, younger consumers, non-white purchasers, and buyers in more densely populated areas exhibit higher demands for more fuel efficient vehicles. The results also indicate that vehicle demands have an approximate unitary elasticity with respect to capital cost and are elastic with respect to operating costs.

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1. Introduction

Prior to the fuel crises during the seventies, the United States automobile market was dominated by its domestic producers with imports accounting for only 5-7% of market share. Following the fuel crises, however, market share had shifted towards manufacturers with a competitive advantage in lighter and more fuel efficient vehicles, especially the Japanese. By 1980, the total import share rose to nearly 30% of which Japan accounted for 79%. Also in response to the fuel crises, the US Congress passed the Energy Policy Conservation Act in 1975 which established mandatory fuel economy standards for all new automobiles sold in the United States.

United States automobile manufacturers responded to the competitive pressures and the government mandated Corporate Average Fuel Economy (CAFE) requirements by significantly increasing the fuel economy characteristics of new vehicles. In 1974, cars rolling off Detroit's assembly lines averaged 13.2 miles per gallon (mpg) (Reynolds, 1991) which, by 1985, had increased to 27.5 mpg (Greene, 1990). Although fuel prices had fallen in real terms by the late 1980s, the average fuel efficiency of American cars had remained around the 27.5 mpg CAFE requirements.

The Persian Gulf crises in the early 1990s rekindled Congressional interest in fuel efficiency (Nivola, 1991) and sparked consumer interests in higher mileage cars (Reynolds, 1991), a fact that has not gone unnoticed in manufacturers' advertisements promoting fuel economy (Serafin, 1990). On the supply side, the nation's environmental concerns with internal combustion engines continue to press manufacturers to produce more environmentally clean vehicles. Consumers' acceptance of these vehicles, however, is unclear and will be dramatically tested in 1998 when California requires that 2% of the cars sold by the state's largest automobile sellers must be zero emission vehicles (Turrentine, 1995).

On the demand side, policy makers are looking at fiscal incentives, including registration fees and fuel taxes,to increase scrappage rates of older vehicles and induce consumers to purchase more fuel efficient vehicles (Crawford and Smith, 1995). In one of the more radical plans, Lave (1980) argued that instead of constructing fixed rail transit systems, a policy restricting morning and evening rush hours to small commuter cars and offsetting the welfare loss by giving mini-cars to each harmed household would lead to a net savings in energy consumption. Although unlikely to materialise, the policy illustrates the important point that the nation can experience significant energy savings if a majority of drivers use fuel efficient vehicles.

This paper hopes to provide some insights into consumer demands for fuel efficient vehicles. In particular, the purpose of the paper is to develop and estimate nested multinominal logit (NMNL) models of new vehicle demands where the lower level of the nest represents make/model choice and the upper level models the fuel efficiency of vehicles. The nested logit structure provides a potential improvement over the commonly used multinomial logit model (MNL). Because the number of new vehicle make-models is large, the independent from irrelevant alternatives (IIA) property of the MNL model may be an important restriction in modeling new vehicle choices. The NMNL structure relaxes this restriction by permitting correlated disturbances among alternatives in a given subset or nest.

By identifying important determinants of fuel efficiency and make/model choice, this analysis provides insights on consumer sensitivity to fuel efficiency and identifies which groups of consumers are most sensitive to changes in fuel efficiency. Section 2 develops the NMNL model , Section 3 summarises the data and defines the variables used in the model, Sections 4, 5 and 6 discuss the estimation results, and Section 7 offers concluding comments.

2. Nested Logit Model of Fuel Efficiency and Make-Model Choice

Consider household n that has decided to purchase a new vehicle from the set Ω_n of new vehicles available in a given model year. In general, the household faces a straightforward decision: compare the attributes offered by each vehicle and select the vehicle that yields the highest utility. Although a rational household is assumed to make the choice in a deterministic setting, an analyst is unable to observe all the factors that influence the household's decision. This observational discrepancy leads to deviations from the expected outcome which, in a random utility framework, are captured by a random component. Thus, the indirect utility U_i^n of household n associated with vehicle i is

(1) $$U_i^n = V_i^n + \varepsilon_i^n$$

where V_i^n is the deterministic part of household n's indirect utility and ε_i^n is an unobserved random component of its indirect utility.

Since a household is assumed to select the alternative with the highest utility, the probability that an alternative i is chosen by household n is equal to the probability that the alternative yields higher utility than all other alternatives available in the choice set Ω_n.

(2) $$P_i^n = P(V_i^n + \varepsilon_i^n > V_j^n + \varepsilon_j^n) \qquad i, j \in \Omega_n ; i \neq j$$

If the unobserved error term is distributed identically and independently Weibull, then the multinomial logit model (MNL) describes household new vehicle choice (Ben-Akiva and Lerman, 1985) and the choice probability for alternative i is

(3) $$P_i^n = \frac{\exp\{V_i^n\}}{\sum_{j \in \Omega_n} \exp\{V_j^n\}} \qquad i \in \Omega_n$$

One potentially important drawback of the MNL model is the independence-of-irrelevant alternatives (IIA) property, which states that the ratio of two choice probabilities is independent of the systematic utilities of other alternatives.[1] An implication of this property is that if two alternatives are closely related, then the MNL will overpredict the choice probabilities of these alternatives and underpredict the probability of unrelated alternatives.

Because the number of new vehicle make-models is large, the IIA property of the MNL model may be an important restriction in modeling new vehicle choices. The larger the number of elemental alternatives, the more likely will a particular make-model be closely related to one subset of make-models than it is to some other subset of make-models. Consider, for example, two types of vehicles, pick-up trucks and sport utilities. If, as one might expect, each pick-up truck is more highly correlated with other pick-up trucks than it is

[1] This is easily seen from equation (3) since the ratio of P_i^n over P_j^n depends only upon the attributes of alternatives i and j (i, j $\in \Omega_n$).

with convertible automobiles, the IIA property is not satisfied and the MNL model is an inappropriate description of choice behaviour.

McFadden (1978) demonstrated that, under certain conditions, the IIA property of the MNL model could be relaxed in such a way as to accommodate correlations among elemental alternatives in a given subset or nest while maintaining the IIA restriction across nests. Thus, elemental alternatives in a given nest need not satisfy the IIA restriction but alternatives in one nest are assumed to be independent of alternatives in other nests.

For this analysis, we assume that fuel efficiency separates the make-models and define three nests of vehicles: high, medium and low fuel efficiency vehicles. By this criterion, we are assuming that make-models in each fuel efficiency nest have similar unobserved characteristics and, accordingly, are correlated. Make-models across vehicle nests, however, are assumed to have unobserved attributes that are uncorrelated. Figure 1 depicts the nested structure which identifies fuel efficiency as the upper branch and make-model choice as the lower branch.

Although we have defined a nested structure based upon an hypothesis of correlation among elemental alternatives in a given nest, the nest depicted in Figure 1 is not inconsistent with a behavioural interpretation that a household initially weighs the attributes of those make-models that satisfy a certain fuel efficiency criterion and then selects a particular make-model from this subset.[2]

To develop the nested logit model, we partition Ω_n into three disjoint subsets S_f ($f \in \Phi = \{l, m, h\}$) reflecting low (l), medium (m), and high (h) fuel efficiency. Each alternative is then indexed by a double subscript(i, f) which denotes the fuel efficiency category and the specific make-model within each category. The indirect utility of household n for vehicle (i, f) can be written as

$$U_{if}^{n} = V_{if}^{n} + \varepsilon_{if}^{n} \qquad i \in \Omega_n;\ f \in \Phi \tag{4}$$

[2] Unlike Bucklin and Gupta (1992), Bucklin and Lattin (1991) and Fotheringham (1988) which use a nested structure to describe the household decision process, the primary reason for using a nested structure in this analysis is to exploit the hypothesized correlation that exists among the unobserved attributes of elements in a set of alternatives.

where V_{if}^n and ε_{if}^n are the systematic and random components of the indirect utility function respectively.

Consistent with most discrete choice models, we assume that household n has an indirect utility U_{if}^n for alternative (i,f) that is a linear-in-parameters function of household attributes, attractiveness of each fuel efficiency category and attributes of the make-models within each category. Further, by extension of the partitioning of vehicles into fuel efficiency classes, we can classify these independent variables into factors Z_f^n that only influence the choice of fuel efficiency and other variables X_{if}^n that affect both fuel efficiency and make-model decisions:

$$(5) \qquad U_{if}^n = V_{if}^n + \varepsilon_{if}^n = \alpha Z_f^n + \beta X_{if}^n + \varepsilon_{if}^n \qquad i \in \Omega_n ; f \in \Phi$$

where α and β are parameters to be estimated.

Suppose the random component of the indirect utility function in equation (15) has a multivariate extreme valued distribution function, given by

$$(6) \qquad F(\varepsilon_{if}^n ; i \in \Omega_n, f \in \Phi) = \exp\left\{ -\sum_f \left(\sum_{i \in S_f} (e^{-\varepsilon_{if}^n})^{1/(1-\sigma_f)} \right)^{1-\sigma_f} \right\}$$

where σ_f are parameters and S_f is the set of make-models associated with fuel efficiency type f. McFadden (1978) demonstrates that this function generates joint choice probabilities that are the product of the conditional and marginal choice probabilities,

$$(7) \qquad P_{if}^n = P_{i|f}^n \, P_f^n \qquad i \in \Omega_n ; f \in \Phi$$

Moreover, the conditional and marginal choice probabilities have MNL forms,

$$(8a) \qquad P_{i|f}^n = \frac{\exp\{\beta X_{if}^n\}}{\sum_{j \in S_f} \exp\{\beta X_{jf}^n\}} \qquad i \in S_f \subset \Omega_n$$

(8b) $$P_f^n = \frac{\exp\{\alpha Z_f^n + \mu_f I_f^n)}{\sum\limits_{g \in \Phi} \exp\{\alpha Z_g^n + \mu_g I_g^n)} \qquad f \in \Phi$$

where $I_f^n = \ln[\sum\limits_{i \in S_f} \exp\{\beta X_{fi}^n\}]$ and $\mu_f = (1-\sigma_f)$. I_f^n is the inclusive value associated with fuel efficiency category f and reflects the expected maximum utility of make-model choice in fuel efficiency category f. μ_f are scale parameters to be estimated. Further, when μ_f lies in the open unit interval ($0 < \mu_f < 1$), the above nested structure is consistent with random utility maximisation and ($1 - \mu_f$) is a measure of the similarity of alternatives in nest f (McFadden, 1979). Alternatively, if $\mu_f = 1$ for all f then a joint choice framework is more appropriate and the model collapses to a standard multinomial logit model.

Full information maximum likelihood methods will be used in this study to estimate the model. The likelihood function for the nested logit model in equation (7) is

(9) $$L = \prod_{n=1}^{N} \prod_{\substack{i \in \Omega_n \\ f \in \Phi}} [P_{if}^n]^{y_{if}^n}$$

$$= \prod_{n=1}^{N} \prod_{\substack{i \in \Omega_n \\ f \in \Phi}} [P_{i|f}^n \; P_f^n]^{y_{if}^n}$$

$$\Rightarrow \quad \ln L = LL = \sum_{n=1}^{N} \sum_{\substack{i \in \Omega_n \\ f \in \Phi}} y_{if}^n \ln[P_{i|f}^n \; P_f^n]$$

where $y_{if}^n = 1$ if household n chooses alternative (i, f) and equal to zero otherwise. Substituting for $P_{i|f}^n$ and P_i^n from equations (8a) and (8b) and maximising the log-likelihood function with respect to β and α, the coefficient vector in the conditional and marginal model respectively, and μ_f, , the coefficient of the inclusive term, yield full information maximum likelihood estimates that are consistent and asymptotically efficient.

3. Data

A 1989 New Car Buyer Competitive Dynamics Survey of 33,284 principle purchasers of new vehicles, conducted by J.D. Power and Associates, provided the primary data for this analysis. Among the information collected, the survey reported household information on the make-model purchased and attributes of the new vehicle, financing arrangements, search activities, and numerous household socioeconomic and demographic characteristics. From this raw data set, a usable data set of 1564 observations was developed by first excluding those observations with missing information on variables of interest (which reduced the total sample to 28,235 observations) and then taking an approximate 5% sample under the constraint that the make-model share in the sample reflected the make-model share in the population.[3] Supplementary data sources provided information on vehicle attributes not included in the survey (e.g. base vehicle prices, warranties, exterior and interior size, fuel economy, reliability, and safety, gasoline prices, and population).[4]

Because the model is not computationally tractable if all available alternatives, 191 make-models in 1989, are included in a consumer's choice set, for estimation purposes, a random sampling procedure was used to define a consumer's choice set for each fuel efficiency nest. In particular, a choice set comprised of 10 alternatives randomly drawn from the subset of vehicles within the same fuel efficiency nest. For the chosen nest, the actual vehicle purchased was included as one of the 10 alternatives. Although, in general, choice set sampling procedures introduce sampling biases, McFadden (1978) has shown that the bias correction for the choice set sampling procedure used in this study is identical for each observation, a result which is particularly convenient in a multinomial logit framework because it implies that standard multinomial logit algorithms are appropriate for model estimation.[5]

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[3] The constraint was necessary since the original sample was a quota-based. By constraining the estimation sample to replicate the make-model proportions observed in the population, standard estimation software programs will produce consistent parameter estimates (Ben-Akiva and Lerman (1985)).

[4] Sources included the 1989 Automotive New Market Data Book, Consumer Reports, 1989 Car Book , the Oil and Gas Journal, and the Bureau of the Census.

[5] Let ω_n be the assigned choice set for observation n. If $P(\omega_n | i) = P(\omega_n | j)$ then the sampling strategy satisfies a uniform conditioning property (McFadden (1978)). Thus, the logit model correction term, $\ln(P(\omega_n | i))$ is equal for each alternative in the assigned choice and cancels out in the choice probabilities.

For this study, the definition of fuel efficiency is based upon a vehicle's miles per gallon (mpg) data for city driving. Table 1 shows the distribution of make-models by fuel efficiency and consumers who purchase vehicles within a given fuel efficiency level. It should be noted that any definition of a fuel efficient vehicle is necessarily arbitrary.[6] Based upon the sample distribution of fuel efficiency, we defined our thresholds with a twofold objective: first, that each nest have a reasonable number of observations for estimation; and second, that each nest include a reasonable number of make-models. Nine samples were constructed with inclusive boundaries for the medium fuel efficiency category set at 18, 19 and 20 for the lower end and 22, 23 and 24 for the higher bound. In general, coefficient estimates from the different samples were fairly robust. The nested structure, however, provided a significant improvement over the standard MNL in six of the nine samples.[7] This result may not be surprising because the defined nests for some samples, could include alternatives that are not highly correlated so that the NMNL model collapses to the MNL model.

The final sample selected for further analysis has a lower boundary of 18 mpg and an upper limit of 23 mpg for the medium fuel efficiency category.[8] For this sample, the low fuel efficiency nest comprises 37 make-models or 19.4% of the available alternatives, the medium fuel efficiency nest contains 120 (62.8%) make-models and the high fuel efficiency nest includes 34 (17.8%) make-models. Furthermore, based on these classifications, 13.7% , 60.3% and 26.0% of the households purchased low, medium and high fuel efficiency vehicles respectively.

Table 2 provides a descriptive analysis of the socioeconomic profile for the sample of purchasers as well as for each of the fuel efficiency categories. Compared to aggregate market shares, a relatively higher proportion of lower income and smaller households, respectively, bought high fuel efficiency vehicles. Conversely, a relatively larger proportion of higher income and larger households, respectively, purchased low fuel efficiency vehicles.

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6 One strategy is to define fuel efficiency in terms of the federally mandated 27.5 mpg CAFE standard. Vehicles with an mpg rating no less than 27.5 would be classified as fuel efficient while those with a rating less than 27.5 mpg would be fuel 'inefficient'. However, by this definition, over 91% of our sample purchased fuel inefficient vehicles.

7 A nested logit structure is a significant improvement if the inclusive value falls in the (0, 1) range and is significantly different from zero and one.

8 Since the efficiency nests include different make-models for each fuel efficiency stratification, the results from each of the nine models are not directly comparable. Based upon goodness of fit statistics and the sign and significance of included variables, the reported model provided the best overall fit of the data.

In addition, younger buyers, females, singles and minorities have a higher tendency, on average, to purchase higher fuel efficiency vehicles. A disproportionately large share of the buyers with less than high school education preferred vehicles with medium fuel efficiency over makes with lower or higher fuel efficiencies.

For the estimated model, Table 3 defines the explanatory variables which include cost related attributes, vehicle attributes, socio-economic characteristics and manufacturer country of origin.[9] A priori, we expect that each of the cost related attributes will reduce the probability of a make-model being chosen, all else held constant. However, for vehicle operating cost, there is a potential self-selection problem since consumers purchasing high (low) efficiency vehicles will have low (high) operating costs. To avoid possible endogeneity biases, predicted operating cost, defined as the predicted value from a regression of operating cost on vehicle weight, net horsepower, length, and vehicle make dummy variables, is used as an instrumental variable for actual operating cost.

In general, the vehicle attributes included in the model reflect a vehicle's size (Length, and Trunk), safety (Airbag), and style (Sport Utility, Van, and Pick-up). All else held constant, it is expected that increases in size and safety will increase the probability of a make-model being purchased. On the other hand, relative to automobiles, the effect of style is ambiguous.

In order to distinguish consumption patterns by location and age, two additional variables were included in the model: 'Pacific Coast - Japanese' and 'Age $\geq$ 45 - American'. The former variable reflects an underlying hypothesis found in other studies (Lave and Bradley, 1980; McCarthy, forthcoming) that consumers in Pacific Coast states are more likely to purchase Japanese vehicles. The second variable, in contrast, tests the hypothesis that older individuals are more likely to purchase American vehicles, all else held constant.

Re-purchasing the same brand is expected to increase the probability of a make-model's purchase, all else held constant. However, including a dummy variable for brand loyalty in the estimation equation is equivalent to entering a lagged dependent variable which may lead to biases in the estimated coefficients. In order to control for this, a brand loyalty binary logit model was first estimated on a set of explanatory variables that included annual income, education, residence, gender, household position, and vehicle make. Predicted brand loyalty

[9] Manufacturer is the nameplate country of origin rather than manufacturing production site.

from this estimated equation was then used in the present model to capture the effect of brand loyalty on purchase behaviour.

Consumer Satisfaction Index is a variable that J.D. Powers and Associates generate from survey data.[10] Since higher index numbers are associated with higher perceived quality, an increase in the index is expected to increase the demand for a given make-model, all else constant.

To capture the effect of unobservable data associated with a manufacturer's make-models, manufacturer dummy variables for General Motors, Ford, Chrysler, Honda, Nissan, Toyota, and Mazda are included in the model. Relative to these manufacturers, the normalising manufacturers are the remaining Pacific Rim as well as all European manufacturers.

We also see in Table 3 that a consumer's fuel efficiency choice is related to various socioeconomic characteristics (Income, Gender, Age, Minority, and Population of area), a search variable (Dealer Visits), and the Price of Gasoline. Since household budgets, vehicle size preferences, and environmental considerations affect fuel efficiency choice, the net effects of these socioeconomic characteristics on choice may be ambiguous. To the extent that there is a positive correlation between vehicle size and luxury, for example, there will be an inverse relationship between fuel efficiency and vehicle luxury. At the extremes, one can easily imagine that the smallest, least comfortable and lightest vehicles will have the highest fuel efficiency whereas the largest, heaviest, and most comfortable will be the least fuel efficient. Also, since vehicle comfort and amenity generally increase with size, and therefore decrease with fuel efficiency, one would expect rising income to reduce the demand for fuel efficient vehicles, all else held constant. This negative expectation is further reinforced by the findings of a negative correlation between income and environmental concern by Van Liere and Dunlap (1978) and Grossman and Potter (1977).

Dardis and Soberon-Ferrer (1992) found that female and younger buyers are more likely to purchase small cars than other households. In addition, they found that blacks (minorities) have a higher demand for small cars than non-black consumers when prices are above \$11,011. To the extent that small cars are correlated with high fuel efficiency vehicles, we

[10] Also, because it is based upon responses from a group of consumers different from those in this study, the satisfaction index is exogenous to respondent choice decisions.

can expect similar results in our model. Furthermore, age and the male gender have been widely found to be negatively correlated with environmental concerns (Van Liere and Dunlap, 1980; Anderson and Cunningham, 1972). Therefore, it is expected that younger, female and minority consumers are more likely to purchase higher fuel efficiency vehicles.

Increases in metropolitan population are expected to increase the demand for fuel efficient vehicles. As an area's population rises, so does the amount of vehicle traffic and congestion which gives a comparative advantage to smaller and more fuel efficient vehicles. Not only is the operating cost of smaller fuel efficient vehicles less in congested traffic but the smaller vehicle is also more manoeuvrable and has less difficulty with parking. Furthermore, urban residents are more likely to be environmentally concerned than rural residents because they are exposed to higher levels of pollution and other types of environmental deterioration (Van Liere and Dunlap, 1980).

Because of its influence on the operating cost of vehicles, the price of gasoline is expected to increase the demand for fuel efficient vehicles, all else held constant. Similarly, the higher the concerns for fuel efficiency, the greater will be the expected fuel economy benefits to the consumer from further search. All else constant, this implies that increasing search activities will disproportionately increase the demand for fuel efficient vehicles. Conversely, if fuel efficiency is not of concern to consumers then we would not expect increasing search to have a differential effect by fuel efficiency.

Finally, if the nested logit model is consistent with the random utility maximisation hypothesis, the inclusive variable, which represents the expected maximum utility associated with the make-model choice, will lie in the open unit interval.

4. Estimation Results

Table 4 reports the FIML estimation results of the nested logit model of fuel efficiency and make-model choices. Overall, the model fits the data well with a rho-squared statistic of 0.180 and a chi-square statistic that strongly rejects the null hypothesis of no explanatory power. Furthermore, each of the explanatory variables has its expected sign and is significantly different from 0.

Focusing initially upon the make-model estimation results, we see that increases in a make-model's price and operating cost decreases the demand for the vehicle whereas increases in length, trunk size, and the presence of an airbag increase vehicle demand. The positive sign and magnitude of the coefficients on Sport Utility/Van and Pick-up, respectively, indicate that, holding all else constant, consumers' preference ranking is Sport/Utility, Pick-up, and automobile.

Also as expected, the demand for Japanese vehicles is greater on the Pacific Coast than elsewhere in the United States; the demand for American-made vehicles is greater for purchasers 45 years of age or older; brand loyalty has a significant positive effect on make-model demand; and the higher the perceived quality of a vehicle, the greater is its demand.

An examination of the manufacturer dummy variables provides some indication of consumer preferences for a manufacturer's country of origin, all else constant. Relative to the normalised alternatives (the non-included Pacific Rim and European manufacturers), the estimated coefficients indicate that consumers exhibit the strongest preferences for Nissan followed, in decreasing order, by Toyota , Honda, Ford, General Motors, and Mazda.

With only a few exceptions, we see that the hypothesised variables have significant influences upon the choice of fuel efficiency. In particular, relative to low fuel efficient vehicles (the normalising alternative) the demand for fuel efficient vehicles is greater for females, minorities, and younger purchasers. The negative signs on the two income variables indicate that increasing income, as expected, reduces the demand for fuel efficient vehicles. Relative to low efficiency vehicles, rising incomes reduce the demands for high and medium fuel efficient vehicles (–6.56E-06 versus –9.53E-06) and increases the demand for medium relative to high fuel efficient vehicles. Also, and consistent with the hypothesis that increasing congestion raises the comparative advantage of fuel efficient vehicles, we see in Table 4 that an increase in population increases the demand for high fuel efficient vehicles, all else constant. Furthermore, these findings are consistent with the profile of environmentally concerned consumers.

The effect of rising gasoline prices is also consistent with expectations. Relative to fuel inefficient vehicles, a price rise increases the demand for medium and high fuel efficient vehicles. And the effect of dealer visits is consistent with the underlying hypothesis that consumers concerned with fuel efficiency engage in more search. Relative to vehicles with lower fuel efficiency, an additional dealer visit increases the demand for medium and high fuel efficiency vehicles, with the greatest effect on the demand for high fuel efficient vehicles.

It is also seen in Table 4 that the expected maximum utility associated with the make-model choice increases the demand for vehicle fuel efficiency type choice, as expected. In addition to rejecting the null hypothesis that the coefficient equals 0 (t-statistic equals 6.18), we can also reject, at the .05 level, the null hypothesis that the coefficient equals 1 (t-statistic equals –8.18). Thus, the results reported in Table 4 are consistent with the maintained hypothesis of random utility maximisation.

5. Choice Elasticities

Of interest in this study is the vehicle price and operating cost elasticities of demand. To calculate these demand sensitivity measures, recall that the joint choice probability for the nested logit model is the product of MNL conditional and marginal probabilities, $P_{if}^{n} = P_{i|f}^{n} P_{f}^{n}$ $(i \in \Omega_n ;\ f \in \Phi)$. Differentiating the logarithm of this expression with respect to the logarithm of an explanatory variable yields the choice elasticity. In particular, the percentage effect on choice probability (i, f) from a 1% increase in the kth attribute of make-model (j, g), $x_{jg,k}$, is

$$E_{x_{jg,k}}^{P_{if}} = \frac{\partial \ln P_{if}^{n}}{\partial \ln x_{jg,k}}$$

$$= \frac{\partial \ln P_{i|f}^{n}}{\partial \ln x_{jg,k}} + \frac{\partial \ln P_{f}^{n}}{\partial \ln x_{jg,k}}$$

(10) $$= \beta_k\, x_{jf,k}\, (\delta_{ij} - P(j \mid f))\delta_{fg} + \mu\beta_k\, x_{jg,k}\, P(j \mid g)(\delta_{fg} - P(g))$$

where δ_{ij} = 1 if i = j and 0 otherwise. Similarly, δ_{fg} = 1 if f = g and 0 otherwise. From equation (10), we can identify several cases:

1) if i = j and f = g, equation (10) gives the own elasticity, that is, the percentage change in a make-model's choice probability resulting from a 1% change in one of its attributes:

$$E^{P_{if}}_{x_{if,k}} = \beta_k x_{if,k} (1 - P(i \mid f)) + \mu\beta_k x_{if,k} P(i \mid f)(1 - P(f))$$

2) if i ≠ j and f = g, equation (10) gives the within-nest cross elasticity

$$E^{P_{if}}_{x_{jf,k}} = \beta_k x_{jf,k} (- P(j \mid f)) + \mu\beta_k x_{jf,k} P(j \mid f)(1 - P(f))$$

Since no term in this expression depends upon i or g, we get the usual result that the cross elasticity is constant across alternatives within the nest.

3) if i ≠ j and f ≠ g, equation (10) gives the between-nest cross elasticity

$$E^{P_{if}}_{x_{jg,k}} = \mu\beta_k x_{jg,k} P(j \mid g)(- P(g))$$

There are two points to notice about these expressions. First, as long as μ lies in the unit interval, the between-nest cross elasticity is less than the within-nest elasticity, which reflects a general property in nested logit models that the effect of attribute changes decreases with distance from the nest. Second, the elasticity term does not depend upon other nests so that the cross elasticity effect is the same for all elemental alternatives in other nests.

Table 5 summarises the vehicle price and operating cost elasticity measures for the model. However, only the ranges of elasticities rather than separate elasticities are provided. In general, calculating elasticities measures for each alternative due to changes in an attribute leads to a voluminous amount of output since, for this model, each attribute change is associated with an own elasticity and 29 cross elasticities. Also, since the elemental alternatives in the model are unordered, the elasticity measures for each observation are not specific to a particular make-model. In Table 5, therefore, we provide own and cross elasticity ranges in order to evaluate whether there are systematic differences across the fuel efficiency nests. It must also be remembered that the demand elasticities are sensitive to the magnitudes of choice probabilities. The effect of an attribute change, for example, will produce a larger percentage effect on the demand for a rarely chosen alternative (whose choice probability is low) in comparison with a frequently chosen alternative (whose choice probability is high).

Based upon the estimated model, the demand for new vehicles exhibits an approximate unitary price elasticity of demand but with a general decrease as vehicles move from lower to higher fuel efficiency.[11] Whereas the range of own price elasticities lies between −1.107 and −1.024 for low fuel efficiency vehicles, the price elasticities drop to between −0.912 and −0.839 for the high fuel efficient vehicles. With respect to cross price elasticities there is a fall in the elasticities for the low and high groups as compared to the medium fuel efficiency category. This result may be attributed to the relatively greater ease of substitution for vehicles in the medium category. The high fuel efficiency group is the least sensitive to price changes within its own group whereas the low fuel efficiency group is the least sensitive to price changes in other categories. Furthermore, the cross price elasticities between nests are uniformly lower than the within-nest elasticities, an expected result given that the estimated inclusive value parameter lies in the open unit interval.

The sensitivity of new vehicle demands to operating cost is reported in the lower half of Table 5. A 1% increase in the operating cost of a vehicle decreases its own demand from 1.5% - 2.3%. Again, we observe an inverse relationship between fuel efficiency and the own operating cost elasticity. The higher the efficiency, the lower the own elasticity of demand. Moreover, elasticity patterns similar to the vehicle price elasticities are seen for both the within and between nest cross elasticities.

Table 6 reports the own vehicle price and operating cost elasticities by market segment. In general, the vehicle price and operating cost elasticities are inversely related to fuel efficiency which may reflect differential cost savings. Consistent with earlier results, females,

[11] Although price enters the model as a proportion of income, the price share elasticity is equivalent to price elasticity of demand, assuming no change in income. In general, $\frac{\partial y}{\partial (x/z)} \frac{x/z}{y} = \frac{\partial y}{(1/z)\partial x} \frac{x/z}{y} = \frac{\partial y}{\partial x} \frac{x}{y}$. In a multinomial logit analysis using the same data and a slightly different specification, McCarthy (forthcoming) reported an overall vehicle price elasticity equal to .87. This suggests that exploiting the correlation among elemental alternatives increases consumers' price sensitivity in new vehicle purchases.

minorities and consumers with some college education are found to have more elastic demands.

6. Additional Results

The model presented in Table 4 assumes that the inclusive value coefficient is identical across each of the fuel economy nests. Although the results are consistent with a random utility maximisation hypothesis, an alternative model specification relaxes the assumption on the inclusive value by estimating separate inclusive value coefficients for each of the nests. Qualitatively and quantitatively, the estimation results from this model are very similar to those reported in Table 4 with two exceptions. Relative to the demand for low fuel efficient vehicles, increases in gasoline prices have no effect upon the demand for high fuel efficient vehicles and increase the demand for medium fuel efficient vehicles at the .10 level. This contrasts with Table 4 where an increase in gasoline prices raised the demand for both medium and high fuel efficient vehicles relative to low fuel efficient vehicles. A second difference relates to the estimated inclusive values, which are given below (with t-statistics in parentheses):

Inclusive Value - Low Efficiency	.832 (5.54)
Inclusive Value - Medium Efficiency	.610 (4.92)
Inclusive Value - High Efficiency	.602 (4.14)

The inclusive value for the high and medium efficiency nests are virtually identical. But these values differ from the estimated inclusive value for the low efficiency nest whose value is .832. The reported t-statistics indicate that each inclusive value is significantly different from 0. Moreover, we can further reject the null hypothesis that each coefficient equals 1. However, based upon the restricted and unrestricted log-likelihoods at convergence, we cannot reject at the .05 level the null hypothesis that the inclusive value coefficients are equal.[12]

[12] Let LL_u and LL_r be the log-likelihood for the unrestricted and restricted models respectively. Then $-2(LL_r - LL_u) \sim \chi^2$ with degrees of freedom equal to the number of restrictions. For the unrestricted model, the log-likelihood at convergence was -4369.37. The chi-squared statistic is 2.3 which is less than the 5.99 critical value for a .05 critical region. We also estimated a model which only restricted the inclusive value coefficients of the medium and high efficiency nests to be equal. At the .05 level, we could reject the null

7. Conclusion

Because of their implications for energy demands, vehicle-related air pollution, traffic safety, and urban congestion, fuel efficient vehicles are an important component of our nation's transportation landscape. However, notwithstanding considerable work on vehicle choice demands, there has been relatively little research on the demand for fuel efficient vehicles. In order to investigate whether the structure of demand for fuel efficient vehicles differs from more fuel inefficient vehicles, this analysis developed and estimated a nested logit model of make-model new vehicle demands.

Consistent with expectations, improvements in size, safety, and an index of consumer satisfaction increase a vehicle's probability of purchase whereas higher costs reduce its purchase probability. Furthermore, households on the Pacific coast were found to prefer Japanese cars while consumers over 45 years of age prefer American vehicles, all else constant.

Consistent with the profile of environmentally concerned consumers, our results indicate that females, minorities, and residents in more densely populated areas exhibit higher demands for fuel efficient vehicles. Higher income households and individuals older than 45 years of age, on the other hand, prefer less fuel efficient vehicles. And, as expected, increasing gasoline prices increased the demands for medium and high fuel efficient vehicles relative to low fuel efficiency vehicles. Also, increasing vehicle search was found to increase the demand for fuel efficient vehicles

As expected, increases in the expected maximum utility associated with the make-model choice in a fuel efficiency category increase the demand for that fuel efficiency type. Further, since the inclusive value coefficient lay in the open unit interval, the results are consistent with random utility maximisation and a nested logit structure.

hypothesis that the inclusive value for the low efficiency nest equals the inclusive value for the medium and high efficiency nests.

Overall, the demand for vehicles has an own price elasticity that lies just below unity and is elastic to changes in operating cost. However, the results also demonstrate that the structure of vehicle demands is not independent of fuel efficiency category. In general, there was an inverse relationship between own price and operating cost elasticities and fuel efficiency. The higher the fuel efficiency category, the lower the price and operating cost elasticity, all else constant. With respect to cross price and operating cost elasticities, however, consumers purchasing vehicles in the medium fuel efficiency category are most sensitive to changes in other categories, a result which likely reflects the larger number of substitutes in this category.

References

Anderson T and Cunningham W (1972). The Socially Conscious Consumer. *Journal of Marketing*, 36(2): 23-31.

Ben-Akiva, Moshe and Lerman, Steve (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge: MIT Press.

Bucklin, Randolph and Gupta, Sunil (1992). Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach. *Journal of Marketing Research*, XXIX, 201-15.

Bucklin, Randolph and Lattin, James (1991). A Two-Stage Model of Purchase Incidence and Brand Choice. *Marketing Science*, 10 (1): 24-39.

Dardis, Rachel and Soberon-Ferrer, Horacio (1992). The Demand for Small Cars in the United States: Implications for Energy Conservation Strategies. *Journal of Consumer Policy, 15:1-20.*

Fotheringham, Stewart (1988). Consumer Store Choice and Choice Set Definition. *Marketing Science*, 7(3): 299-310.

Greene, David (1990). CAFE or Price?: An Analysis of the Effects of Federal Fuel Economy Regulations and Gasoline Price on New Car MPG, 1978-1899. *Energy Journal*, 11 (3): 37-57.

Grossman G M and Potter H R (1977). A Trend Analysis of Competing Models of Environmental Attitudes. Working paper #127, Institute for the Study of Social Change, Department of Anthropology, Purdue University.

Lave, Charles A. and Joan Bradley (1980). "Market Share of Imported Cars: A Model of Geographic and Demographic Determinants," *Transportation Research*, 14A, 379-387.

Maddala, G S (1983). *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge: Cambridge University Press.

McCarthy, P S. "Market Price and Income Elasticities of New Vehicle Demands," *Review of Economics and Statistics*, forthcoming.

McFadden, Daniel (1978). Modeling Choice of Residential Location. In A. Karlquist et. al. (eds.), *Spatial Interaction Theory and Residential Location.* Amsterdam: North-Holland.

_______ (1979). "Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments." Chapter 13 in David A. Hensher and Peter R. Stopher (eds.). *Behavioural Travel Modelling.* London: Croom Helm.

Nivola, Pietro (1990). Deja Vu All Over Again: Revisiting the Politics of Gasoline Taxation. *The Brookings Review*, Winter 1990/91, 29-35.

Reynolds, Larry (1991). Congress fuels the fleet economy debate. *Management Review*, November 1991, 23-24.

Serafin, Raymond (1990). GM, Chrysler Try Mileage Claims. *Advertising Age*, 61 (41): 50.

Turrentine, Thomas (1995). Who Will Buy Electric Cars? *Access*, Spring (6): 19-24.

Train, Kenneth. (1986) Qualitative Choice Analysis. Cambridge, MA.: The MIT Press.

Van Liere K and Dunlap R (1978). Environmental Concern: Consistency Among its Dimensions, Conceptualisations and Empirical Correlates. Paper presented at the Annual Meeting of the Pacific Sociological Association, Spokane, Washington.

_____ (1980). The Social Base of Environmental Concern: A Review of Hypotheses, Explanations and Empirical Evidence. *Public Opinion Quarterly*, 44(2): 181-197.

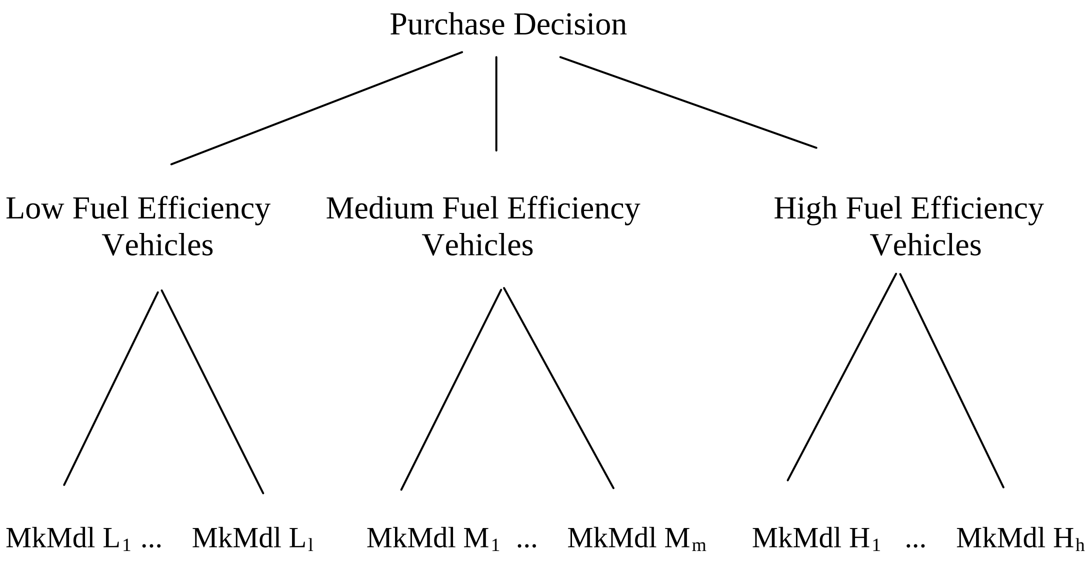

Figure 1
Nested Logit Model for Fuel Efficiency and Make-Model Choices

Table 1
Fuel Efficiency Description and Sample Characteristics

City MPG	No. of Vehicles	Relative Frequency	No. of Consumers	Relative Frequency
≤17	27	19.4	280	17.9
18	33	17.3	155	9.9
19	22	11.5	136	8.7
20	16	8.4	60	3.8
21	12	6.3	128	8.2
22	13	6.8	75	4.8
23	13	6.8	214	13.7
24	11	5.8	112	7.2
≥ 25	34	17.8	404	25.9

Authors' calculations.

Table 2
New Car Purchase Profile by Fuel Efficiency

	Total Sample (%)	Low Fuel Efficiency (%)	Medium Fuel Efficiency (%)	High Fuel Efficiency (%)
Market Share		13.7	60.3	26.0
Socioeconomic Attribute				
Household Income				
< $25,000	17.9	8.5	54.1	37.4
$25,000 - $44,999	32.2	11.5	63.4	25.2
$45,000 - $59,999	18.8	12.4	66.9	20.8
≥ $60,000	31.0	20.2	57.5	22.3
Household Size				
1	12.0	7.4	52.1	40.4
2	31.4	16.1	62.3	21.6
3	18.0	14.2	61.2	24.6
4	14.3	14.7	60.9	24.4
> 4	8.4	15.9	57.6	26.5
Respondent's Age				
< 25	9.9	1.9	51.6	46.5
25 - 44	47.4	8.9	62.9	28.2
> 44	42.7	21.9	59.4	18.7
Respondent's Education				
Less than High School	10.4	12.8	72.5	14.8
High School Graduate	20.9	16.5	57.9	25.6
Attended College	26.9	11.9	59.4	28.7
College Graduate	42.6	13.8	59.3	26.9
Respondent's Sex				
Male	64.3	15.9	61.8	22.3
Female	35.7	9.8	57.6	32.6
Respondent's Ethnicity				
White	91.4	14.5	60.8	24.8
Minority	8.6	6.0	55.2	38.8
Respondent's Marital Status				
Single	34.0	7.5	57.0	35.5
Married	66.0	17.0	62.0	21.0

* Total sample size is 1564. The respondent for this survey was the principle purchaser of the new vehicle.

Table 3

Variable Definition for Make-Model and Fuel Efficiency Choices

Independent Variable	Variable Definition
Make-Model Choice	
1. Cost Related Attributes	
Vehicle Price/Annual Income	Vehicle price divided by household annual income
Operating Cost per Mile	Average gas price in the respondent's state divided by the vehicle's gas mileage, in cents per mile
2. Vehicle Attributes	
Airbag	Equals 1 if vehicle equipped with an airbag, 0 otherwise
Length	Overall vehicle length, in inches
Trunk	Trunk space, in cubic feet, and defined only for automobiles.
Sport Utility, Van	Equals 1 if vehicle is a sport utility or van, 0 otherwise
Pick-up	Equals 1 if vehicle is a pick-up truck, 0 otherwise
3. Socio-Economic and Other Attributes	
Pacific Coast - Japanese Vehicle	Equals 1 if Japanese vehicle and respondent lives in a Pacific Coast state, 0 otherwise
Age $\geq$ 45 -American Vehicle	Equals 1 if American vehicle and respondent is 45 years of age or older, 0 otherwise
Re-Purchase Same Brand	Equals 1 if purchases make-model the same as previous make-model, 0 otherwise
Consumer Satisfaction Index	J.D. Powers index of consumer satisfaction. Available for automobiles only.
4. Manufacturer Dummy Variable	Equals 1 for a particular manufacturer, 0 otherwise
Fuel Efficiency Choice	
Income	Annual household income
Female	Equals 1 if purchaser is female, 0 otherwise
Age	Age of purchaser
Minority	Equals 1 if purchaser is non-white, 0 otherwise
Metropolitan Population if $\geq$ 50,000	Population of area in which purchaser resides
Dealer Visits	The number of different dealerships the purchaser visited
Gasoline Price	The average gasoline price in the purchaser's state
Inclusive Value	Value of Expected Maximum Utility of Make-Model Choice; defined as $I_g = \ln[\sum_{i \in S_g} \exp\{\beta' X_{gi}\}]$

Table 4
Estimation Results for Make-Model and Fuel Efficiency Choices

Independent Variable	Coefficient Estimate	(t-stat)
Make-Model Choice		
1. Cost Related Attributes		
Vehicle Price/Annual Income	–3.293	(–10.30)***
Operating Cost per Mile	–.519	(–4.26)***
2. Vehicle Attributes		
Airbag	0.219	(3.10)***
Length	.0452	(9.05)***
Trunk	0.035	(4.10)***
Sport Utility, Van	2.732	(8.16)***
Pick-up	1.792	(5.59)***
3. Socio-Economic and Other Attributes		
Pacific Coast - Japanese Vehicle	1.109	(6.53)***
Age $\geq$ 45 - American Vehicle	0.511	(3.90)***
Re-Purchase Same Brand	2.107	(1.61)*
Consumer Satisfaction Index	0.0064	(2.51)***
4. Manufacturer Dummy Variable		
General Motors	0.591	(4.93)***
Ford	0.742	(5.67)***
Chrysler	-0.138	(-0.93)
Honda	1.097	(6.72)***
Nissan	1.920	(11.41)***
Toyota	1.354	(8.81)***
Mazda	0.316	(1.78)*
Fuel Efficiency Choice		
Income - Medium Efficiency	–6.56E-06	(–3.78)***
Income - High Efficiency	–9.53E-06	(–3.98)***
Female - Medium Efficiency	0.429	(2.46)***
Female - High Efficiency	0.795	(4.12)***
Age - High Efficiency	–0.235	(–5.43)***
Metropolitan Population - High Efficiency	2.41E-05	(2.09)**
Minority - High Efficiency	0.561	(2.83)***
Dealer Visits - Medium Efficiency	0.067	(2.92)***
Dealer Visits - High Efficiency	0.092	(3.73)***
Gasoline Price - Medium Efficiency	0.038	(2.34)**
Gasoline Price - High Efficiency	0.034	(1.81)*
Inclusive Value	0.696	(6.18)***
Constant - Medium Efficiency	–1.561	(–1.14)
Constant - High Efficiency	–1.536	(–0.96)

Number of Records	46890
Log-likelihood at Convergence	–4370.53
Log-likelihood at 0	–5319.47
Degrees of Freedom	33
Chi-squared Statistic	1897.90
$\bar{\rho}^2$	0.178

*** significant at the .01 level, 2-tail test
** significant at the .05 level, 2-tail test
* significant at the .10 level, 2-tail test

Table 5
Vehicle Price and Operating Cost Elasticity Ranges

	Own Elasticity	**Within Nest Cross Elasticity**	**Between Nest Cross Elasticity**
Vehicle Price			
Low Fuel Efficiency	(-1.107, -1.024)	(0.100, 0.113)	(0.025, 0.027)
Medium Fuel Efficiency	(-1.012, -0.945)	(0.130, 0.154)	(0.076, 0.091)
High Fuel Efficiency	(-0.912, -0.839)	(0.087, 0.109)	(0.038, 0.051)
Operating Cost			
Low Fuel Efficiency	(-2.297, -2.258)	(0.226, 0.245)	(0.064, 0.076)
Medium Fuel Efficiency	(-1.873, -1.850)	(0.248, 0.272)	(0.145, 0.159)
High Fuel Efficiency	(-1.539, -1.515)	(0.153, 0.170)	(0.064, 0.076)

Table 6
Own Vehicle Price and Operating Cost Elasticity Ranges by Market Segment

Market Segment	Vehicle Price	Operating Cost
Non-white		
Low Fuel Efficiency	(-1.202, -1.010)	(-2.378, -2.211)
Medium Fuel Efficiency	(-1.125, -0.881)	(-1.953, -1.804)
High Fuel Efficiency	(-1.042, -0.822)	(-1.544, -1.460)
White		
Low Fuel Efficiency	(-1.106, -1.024)	(-2.297, -2.263)
Medium Fuel Efficiency	(-1.006, -0.947)	(-1.865, -1.845)
High Fuel Efficiency	(-0.918, -0.831)	(-1.546, -1.522)
Female		
Low Fuel Efficiency	(-1.145, -1.056)	(-2.316, -2.275)
Medium Fuel Efficiency	(-1.101, -0.983)	(-1.888, -1.838)
High Fuel Efficiency	(-0.961, -0.878)	(-1.542, -1.496)
Male		
Low Fuel Efficiency	(-1.098, -1.010)	(-2.293, -2.248)
Medium Fuel Efficiency	(-0.989, -0.906)	(-1.876, -1.838)
High Fuel Efficiency	(-0.893, -0.818)	(-1.562, -1.527)
No College Experience		
Low Fuel Efficiency	(-1.093, -0.997)	(-2.301, -2.256)
Medium Fuel Efficiency	(-0.995, -0.931)	(-1.876, -1.847)
High Fuel Efficiency	(-0.909, -0.829)	(-1.551, -1.522)
Some College Experience		
Low Fuel Efficiency	(-1.168, -1.042)	(-2.316, -2.237)
Medium Fuel Efficiency	(-1.071, -0.935)	(-1.887, -1.814)
High Fuel Efficiency	(-0.945, -0.832)	(-1.545, -1.496)