VEHICLE CHOICE BEHAVIOR AND THE DECLINING MARKET SHARE OF U.S. AUTOMAKERS

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Abstract: We develop a consumer-level model of vehicle choice to investigate the reasons behind the erosion of the U.S. automobile manufacturers' market share during the past decade. Our model accounts for the influence of vehicle attributes, brand loyalty, product line characteristics, and dealerships on choice. We find that nearly all of the loss in market share for U.S. manufacturers can be explained by changes in the basic attributes of a vehicle: price, size, power, operating cost, and body type. During the past decade, U.S. manufacturers have improved their vehicles' attributes but not as much as Japanese and European manufacturers have improved the attributes of their vehicles.

Introduction

Until the energy shocks of the 1970s opened the U.S. market to foreign automakers by spurring consumer interest in small fuel-efficient cars, General Motors, Ford, and Chrysler sold nearly 9 out of every 10 new vehicles on the American road. After gaining a toehold in the U.S. market, Japanese automakers, in particular, have taken significant share from what was once justifiably called the Big Three (table 1). Today, only about 50 percent of the nation's new cars and 75 percent of its light trucks are sold by U.S. producers.[1] And new competitive pressures portend additional losses in share, especially in the light truck market—a traditional stronghold for U.S. firms partly because of a 25 percent tariff on light trucks and the historical absence of European automakers from this market.[2] Japanese automakers are building light trucks in the United States to avoid the tariff and introducing new minivans, SUVs, and pickups, while European automakers are starting to offer SUVs.

The domestic industry's loss in market share is not attributable to the problems experienced by any one automaker (table 2). Indeed, GM, Ford, and Chrysler are all losing market share at the same time. Toyota and Honda have recently surpassed Chrysler as the third largest seller of new cars in the United States and are within reach of Ford.[3] Both companies as well as Nissan (not shown) are also likely to increase their share of the light truck market as their new offerings become available. On the other hand, General Motors' share of new car and light truck sales has fallen below 30 percent for the first time since the 1920s.

The forces that cause a tight oligopoly to lose its market dominance are central to our understanding of competition and industry performance. Academic researchers and industry analysts have therefore offered various supply-side and demand-side explanations

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[1] Ford and General Motors have partial ownership of some foreign automakers. However, the industry and manufacturer shares reported here would not be affected very much if Ford's and GM's sales included, on the basis of their ownership shares, the sales of these automakers

[2] As part of NAFTA, the tariff on light trucks currently does not apply to vehicles built in Mexico and Canada.

[3] Chrysler's merger with Daimler-Benz in 1998 has not enabled it to regain its number three position.

for the U.S. automakers' decline. Aizcorbe, Winston, and Friedlaender (1987) found that Japanese automakers were able to build an additional small car during the 1970s and early 1980s for $1,300 to $2,000 less than it cost the U.S. automakers to build the same car. This cost advantage translated into greater market share for the Japanese firms. However, recent evidence compiled by Harbour and Associates suggests that the U.S.-Japanese cost differential has narrowed. For example, an average GM vehicle now requires 24 hours of assembly time while an average Honda North American vehicle requires 22.3 hours. Compared with Japanese transplants, American plants have also significantly reduced the labor that they require to build a car.

From a consumer's perspective, foreign automakers have developed a reputation for building high-quality products. Using various measures of quality and reliability, widely-cited publications such as *Consumer Reports* and the *J.D. Power Report* have generally given their highest ratings in the past few decades to cars made by Japanese and European manufacturers rather than by American manufacturers. Changes in market share since the 1970s could therefore partly reflect the relative attributes of domestic and foreign producers' vehicles.

Economic theory suggests that product line rivalry is an important aspect of competition in the passenger-vehicle market because consumers have strongly varying preferences. Industry analysts stress that it is important for automakers to develop attractive product lines that anticipate or respond quickly to changes in consumer preferences. General Motors, for example, has been faulted for offering an assortment of vehicles that missed major trends such as the growth in the small-car market in the late 1970s and early 1980s, the interest in more aerodynamic midsize cars in the late 1980s, and the rise of sport utility vehicles based on pickup truck designs in the 1990s. The competitiveness of a product line is also affected by an automaker's network of dealers. Changes in market share since the 1970s could therefore reflect the relative strengths of domestic and foreign manufacturers' product lines and distribution systems.

Finally, brand loyalty is inextricably related to developing, maintaining, and protecting market share. Mannering and Winston (1991) found that a significant fraction of GM's loss in market share during the 1980s could be explained by the stronger brand loyalty that American consumers developed toward Japanese producers' vehicles compared with the loyalty that they had for American producers' vehicles. Ford and Chrysler were able to retain their share during that period, but the American firms' subsequent losses in share may be partly attributable to the intensity of consumer loyalty toward Japanese and European automakers.

Given that foreign firms appear to have maintained demand-related advantages over U.S. firms in the past few decades, this paper develops a disaggregate model of consumer vehicle choice to identify the major cause of the domestic industry's shrinking market share. Choice models are a natural way to quantify a variety of influences on consumer behavior, some of which may prove useful for understanding the industry's decline. However, these models have accumulated several specification and estimation concerns including: the independence of irrelevant alternatives (IIA) assumption maintained by the multinomial logit model that is often used to analyze choices; the possibility that vehicle price is endogenous because it is related to unobserved vehicle attributes; the importance of accounting for heterogeneity among vehicle consumers; and the appropriate treatment of dynamic influences on choice such as brand loyalty.

We address these concerns in the process of estimating the choices of U.S. consumers who acquired new vehicles in 2000. We find that choices are strongly influenced by vehicle attributes, brand loyalty, and automobile dealerships but surprisingly that they are not affected by product line characteristics. We use the choice model to simulate market shares under alternative scenarios and find that the U.S. industry's loss in share during the past decade can be explained almost entirely by the relative decline in the attractiveness of the price and non-price attributes of U.S. automakers' vehicles compared with the attributes of foreign automakers' vehicles. The remaining puzzle is why the U.S. automobile industry seems unable to improve the relative quality and value of its vehicles.

A Brief Overview of Methodological Issues

Disaggregate vehicle type choice models assume that consumers or households select a vehicle characterized by make (e.g., Toyota), model (e.g., Camry), and vintage (e.g., 2000) that maximizes their utility. Researchers were initially attracted to these models because they were able to control for brand loyalty and specify a rich set of vehicle attributes such as purchase price, operating costs, horsepower, wheelbase, and so on, thereby improving upon aggregate automobile demand models that use average values or are unable to measure these influences. Subsequent research has integrated vehicle type choice models with other car-related decisions including how many vehicles to own, how much to drive them, and how to acquire them financially (see, for example, Train (1986), Hensher et al. (1992), and Mannering, Winston, and Starkey (2002)). Notwithstanding their advantages, disaggregate vehicle type choice models encounter several econometric problems that have fortunately been addressed by recent methodological advances.

Independence of Irrelevant Alternatives (IIA). Most vehicle type choice models have used the multinomial or nested logit specification for the probability of choosing a given vehicle (exceptions are Brownstone and Train (1999), Berry, Levinsohn, and Pakes (1999, 2004), and Petrin (2002)). Both specifications assume that the error terms for alternative vehicles are independent.[4] This so-called IIA property implies that a change in the price of a given vehicle will have the same effect on the choice probabilities of all alternative vehicles. McFadden and Train (2000), among others, have shown that the restrictions on consumer behavior imposed by IIA can be relaxed by using the mixed logit specification for vehicle choice probabilities that allows errors to be correlated across vehicles.[5] Choice probabilities are estimated using simulation methods to integrate the computationally difficult parts of the error distribution.

Endogeneity of vehicle price. Disaggregate choice models have generally treated the price of the good or service under consideration as exogenous because it is reasonable to assume that an individual consumer's choice will not affect the market price. In addition, most choice models involve a relatively small number of alternatives thus researchers have included alternative specific dummy variables that capture omitted non-price attributes that may be correlated with price.

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[4] A nested logit model allows for the correlation of errors arising from the vehicle type choice and, say, the choice of how many vehicles to own. But even a nested logit model assumes that the errors within the vehicle type choice model are independent.

[5] Hausman and Wise (1978) developed a random parameters probit model to avoid the IIA restriction. Berry, Levinsohn, and Pakes use a variant of a random parameters model in their vehicle choice models.

In the case of passenger vehicles, a consumer chooses among hundreds of different makes and models; thus, most disaggregate vehicle choice models have not included alternative specific (make and model) dummies. This omission raises the possibility that parameter estimates are biased because the purchase price is correlated with unmeasured vehicle attributes. Berry (1994) has shown that by including alternative-specific constants for each vehicle make and model when estimating the choice model, one can then regress the estimated constants against vehicle attributes and use appropriate instruments to correct for the endogeneity of vehicle prices.[6] Berry, Levinsohn, and Pakes' (1995, 2004) and Petrin's (2002) vehicle choice models have used this procedure. We implement the procedure to correct for the endogeneity of the purchase price and a vehicle's expected retained value, which is derived from the purchase price.

Unobserved heterogeneity. Consumers may exhibit preference heterogeneity in their vehicle choices by observable characteristics, such as income and family size, or unobserved characteristics, such as their personality and attitude toward driving. The latter can be captured with random coefficients as specified in the mixed logit model. Our application of the model includes a stochastic utility component that has the double-exponential distribution standard for logit models and a second component that represents random variation in the coefficients to capture unobserved heterogeneity in tastes. Brownstone and Train (1999), Calfee, Winston, and Stempski (2001), Small, Winston, and Yan (2004), and Berry, Levinsohn, and Pakes (2004) among others have found that they were able to identify the taste variation coefficients by estimating multiple choices made by each sampled consumer. In our analysis, we simultaneously estimate consumers' vehicle type choices and their ranking of the vehicles that they strongly considered purchasing.

Brand Loyalty. In the process of making vehicle choices over their lifetimes, consumers develop an attitude toward a brand that results from vehicle ownership and cumulative reinforcing information from friends, advertising, and other sources of

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[6] Lave and Train (1979) and Train (1986) among others have developed models of choice among vehicle *classes* (e.g., compact, mid-size, and so on) as opposed to *makes and models* that included constants for each class, thereby avoiding this bias. However, these studies do not regress the class-specific constants against the average attributes of the vehicle classes to capture consumers' full responses to changes in the attributes.

information. The preferred brand then becomes the standard against which alternatives are judged. Previous vehicle choice models have characterized brand loyalty in different ways. Manski and Sherman (1980) and Train and Lohrer (1982) used a dummy variable to indicate whether a new vehicle purchase was the same make as the previous vehicle that was owned; Mannering and Winston (1985) specified the VMT (vehicle-miles traveled) for the make of the vehicle that was previously owned; and Mannering and Winston (1991) used the number of consecutive purchases of the same brand of vehicle.

Of course, important influences on vehicle choice such as price and quality variables must be held constant for these measures to capture brand loyalty. An additional consideration is that brand loyalty, however measured, may be endogenous because as a variant of a lagged dependent variable it could be correlated with unobserved vehicle attributes. We measure brand loyalty by a consumer's consecutive purchases of the same brand of vehicle and, in contrast to previous research, use an error components model to control for its possible endogeneity.

<u>Model</u>

Our analysis is based on a random utility function that characterizes consumers' choices of new vehicles by make and model. A mixed logit model relates this choice to the average utility of each make and model (i.e., average over consumers), the variation in utility that relates to consumers' observed characteristics, and the variation in utility that is purely random and does not relate to observed consumer characteristics. In an auxiliary regression equation, the average utility of each make and model is related to the observed attributes of the vehicle, using an estimation procedure that accounts for the possible endogeneity of vehicle prices.

We index consumers by $n = 1,\ldots,N$, and the available makes and models of new vehicles by $j = 1,\ldots,J$. The utility, U_{nj}, that consumer n derives from vehicle j is given by:

$$U_{nj} = \delta_j + \beta' x_{nj} + \mu_n' w_{nj} + \varepsilon_{nj}, \qquad (1)$$

where δ_j is "average" utility (or, more precisely, the portion of utility that is the same for all consumers[7]), x_{nj} is a vector of consumer characteristics interacted with vehicle attributes, product line and distribution variables, and brand loyalties (capturing observed heterogeneity); β represents the mean coefficient for each of these variables in the population; w_{nj} is a vector of vehicle attributes that may be interacted with consumer characteristics (capturing unobserved heterogeneity); μ_n is a vector of random terms with zero mean that is the same length as w_{nj} ; and ε_{nj} is a random scalar that captures all remaining elements of utility provided by vehicle *j* to consumer *n*.

Brownstone and Train (1999) point out that the terms $\mu_n' w_{nj}$ represent random coefficients and/or error components. Each term in $\mu_n' w_{nj}$ is an unobserved component of utility that induces correlation and non-proportional substitution between vehicles, thus overcoming the IIA restriction imposed by the standard logit model. Note that elements of w_{nj} can correspond to an element of x_{nj}, in which case the corresponding element of β represents the average coefficient and the corresponding element of μ_n captures random variation around this average. Elements of w_{nj} that do not correspond to elements of x_{nj} can be interpreted as capturing a random coefficient with zero mean.

Denote the density of μ_n around its mean as $f(\mu \mid \sigma)$, which depends on parameters σ that represent, for example, the covariance of μ_n. We assume that ε_{nj} is iid extreme value and has the same mean for all consumers and vehicles, which is reasonable because even if some vehicle attributes are not included in the model, the average utility associated with omitted attributes is absorbed into δ_j. Given the distributional assumption on ε_{nj}, the probability that consumer *n* chooses alternative *i* is given by the mixed logit model (see, e.g., Revelt and Train (1998)):

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[7] The explanatory variables x_{nj} have non-zero mean in general, thus average utility is actually δ_j plus the mean of $\beta' x_{nj}$. We use the term "average utility" to refer to δ_j because other terms, such as "common utility" or "fixed portion of utility," seem less intuitive. The main point is that δ_j does not vary over customers while the other portions of utility do.

$$P_{ni} = \int \frac{e^{\delta_i + \beta' x_{ni} + \mu' w_{ni}}}{\sum_j e^{\delta_j + \beta' x_{nj} + \mu' w_{nj}}} f(\mu | \sigma) d\mu \ . \tag{2}$$

McFadden and Train (2000) demonstrate that by making an appropriate choice of variables and mixing distribution, a model taking this form can approximate any random utility model—and pattern of vehicle substitution—to any level of accuracy.

Market (or aggregate) demand is the sum of individual consumers' demand. The true (observed) share of consumers buying vehicle i is S_i . The predicted share, denoted $\hat{S}_i(\theta, \delta)$, is obtained by calculating P_{ni} with parameters θ = $\{\beta,\sigma\}$ and $\delta = \{\delta_1, \ldots, \delta_J\}$ and summing P_{ni} over the consumers in the sample. Berry (1994) has shown that for any value of θ, there exists a unique δ such that the predicted market shares equal the actual market shares. This fact allows δ to be expressed as a function of θ, thereby reducing the number of parameters that enter the likelihood function. We denote $\delta(\theta,S)$, where $S = \{S_1, \ldots, S_J\}$, as satisfying the relation:

$$S_i = \sum_n \hat{S}_i(\theta, \delta(\theta, S)) \quad i = 1, \ldots, J \ . \tag{3}$$

The parameters of the choice model θ are estimated by maximum likelihood procedures described below, while δ is calculated such that predicted market shares match observed market shares at θ.

The alternative-specific constant for each vehicle, $\delta_j(\theta, S)$, captures the average utility associated with observed as well as unobserved attributes, while the variables that enter the random utility model capture the variation of utility among consumers. To complete the model, we specify average utility as a function of vehicle attributes, z, with parameters, α, that do not vary over consumers:

$$\delta_j(\theta, S) = \alpha' z_j + \xi_j \ , \tag{4}$$

where ξ_j captures the average utility associated with omitted vehicle attributes.[8]

Vehicle price, an element of z_j, is likely to be affected by unobserved attributes, such that ξ_j does not have a zero mean conditional on z_j. To address this problem, let y_j be a vector of instruments that includes the non-price elements of z_j plus other exogenous variables that we discuss below. The assumption that $E(\xi_j | y_j) = 0$ for all j is sufficient for the instrumental variables estimator of α to be consistent and asymptotically normal, given θ.

Estimation Procedures

Estimation of the random utility function presented here is complicated by our efforts to capture preference heterogeneity (i.e., σ), the average utility for each make and model (i.e., δ), and the effect of brand loyalty on vehicle choice. We discuss each of these issues in turn.

Preference Heterogeneity and Vehicles Considered

The set of vehicles that consumers consider before making a purchase provides additional information on their tastes that may be useful in identifying preference heterogeneity. We therefore asked consumers in our sample to list the vehicles that they seriously considered in addition to the vehicle that they purchased. Most consumers indicated that they considered only one vehicle besides their chosen vehicle; no consumer listed more than five vehicles.

We included this information in estimating the choice model by treating the chosen vehicle and the vehicles that were seriously considered as constituting a ranking. Consumers who indicated only one "considered" vehicle generated a utility ranking of $U_{ni} > U_{nh} > U_{nj}$ for all $j \neq i, h$ for chosen vehicle i and considered vehicle h. Consumers who indicated more than one considered vehicle generated a utility ranking in the order that they listed the vehicles.

[8] Note that elements of w_{nj} in the random utility function given in equation (1) can correspond to an element of z_j.

Luce and Suppes (1965) demonstrated that when the unobserved component of utility is iid extreme value, the probability of a utility ranking, starting with the first-ranked alternative, is a product of logit formulas. Therefore, conditional on μ_n , the probability, $L_n(\mu_n)$, that a consumer buys vehicle *i* and also considered vehicle *h* is:

$$L_n(\mu_n) = \left(\frac{e^{\delta_i(\theta,S)+\beta' x_{ni}+\mu_n' w_{ni}}}{\sum_{j=1}^{J} e^{\delta_j(\theta,S)+\beta' x_{nj}+\mu' w_{nj}}} \right) \left(\frac{e^{\delta_h(\theta,S)+\beta' x_{nh}+\mu_n' w_{nh}}}{\sum_{j=1,\, j\neq i}^{J} e^{\delta_j(\theta,S)+\beta' x_{nj}+\mu' w_{nj}}} \right), \tag{5}$$

where the sum in the second logit formula is over all vehicles except *i*. The probability of the consumer's ranking conditional on μ_n is defined analogously for consumers who listed more than one considered vehicle. The unconditional probability of the consumer's ranking is then:

$$R_n = \int L_n(\mu) f(\mu|\sigma) d\mu \,. \tag{6}$$

We found in preliminary estimations that it was essential to include the vehicles that consumers considered to estimate the distribution of their tastes. When we included only the choice of the vehicle that consumers purchased, we did not obtain any statistically significant error components. In contrast, the standard deviations for several elements of μ_n were found to be significant when we included the vehicles that consumers seriously considered. Berry, Levinsohn, and Pakes (2004) also reported that they were unable to estimate unobserved taste variation without including consumers' rankings.

Average Preferences

We included dummy variables for all the makes and models in our sample to estimate consumers' average value of utility from each vehicle. In the numerical search for the maximum of the likelihood function (see below), δ is calculated for each trial value of θ. Following Berry (1994), we use a contraction procedure where at any given value of θ, the following formula is applied iteratively until predicted shares equal actual shares (within a given tolerance):

$$\delta_j^t(\theta,S) = \delta_j^{t-1}(\theta,S) + \ln\left(S_j - \hat{S}_j\left(\theta, \delta^{t-1}(\theta,S)\right)\right) \quad j = 1,\ldots,J. \tag{7}$$

As in previous applications of this procedure, we found that the algorithm attains convergence quickly.

<u>Brand Loyalty</u>

We include “brand loyalty” variables defined as the number of previous consecutive purchases from the same manufacturer. Separate variables are specified in the model for GM, Ford, Chrysler, Japanese manufacturers as a group, European manufacturers as a group, and Korean manufacturers as a group. However, one must be careful when interpreting these coefficients (Mannering and Winston (1991)). One interpretation, which is based on the idea of state dependence that we are attempting to capture, posits that a consumer’s ownership experience with a manufacturer’s products builds confidence in that manufacturer (e.g., reduces perceived risk) and translates into a greater likelihood of buying the manufacturer’s products in the future. A consumer’s actual experiences with a manufacturer’s vehicles determine the intensity of his or her loyalty—positive experiences are reflected in a large coefficient for the manufacturer’s loyalty variable. An alternative interpretation is that the loyalty variable captures unobserved taste heterogeneity among consumers that is not controlled for elsewhere in the model: previous purchases reflect consumers’ tastes that influence their current purchase.

As Heckman (1991) pointed out, state dependence and consumer heterogeneity are fundamentally indistinguishable unless one imposes some structure on the way observed and unobserved variables interact. In our case, we suggest that it is more likely that brand loyalty is capturing state dependence rather than heterogeneity because it is defined for manufacturers that produce a wide range of vehicles, especially when Japanese and European vehicles are each considered as a group. Unobserved heterogeneity is more likely to be associated with makes and models than with manufacturers. For example, if a middle-aged male bought a Honda S2000 in the past because it best matched his tastes, then, based on his revealed tastes, it is reasonable to expect that he would be more likely to buy a Porsche Boxer or a Mercedes SLK in his current choice than to buy a Honda Accord or Toyota Camry.

Our brand loyalty variables could nevertheless be subject to endogeneity bias to the extent that they relate to unobserved tastes for vehicle attributes; that is, the distribution of random terms in the choice model may be different conditional on different values of the brand loyalty variables. Accounting for these differences in a completely general way is a daunting task. First, it would require data on the attributes of the vehicles that were available at the time of each previous purchase by all sampled consumers (beginning with the first vehicle that they purchased). Second, it would entail simultaneous estimation of previous and current vehicle choice probabilities incorporating these data and a plausible specification of how consumers' tastes are likely to change over time.

We therefore take a simpler approach here that can be expected to capture the primary differences in the error distribution of the random utility function conditional on our brand loyalty variables. We represent the information contained in the variables about consumers' preferences across manufacturers by denoting each consumer's manufacturer preference as η_{nm}, with m =1,...,6 indexing the six manufacturer groups (GM, Ford, Chrysler, Japanese, European, and Korean.) These preferences result from the manufacturers' offerings and consumers' tastes for the vehicles' attributes. In the past, consumer n chose the manufacturer with the highest value of η_{nm}. The unconditional distribution of $\eta_n = \{\eta_{n1}, \ldots, \eta_{n6}\}$ is $g(\eta_n)$. The distribution of η_n conditional on the consumer having chosen manufacturer m is:

$$h(\eta_n | \eta_{nm} > \eta_{ns} \forall\ s \neq m) = \frac{I(\eta_{nm} > \eta_{ns}\ \forall\ s \neq m) g(\eta_n)}{\int I(\eta_{nm} > \eta_{ns}\ \forall\ s \neq m) g(\eta_n) d\eta_n}, \tag{8}$$

where $I(\cdot)$ is a 0-1 indicator of whether the statement in parentheses is true.

For the current choice, the utility of vehicle j, which is produced by manufacturer $s(j)$, is as previously specified plus a term $\lambda\eta_{ns}$, where λ is the coefficient of the additional element of utility. Conditional on the past choice of manufacturer, the choice probability is then the logit formula with this term added to its argument, integrated over the conditional density of η_n. Formally, the probability that consumer n chooses vehicle i produced by manufacturer $s(i)$, given that the consumer chose a vehicle by manufacturer m in the past (where m may equal $s(i)$) is:

$$P_{ni} = \iint \frac{e^{\delta_i + \beta' x_{ni} + \mu_n' w_{ni} + \lambda\eta_{ns(i)}}}{\sum_{j=1}^{J} e^{\delta_j + \beta' x_{nj} + \mu' w_{nj} + \lambda\eta_{ns(j)}}} f(\mu|\sigma) h(\eta_n | \eta_{nm} > \eta_{ns}\ \forall s \neq m) d\mu d\eta_n. \tag{9}$$

This choice probability is a mixed logit with an extra error component whose distribution is conditioned on the consumer's past choice of manufacturer.

Estimators

The choice probabilities, P_{ni}, in equation *(9)* and the ranking probabilities, R_n, in equation *(6)*, are integrals with no closed form solution. We use simulation to approximate the integrals. The simulated choice probability is:

$$\tilde{P}_{ni} = \frac{1}{R}\sum_{r=1}^{R}\frac{e^{\delta_i(\theta,S)+\beta' x_{ni}+\mu_r' w_{ni}+\lambda\eta_{ns(i)}}}{\sum_j e^{\delta_j(\theta,S)+\beta' x_{nj}+\mu_r' w_{nj}+\lambda\eta_{ns(j)}}}\ , \qquad (10)$$

for draws μ_r, $r = 1,\ldots,R$ from density $f(\mu \mid \sigma)$ and draws from the conditional distribution h. The ranking probabilities are simulated similarly.

The simulated log-likelihood function for the observed choices in the sample, $LL = \sum_n \ln \tilde{P}_{ni}$, is maximized with respect to parameters $\theta = \{\beta,\sigma\}$ and λ. We obtain estimates of $\delta = \{\delta_1,\ldots,\delta_J\}$ using the iteration formula in equation (7) to ensure that predicted shares equal market shares. The simulated log-likelihood for the ranking probabilities is expressed and optimized in a similar manner.

We use 200 Halton draws for estimation and forecasting. Halton draws are a type of low-discrepancy sequence that, as R rises, has coverage properties that are superior to pseudo-random draws. For example, Bhat (2001) and Train (2000) found that 100 Halton draws achieved greater accuracy in mixed logit estimations than 1000 pseudo-random draws.[9] Draws from the conditional distribution h are easily obtained by an accept/reject procedure: draw values of η_n from $g(\eta_n)$ and retain those for which $\eta_{nm} > \eta_{ns}$ for all $s \neq m$. In estimation, we assume $g(\eta_n)$ is a product of standard normal variables and use 200 accepted draws in the simulation of the integral over η_n.

[9] Other forms of quasi-random draws have been investigated for use in maximum simulated likelihood estimation of choice models. Sándor and Train (2004) explore (*t,m,s*)-nets, which include Sobol, Faure, Niederreiter and other sequences. They find that Halton draws performed marginally better than two types of nets and marginally worse than two others, and that all the quasi-random methods vastly outperformed pseudo-random draws. In high dimensions, when Halton draws tend to be highly correlated over dimensions, Bhat (2003) has investigated the use of scrambled Halton draws, and Hess et al. (2004) propose “shuffled and shifted uniform vectors.” The dimension of integration in our model is not sufficiently high to require these procedures.

We also estimate a regression model for the alternative specific constants that capture average utilities, using vehicle attributes as regressors. As noted, we use instrumental variables because price is likely to be correlated with omitted attributes. Nash equilibrium in prices implies that the price of each vehicle depends on the attributes of all the other vehicles, which indicates that appropriate instruments can be constructed from these attributes. Letting d_{ji} be the difference in an attribute, say fuel economy, between vehicle *j* and *i*, we calculate four instruments for vehicle *i* for each attribute: the sum of d_{ji} over all *j* made by the same manufacturer, the sum of d_{ji} over all *j* made by competing manufacturers, the sum of d_{ji}^2 over all *j* made by the same manufacturer, and the sum of d_{ji}^2 over all *j* by competing manufacturers.

The first two measures have been used by Berry, Levinsohn, and Pakes (2004) and Petrin (2002). The latter two measures, which have not been used before, capture the extent to which other vehicles' non-price attributes differ from vehicle *i's* non-price attributes. We found them to be quite useful in our estimations because without them parameter estimates tended to be less stable across alternative specifications.

Model Specification, Data, and Estimation Results

The random utility function in equation *(1)* posits that consumers' vehicle choices and their ranking of vehicles that they seriously considered are determined by vehicle attributes, their socioeconomic characteristics and brand loyalty, and an automaker's product line and distribution network. The regression model specifies utility to the average consumer as a function of vehicle attributes.

In addition to a vehicle's purchase price, the attributes that we include in the models are fuel economy, horsepower, curb weight, length, wheelbase, reliability, transmission equipment, and size classifications. These attributes encompass those used in previous research. Because automobiles are a capital good, consumers' choices may also be influenced by their expectations of how much a vehicle's value will depreciate. We therefore include as a separate variable the percentage of a vehicle's purchase price in 2000 (consistent with the sample discussed below) that it is expected to retain after two years of ownership.[10] We expect that consumers are more likely to select a vehicle that retains its value (i.e., the coefficient should have a positive sign) because it could be sold or traded in for a higher price than a vehicle that retains little of its value. As noted, we measure brand loyalty by a consumer's consecutive purchases of the same brand of vehicle. The socioeconomic characteristics that we include are sex, age, income, residential location, and family size.

Our specification extends previous vehicle demand models by exploring the effect of automakers' product line and distribution network on choice. Researchers have typically used brand preference dummy variables to capture these influences. Economic theory suggests that broad product lines can create first mover advantages to a firm and overcome limited information in a market; thus, we specify the number of distinct models offered by an automaker to capture these possible effects. Industry analysts stress that automakers benefit from having a "hot car" in their product line because it may draw attention to other vehicles that they produce. For many decades, a well-known axiom among the Big Three was: "bring them into the showroom with a convertible, and sell them a station wagon." We define a hot car as having sales equal to the mean sales of its subclass plus twice the standard deviation of sales. (We also explored other definitions.) An automaker's network of dealers distributes its products to potential customers; thus, we also include the number of each manufacturing division's dealerships.

We performed estimations based on a random sample of 458 consumers who acquired—that is, paid cash, financed, or leased—a new 2000 model year vehicle.[11] The sample was drawn from a national household panel administered by National Family Opinion, Inc., and managed by Allison-Fisher, Inc.[12] It is composed of consumers' new vehicle choices by make and model, the vehicles they seriously considered acquiring, vehicle ownership histories, which are used to construct the brand loyalty variables, and

[10] The best statistical fit was obtained by using the retained value after two years of ownership. Using the value based on three years of ownership produced a slightly worse fit, while using the value based on four years of ownership produced a noticeably worse fit.

[11] We found that it was statistically justifiable to combine these consumers in the estimation of a single model.

[12] The response rate for the sample exceeded 70 percent.

socioeconomic characteristics. Vehicle attributes and product line variables are from issues of *Consumer Reports,* the *Market Data Book* published by Automotive News, and *Wards' Automotive Yearbook*. Vehicles' expected retained values were obtained from the *Kelley Blue Book*: *Residual Value Guide*. The number of division dealerships within 50 miles of a respondent's zip code was obtained from the automakers' websites.[13]

Each consumer's choice set consisted of the roughly 200 makes and models of new 2000 vehicles.[14] Given this choice set, we estimated a mixed logit model that included brand loyalty, product line and distribution variables, and vehicle attributes interacted with consumer characteristics, error components, and an alternative specific constant for each vehicle make and model. The estimated constants, which capture average utility, were then regressed against vehicle attributes using instrumental variables. Table 3 presents estimation results for all parts of the model because each part contributes to consumers' utility.[15] The first panel gives coefficients for two specifications of average utility; for reasons explained below, one does not include the retained value and the other does. The second panel contains the estimated coefficients for the variation in utility that relates to consumers' observed characteristics; and the third, coefficients for the error components, assumed to be normally distributed, that capture variation in utility that is not related to observed characteristics.

Price Coefficients. Consumers' response to a change in the price of a given vehicle is captured by an average effect, an effect that varies with income, and an effect that varies over consumers with the same income. That is, for the model without retained value, the estimate of the derivative of utility with respect to price is: -0.073 -1.60/consumer income

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[13] A 50-mile radius seems appropriate for our analysis because CNW Marketing Research found that consumers travel 22 miles, on average, to acquire a new vehicle. In addition, some automaker's web pages only display dealerships within 50 miles of the inputted zip code.

[14] We treated a number of manufacturers that merged in the late 1990s, for example, Daimler-Benz and Chrysler, as offering distinct makes because it was likely that consumers had not yet perceived that their vehicles were made by the same manufacturer. Indeed, we obtained more satisfactory statistical fits under this assumption than using the merged entity as a unit of analysis.

[15] Estimations were performed using GAUSS.

+0.86 η/consumer income (where η is distributed standard normal). As previously indicated, the first term is estimated using instrumental variables (IV); when ordinary least squares (OLS) is used the coefficient falls to –0.043 indicating that omitted attributes are correlated with price and that it is important to correct for endogeneity in estimation. Based on these coefficients, the average price elasticity for all vehicles is -2.32, which is consistent with estimates obtained by Berry, Levinsohn, and Pakes (2004).

When a vehicle's expected retained value is specified as an additional explanatory variable, it appears to play an important role in controlling for the endogeneity of price. We isolate this effect in table 4, which reports the coefficients for the purchase price and the retained value estimated by OLS and IV. Given that the retained value is derived from the purchase price, it is likely to be correlated with unobserved attributes of the vehicle and should therefore be estimated by IV. As noted, when we include price but not the retained value in the specification, the OLS and IV estimates indicated a considerable degree of endogeneity. But when we also include the retained value, it appears that it absorbs most of the endogeneity bias while the OLS and IV estimates of the purchase price are very similar. This suggests that unobserved attributes are correlated with a vehicle's retained value but not with the *difference* between its price and retained value (i.e., expected vehicle depreciation).

Note that the retained value represents about 60 percent, on average, of the purchase price (as measured by the MSRP) of a vehicle; thus, the combined effect, regardless of whether it is estimated by OLS or IV, of the retained value and price on average utility is roughly the same as the effect of price when it is entered by itself. This relation suggests that the model with the retained value effectively decomposes the two components of price to which a consumer responds. Moreover, holding retained value constant, table 4 shows that consumers' response to price (i.e., the average price elasticity) is clearly higher than when the retained value is allowed to vary. The reason is that the retained value is determined by competitive used-vehicle markets; hence, if a manufacturer raises the price of a new vehicle without improving its attributes, the retained value will not rise proportionately and may not rise at all.

As expected, the separate price effects are estimated with less precision than the combined effect. Indeed, the estimated coefficient of retained value obtains a t-statistic of only 0.5, which suggests that the hypothesis that consumers do not differentiate between the two components of price cannot be rejected. Nonetheless, the pattern of estimates is consistent with rational behavior and a plausible form of endogeneity, and may have important implications for estimating the price elasticity that is actually relevant to firms' behavior. It therefore seems reasonable to maintain the concept of retained value as a potential influence among the set of vehicle attributes affecting consumer choice and subject it to further exploration in future research.[16]

Other Coefficients. The non-price vehicle attributes in table 3 enter utility with plausible signs and are nearly always statistically significant. Vehicle reliability, horsepower divided by curb weight, automatic transmission included as standard equipment, wheelbase, and vehicle length beyond the wheelbase have a positive effect on the likelihood of choosing a given vehicle, while fuel consumption per mile (the inverse of miles per gallon) has a negative effect. Note that wheelbase tends to reflect the size of the passenger compartment and therefore, as expected, has a larger coefficient than vehicle length beyond the wheelbase.[17]

Our findings that the (dis)utility of price is inversely related to income and that reliability has a positive and statistically significant effect on utility for women over 30 years of age but has an insignificant effect for men and for women under 30 exemplify observed heterogeneity in consumer preferences. Other examples are that consumers who

[16] The inclusion of retained value may alternatively be interpreted as an application of Matzkin's (2004) method of correcting for endogeneity. Retained value would qualify as the extra variable needed for Matzkin's approach if it is related to the price only through exogenous perturbations, but is correlated with the unobserved attributes of a vehicle. Under these conditions, the original error term may be expressed as a function of the retained value and a new error term that is independent of all the explanatory variables incuding price, which would permit OLS estimatioin of the regression to yield consistent parameter estimates. As expected from an endogeneity correction, the OLS estimate of the price coefficient rises when the retained value is included in the model (compare the OLS estimate in the third column of table 4 with the OLS estimate in the first column) and is similar to the IV estimate of the price coefficient (in the second column). We also estimated the function of retained value non-parametrically and obtained essentially the same results as when we specified retained value linearly.

[17] Other measures of vehicle size, such as width and a proxy for interior volume, did not have statistically significant effects. We also preformed estimations that included engine size (in liters), but it had a statistically insignificant effect.

lease a vehicle are more likely to engage in upgrade behavior by choosing a luxury or sports car than customers who purchase a vehicle (Mannering, Winston, and Starkey (2002) discuss this phenomenon), and that households with adolescents are more likely to choose a van or SUV than other households.

Unobserved preference heterogeneity is captured in error components related to vehicle price, horsepower, fuel consumption, and consumers' preferences for cars versus trucks (including light trucks, vans, and SUVs). The last coefficient reflects greater substitution among cars and among trucks than across these categories, which is confirmed by our estimates of vehicle cross-elasticities. For example, we find that the cross-elasticity of demand with respect to the price of a given make and model of a van is, on average: 0.038 for other makes and models of vans; 0.026 for makes and models of SUVs; 0.018 for makes and models of pickup trucks; 0.0025 for makes and models of regular cars; and 0.0021 for makes and models of sports and luxury vehicles.[18] As expected, cross-elasticities are higher for more similar types of vehicles. We also found reasonable cross-elasticity patterns for the prices of other vehicle types. In contrast, a model that maintained the IIA property would restrict the cross-elasticity of demand with respect to a given vehicle's price to be the same for all vehicles.

Surprisingly, we found that, all else constant, consumers were not more likely to purchase a vehicle from automakers that offered a large number of models or that produced a "hot car." These product line attributes and others we explored had a statistically insignificant effect on consumer choice.[19] Although automakers cannot rely on product line "externalities" to improve their sales, we found that their dealer network does have a statistically significant effect on choice. We constructed the dealership variable by division as the natural log of one plus the actual number of dealers within 50 miles of the consumer up to a maximum of three. Thus, the variable takes on a value of zero if no dealers within

[18] To put the magnitude of the cross-elasticities in perspective: if a vehicle had a market share of 0.005 (i.e., the average share because there are 200 makes and models of vehicles) and had an own-price elasticity of –3.0, then the cross-price elasticity for each other vehicle, assuming it did not vary, would be 0.0151.

[19] We tried various specifications for "hot cars" based on deviations from mean sales and sales growth, but they were all statistically insignificant.

the circumscribed area sell the vehicle. In addition, the functional form assumes that the impact of having one dealer instead of none is greater than the extra impact of having a second dealer instead of one, and so on, with the impact of additional dealers negligible beyond three. This specification fit the data better than a linear specification, indicating that it is important for automakers to have a dealer within reasonable proximity to potential customers but that additional dealers will have a diminishing impact on sales.

Finally, we included separate brand loyalty variables for GM, Ford, and Chrysler as well as for the Japanese and European automakers as distinct groups.[20] The estimated coefficients are positive, statistically significant, and fairly large while the error component for brand (manufacturer) loyalty is statistically significant. We found that the likelihood function increased when we used the conditional distribution of η_n rather than its unconditional distribution, which indicates that conditioning provides useful information about consumers' choices.

When our estimates are assessed in the context of previous findings, it becomes clear that loyalties have undergone considerable shifts as consumers have gained experience with and adjusted to new information about automakers' products. Mannering and Winston (1991) found that during the 1970s, American consumers had the greatest brand loyalty toward Chrysler, had comparable loyalty toward GM and Japanese automakers, and the least loyalty for Ford. During the 1980s, after American consumers developed greater experience with Japanese vehicles, Mannering and Winston found that loyalty toward Japanese automakers exceeded loyalty toward any American automaker. But during the mid-1990s, as American consumers gained experience with certain automakers by leasing their vehicles and purchasing a greater share of light trucks, Mannering, Winston, and Starkey (2002) found that Americans developed strong brand loyalty toward European automakers and revived some of their loyalty toward American firms.

[20] Preliminary estimations indicated that it was statistically justifiable to aggregate the Japanese and European automakers into single loyalty variables. We could not estimate a brand loyalty parameter for Korean automakers because only one consumer in the sample chose a Korean vehicle in their most recent previous purchase.

Our brand loyalty estimates indicate that this recent shift is intact because consumers have the strongest loyalty toward European automakers while loyalty for Ford and Chrysler now exceeds loyalty toward Japanese automakers. Of course, Ford's and Chrysler's loyalty coefficients may indicate that as their market shares have fallen, they have retained a smaller but more loyal group of customers. GM has the least loyalty and, in contrast to Ford and Chrysler, appears to be retaining only loyal rural customers as its share falls.

We acknowledge that our interpretations should be qualified because the loyalty coefficients could also be capturing heterogeneity in tastes. However, we point out that our estimates of the non-loyalty coefficients were robust to alternative treatments of brand loyalty. We performed estimations without a manufacturer error component and without including the brand loyalty variables. In both cases, the other (non-brand loyalty) parameters were nearly the same as those presented in table 3, which indicates that any endogeneity bias induced by the loyalty variables does not affect the other parameters of the model. Moreover, this finding suggests that the phenomenon we are capturing is trust in the manufacturer based on ownership experience rather than tastes for vehicle types because it is likely that tastes would be correlated with some of the other variables in the model.

Assessing the U.S. Automakers' Decline

The main purpose of the vehicle choice model is to guide a systematic assessment of the ongoing decline in U.S. automakers' market share by quantifying the contribution that changes in brand loyalty, product line and distribution variables, and vehicle attributes have made to changes in market share. The statistically insignificant parameter estimates for the product line variables and the apparent relative improvement in brand loyalty for Ford and Chrysler suggest that these factors are unlikely to have been a major source of the industry's problems during the past decade. We therefore examine the impact on market shares of changes in vehicle attributes over time.

We use data on the vehicles offered in 1990 and their attributes to forecast the change in market shares during the decade that is attributable to changes in vehicle attributes. By construction, forecasted shares equal actual shares in 2000 when the forecasts are obtained with the choice probabilities P_{ni} estimated in table 3. These forecasts rely on δ_j for all j, including its unobserved component ξ_j. Because ξ_j is not known for any time period other than that used in the estimations, we integrate over it using the empirical distribution, $g(\xi_j \mid z_j)$, of the errors from our regression and calculate the choice probability as:

$$Q_{ni} = \iiint \frac{e^{\alpha' z_i + \beta' x_{ni} + \mu_n' w_{ni} + \lambda \eta_{ns(i)} + \xi_i}}{\sum_{j=1}^{J} e^{\alpha' z_j + \beta' x_{nj} + \mu' w_{nj} + \lambda \eta_{ns(j)} + \xi_j}} f(\mu|\sigma) h(\eta_n | \eta_{nm} > \eta_{ns} \; \forall s \neq m) g(\xi|z) d\mu d\eta_n d\xi. \quad (11)$$

Market shares are estimated using the 2000 vehicle offerings and attributes and re-estimated using the 1990 vehicle offerings and attributes, thereby allowing us to compare consumers' 2000 choices with a prediction of what vehicles they would have purchased in 2000 had they been offered the vehicles (and attributes) that were available in 1990.[21] Because some vehicles were offered in 2000 but not in 1990, and vice versa, and others were offered throughout the decade, we are assessing improvements in the attributes of ongoing models and the attributes of new models. A simple consumer surplus calculation indicated that all of the automakers (by geographical origin) improved the attributes of their vehicles over the decade; thus, the change in an automaker's market share reflects the relative improvement in its vehicles.[22]

We find that the actual changes in market share for each manufacturer are explained to varying degrees by the change in their vehicle offerings and attributes (table 5).[23] American manufacturers' market share fell 6.80 percentage points during the past decade with the change in offerings and attributes accounting for 6.71 percentage points. This important but disturbing finding suggests that although the

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[21] Data for vehicle offerings and attributes in 1990 were obtained from *Consumer Reports*, Automotive News' *Market Data Book*, and *Wards' Automotive Yearbook*. Prices for vehicles in 1990 were expressed in 2000 dollars.

[22] We calculated the net change in consumers' welfare attributable to the change in each automakers' vehicle attributes over the decade by using the familiar consumer surplus "log sum" expression for the logit model.

[23] The figures in the last column of table 5 are based on the model with the retained value. The model without the retained value gives slightly smaller magnitudes for all countries.

American industry has received various kinds of trade protection for more than two decades ostensibly to help it "retool" and has benefited from robust macroeconomic expansions during the 1980s and 1990s, it continues to lag behind foreign competitors when it comes to producing a vehicle of quality and value. It is particularly noteworthy that the loss of the American industry's market share can be explained by changes in the basic attributes—price, fuel consumption, horsepower, and so on—that are included in our model, rather than subtle attributes such as styling and various options.[24]

We performed a simulation to determine how much U.S. manufacturers would have to reduce their prices in 2000 to attain the same market share in 2000 that they had in 1990 and found that prices would have to fall more than 50 percent.[25] Although it would not be profit maximizing for U.S. firms to contemplate such a strategy, they have recently attempted to retain and possibly recover some of their market share by offering much larger incentives, such as cash rebates and interest free loans, than foreign automakers offer. However, even this short-term fix has had little effect on their sales; as suggested by our simulation, the price reductions that would be needed to affect their share are considerably larger than those being offered.

In contrast to the U.S. automakers, European firms' market share increased significantly over the decade, partly because they intensified competitive pressure on the U.S. automakers by offering attractive mid-priced vehicles such as the Audi A4. Indeed, European automakers achieved a net gain of 12 makes and models over the decade, while U.S. and Japanese automakers' net change was negligible. Japanese automakers gained roughly a percentage point of share, but would have experienced a loss overall based solely

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[24] Danny Hakim, "G.M. Executive Preaches: Sweat the Smallest Details," *New York Times*, January 5, 2004 reports Robert Lutz, General Motors' vice chairman for product development, as claiming that inattention to details such as the way a stereo knob feels and the cheap looking shine from plastics used in interiors are a turnoff to consumers. Although this may be true, our findings suggest that GM's competitive problems stem from the essential attributes of a vehicle.

[25] This large price reduction is reasonable because U.S. manufacturers' market share in 2000 is roughly two-thirds and the price elasticity with respect to a simultaneous change in all U.S. vehicle prices is small. (The price elasticities between -2.0 and -3.0 that we reported previously refer to the change in the price of an *individual* make and model of a vehicle.)

on the relative changes in their attributes, especially price, because they expanded their presence in the high end of the market with models such as the Lexus LX470, Infiniti I30, and Acura RL.

We speculate that another source of the change in Japanese and European firms' share over the decade is informational inertia that we have been unable to capture in the model. Japanese automakers have developed a strong reputation for producing vehicles of high quality and value among a large segment of the public and may have benefited from this reputation when they expanded into luxury vehicles and light trucks—even among consumers who had not developed brand loyalty toward Japanese vehicles. In contrast, a few European automakers have developed a reputation for building high quality but expensive vehicles that cater to a small share of consumers. Although European automakers have introduced new models to reach a broader range of consumers, it may take time for some less affluent consumers to be persuaded that these vehicles represent good value. In contrast to their knowledge about foreign automakers' current offerings, American consumers' knowledge about the quality and value of U.S. automakers' vehicles is up-to-date.

Conclusion

Concerns about the competitiveness of the U.S. automobile industry developed in the early 1980s when Chrysler needed a bailout from the federal government to avoid financial collapse and Ford and General Motors suffered large losses. Since then, the profitability of the domestic industry has fluctuated while its market share has steadily declined. Investors in the stock market, who are the most experienced and credible soothsayers of an industry's future, envision that difficult times lie ahead for Ford, General Motors, and Daimler-Chrysler as the sum of their current market capitalization is less than half the combined market capitalization of Honda, Toyota, and Nissan and less than Toyota's market capitalization alone. Toyota's consistent profits have allowed it to invest in environmental technologies, like hybrid engine systems, and to take risks, like starting a youth-focused brand, Scion, thereby increasing pressure on other automakers.

We have applied recent econometric advances to analyze the vehicle choices of American consumers and found that the U.S. automakers' loss in market share during the past decade can be explained almost entirely by the difference in the basic attributes that measure the quality and value of their vehicles and foreign automakers' vehicles. Recent efforts by U.S. firms to offset this disadvantage by offering much larger incentives than foreign automakers offer have not met with much success. The only way that the U.S. industry can stop its decline is to start building better cars than its foreign competitors. The transparency and timelessness of this conclusion suggests that the domestic firms face competitive difficulties that researchers and industry analysts have yet to identify.

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Table 1. U.S. and Foreign Automakers' Market Share of Vehicle Sales in the United States*

		Manufacturer by Geographic Origin		
	Year	*US*	*Japan*	*Europe*
Market Share of Cars (percent)	*1970*	*86*	*3*	*8*
	1975	*82*	*9*	*7*
	1980	*74*	*20*	*6*
	1985	*75*	*20*	*5*
	1990	*67*	*30*	*5*
	1995	*61*	*31*	*5*
	2001	*51*	*38*	*11*
*Market Share of Light Trucks (percent)***	*1970*	*91*	*4*	*4*
	1975	*93*	*6*	*1*
	1980	*87*	*11*	*2*
	1985	*81*	*18*	*0*
	1990	*84*	*16*	*0*
	1995	*87*	*13*	*0*
	2001	*77*	*21*	*1*
Market Share of Cars and Light Trucks (percent)	*1970*	*87*	*4*	*7*
	1975	*85*	*8*	*6*
	1980	*77*	*18*	*6*
	1985	*77*	*19*	*4*
	1990	*72*	*24*	*3*
	1995	*72*	*23*	*3*
	2001	*64*	*27*	*6*

*Shares generally do not sum to 100 because of rounding, the omission of Korean manufacturers, and imports that Automotive News does not assign to any manufacturer or country of origin.

**Light trucks include SUVs, minivans, and pickups weighing over 6000 pounds.

Source: Automotive News Market Data Book (1980-2002)

Table 2. “Big Three” and Selected Foreign Automakers’ Market Share of Vehicle Sales in the United States

		Manufacturer				
	Year	*General Motors*	*Ford*	*Chrysler (Domestic)*	*Toyota*	*Honda*
Market Share of Cars (percent)						
	1970	*40*	*26*	*16*	*2*	*0*
	1975	*44*	*23*	*11*	*3*	*1*
	1980	*46*	*17*	*9*	*6*	*4*
	1985	*43*	*19*	*11*	*5*	*5*
	1990	*36*	*21*	*9*	*8*	*9*
	1995	*31*	*21*	*9*	*9*	*9*
	2001	*26*	*16*	*8*	*11*	*10*
*Market Share of Light Trucks (percent)**						
	1970	*38*	*38*	*9*	*1*	*0*
	1975	*42*	*31*	*15*	*2*	*0*
	1980	*39*	*33*	*11*	*6*	*0*
	1985	*36*	*27*	*14*	*7*	*0*
	1990	*35*	*30*	*14*	*6*	*0*
	1995	*31*	*33*	*16*	*5*	*1*
	2001	*30*	*28*	*13*	*9*	*4*
Market Share of Cars and Light Trucks (percent)						
	1970	*40*	*28*	*15*	*2*	*0*
	1975	*43*	*25*	*12*	*3*	*1*
	1980	*45*	*20*	*9*	*6*	*3*
	1985	*41*	*21*	*12*	*6*	*4*
	1990	*35*	*24*	*11*	*8*	*6*
	1995	*31*	*26*	*12*	*7*	*5*
	2001	*28*	*22*	*11*	*10*	*7*

*Light trucks include SUVs, minivans, and pickups weighing over 6000 pounds.
Source: Automotive News Market Data Book (1980-2002)

Table 3. Vehicle Demand Model Parameter Estimates*

Average utility: elements of $\alpha' z_j$	**Coefficient (Standard Error)**	
Constant	-7.0318 (1.4884)	-6.8520 (1.5274)
Manufacturer's suggested retail price *(in thousands of 2000 dollars)*	-0.0733 (0.0192)	-0.1063 (0.0635)
Expected retained value after 2 years *(in thousands of 2000 dollars)*	---	0.0550 (0.1011)
Horsepower divided by weight *(in tons)*	0.0328 (0.0117)	0.0312 (0.0120)
Automatic transmission dummy *(1 if automatic transmission is standard equipment; 0 otherwise)*	0.6523 (0.2807)	0.6787 (0.2853)
Wheelbase *(inches)*	0.0516 (0.0127)	0.0509 (0.0128)
Length minus wheelbase *(inches)*	0.0278 (0.0069)	0.0279 (0.0069)
Fuel consumption *(in gallons per mile)*	-0.0032 (0.0023)	-0.0032 (0.0023)
Luxury or sports car dummy *(1 if vehicle is a luxury or sports car, 0 otherwise)*	-0.0686 (0.2711)	-0.0558 (0.2726)
SUV or station wagon dummy *(1 if vehicle is a SUV or wagon, 0 otherwise)*	0.7535 (0.4253)	0.7231 (0.4298)
Minivan and full-sized van dummy *(1 if vehicle is a minivan or full-sized van, 0 otherwise)*	-1.1230 (0.3748)	-1.1288 (0.3757)
Pickup truck dummy *(1 if the vehicle is a pickup truck, 0 otherwise)*	0.0747 (0.4745)	0.0661 (0.4756)
Chrysler manufacturer dummy	0.0228 (0.2794)	0.0654 (0.2906)
Ford manufacturer dummy	0.1941 (0.2808)	0.2696 (0.3060)
General Motors manufacturer dummy	0.3169 (0.2292)	0.3715 (0.2507)
European manufacturer dummy	2.4643 (0.3424)	2.4008 (0.3624)
Korean manufacturer dummy	0.7340 (0.3910)	0.8017 (0.4111)

Utility that varies over consumers related to observed characteristics: elements of $\beta' x_{nj}$	**Coefficient (Standard Error)**
Manufacturers' suggested retail price divided by respondent's income	-1.6025 (0.3309)
Vehicle reliability based on the *Consumer Reports'* repair index for women aged 30 or over *(0 otherwise)* [a]	0.3949 (0.0540)

Luxury or sports car dummy for lessors *(1 if the vehicle is a luxury or sports car and the respondent leased , 0 otherwise)*	0.6778 (0.3827)
Minivan and full-sized van dummy for households with an adolescent *(1 if the vehicle is a van and the respondent's household has children aged 7 to 16, 0 otherwise)*	3.2337 (0.4296)
SUV or station wagon dummy for households with an adolescent *(1 if vehicle is a SUV or Wagon and the respondent's household includes a child aged 7 to 16, 0 otherwise)*	2.0420 (0.4253)
ln(1+Number of dealerships within 50 Miles of the center of a respondent's zip code) [b]	1.4307 (0.2479)
Number of previous consecutive GM purchases	0.3724 (0.1263)
Number of previous consecutive GM purchases for respondents who live in a rural location [c]	0.3304 (0.1785)
Number of previous consecutive Ford purchases	1.1822 (0.1314)
Number of previous consecutive Chrysler purchases	0.9652 (0.1708)
Number of previous consecutive Japanese manufacturer purchases	0.7560 (0.1453)
Number of previous consecutive European manufacturer purchases	1.7252 (0.5137)
Utility that varies over consumers unrelated to observed characteristics (error components): elements of $\mu_n' w_{nj} + \lambda \eta_{ns}$	**Coefficient (Standard Error)**
Manufacturer's suggested retail price divided by respondent's income times a random standard normal	0.8602 (0.4116)
Horsepower times a random standard normal	45.06 (46.95)
Fuel consumption *(gallons of gasoline per mile)* times a random standard normal	-0.0102 (0.0014)
Light truck, van, or pickup dummy *(1 if vehicle is a light truck, van, or pickup truck; 0 otherwise)* times a random standard normal	6.8505 (1.7127)
Manufacturer loyalty: conditional standard normal as described in text.	0.3453 (0.1239)

*Estimated coefficients for vehicle make and model dummies not shown.
Number of observations: 458
Log likelihood at convergence for choice model: -1994.93
R^2 for regression model: 0.394 without retained value, 0.395 with retained value.

Notes:

a. The *Consumer Reports'* repair index is a measure of reliability that uses integer values from 1 to 5. A measure of 1 indicates the vehicle has a "much below average" repair record, 3 is "average," while 5 represents "much better than average" reliability.

b. A dealership is defined as a retail location capable of selling a vehicle produced by a given division. The dealership variable is equal to 0,1,2, or 3 (with 3 representing areas with 3 or more dealerships within a fifty-mile radius of the center of the respondent's zip code). This variable is defined for divisions (not manufacturers), because a Chevrolet dealership might sell Chevrolet vehicles without selling Saturn vehicles (GM manufactures both Chevrolet and Saturn).

c. A respondent is classified as living in a rural location if he or she does not live in a Metropolitan Statistical Area or lives in a Metropolitan Statistical Area with less than 1 million people.

Table 4. Estimated Price Coefficients and Elasticities for Models With and Without the Retained Value

	Model without retained value		Model with retained value	
	OLS	*IV*	*OLS*	*IV*
Price	*-0.043* *(0.0094)*	*-0.073* *(0.0192)*	*-0.122* *(0.0362)*	*-0.106* *(0.0635)*
Retained value	---	---	*0.130* *(0.0577)*	*0.055* *(0.1011)*
Average price elasticity	*-1.7*	*-2.3*	*-3.2*	*-2.9*

Table 5. Change in Market Share by Manufacturer Origin

Manufacturer Origin	Actual Market Share in 2000 (percent)	Change in Market Share from 1990 to 2000 (percentage points)	Change in Market Share Due to Attributes (percentage points)
United States[a]	*65.65*	*-6.80*	*-6.71*
Europe[b]	*6.20*	*4.61*	*9.21*
Japan[c]	*25.62*	*0.63*	*-4.34*
Korea[d]	*2.53*	*1.55*	*1.84*

[a] United States automakers included GM (excluding Saab), Ford (excluding Jaguar and Volvo), and Chrysler (excluding Mercedes).
[b] European automakers included BMW, Mercedes, Jaguar, Saab, Volvo, Volkswagen (including Audi), and Porsche.
[c] Japanese automakers included Toyota (including Lexus), Honda (including Acura), Nissan (including Infinity), Subaru, Suzuki, Mitsubishi, Mazda, and Isuzu.
[d] Korean automakers included Hyundai, Kia, and Daewoo.