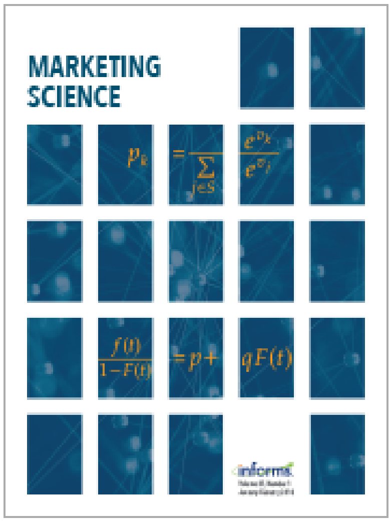

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Competitive Pricing Behavior in the Auto Market: A Structural Analysis

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Abstract

In a competitive marketplace, the effectiveness of any element of the marketing mix is determined not only by its absolute value, but also by its relative value with respect to the competition. For example, the effectiveness of a price cut in increasing demand is critically related to competitors' reaction to the price change. Managers therefore need to know the nature of competitive interactions among firms.

In this paper, we take a theory-driven empirical approach to gain a deeper understanding of the competitive pricing behavior in the U.S. auto market. The ability-motivation paradigm posits that a firm needs both the ability and the motivation to succeed in implementing a strategy (Boulding and Staelin 1995). We use arguments from the game-theoretic literature to understand firm motivation and abilities in different segments of the auto market. We then combine these insights from the game-theoretic literature and the ability-motivation paradigm to develop hypotheses about competition in different segments of the U.S. auto market. To test our hypotheses of competitive behavior, we estimate a structural model that disentangles the competition effect from the demand and cost effects on prices.

The theory of repeated games predicts that firms with a long-run profitability objective will try to sustain cooperative pricing behavior as a stable equilibrium when conditions permit. For example, markets with high concentration and stable market environments are favorable for sustaining cooperative behavior and therefore provide firms with the *ability* to cooperate. The theory of switching costs suggests that in markets in which a firm's current customers tend to be loyal, firms have a *motivation* to compete very aggressively for new customers, recognizing the positive benefits of loyalty from the customer base in the long run. As consumer loyalty in the market increases, the gains from increasing market share by means of aggressive competitive behavior are more than offset by losses in profit margins. Firms therefore have the *motivation* to price cooperatively.

Empirically, we find aggressive behavior in the minicompact and subcompact segments, cooperative behavior in the compact and midsize segments, and Bertrand behavior in the full-size segment. These findings are consistent with our theory-based hypotheses about competition in different segments.

In estimating a structural model of the auto market, we address several methodological issues. A particular difficulty is the large number of car models in the U.S. auto market. Existing studies have inferred competitive behavior only in markets with two to four products. They also use relatively simple functional forms of demand to facilitate easy estimation. Functional forms of demand, however, impose structure on cross-elasticities between products. Such structure, when inappropriate, can bias the estimates of competitive interaction. We therefore use the random coefficients logit demand model to allow flexibility in cross-elasticities. We also use recent advances in New Empirical Industrial Organization (NEIO) to extend structural estimation of competitive behavior to markets with a large number of products. We use the simulation-based estimation approach developed by Berry et al. (1995) to estimate our model.

A frequent criticism of the NEIO approach is that its focus on industry-specific studies limits the generalizability of its findings. In this study, we retain the advantages of NEIO methods but partially address the issue of generalizability by analyzing competitive behavior in multiple segments within the auto industry to see whether there is a consistent pattern that can be explained by theory. Theoretical modelers can use our results to judge the appropriateness of their models in predicting competitive outcomes for the markets that they analyze.

A by-product of our analysis is that we also get estimates of demand and cost apart from competitive interactions for the market. Managers can use these estimates to perform "what-if" analysis. They can answer questions about what prices to charge when a new product is introduced or when an existing product's characteristics are changed.

(*Auto Market; Competition; Structural Models; New Empirical Industrial Organization; Game Theory; Ability-Motivation Paradigm*)

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1. Introduction

In a competitive marketplace, the effectiveness of any element of the marketing mix is determined not only by its absolute value, but also by its relative value with respect to the competition. For example, the effectiveness of a price cut in increasing demand is critically related to competitors' reaction to the price change. Managers therefore need to know the nature and extent of competitive reactions. Recognizing this, there is substantial literature on the estimation of competitor *reaction functions.* For example, see Hanssens (1980) and Leeflang and Wittink (1992, 1996). Because the reaction function methodology is a reduced-form technique, the reaction coefficients do not separate out demand, cost, and competitive effects. Therefore the reaction coefficients are useful to managers only when the demand and cost structure of the market is the same as for the period of estimation. In the case of the auto market, which is the focus of this paper, new models of cars are routinely introduced, and model changes are an annual feature. Hence, the reaction coefficients are of limited value in predicting competitive response.

In this paper, we therefore take a theory-driven empirical approach to gain a deeper understanding of competitive behavior of firms in the U.S. auto market that is not a function of either demand or cost characteristics at any point of time. The firm-level ability-motivation paradigm posits that a firm needs both the ability and the motivation to succeed in implementing a strategy (Boulding and Staelin 1993). We combine predictions from the game theoretic literature and the firm-level ability-motivation paradigm (Boulding and Staelin 1993) to generate our hypotheses about competitive behavior in different segments of the auto market.[1] To test these hypotheses about competitive behavior, we need an empirical approach that can disentangle the effects of competitive behavior from the demand and cost characteristics that drive the observed prices in the market. The structural modeling approach in the New Empirical Industrial Organization (NEIO) framework is an ideal methodology for our purposes. We therefore estimate a structural model of the U.S. auto market with specific focus on the differences in competitive behavior in different segments of the market.

1.1 Expectations About Competitive Behavior

Besanko et al. (1996) and Carlton and Perloff (1994) offer an exhaustive list of conditions in which firms taking a long-term perspective can sustain cooperation and generate higher long-term profits. Two of the conditions that they mention are (i) *high concentration* and (ii) *stable market environments.* When a market is highly concentrated, firms find it easier to achieve cooperation because coordination is needed only among fewer firms. In a stable market environment, deviation by any firm from the cooperative equilibrium can be more easily detected. This permits the other firms in the market to punish the firm deviating from the cooperative level of prices or quantities. Such credibility of punishment threats in stable environments enable firms to sustain cooperation. Therefore, firms are *able* to coordinate and price cooperatively in concentrated markets with stable environments. Conversely, firms are *unable* to sustain cooperation in unstable markets and markets with low share concentration.

Table 1 contains the characteristics of different segments of the auto market. Because concentration is greater in the larger-car segment, firms should be able to sustain cooperation in the larger-car segments. They would be unable to sustain cooperation in smaller-car segments. In terms of share volatility,[2] the smallest-car segments tend to have the highest volatility. Hence, they will be unable to sustain cooperation in these segments.

The theory of switching costs (for example, see Klemperer 1987) suggests that when a firm's existing customers tend to be loyal, firms should price lower

[1]The firm level paradigm is itself based on the individual-level ability-motivation framework attributable to Heider (1958). The firm-level paradigm was presented as an empirical generalization in Boulding and Staelin (1995). We thank the Area Editor for suggesting the use of this paradigm in generating the hypotheses.

[2]We follow Caves and Porter (1978) in defining share volatility in a segment, by averaging over the changes in firms' shares within a segment. Volatility $= 1/TF \, \Sigma_{f=1}^{F} \, \Sigma_{t=1}^{t} \, [(\text{Share}_{ft} - \text{Share}_{ft-1})/\text{Share}_{ft}]^2$, where f indicates firm, t indicates time period, F is the number of firms in the market, and T is the number of time periods in the data.

Table 1 Average Segment Characteristics (1981—1990) with Potential Impact on Competitive Behavior

	Minicompact	Subcompact	Compact	Mid-size	Full-size
Share volatility	0.236	0.149	0.049	0.071	0.106
3-Firm concentration	0.66	0.57	0.71	0.92	1.00
Domestic concentration	0.44	0.53	0.70	0.92	1.00
Share of Japanese firms	0.51	0.41	0.26	0.03	0.00
Mean buyer age	*	35.2	41.1	49.2	59.3
Buyer age <25 years (%)	*	22.7	10	5.4	0.4
First new car (%)	*	40.2	20.1	10.2	2.3
Segment share	0.04	0.21	0.29	0.25	0.10

The *Newsweek* data combined the minicompact and subcompact segments into one segment. Hence, the information on Mean buyer age, Percentage of buyers below 25 years, and Percentage of first time new car buyers are averages across both segments. The total Segment share of all segments is less than 100%, because we do not report the share of the luxury segment.

than their short-term optimal prices and compete very aggressively for first-time buyers, so that they can reap the rewards of their later loyalty through higher prices in future purchases. In the auto market, consumers have significant loyalty to ''country of origin'' (Goldberg 1995). They also have significant ''firm loyalty.'' A recent study by R. L. Polk and Company (*Los Angeles Times* 1996) indicates that the percentage of households owning a GM, Ford, or Chrysler car that bought the same company's car again was 67%, 63%, and 49%, respectively. Firms therefore have the *motivation* to be aggressive in segments targeting young or first-time buyers who will reward them with a lifetime of loyalty. However, in segments targeted to older or repeat buyers, customers are more loyal and less price-sensitive. Hence, the gains in new customers from aggressive competition will be more than offset by the losses in profit margins from their existing customer base. Firms therefore have the *motivation* to be cooperative.

As seen in Table 1, we find that the average age of car buyers is increasing in the size of cars.[3] Also the percentage of buyers under the age of 25 in the minicompact and subcompact segments is more than double the percentage in the other segments. Also the proportion of first-time buyers in the minicompact and subcompact segments is double that of the compact segment and much larger than that of the mid-size and full-size segments. This indicates that firms have a motivation to be aggressive in the minicompact and subcompact segments but to be cooperative in the larger-car segments. This effect is magnified by the country-of-origin loyalty. Because the Japanese have much smaller market shares in the larger-car segments, compared to those in the smaller-car segments, domestic firms would find it optimal to be aggressive in the smaller-car segments so that they do not lose further market share to Japanese firms, which can be detrimental to their long-term market share. Japanese firms should also find it optimal to compete aggressively in the smaller-car segment for market share, because the resulting ''country-of-origin'' effect could be beneficial in the long run through spillover effects in the sales of their larger cars.

A recent *Wall Street Journal* article (White 1999) explaining GM's logic for aggressive pricing of the Chevy Cavalier provides face validity to the motivation argument.

> GM loses about $1000 on every Cavalier it now sells. . . . After all Chevrolet needed an entry-level car to compete with the domestic rivals and imports like the Toyota Corolla and the Honda Civic. The Cavalier, the logic went, brought young buyers into the GM family. . . . Its role within GM is a very, very strategic one.

In contrast, firms have the motivation to be cooper-

[3]This data is from a *Newsweek* survey of New Car Buyers in 1988. *Newsweek* did not separate subcompact and minicompact segments in their report. We caution however that this general pattern has mildly changed during the last decade. A 1997 study by Mediamark Research, New York finds that there is hardly any age difference between subcompact and compact buyers. It should be interesting to study the impact of these changes in demographics of car buyers in these segments on competitive behavior in future research.

ative regarding the mid-size and full-size car segments toward which older customers tend to be more loyal, because aggressive pricing reduces margins without increasing demand. Therefore the motivation is to be cooperative regarding the larger car segments and aggressive with the smaller car segments.

In summary, firms with long-term perspective are therefore "able" and "motivated" to cooperate in the larger-car segments. In contrast, in the small-car segments firms have the "motivation" to be aggressive and limited "ability" to cooperate. Overall, we therefore expect cooperative behavior in the larger-car segments and aggressive behavior in the smaller car segments.

1.2 Methodological Issues in Estimating a Structural Model of the Auto Market

To estimate a structural model of the auto market, we need to address several methodological issues that have not yet been tackled in the current NEIO-based literature in marketing. Existing studies limit themselves to interactions between two–four products and two–three firms. This makes sense when there are a few dominant products and dominant firms in the industry (Coke-Pepsi rivalry studied by Gasmi et al. 1992 and the Fuji-Kodak rivalry studied by Kadiyali 1996 are examples). In other cases, the analysis aggregates demand for differentiated products with a single brand name as demand for that one brand. There is questionable justification for this when the differentiated products are part of a product line for which firms choose separate prices for each of the differentiated products with the goal of maximizing overall profits. This is precisely the case of the auto market, in which there are more than 150 models targeted to different segments. A structural model of the auto market therefore needs to be able to handle high product variety.

Existing NEIO studies typically specify an aggregate demand equation for each product, such that demand is a function of the firm's own and competitors' marketing mix. If there are n products and price is the only marketing mix variable, then there would be n demand equations in the following form[4]:

$$q_i = a_i - \sum_{j=1}^{n} b_{ij} p_j, \qquad j = 1, \ldots, n.$$

Such a demand system, with no structure of its own and cross-price effects, has $n(n + 1)$ parameters. As n becomes large (as in the case of the auto market), the number of parameters explodes, and the model cannot be estimated. Clearly, some structure needs to be imposed in the demand model to facilitate estimation.

A standard approach to impart structure is to follow Lancaster (1971) in treating the product as a bundle of characteristics and assume that consumers derive utility from these observed characteristics of a product. The demand system can now be described by a much smaller set of parameters—one for each characteristic describing the products. This ensures that the number of products have no impact on the number of parameters to be estimated.

In specifying the utility model, researchers have a choice of deterministic and random utility models. In their analysis of the auto market, Bresnahan (1987) and Feenstra and Levinsohn (1995) use *a deterministic utility* model; Berry et al. (1995) use a *random utility* model. Deterministic utility models do not allow for unobserved taste differences among consumers for products that are identical on observed characteristics. Hence, two products with identical observed characteristics have zero profit margins in a deterministic utility model.[5] The random utility model however recognizes that consumers have unobservable taste differences, and this allows for nonzero profit margins, even among products that are identical for observed characteristics. We therefore prefer the random utility approach.

In a structural model of competitive behavior, the functional form of the demand equation can have important implications for pricing behavior. Studies in marketing in the NEIO framework have previously used relatively simple functional forms for demand to facilitate easy estimation. Such functional forms of demand impose severe structure on the nature of

[4]Some researchers may use a log-linear or log-log specification, but the problems are the same.

[5]Feenstra and Levinsohn (1995) computed that the Honda Accord has zero profit margins, because it had identical observed characteristics with some other brand in their analysis.

Table 2 Relationship with Existing Literature on Structural Models of Competitive Interactions

	Limited Firms/Limited Variety	Several Firms/High Variety
Bertrand Competition assumed	Bresnahan (1981)	*Deterministic Utility Approach* Feenstra and Levinsohn (1995) *Random Utility Approach* Berry et al. (1995) Verboven (1996) Besanko et al. (1998)
Pick nature of competition based on fit with data	Gasmi et al. (1992) Roy et al. (1994) Kadiyali (1996) Vilcassim et al. (1999) Putsis and Dhar (1997)	*Deterministic Utility Approach* Bresnahan (1987) *Random Utility Approach* This paper

cross-elasticities between products, which in turn affect the supply equations and can bias the estimation of competitive behavior. For a recent study that has explored the importance of the functional form of demand—in the estimation of competitive behavior—refer to Putsis and Dhar (1998). Berry (1994) and Berry et al. (1995) have developed methods to estimate a random coefficients logit demand model that can model heterogeneity in consumer preferences using aggregate data. Because the flexibility of this demand model minimizes the potential for bias, we use the random coefficient logit model in this paper.

Berry et al. focus on estimating unbiased demand and cost parameters of the auto market, so they assume the Bertrand equilibrium in their paper. In contrast, our focus in this paper is to estimate not only the demand and cost parameters but also to identify the differences in competitive behavior in different segments of the auto market.

Table 2 positions this paper with respect to previous work on structural estimation of oligopolistic markets. We classify previous research along two main dimensions: (1) Are competitive interactions *assumed* or *inferred* from the data? (2) Do they deal with markets with *limited variety* or *high product variety*? Among papers that deal with high product variety, we classify papers on the basis of whether the demand model uses a *deterministic utility* or *random utility* framework.

In terms of its methodological contribution, this paper is thus the first to *estimate* competitive interactions among firms in markets with *many* competing products using a *random utility* approach, especially the *flexible* random coefficients logit demand model. From a substantive point of view, this paper is the first to focus on differences in the *competitive interaction in each segment* of the auto market. In contrast, studies such as that of Bresnahan (1987) estimated an average competitive interaction across all segments of the auto market. Also Nevo (forthcoming Ref. a) has compared the reasonableness of inferred costs under assumptions of Bertrand and cooperative behavior to pick the appropriate form of competition.

The rest of this paper is organized as follows. Section 2 describes the model. We derive the demand and supply estimation equations under various models of competition. Section 3 describes the estimation procedure. Section 4 describes the empirical analysis. Section 5 concludes with a discussion of some of the applications and limitations of the paper.

2. Model

An empirical model of a competitive market following the NEIO framework has three basic components: (1) demand specification, (2) cost specification, and (3) assumption on the nature of competitive interactions in equilibrium.

2.1 Demand Specification

As discussed earlier, we use a flexible random coefficients logit model of demand. A utility maximizing consumer who has a choice of J car models (denoted by $j = 1, \ldots, J$) in period t ($T = 1, \ldots, T$) and an outside good (the option of not purchasing, denoted by $j = 0$) is assumed to solve the optimization problem:

$$\max_{j \in \{0,\ldots,J\}} u_{ijt} = \alpha \ln(y_{it} - p_{jt}) + \sum_k x_{jkt}\beta_k + \xi_{jt} + \sum_k \sigma_k x_{jkt} \upsilon_{ik} + \epsilon_{ijt}, \quad (1)$$

where u_{ijt} is the utility of model j to consumer i in period t. For model j in period t, x_{jkt} is the kth observed characteristic, p_{jt} is the price, ξ_{jt} is the level of unobserved model quality, and y_{it} is the income of consumer i. ϵ_{ijt} is the random utility across models and consumers and is assumed to be distributed i.i.d. Type I extreme value across models and consumers.

A characteristic x_{jkt} contributes $x_{jkt}(\beta_k + \sigma_k\upsilon_{ik}$ to the utility of the consumer i. $\beta_k x_{jkt}$ represents the average utility to all consumers from characteristic k, whereas $\sigma_k\upsilon_{ik}x_{jkt}$ represents the individual i's deviation from that average. We assume that υ is drawn from a standard normal distribution and σ_k is the standard deviation in the utility that consumers get from characteristic k. Unlike the unknown preference distribution for model characteristics (which we estimate in the model), we know the distribution for the income variable (y_{it}) from the Current Population Survey (CPS). So we draw y_{it} from a log-normal distribution, whose parameters are estimated from the CPS data. The advantage of using distributional information from external sources is that we reduce the number of parameters that need to be estimated from the data.

The utility for the outside good ($p_{0t} = 0$, $x_{0kt} = 0$) is

$$u_{i0t} = \alpha \ln(y_{it}) + \xi_{0t} + \sigma_0\upsilon_{i0} + \epsilon_{i0t}. \quad (2)$$

The outside good captures utility from products other than new models of cars (which are the inside goods). We capture the heterogeneity in valuation of the outside good by the $\sigma_0\upsilon_{i0}$ term. Because market shares in a logit model are only a function of differences in utility with respect to a base good, we use $U_{ijt} = u_{ijt} - u_{i0t}$ in computing market shares for the inside goods. Given this differencing, the random coefficient on the constant term of the inside goods captures the heterogeneity for the outside good.

Note that price enters the utility equation as $\ln(y_{it} - p_{jt})$, rather than as just $y_{it} - p_{jt}$. If we had just used $y_{it} - p_{jt}$, an individual's probability of buying a model would be independent of income, because the difference between a model's utility and the utility of the outside good determines the purchase probability for a model (y_{it} would have just cancelled out). Using a log-specification not only overcomes that problem, but also it is very intuitive because a higher price has much lower impact on a high-income consumer's utility than on a low income consumer's utility.[6] This implies that a higher income consumer is more likely to buy a more expensive car model than a low income consumer.

Berry et al. (1995) interpret the unobservable component (ξ_{jt}) to be "the difficult to quantify aspects of style, prestige, reputation and past experience that affect the demand for different products, as well as the effects of quantifiable characteristics of the car that we simply do not have in our data." For example, advertising can affect a model's perceptions in the market. We do not have advertising data in our analysis, so advertising effects and other unobserved characteristics are captured in our model by ξ_{jt}. This unobservable component is, however, perceived by both the consumers and the price setting firm, and it therefore influences prices.

The utility equation may be decomposed as follows:

$$U_{ijt} = \delta(x_{jt}, p_{jt}, \xi_{jt}, \theta_1) + \mu(x_{jt}, p_{jt}, \upsilon_i, \theta_2) + \epsilon_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt}, \quad (3)$$

where $\theta_1 = (\beta_1, \ldots, \beta_k)$ is the set of parameters that is associated with consumer independent characteristics, $\theta_2 = (\alpha_1, \sigma_1, \ldots, \sigma_k)$ is the set of parameters associated with consumer characteristics, and $\upsilon_1 = (y_i, \upsilon_{i1}, \ldots, \upsilon_{iK})$. $\delta(x_{jt}, p_{jt}, \xi_{jt}, \theta_1)$ is independent of the in-

[6] We also tried a Box-Cox transformation $[(y_{it} - p_{jt})/\lambda]^\lambda$ in the utility specification. The log transformation is a special case of the Box Cox transformation ($\lambda = 0$). However, the actual value of λ did not have a serious impact on the results here. So we report results only for the case of $\ln(y_{it} - p_{jt})$.

dividual consumer characteristics, and $\mu(x_{jt}, p_{jt}, \upsilon_i, \theta_2)$ is a function of individual consumer characteristics.

Given the above utility we get the well-known logit formula for the probability of an individual buying model j in period t:

$$s_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} \exp(\delta_k + \mu_{ikt})}. \tag{4}$$

Hence, the market share of model j in period t is

$$s_{jt} = \int_{\upsilon} \frac{\exp(\delta(x_{jt}, p_{jt}, \xi_{jt}, \theta_1) + \mu(x_{jt}, p_{jt}, \upsilon_i, \theta_2))}{1 + \sum_{k=1}^{J} \exp(\delta(x_{kt}, p_{kt}, \xi_{kt}, \theta_1) + \mu(x_{kt}, p_{kt}, \upsilon_i, \theta_2))} \times P(\upsilon)\, d\upsilon, \tag{5}$$

where $P(\upsilon)$ is the joint distribution over all of the elements of $\upsilon_i = (y_i, \upsilon_{i1}, \ldots, \upsilon_{iK})$. The above equation involves a multidimensional integral that has no closed form. Hence, we need to use simulation to compute the above integral. Drawing n vectors of υ_i from $P(\upsilon)$, we have an approximation to the integral

$$s_{jt} = \frac{1}{n} \sum_{i=1}^{n} \frac{\exp(\delta_{jt} + \mu(x_{jt}, p_{jt}, \upsilon_i, \theta_2))}{1 + \sum_{k=1}^{J} \exp(\delta_{kt} + \mu(x_{kt}, p_{kt}, \upsilon_i, \theta_2))}. \tag{6}$$

Because, as noted earlier, the error ξ_{jt} is correlated with a regression variable (price), we have an endogeneity problem.[7] We therefore need to use instrumental variable estimation techniques. However, errors ξ_{jt} enter equation (6) nonlinearly. Because instrumental variable estimation techniques are not well developed for nonlinear equations, Berry (1994) suggests an approach that enables the use of well-developed linear instrumental variables estimation. We outline this procedure below:

Berry et al. (1995) use Berry's idea and suggest the following contraction mapping to solve for δ_{jt}:

$$\delta_{jt}^{h+1} = \delta_{jt}^{h} + \ln(S_{jt}) - \ln(s(p_{jt}, x_{jt}, \delta_{jt}^{h}, P_n; \theta_2)), \tag{7}$$

where P_n represents the actual n vectors drawn from the $P(\upsilon)$ distribution, S_{jt} is the observed market share, and $s(p_{jt}, x_{jt}, \delta_{jt}^{h}, P_n; \theta_2)$ is the computed market share from Equation (6).

In practice, to reduce computing logarithms, we follow Nevo (2000) by solving for $w_{jt} = \exp(\delta_{jt})$ with the following contraction mapping:

$$w_{jt}^{h+1} = w_{jt}^{h} \frac{S_{jt}}{s(p_{jt}, x_{jt}, \delta_{jt}^{h}, P_n; \theta_2)}. \tag{8}$$

We iterate on this equation until we get convergence. To get quick convergence, we need good starting values, i.e., δ_t^0. We use $\delta_{jt}^0 = \ln(S_{jt}) - \ln(S_{0t})$, the solution to the homogeneous logit model, as our starting values.

We then compute the demand side errors conditional on θ_2 as

$$\xi_{jt} = \delta_{jt}(\theta_2) - x_{jt}\theta_1. \tag{9}$$

Because ξ_{jt} enters linearly in δ_{jt}, we can use linear instrumental variables estimation methods.

2.2 Cost Specification

We assume a log-linear marginal cost function. For a firm that produces model j in period t with a vector of characteristics w_{jt}, the marginal cost is given by:

$$\ln(c_{jt}) = \gamma w_{jt} + \omega_{jt}, \tag{10}$$

where ω_{jt} is the unobserved idiosyncratic cost associated with model j. w_{jt} may include the same characteristics that affect demand x_{jt} or different characteristics. For example, scale economies in manufacturing affect costs but not demand.

2.3 Competitive Interactions

We measure cooperative or aggressive behavior by the degree of deviation from Bertrand prices. By measuring competitive behavior in terms of the deviation from Bertrand pricing, we separate out demand and cost effects from the competitive effects, because the Bertrand price takes into account the effects of demand and cost. We use an "as-if" technique to infer deviations from Bertrand behavior. When firms use an objective that places a positive weight on their competitor's profits, the equilibrium outcomes will be more cooperative relative to the Bertrand equilibrium. This is intuitive, because perfect cooperation

[7]This endogeneity problem affects even studies with individual data, as shown by Villas-Boas and Winer (1999).

(monopoly behavior) is obtained by putting equal positive weights on all competing firms' profits. Similarly, if a firm uses an objective in which it places a negative weight on its competitor's profits, the equilibrium outcome will be more competitive relative to the Bertrand equilibrium.

We implement this idea with the following objective function for firm r:

$$\Pi_{rt} = \sum_{j \notin J_{rt}} (p_{jt} - c_{jt}) s_{jt} M_t + \sum_{j \notin J_{rt}} \phi_{s(j)} (p_{jt} - c_{jt}) s_{jt} M_t, \tag{11}$$

where J_r is the set of models produced by firm r and $\phi_{s(j)}$ is the weight on a competitor's profit from model j that belongs to segment s. $\phi_s > 0$ implies cooperative behavior relative to Bertrand in segment s, whereas $\phi_s < 0$ implies aggressively competitive behavior relative to Bertrand in segment s. The first-order conditions for firms setting prices for each of its models under the assumption of a cooperative pricing equilibrium is given below:

$$\frac{\partial \Pi_{rt}}{\partial p_{kt}} = M_t \left[\sum_{j \in J_{rt}} (p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{kt}} + \sum_{j \notin J_{rt}} \phi_{s(j)} (p_{jt} - c_{jt}) \frac{\partial s_{jt}}{\partial p_{kt}} + s_{kt} \right] = 0. \tag{12}$$

The first-order conditions may be summarized by the following equation in matrix form for all models sold in period t. It therefore contains as many rows as the number of models in the market.

$$p_t = \underbrace{c_t}_{\text{Cost}} + \underbrace{\left[\left(-\frac{\partial s_t}{\partial p_t} \right) .* \left(\Theta^{Own} + \sum_s \Theta_s^{Comp} \right) \right]^{-1} s_t}_{\text{Margin}}, \tag{13}$$

where

$$\Theta_{i,j}^{Own} = \begin{cases} 1, & \text{if } i, j \text{ are produced by same firm,} \\ 0, & \text{otherwise,} \end{cases}$$

and

$$\Theta_{s\ i,j}^{Comp} = \begin{cases} \phi_s, & \text{if } i, j \text{ belong to segment } s \text{ and} \\ & \quad \text{are not produced by same firm,} \\ 0, & \text{otherwise.} \end{cases}$$

Rewriting the pricing equation with the functional form of the cost equation, we have

$$p_t = \underbrace{\exp(\gamma W_t + \omega_t)}_{\text{Cost}} + \underbrace{\left[\left(-\frac{\partial s_t}{\partial p_t} \right) .* \left(\Theta^{Own} + \sum_s \Theta_s^{Comp} \right) \right]^{-1} s_t}_{\text{Margin}}. \tag{14}$$

Hence, the supply side errors are given by

$$\omega_t = \ln \left\{ p_t - \left[\left(-\frac{\partial s_t}{\partial p_t} \right) .* \left(\Theta^{Own} + \sum_s \Theta_s^{Comp} \right) \right]^{-1} s_t \right\} - \gamma W_t. \tag{15}$$

[8]

3. Estimation

Because price is correlated with the error term in the demand equation (ξ), we need to use instruments for price in the demand estimation.[9] Price is also correlated with the error term in the cost equation (ω). Because the demand and supply error terms are correlated through the price term, there is a gain in efficiency from using a simultaneous-equations estimation technique. We therefore need an instrumental variables-based simultaneous equations estimation procedure.

Following Berry et al. (1995), we use the generalized method of moments (GMM) estimation procedure. The GMM procedure for a system of nonlinear equations is outlined in Hamilton (1994). The basic procedure is as follows: Let z be the set of instruments to be used. We assume z is exogenous and independent of the error terms in the demand and pricing equations ξ and ω. This implies that z is

[8] In an earlier version of this paper, we used a homogeneous logit model and estimated competitive interactions on a segment-by-segment basis. This assumption enabled us to derive closed form estimation equations for both the demand and the supply side equations. This considerably simplified estimation, because we could use closed form nonlinear estimation equations. Details of these derivations are available from the author. The derivations can also be extended to a nested logit model.

[9] We discuss the instruments that we use in §4.2.

orthogonal to both ξ and ω. Therefore, $E(z\xi) = 0$ and $E(z\omega) = 0$. These serve as the moment equations in our method of moments procedure. Let $\zeta = (\zeta', \omega')$. Let $\theta = \{\theta_1, \theta_2\ \gamma, \phi_s\}$ be the set of parameters to be estimated.

The GMM estimator given our moment conditions is defined as

$$\min_{\theta} \zeta' z(z'\Omega z)^{-1} z'\zeta, \tag{16}$$

where Ω is the standard weighting matrix given by $E(\zeta\zeta')$.

Note that in the minimization problem, conditional on θ_2 and ϕ_s, the first order conditions on parameters θ_1 and γ are linear and can be easily solved. Optimizing over θ_2 and ϕ_s is computationally cumbersome, because these first-order conditions are nonlinear. In the optimization, we therefore use a two-step approach. We first use a nonderivative simplex routine (Nelder and Mead 1965) to optimize over θ_2 and ϕ_s and then, conditional on them, the linear parameters θ_2 and γ are estimated. This approach substantially reduces the estimation time.

The problem with this algorithm is that it is circular. The optimal weighting matrix Ω is a function of the estimated parameters, and the estimated parameters are a function of Ω. We therefore start with initial values of θ obtained by solving the homogeneous logit model and compute Ω based on these values. We then optimize the θ. There are two options here. We can either stop here or iterate further. Estimate a new Ω conditional on the new θ and iterate until θ converges. However, because the iterative procedure is computationally cumbersome and has not been found to be dominant in finite samples over the noniterative procedure (Hansen et al. 1996), we do not iterate over the Ω estimates.[10]

4. Empirical Analysis

4.1 Data

We analyze pricing behavior in the auto market during the period from 1981 to 1990. By 1981, the effects of the oil price shock of the 1970s had boosted the demand for smaller cars. This period can thus be treated as a time when customer preferences for characteristics like miles per gallon, size, etc. were stable. Because we pool data across time in our estimation, it is necessary that parameters be reasonably homogeneous across time.

The data on model characteristics, prices and quantities are obtained from *Ward's Automotive Handbook* for the period from 1981 to 1990.[11] Data on Consumer Price Indices published in the Statistical Abstracts are used to normalize the prices in constant 1983 dollars.

Ward's Automotive Yearbook (1981–1990) segments the car market into several segments based on the marketing intent of manufacturers: minicompact, subcompact, compact, mid-size, large, and luxury.[12] Segmentation along these lines is common in analyzing the auto market (Train 1986, Goldberg 1995, Verboven 1996). To provide the reader with a sense of which cars belong to which segment in Ward's classification scheme, we provide some examples of car models in the different segments (see below).

Minicompact: Ford Festiva, Geo Metro, Dodge Colt, Toyota Tercel
Subcompact: Geo Prizm, Ford Escort, Honda Civic, Toyota Corolla, Nissan Sentra
Compact: Buick Skylark, Ford Tempo, Dodge Shadow, Honda Accord, Toyota Camry, Nissan Stanza
Mid-size: Buick Century, Chevy Celebrity, Ford Taurus, Nissan Maxima
Full-Size: Buick LeSabre, Mercury Grand Marquis, Chevy Caprice, Dodge Diplomat
Luxury: The Cadillac line, Lincoln line, BMW, Mercedes Benz, Porsche, Lexus

Note that even though in terms of size, some cars in the luxury lines may be comparable to subcompact, compact, or large cars, Ward's classifies them as

[10] We direct the reader who is interested in the nitty-gritty of this simulation-based estimation procedure to the excellent implementation-oriented paper by Nevo (2000).

[11] We thank James Levinsohn for providing the bulk of the data used in this analysis.

[12] Further segmentation is into regular, specialty, and sporty subgroups. We restrict our analysis to the group level in this paper. Nevertheless we model this segmentation by allowing for preference heterogeneity in variables such as Horsepower and Miles per Gallon. We discuss later how we use this additional segmentation in generating instruments.

luxury cars, because they take into account the marketing intent. We use Ward's segmentation scheme for our analysis. We do not analyze the luxury market, because these markets tend to be thin markets with idiosyncratic demand, and an equilibrium analysis may be inappropriate for such thin markets.[13]

We use the following characteristic variables in the demand equation: Horsepower (HP) gives us a measure of the degree of power and acceleration of a car.[14] Although the fuel efficiency of a car could be relevant, the importance of fuel efficiency could vary, depending on the cost of fuel itself. We therefore use the variable Miles per Dollar (MP$) by dividing Miles per Gallon by Price per Gallon (price normalized by the Consumer Price Index). We also use size of the car as an explanatory variable. These variables are also used in Berry et al. (1995). In addition, we use reliability of the car as an explanatory variable.[15] Additionally, we use four dummy variables: GM, Ford, European, and Japanese.[16]

We did not include certain variables to reduce problems of multicollinearity. For example, the number of cylinders and miles per gallon (MPG) are highly correlated. We use MPG but ignore the number of cylinders, because there is more variation in the MPG variable compared to the cylinder variable.

We use all of the above variables, except MP$, as explanatory variables for costs in the pricing equation. We drop MP$ and use Miles per Gallon (MPG), as this is the more relevant variable for production costs. Note that as a cost variable, Captive imports (cars manufactured by Japanese firms and sold by American firms) are treated as Japanese. Transplants (cars manufactured in the United States by Japanese firms) are treated as domestic. In addition to the demand variables—to measure economies of scale—we use the log of total production of that model (we proxy it with worldwide sales) as a variable in the cost equation. Note that for domestic cars, most models were sold only in the United States and, therefore, total worldwide sales were equal to domestic sales.

We also need information on potential market size (M_t). Berry et al. (1995) use the number of households in the United States as a measure of the size of the market. However, it is unlikely that a household that purchased a car this year will be in the market the next year. According to the Motor Vehicles Manufacturers Association (1990), the average age of a car in the United States during the 1980s was stable at around 7.6 years. The average number of cars for a U.S. household was 1.8. So we estimate the potential market size in year t for cars as[17]:

$$\begin{aligned}&\text{Potential Market Size}(t)\\&\quad= [\text{No. of Households}(t)\\&\qquad\times \text{Average No. of Cars Per Household}]\\&\qquad\div \text{Average Age of Cars.}\end{aligned}$$

Note that we use the income variable in our demand model. We use information about the mean and variance of income in the United States from the Current Population Survey during the period from 1981 to 1990. Because the CPI-adjusted mean and variances from 1981 to 1990 did not differ much across years we used an average mean and variance for the period. We assumed that income was drawn from a log-

[13]Because Ward's classification is based on marketing intent, it classifies all cars from luxury car makers, such as BMW, Mercedes, Lexus, Infiniti, etc. as luxury cars, even though in terms of size alone the cars may have been fitted into the sub-compact, compact, or large categories. We also do not analyze the minivan, SUV, and truck segments.

[14]We also used Horsepower/Weight as a variable following Berry et al. (1995) to account for the fact that for the same horsepower, a heavier car can have lower acceleration. The results were similar.

[15]Reliability data is from *Consumer Reports. Consumer Reports* provides data on surveys of previous year's models. Because ratings in period t affect consumer demand, we used the ratings of period t for the demand model in period t. However, for the cost equation we used reliability data from period $t + 1$. I thank a reviewer for drawing our attention to this subtle but important issue.

[16]Hence, the utilities are relative to Chrysler, for which we do not use a dummy. To reduce the number of dummy variables, we do not use manufacturer-specific dummies for Japanese and European manufacturers but only country-of-origin variable. One may wonder why we did not estimate segment-level dummies. Because size is highly correlated with the segment classification, it enabled us to efficiently capture the segment effects with just one coefficient, instead of using multiple-segment dummy coefficients. This also helped us to improve the precision of our other estimates.

[17]Potential market size here means the total market for new and used cars.

Table 3 Average of Segment Characteristics for 1981–1990

	Minicompact	Subcompact	Compact	Mid-size	Full-size
Number of models	6.10	23.60	32.40	27.70	7.20
Number of domestic models	1.70	11.20	17.40	20.90	7.20
Number of Japanese models	2.20	10.70	10.90	1.20	0.00
Reliability (1–5 scale)	3.57	3.26	2.99	2.62	2.25
Horsepower (hp)	67.62	81.14	105.04	109.86	129.76
Size (Length × Width) in sq. in	9673.33	10,823.59	11,974.83	13,423.72	15.525.75
MPG	32.39	28.53	23.72	21.51	17.93
MP$	29.47	26.06	21.48	19.38	16.47
Price/CPI	5200	6802	8428	10,251	10,613

normal distribution to ensure positive draws from the distribution.

The averages of the characteristics for different segments during the period from 1981 to 1990 are listed in Table 3.

As one would expect, characteristics such as size and HP increase for larger segment sizes. MP$ and MPG fall for larger-segment sizes. The greater share of Japanese cars in the smaller-car segment explains the greater reliability of cars in the smaller-car segments. The average number of models in the minicompact segment was 6.7, and in the full size segment it was 7.1. These numbers are relatively small, compared to the number of models in other segments. In all we had 932 observations over the five segments for 10 years, i.e., an average of 93 models in each of the 10 years of analysis.

4.2 Identification

We assume that the model characteristics x_j and w_j (except for the economies of scale variable in w_j, which is endogenous) are exogenous and that, consequently, they are orthogonal to the error terms (ξ_j and ω_j). This identification assumption is reasonable, considering that in the short run (within a year), firms cannot quickly change the characteristics of the cars that they sell.[18]

Prices and market shares are endogenous and are correlated with the error terms ξ_j and ω_j, even in the short run. This is because they are simultaneously determined in equilibrium. For homogeneous goods models of supply and demand, we have ready instruments to deal with the endogeneity problem: There are enough exogenous variables that affect demand alone and not costs, and vice versa. In differentiated markets, however, most of the exogenous variables are model characteristics, and these affect both demand and costs. Hence, we cannot use traditional instruments based on exclusion restrictions.

Because prices are determined by means of an equilibrium, the physical characteristics of each car's competitors will be correlated with the car's own price and demand. Berry et al. (1995) analyze generation of efficient instruments when competitor characteristics are candidates. They suggest using: (1) the exogenous variable elements in the vectors x_j and w, (2) the average or sum of all of the exogenous elements of x_j and w_j across all cars produced by the same firm (within firm sum or average), and (3) the average or sum of all the exogenous elements of x_j and w_j across all cars not produced by the same firm (without firm sum or average).[19]

We find that the quality of instruments is some-

[18]The endogeneity of product characteristics might be an issue of interest when studying issues related to choice of characteristics in a product line. Modeling that endogeneity would be of particular interest in doing a what-if analysis. We discuss this issue in the conclusion.

[19]These instruments are useful because of the form of the demand equation that we use. In our demand equation, $\ln(s_j/s_0)$ is independent of the characteristics of competitor models. A wide range of logit specifications that are widely used in empirical work satisfies this property. However if in the demand equation for each model, competitor model characteristics also enter the right-hand side of the equation, then these instruments will not be useful. We thank a reviewer for drawing our attention to this issue.

what poor (i.e., the correlation of instruments based on this approach is low). We therefore refine the instruments using arguments similar to those of Bresnahan et al. (1997), who compute the characteristic averages only within a subset of similar models and not for all the models in the entire market. Along with the segment information, we use country of origin and the regular/specialty/sporty classification that Ward's provides in creating these subsets. Thus the two similar subsets we create for each car are (i) all cars belonging to the same segment with the same country of origin as the car and (ii) all cars belonging to the same segment with the same regular/specialty/sporty classification as the car. For example, the Ford Taurus is a domestic, regular mid-size car. Hence, the similarity subset for the Ford Taurus will be (i) all domestic mid-size cars and (ii) all regular mid-size cars. Note that these subsets may vary from year to year, depending on what cars are present in each subset in any given year. Furthermore, even when the same cars are there in the subsets, the characteristics of the cars can change from year to year and, therefore, the instruments vary from year to year. We thus compute the within-firm model average and the without-firm model average for the two similarity sets to generate instruments. Thus we generate four instruments for each variable.

We estimate 15 parameters on the demand side (the mean coefficients on the four dummy variables and price, the mean and standard deviation coefficients on intercept, Reliability, HP, Size, MP$). On the cost side, we estimate 10 parameters (the intercept, the coefficients on the four dummy variables, Reliability, HP, Size, MPG, and ln(total production). We also estimate five competition parameters, one for each segment. In all, there are 30 parameters to estimate.[20]

We have nine exogenous variables (a constant, four dummies, and four characteristics of cars) in x_j and nine exogenous variables (a constant, four dummy variables, and four characteristics of cars) in w_j. Because production is endogenous, we cannot use this variable for exogeneity restrictions, so we have only 18 instruments based on the exogeneity restrictions, and we need more instruments to identify the model. We get overidentifying restrictions by generating instruments that we discussed earlier. For each of the four physical characteristics used in x_j, we compute a within-firm average (excluding the car for which we generate the instruments) and without-firm average for the two similarity subsets. For the constant term, we compute a within-firm and without-firm sum, reflecting the number of competitors for the model. This produces $5 \times 4 = 20$ instruments. With the 18 other instruments, we have in all 38 instruments. Now the model is overidentified.

4.3 Results

Table 4 contains the estimation results. The identifying restrictions cannot be rejected at the 95% level, implying that the model fits the data well.[21] We discuss the demand, cost, and competition estimates in turn.

Demand. The β coefficients measure the average preference, and the σ coefficients measure the heterogeneity in preferences for the characteristics. As expected, consumers value reliable cars. It is interesting, however, that there is no significant heterogeneity in the value they place on the reliability of cars (as indicated by the insignificance of the σ coefficient). In contrast, consumers are heterogeneous in their valuation of horsepower. However, everyone has a positive utility from higher horsepower, as indicated in the much smaller standard deviation (1.06) relative to the mean (24.87). The size variable is similar. People, on average, prefer larger cars, but there is also significant heterogeneity in the preference for size. As per the coefficients on miles per dollar, consumers on average prefer more fuel-efficient cars. However, there is no significant heterogeneity in the valuation for fuel efficiency. Note, however, that larger cars usually have lower fuel efficiency, and so the heterogeneity in fuel efficiency can also be captured in the heterogeneity in valuation of car size. What we find

[20]We estimate other models, one in which we constrain the competition parameters to be the same for minicompacts and subcompacts. In that model, we estimate only four competition parameters.

[21]With 38 instruments (identifying restrictions) and 30 parameters, there are 8 degrees of freedom. The minimized value of the objective function (1.42) is less than Ψ^2, therefore the identifying restrictions cannot be rejected.

Table 4 Model Estimates with Competitive Interaction for 5 Segments

	Estimate	Standard Deviation*	*t*-stat	Estimate	Standard Deviation*	*t*-stat
		β			σ	
Demand						
GM	0.8670	0.1105	7.8431			
Ford	0.7348	0.1346	5.4593			
Japan	0.2397	0.1359	1.7639			
Europe	0.4072	0.1775	2.2945			
Constant	−9.0852	0.6347	−14.3139	0.0274	0.0377	0.7257
Reliability	0.2213	0.0419	5.2771	0.0102	0.0143	0.7119
Horsepower (hp)	24.8746	2.9506	8.4302	1.0592	0.4384	2.4161
Size	0.3190	0.0459	6.9463	0.0076	0.0037	2.0369
MP$	17.1078	12.6180	1.3558	1.5875	1.3862	1.1452
ln(Income-Price)	6.3560	0.5830	10.9028			
Costs						
GM	−0.0258	0.0224	−1.1509			
Ford	−0.0600	0.0225	−2.6679			
Japan	0.1474	0.0317	4.6492			
Europe	0.2203	0.0360	6.1173			
Constant	7.5975	0.2470	30.7574			
Reliability	0.0356	0.0080	4.4504			
Horsepower (hp)	5.3137	0.4897	10.8512			
Size	0.0611	0.0117	5.2198			
MPG	−0.0138	0.0040	−3.4815			
ln(Production)	−1.589E-07	5.195E-08	−3.0602			
Competitive interaction						
Minicompact	−1.1239	10.3489	−0.1086			
Subcompact	−2.8660	1.4171	−2.0224			
Compact	1.0678	0.5639	1.8935			
Mid-size	2.2212	0.6549	3.3916			
Full	0.1768	3.4287	0.0516			
Objective Function	1.42					
$\Psi^2(0.95,8) = 2.73$						

* SD.

is that the residual heterogeneity of fuel efficiency after adjusting for size is not significant. As expected ln(Income − Price) has a positive coefficient, indicating price sensitivity of consumers. The log specification ensures that higher-income customers are less price-sensitive than lower-income customers.

In terms of the dummy variables, we find that GM and Ford have larger coefficients than for Japanese, European, and Chrysler cars (whose utility is normalized to zero). However, because Japanese and European cars have a greater reputation for quality, one should expect that Japanese and European cars should have larger intrinsic utility. This apparent anomaly is easily explained when we recognize that the Japanese and European dummies are capturing the residual utility after the effect of reliability has been accounted for. Because Japanese and European cars score higher on reliability, the results are still consistent with intuition.

Costs. Our cost equation estimates are also in line with expectations. It costs more to produce reliable cars, larger cars and cars with higher horsepower. It is cheaper to produce fuel-efficient cars. Although this result is not obvious, it can be easily explained when we recognize that miles per gallon is highly correlated with the number of cylinders of and the weight of a car. Essentially, this result implies that it is costlier to make heavier cars with a greater number of cylinders.

One surprising result is the positive coefficient on Japan in the cost equation, given the reputation of Japanese car manufacturers for their low costs of production. Petrin (1999) also finds a similar result in his study of the minivan market. There are two reasons for this. First, the strength of the yen relative to the dollar in the 1980s put Japan at a competitive cost disadvantage, even though its manufacturing was more efficient than that of domestic manufacturers.[22] Second, the voluntary export restraint (VER) was binding on Japanese firms in many years during the 1980s (Goldberg 1995). Goldberg interprets the positive coefficient for Japanese cars as a Langrangean multiplier associated with the quota constraint for Japanese cars. With such a binding constraint on the total quantity of sales in the United States, Japanese firms may have had to price higher than if they were involved in pure Bertrand competition without such binding constraints.

Competition. Of greater interest to us in this paper are the estimates of competitive interaction in each segment. Based on insights from game theory and the ability-motivation paradigm that we discussed in the Introduction, we expected aggressive behavior in the smaller-car segments and cooperative behavior in the larger-car segments. Consistent with this, we find aggressive competitive behavior in the minicompact segment, although the estimate is not significant. In the subcompact segment we find aggressive competitive behavior. For the compact and mid-size segments, we find cooperative behavior consistent with our expectations.

The full-size segment appears to be a puzzle initially, because our estimates indicate that firms price at the Bertrand level, although we expected cooperative behavior. On closer examination (refer to Table 1), we find that the volatility in this segment is relatively high, compared to that of the mid-size and compact segments. The high volatility inhibits the ability to cooperate. Why is there a high degree of volatility in this segment? Unlike other market segments that have been either gaining or maintaining their segment shares, the market share of the full-size segment is systematically declining. Segment share has fallen from a high of about 12.9% in 1981 to as low as 9% by 1990. In such a declining segment, firms have been attempting to maintain sales by aggressive pricing. Such aggressive pricing leads to changes in market shares from period to period and is reflected in the higher share volatility in this segment. Hence, even though there is motivation to cooperate, the overall declining segment share leads to higher share volatility and limits the ability of firms to cooperate. Without the ability to cooperate, it is not surprising that competitive behavior in this segment is close to the Bertrand short-run equilibrium. Thus, the result is consistent with predictions made using the ability-motivation paradigm. Overall, our estimates of competitive behavior are consistent with the game-theoretic and ability-motivation arguments discussed earlier.

Table 5 Margins

	Price	Margin
Minicompact	5,200	1,439
Subcompact	6,202	1,786
Compact	8,428	2,367
Mid-size	10,251	3,008
Full	10,613	2,719

We tabulate the average margins for different segments in Table 5, based on our estimates in Table 4. Indeed, the margins are lower for smaller cars than for larger cars, as would be expected from the estimates of competitive behavior.

Robustness Issues. We now consider a variety of issues to see whether our inference about competitive behavior is robust. From Table 3, we can see that the number of models in the minicompact and full segments (therefore, observations) are fewer than in the subcompact, compact, and mid-size segments. Could it be that competition estimates for the minicompact

[22]Trade magazines at that time considered this to be the primary competitive advantage for domestic cars, considering the quality disadvantage of domestic cars. For example, see Risen (1988) and Edid et al. (1986).

and full segments are not significantly different from zero because of the small number of observations?

To test this, we check whether we could combine these segments that have few models with their neighboring segments that have a large number of models and see what the impact on the estimates might be. This may be appropriate if the expected competitive interactions in these neighboring segments are similar. Note also that concentration in these neighboring segments is similar, making the hypothesis of similar competitive interaction plausible. We therefore estimate a model with one common competition parameter for the minicompact and subcompact segments. The results are tabulated in Table 6. We find that the estimates of competition are negative and significant in the minicompact and subcompact segments. Comparing the demand and cost estimates in Tables 4 and 6 indicates that these estimates have not changed substantially, lending face validity to this constraint. We could not reject the hypotheses that competition parameters for minicompacts are the same as that of the adjoining sub-compacts by performing the D-Test of Newey and West (1987) at the 5% significance level.[23]

We also estimated a model in which we constrain the parameter estimates of the full and mid-size car segments to be equal to see whether the insignificance in the full-size segment was attributable to the small number of models in this segment. We found that this significantly changed the parameter estimates from the unconstrained version (especially the coefficients for Japan and Europe in the cost equation), indicating that this constraint was inappropriate. This also lends face validity to our original argument that the full-size segment should have a different competitive interaction than the mid-size segment because of the differences in the share volatility of these segments. The D-test rejected this constraint at the 5% significance level.

[23]Essentially this test says the difference in minimized sum of squared errors of the moment restrictions between the restricted and unrestricted models (using the same weighting matrix for both models) follows a $\Psi^2(J)$ distribution, where J is the number of restrictions (in our case, 1). We used the weighting matrix of the unrestricted model for our test.

We tested the robustness of the estimates of competitive interaction to other issues relating to (i) market size definitions, (ii) segment definitions, and (iii) the use of list prices rather than transaction prices. For market size, we estimated different models by varying the average size of the household from 1.5 to 2 (actual value was 1.8). The estimates were not sensitive to these definitions. We also estimated a model with only regular cars in each segment by excluding the specialty cares and sporty cars from the analysis. The competition estimates continued to be substantively similar.

Another important issue that could potentially impact our estimates is that we inferred competitive behavior using list prices, rather than transaction prices. It would have been ideal to estimate the model with transaction prices, but we could get rebate data only for 1989 and 1990. We checked when the parameter estimates for these 2 years changed from the average. The differences were not significant. We caution, however, that this insignificance could be attributable to the sparseness of the rebate data. With the availability of detailed rebate data and transaction prices through such websites as Edmunds.com, future research in this area should evaluate more carefully the implications of using transaction data, as opposed to those of list prices, in inferring competition. With sales and transactional data at the monthly level, it should be possible to gain a deeper understanding of the impact of supply-side dynamics, such as the impact of inventory fluctuations and forecast errors on competitive behavior.

5. Conclusion

We estimated a structural model of the auto market, specifically focussing on inferring competitive behavior in different market segments. We now summarize the main contributions of this paper.

Substantively, we find contrasting types of competitive behavior in different segments of the U.S. auto market. The behavior was consistent with predictions using game-theoretic literature and the ability-motivation framework. The estimates indicate that the pricing behavior of U.S. auto firms is consistent

Table 6 Model Estimates with Competitive Interaction Estimates Restricted for Minicompact and Subcompact Segments

	Estimate	Standard Deviation*	*t*-stat	Estimate	Standard Deviation*	*t*-stat
		β			σ	
Demand						
GM	0.86	0.112	7.674			
Ford	0.737	0.131	5.64			
Japan	0.244	0.136	1.79			
Europe	0.437	0.166	2.64			
Constant	−9.299	0.878	−10.597	0.0035	0.0071	0.4898
Reliability	0.222	0.035	6.338	0.0097	0.0125	0.7775
Horsepower (hp)	26.901	3.954	6.804	0.8494	0.4279	1.9848
Size	0.329	0.073	4.485	0.0121	0.0045	2.6706
MP$	20.742	12.328	1.683	1.4681	0.6191	2.3715
ln(Income-Price)	6.633	0.364	18.231			
Costs						
GM	0.009	0.025	0.36			
Ford	−0.012	0.026	−0.459			
Japan	0.22	0.039	5.626			
Europe	0.273	0.035	7.921			
Constant	7.474	0.215	34.804			
Reliability	0.045	0.007	5.979			
Horsepower (hp)	5.488	0.515	10.66			
Size	0.071	0.01	7.126			
MPG	−0.012	0.003	−3.733			
ln(Production)	−7.48E-07	4.14E-06	−5.535			
Competitive Interaction						
Minicompact & Subcompact	−2.2198	1.0301	−2.1550			
Compact	1.232	0.5231	2.3551			
Mid-size	2.3986	0.4523	5.3030			
Full	0.1908	0.5687	0.3354			
Objective Function $\Psi^2(0.95,9) = 3.33$	1.83					

* SD.

with a long-term perspective. Managerially, this implies that we can look at certain structural characteristics of the market and use theoretical reasoning to predict competitive behavior in markets.

Methodologically, it illustrates how to estimate competitive interactions among firms in markets with a large number of products using a random utility approach. We use a flexible random coefficients logit specification of demand to minimize bias in the estimation of competitive interactions. Estimating such a demand model that accounts for consumer heterogeneity using aggregate data necessitates the use of a simulation-based estimation procedure. The methodology is applicable in estimating competitive interactions in other types of markets in which there is a large amount of variety (cereal markets, personal computers, airlines, etc). The methods used should also be useful when we want to analyze demand for frequently purchased consumer goods at the UPC level, rather than using aggregation to the brand level.

A criticism of NEIO studies is that its findings are not generalizable, because it typically confines analysis to a single market or industry. In this study we retain the advantages of NEIO methods but address the issue of generalizability by analyzing competitive behavior in multiple segments within the auto industry to see whether there is a consistent pattern that can be explained by theory.[24] Nevertheless, more studies are required in other markets and using other structural characteristics of market before we can gain confidence in our ability to predict competitive behavior.

Our estimates of demand, cost, and competitive behavior can be helpful for ''what-if'' analysis. In one of the early papers in marketing in the NEIO tradition, Horsky and Nelson (1992) assume Bertrand competition among firms and choose optimal prices and product positions for new products, based on their demand and cost estimates. Given our finding that there are differences in competition across segments, the optimal prices as well as product positions will change. Optimal prices based on our estimates will be lower for minicompact and subcompact segments but higher for compact and mid-size segments, compared to those of Horsky and Nelson.

Our results are also consistent with research done using the Structure-Conduct-Performance paradigm. There is an established literature using this paradigm on the positive correlation between market share and profitability (Prescott et al. 1986). Similarly, there is a positive correlation between high share stability and higher prices (Caves and Porter 1978). By carefully separating demand, cost, and competitive effects, we are able to show that one of the reasons for the relationship between concentration, volatility, and profitability is attributable to the cooperative conduct achieved in concentrated and stable markets.

We now discuss some of the limitations and possible extensions of our paper. Our model is static and does not have a dynamic component, either on the demand or the supply side. For example, we do not explicitly model how firms choose product characteristics. This implies that we cannot do ''what-if'' analysis, when dynamic effects are important. For example, in response to the increase in gas prices in 1973, by about 1976 manufacturers had started producing smaller, more fuel-efficient cars. In the absence of a dynamic model explaining how characteristics would change over time in response to exogenous events, our predictions would be poor.

Pakes and Ericson (1997) have developed a theoretical model of dynamic industry equilibrium, and Pakes and McGuire (1994) have developed a computational algorithm to estimate such a model. These models need to be extended substantially to accommodate the multifirm, multiproduct nature of the auto market. Doing this would be crucial in generalizing the ''what-if'' analysis that account for changes in product characteristics.

Our model of demand also has no dynamic component. A dynamic model incorporating transaction costs of buying and selling a car, uncertainty about the future, and a used car market for durable goods needs to be modeled carefully to perform a complete policy analysis. Erdem (1997) has developed a structural model of dynamic choice for frequently purchased consumer goods, but such a structural model for durable goods is yet to be developed.

We have modeled heterogeneity using widely available aggregate level data for our analysis. However with disaggregate data, we can model heterogeneity and dynamics in a much richer framework. Goldberg (1995) and Horsky and Nelson (1992) illustrate how to estimate a model using disaggregate data. Berry et al. (1998) explore how to combine disaggregate individual data with aggregate market level data in estimating an equilibrium model of the market.

Our focus in this paper has been on price competition, treating other marketing mix instruments as unobserved variables that exogenously affect demand and, thus, prices. However, investigating how firms coordinate the use of multiple marketing instruments is an important issue for future research. Slade (1995) addresses the issue of multiple strategic weapons (in the context of markets with limited products) by studying price and advertising competition simultaneously.

In this paper, we find that domestic firms price aggressively in entry-level segments, in which the Japanese have gained greater market share but are more

[24]The interested reader is directed to Kadiyali et al. (forthcoming) for a detailed discussion of the conceptual and methodological advantages of the use of NEIO methods for analyzing competitive behavior.

cooperative in larger-car segments. It is well known that multimarket contact provides additional strategies for firms to enhance cooperation (Bernheim and Whinston 1990). Exploring how competitive behavior in one segment affects the behavior of firms in other segments would be a fruitful area for future research.[25]

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