An Econometric Analysis of Brand-Level Strategic Pricing Between Coca-Cola Company and PepsiCo.

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We investigate market structure and strategic pricing for leading brands sold by Coca-Cola Company and PepsiCo. in the context of a flexible demand specification (i.e., nonlinear AIDS) and structural price equations. Our flexible and generalized approach does not rely upon the often used ad hoc linear approximations to demand and profit-maximizing first-order conditions, and

the assumption of Nash-Bertrand competition. We estimate a conjectural variation model and test for different brand-level pure strategy games. This approach of modeling market competition using the nonlinear Full Information Maximum Likelihood (FIML) estimation method provides insights into the nature of imperfect competition and the extent of market power. We find no support for a Nash-Bertrand or Stackelberg Leadership equilibrium in the brand-level pricing game. Results also provide insights into the unique positioning of PepsiCo.'s Mountain Dew brand.

1. Introduction

In this paper, we develop and estimate a structural model of brand-level competition between firms using a flexible nonlinear demand system and relaxing the usual assumption of Bertrand price competition. Analysis of strategic behavior of firms using structural models is widely used in the new empirical industrial organization (NEIO) literature. The basic approach is to specify and estimate market-level demand and cost specifications after taking into account specific strategic objectives of firms. Empirical implementation of these models is complex due to the highly nonlinear nature of flexible demand and cost functions and the specification of strategic firm behavior. As a result, researchers have tended to simplify structural models by specifying ad hoc or approximated demand specifications, and reduced form conditions of the firm's objectives. In this paper, we attempt to overcome some of these shortcomings.

In empirical structural models, the estimation of market power and strategic behavior depends crucially on the estimated price and expenditure elasticities. A major problem with ad hoc demand specifications is that they do not satisfy all the restrictions of consumer theory.[1] As a result, estimated parameters may violate basic tenets of economic rationality. Even if a strategic game is correctly specified, any misspecification of demand may generate spurious results and incorrect policy prescriptions due to incorrect elasticity estimates.

Researchers have tried to overcome these shortcomings of demand specification by specifying flexible demand functions based on well-behaved utility functions. For example, Hausman et al. (1994) and Cotterill et al. (2000) use a linear approximation to the almost ideal demand system (LA-AIDS; see Deaton and Muellbauer, 1980a). In this paper use of AIDS provides more flexibility as we avoid linear approximation to nonlinear price effects.

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1. For example, Gasmi et al. (1992, hereafter GLV) and Golan et al. (2000) use ad hoc linear demand specifications.

To avoid such approximated and ad hoc demand specification, there is another strand of the NEIO literature that uses characteristic based demand system based on the random utility model (Nevo, 2001; Villas-Boas and Zhao, 2005). Empirically this approach is appealing because its parsimonious description enables one to avoid specifying the prices of all brands with the attendant multicolliniarity and parameter estimation problems. However, specification of random utility models often imposes restrictions that may not be implied by general utility theory. In a recent paper, Bajari and Benkard (2003) show that many standard discrete choice models have the following undesirable properties: as the number of product increases, the compensating variation for removing all of the inside goods tends to infinity, all firms in a Bertrand–Nash pricing game have markups that are bounded away from zero, and for each good there is always some consumer that is willing to pay an arbitrarily large sum for the good. These properties also imply that a discrete choice demand curve is unbounded for any price level. To avoid this problem, Hausman (1997) uses linear and quadratic approximations to the demand curve in order to make welfare calculations (e.g., multi stage demand system with LA-AIDS at the last stage), favoring them over the CES specification, which has an unbounded demand curve. Another advantage of an AIDS type demand system is that it avoids the arbitrary and strong assumption of single unit purchases in the discrete choice demand model (Dube, 2004).[2]

In terms of specifying behavioral rules for a firm, two broad approaches can be found in the empirical literature. Gasmi et al. (1992, GLV hereafter), Kadiyali et al. (1996) and Cotterill and Putsis (2001) have derived and estimated profit-maximizing first-order conditions under the assumption of alternative games (e.g., Bertrand or Stackelberg) along with their demand specifications. However, these studies derive estimable first-order conditions based on approximate demand specifications. Cotterill et al. (2000) use the more flexible LA-AIDS but they approximate the profit-maximizing first-order condition with a first-order log-linear Taylor series expansion. Implications of using such approximated first-order conditions have not been fully explored.

In the other strand of the empirical literature, researchers do not specify the first-order conditions. Instead, they rely on features of the panel data to obtain instruments for endogenous prices when

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2. The purpose of our discussions on comparative advantages and disadvantages of different demand systems is not to make the claim that AIDS is the best in all situations. We seek only to justify our choice of model specification. Choice of specification is situation-specific and further research is needed to rigorously compare advantages and disadvantages of different demand systems.

estimating the demand system (e.g., Hausman et al., 1994; Nevo, 2001). The advantage of this approach is that it avoids the pitfall of deriving and estimating complicated first-order conditions. But in terms of estimating market power and merger simulation, this approach restricts itself to Bertrand conjectures and the assumption of constant marginal costs (Werden, 1996).

We overcome some of these shortcomings by specifying a fully flexible nonlinear almost ideal demand specification (AIDS) and derive the corresponding structural first-order conditions for profit maximization. Unlike Cotterill et al. (2000), our derived first-order conditions are generic and avoid the need for linear approximation. As a result, they can be estimated with any flexible demand specification that has closed-form analytical elasticity estimates. We propose to estimate our system (i.e., the demand specification and first-order conditions) using full information maximum likelihood (FIML).

In this paper, we also test for different stylized strategic games, namely Nash equilibrium with Bertrand or Stackelberg conjectures, and collusive games. In the empirical analysis of market conduct, the correct strategic model specification may be as critical as the demand and cost specification. Until now most antitrust analyses of market power have tended to assume Bertrand price conjectures (Cotterill, 1994; Werden, 1996). One exception is Cotterill et al. (2000), who test for Bertrand and Stackelberg game at the product-category level. They test within a product category (e.g., breakfast cereal) for Stackelberg and Bertrand games between two aggregate brands: private label and national brand. As a result, their analysis is based on a "two-player game." Similarly, GLV (1992) estimate and test for strategic behavior of Coke and Pepsi brands. In this paper, we consider games with multiple firms and multiple brands. In such a market, a firm may dominate a segment of the market with one brand and then follow the competing firm in another segment of the market with another brand. So, the number of possible games that need to be tested increases greatly. To the best of our knowledge, this is the first study to test for strategic brand-level competition using conjectural variation approach for multiple brands and multiple firms.

In this paper, we also control for expenditure endogeneity in the demand specification. Most papers in the industrial organization literature have failed to address this issue. Dhar et al. (2003) and Blundell and Robin (2000) have found evidence that expenditure endogeneity is significant in demand analysis and can have large effects on the estimated price elasticities of demand.

Empirically, we study the nature of price competition between the four major brands marketed by PepsiCo. and Coca-Cola Company GLV'

(1992) study was one of the first papers to estimate a structural model for the carbonated soft drink industry (CSD). They developed a strategic model of pricing and advertising between Coke and Pepsi using demand and cost specification. Compared to the GLV study, our database is more disaggregate. As a result, we are able to control for region-specific unobservable effects on CSD demand. In addition, we incorporate two other brands produced by Coca-Cola Company and PepsiCo.: Sprite for Coca-Cola Company, and Mountain Dew for PepsiCo. Of the four brands, three are caffeinated (Coke, Pepsi, and Mountain Dew) and one is a clear noncaffeinated drink (Sprite).[3] Characteristically, Mountain Dew is quite unique. In terms of taste, it is closer to Sprite but due to caffeine content, consumers can derive an alertness response similar to Coke and Pepsi.[4] These four brands dominate the respective portfolios of the two firms.

In the present study, unlike the GLV (1992) and Golan et al. (2000) studies, we do not model strategic interactions of firms with respect to advertising. Due to lack of city- and brand-specific data on advertising, we were unable to account for strategic interactions in advertisement (although we do control for the cost of brand promotion in our structural model). Our analysis is based on quarterly IRI (Information Resources Inc.)-Infoscan scanner data of supermarket sales of carbonated non-diet soft drinks (hereafter CSD) from 1988-Q1 to 1989-Q4 for 46 major metropolitan cities across the United States.[5]

The paper is organized as follows. First, we present our conceptual approach. Second, we discuss our model selection procedures. Third, we present our empirical model specification. Fourth, econometric and statistical test results are presented. And finally we draw conclusions from this study.

2. Model Specification

We specify a brand-level nonlinear almost ideal demand system (AIDS) model. We then derive the first-order conditions for profit maximization under alternative game-theoretic assumptions. Finally, we estimate the model using a FIML procedure.

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3. In terms of caffeine content, for every 12 oz. of beverage Coke has 34 mg, Pepsi has 40 mg and Mountain Dew has the most with 55 mg of caffeine.

4. During the period of our study, Coca-Cola Company did not have any specific brand to compete directly against Mountain Dew. Only in 1996, they introduced the brand Surge to compete directly against Mountain Dew.

5. Information Resources Inc., collects data from supermarkets with more than $2 million in sales from major US cities. These supermarkets account for 82% of grocery sales in the US.

2.1 OVERVIEW OF THE AIDS DEMAND SPECIFICATION

This is the first study to use nonlinear AIDS in analyzing strategic brand-level competition between firms. In this section, we briefly describe derivation of AIDS.

Our derivation of AIDS is based on Deaton and Muellbauer (1980b) and assumes that the expenditure function $E(p, u) \equiv \text{Min}_x\{p'x : U(x) \geq u, x \in R_+^N\}$ takes the general form

$$E(p, u) = \exp[a(p) + ub(p)], \tag{1}$$

where $U(x)$ is the consumer's utility function, $x = (x_1, \ldots, x_N)'$ is $(N \times 1)$ vector of consumer goods, $p = (p_1, \ldots, p_N)'$ is a $(N \times 1)$ vector of goods prices for x, M denotes total expenditure on these N goods, u is a reference utility level, $a(p) = \delta + \alpha' \ln(p) + 0.5 \ln(p)' \Gamma \ln(p)$, $\alpha = (\alpha_1, \ldots, \alpha_N)'$ is a $(N \times 1)$ vector,

$$\Gamma = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1N} \\ \vdots & \ddots & \vdots \\ \gamma_{N1} & \cdots & \gamma_{NN} \end{bmatrix}$$

is a $(N \times N)$ symmetric matrix, and $b(p) = \exp[\sum_{i=1}^N \beta_i \ln(p_i)]$. Using Shephard's lemma, differentiating the log of expenditure function $\ln(E)$ with respect to $\ln(p)$ generates the AIDS specification,

$$w_{ilt} = \alpha_i + \sum_{j=1}^N \ln(p_{jlt}) + \beta_i \ln(M_{lt}/P_{lt}), \tag{2}$$

where $w_{ilt} = (p_{ilt} x_{ilt}/M_{lt})$ is the budget share for the ith commodity consumed in the lth city at time t. The term P can be interpreted as a price index defined by

$$\ln(P_{lt}) = \delta + \sum_{m=1}^N \alpha_m \ln(p_{mlt}) + 0.5 \sum_{m=1}^N \sum_{j=1}^N \gamma_{mj} \ln(p_{mlt}) \ln(p_{jlt}). \tag{3}$$

The above AIDS specification can be modified to incorporate the effects of socio-demographic variables $(Z_{1lt}, \ldots, Z_{Klt})$ on consumption behavior, where Z_{klt} is the kth socio-demographic variable in the lth city at time t, $k = 1, \ldots, K$. Under demographic translating, assume that α_i takes the form $\alpha_{ilt} = \alpha_{0i} + \sum_{k=1}^K \lambda_{ik} Z_{klt}$, $i = 1, \ldots, N$. Then, the AIDS specification (2) becomes

$$w_{ilt} = \alpha_{0i} + \sum_{k=1}^{K} \lambda_{ik} Z_{klt} + \sum_{j=1}^{N} \gamma_{mj} \ln(p_{jlt}) + \beta_i \ln(M_{lt})$$

$$- \beta_i \left[\delta + \sum_{m=1}^{N} \alpha_{0m} \ln(p_{mlt}) + \sum_{m=1}^{N} \sum_{k=1}^{K} \lambda_{mk} Z_{klt} \ln(p_{mlt}) \right.$$

$$\left. + 0.5 \sum_{m=1}^{N} \sum_{j=1}^{N} \ln(p_{mlt}) \ln(p_{jlt}) \right]. \tag{4}$$

The theoretical restrictions are composed of symmetry restrictions,

$$\gamma_{ij} = \gamma_{ji} \quad \text{for all } i \neq j$$

and homogeneity restrictions,

$$\sum_{i=1}^{N} \alpha_{0i} = 1; \quad \sum_{i=1}^{N} \lambda_{ik} = 0, \forall k; \quad \sum_{i=1}^{N} \gamma_{ij} = 0, \forall j; \quad \text{and} \quad \sum_{i=1}^{N} \beta_i = 0. \tag{5}$$

The system of share equations represented by (4) is nonlinear in the parameters. The parameter δ can be difficult to estimate and is often set to some predetermined value (Deaton and Muellbauer, 1980b). For the present analysis, we follow the approach suggested by Moschini et al. (1994) and set $\delta = 0$.

2.2 DERIVATION OF THE PROFIT-MAXIMIZING FIRST-ORDER CONDITIONS

Conjectural variation (CV) models have been widely used in theoretical and empirical modeling and in analyzing the comparative static of different strategic games of firms (see, e.g., Brander and Spencer, 1985; Dixit, 1986; Genesove and Mullin, 1998). CV parameters are interpreted as an intuitive summary measure of market conduct, and as a result in existing empirical literature they are sometimes termed conduct parameters (Brander and Zhang, 1990). Our model based on CV parameters is in the same spirit. Because CV models nest most of the noncooperative games that we investigate (see below), they help simplify the testing of different games. Although the CV approach has been criticized for its weak linkages with game theory (e.g., Tirole, 1988), recent papers by Friedman and Mezzetti (2002), and Dixon and Somma (2003) have shown how static conjectural variations can represent a steady-state equilibrium in dynamic pricing games under bounded rationality. Below, we rely on such arguments to justify the use of static CV model as an empirical representation of strategic firm conduct.

It should be noted that in this paper we implicitly assume that manufacturers maximize profits and retailers follow a fixed markup rule. This is a strong but widely used assumption in marketing and industrial organization literature (e.g., Nevo, 2000; Dubé, 2004). This is also necessitated by the fact that we lack any data on retail pricing rules and supported by the empirical findings that in the retail beverage category a fixed markup rule is the norm (Chen, 2004).[6]

For simplicity of exposition assume that there are two firms and each firm produces two brands (Firm 1 produces brands 1 and 2, and Firm 2 produces brands 3 and 4). So, firm profits (π^1 and π^2) can be written as

$$\pi^1 = (p_1 - c_1)x_1 + (p_2 - c_2)x_2, \text{ for firm 1,} \tag{6}$$

$$\pi^2 = (p_3 - c_3)x_3 + (p_4 - c_4)x_4, \text{ for firm 2.} \tag{7}$$

The firms face demand functions $x_i = f_i(p_1, p_2, p_3, p_4), i = 1, \ldots, 4,$ where $f_i(\cdot)$ is given by the AIDS specification (4) (after omitting the time subscript t and location subscript l to simplify the notation). And p_i's and c_i's are the prices and constant marginal costs of different brands. In this paper, we assume that firms form conjectures such that each brand price is a function of the prices of competing brands price. The nature of this conjecture depends on the strategic game played (see below). Denote by $p_1(p_3, p_4)$ and $p_2(p_3, p_4)$ the conjectures of firm 1, and by $p_3(p_1, p_2)$ and $p_4(p_1, p_2)$ the conjecture of firm 2. As a result, firm i's brand-level demand specification can be written as

$$x_i = f_i(p_1(p_3, p_4), p_2(p_3, p_4), p_3(p_1, p_2), p_4(p_1, p_2)), \quad i = 1, \ldots, 4. \tag{8}$$

From (6) and (7), we first derive the first-order conditions for profit maximization. For firm 1, the corresponding FOCs to the profit function (6) under the CV approach are

$$x_1 + (p_1 - c_1)[\partial f_1/\partial p_1) + (\partial f_1/\partial p_3)(\partial p_3/\partial p_1) + (\partial f_1/\partial p_4)(\partial p_4/\partial p_1)]$$
$$+ (p_2 - c_2)[\partial f_2/\partial p_1) + (\partial f_2/\partial p_3)(\partial p_3/\partial p_1) + (\partial f_2/\partial p_4)(\partial p_4/\partial p_1)] = 0, \tag{9}$$

6. Note that this neglects the possibility of strategic behavior by retailers (e.g., see Besanko et al., 1998; Kadiyali et al., 2000). If retailers do not follow standard markup pricing rules and play strategic games in setting prices, then results from most of these existing studies including the present study will be biased. Investigating such issues remains a good topic for further research and will require detailed store-level data including information on manufacturers–retailers contracts.

and

$$x_2 + (p_1 - c_1)[\partial f_1/\partial p_2) + (\partial f_1/\partial p_3)(\partial p_3/\partial p_2) + (\partial f_1/\partial p_4)(\partial p_4/\partial p_2)]$$
$$+ (p_2 - c_2)[\partial f_2/\partial p_2) + (\partial f_2/\partial p_3)(\partial p_3/\partial p_2) + (\partial f_2/\partial p_4)(\partial p_4/\partial p_2)] = 0.$$
(10)

Similar first-order conditions can be derived for firm 2. Note that (9) and (10) can be alternatively expressed as

$$TR_1 + (TR_1 - TC_1)\psi_{11} + (TR_2 - TC_2)\psi_{12} = 0,$$ (11)

and

$$TR_1 + (TR_1 - TC_1)\psi_{21} + (TR_2 - TC_2)\psi_{22} = 0,$$ (12)

where TR_i denotes revenue, TC_i is total variable cost, $\psi_{11} = [\varepsilon_{11} + \varepsilon_{13} \eta_{31} \times p_1/p_3 + \varepsilon_{14} \eta_{41} p_1/p_4]$, $\psi_{12} = [\varepsilon_{21} + \varepsilon_{23} \eta_{31} p_1/p_3 + \varepsilon_{24} \eta_{41} p_1/p_4,)\psi_{21} = [\varepsilon_{12} + \varepsilon_{13} \eta_{32} p_2/p_3 + \varepsilon_{14} \eta_{42} p_2/p_4]$, $\psi_{22} = [\varepsilon_{22} + \varepsilon_{23} \eta_{32} p_2/p_3 + \varepsilon_{24} \eta_{42} p_2/p_4]$, $\varepsilon_{ij} = \partial\ln(f_i)/\partial\ln(p_j)$ is the price elasticity of demand, and $\eta_{ij} = \partial p_i/\partial p_j$ is the brand j's conjecture of brand i's price response, $i, j = 1, \ldots, 4$. Combining these results with similar results for firm 2 gives

$$TR = (I + \Psi)^{-1}\Psi TC,$$ (13)

where $TR = (TR_1, TR_2, TR_3, TR_4)'$, $TC = (TC_1, TC_2, TC_3, TC_4)'$,

$$\psi = \begin{bmatrix} \Psi_{11} & \Psi_{12} & 0 & 0 \\ \Psi_{21} & \Psi_{22} & 0 & 0 \\ 0 & 0 & \Psi_{33} & \Psi_{34} \\ 0 & 0 & \Psi_{43} & \Psi_{44} \end{bmatrix}$$

is a (4×4) matrix. Equation (13) provides a generic representation of the first-order conditions. This generic representation is similar to Nevo (1998). But, unlike Nevo and Cotterill et al., by transforming the FOCs in terms of elasticities, the supply side can be estimated with complex demand specifications like AIDS or Translog.[7]

As mentioned earlier our derived FOCs are generic and different structures of ψ matrix correspond to different strategic games. For a Nash–Bertrand game the ψ matrix becomes

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7. Elasticites in AIDS can be specified as: Let $\mu_i = \frac{\partial w_i}{\partial \ln M} = \beta_i$ and $\mu_{ij} = \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i(\alpha_j + \sum_k \gamma_{jk} \ln p_k)$. Then the expenditure elasticities are $e_i = \frac{\mu_i}{w_i} + 1$. The uncompensated price elasticities are $e_{ij}^u = \frac{\mu_{ij}}{w_i} - \delta_{ij}$ where δ_{ij} is the Kronecker delta such that for $i = j$ $\delta_{ij} = 1$, else $\delta_{ij} = 0$.

$$\Psi_{\mathrm{B}} = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{21} & 0 & 0 \\ \varepsilon_{12} & \varepsilon_{22} & 0 & 0 \\ 0 & 0 & \varepsilon_{33} & \varepsilon_{43} \\ 0 & 0 & \varepsilon_{34} & \varepsilon_{44} \end{bmatrix}.$$

A comparison of ψ and ψ_{B} matrix indicates that the Nash–Bertrand game restricts all η_{ij}'s in the CV model to zero. So, the Nash–Bertrand game is nested in our CV model.

Finally, note that a fully collusive game corresponds to the following ψ matrix:

$$\Psi_{\mathrm{COL}} = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{21} & \varepsilon_{31} & \varepsilon_{41} \\ \varepsilon_{12} & \varepsilon_{22} & \varepsilon_{32} & \varepsilon_{42} \\ \varepsilon_{13} & \varepsilon_{23} & \varepsilon_{33} & \varepsilon_{43} \\ \varepsilon_{14} & \varepsilon_{24} & \varepsilon_{34} & \varepsilon_{44} \end{bmatrix}.$$

Note that, when collusion is defined over all brands, then the $(I + \psi)$ matrix becomes singular due to the Cournot aggregation condition from demand theory. In this paper, we do not investigate a fully collusive game. Rather, we estimate partial brand-level collusion, such as collusive pricing between Coke and Pepsi with Sprite and Mountain Dew playing a Bertrand game. Given the historic rivalries between Coca-Cola Company and PepsiCo., strategic collusion in pricing is not realistic. Below, we estimate this collusive model mainly for the purpose of testing and comparing with other estimated models.

2.3 REDUCED FORM EXPENDITURE EQUATION

Blundell and Robin (2000), and Dhar et al. (2003) found that expenditure M is endogenous, which has a significant impact on the parameter estimates.[8] This suggests a need to control for endogeneity bias in the model estimation. To do this, in a way similar to Blundell and Robin (2000), we specify a reduced-form expenditure equation where household expenditure in the lth city at time t is specified as a function of median household income and a time trend,

$$M_{lt} = f(\text{time trend, income}). \tag{14}$$

3. MODEL SELECTION PROCEDURES

The analysis by GLV (1992) was one of the first to suggest procedures to test appropriate strategic market models given probable alternative

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8. In AIDS total expenditure is a function of price and quantity. As a result underlying causes of price endogeneity can also lead to endogeneity of expenditure variable.

cooperative and noncooperative games. They use both likelihood ratio and Wald tests to evaluate different model specifications. Of the two types of tests, the Wald test procedure is sensitive to functional form of the null hypothesis. In addition, the Wald test can only be used in situations where models are nested in each other. As such, GLV (1992) suggest estimating alternative models assuming different pure-strategy gaming structures and then testing each model against the other using nested and nonnested likelihood ratio tests.

In our view this is a suitable approach only in the case where the number of firms and products is small (preferably not more than two) and the demand and cost specification are not highly nonlinear. Otherwise as the number of products or firms increases, the number of alternative models to be estimated also increases exponentially. This is due to the fact that a firm may play different strategies for different brands. One brand of the firm may be a Stackelberg leader but the other brand may have a price followship strategy.

It is even possible that firms may be collusive for some brands and at the same time play noncollusive Stackelberg or Bertrand games on other brands. For each brand, managers of Coca-Cola Company and PepsiCo. hypothetically can choose from four stylized pure strategies. These strategies are Stackelberg leadership, Stackelberg followship, noncooperative Bertrand, and collusion. For each brand, this implies four conceivable pure strategies in pricing against each of the competing brands. In Table I, we diagrammatically present the strategy profile for each brand. With four brands and four pure strategies in pricing, there are 256 (i.e., four firms with four strategies: 4^4) pure-strategy equilibria. Given the large numbers of pure-strategy games and highly nonlinear functional forms of our models, the use of likelihood ratio-based tests is not very attractive for our analysis. Indeed, we would need to estimate 256 separate models to test each model against the other. Out-of-sample information may help us eliminate some of the games.

In Table II, we present a sample of 12 representative games based on pure-strategy pricing as described in Table I. Of all the probable games, only the collusive game (1) is not nested in our CV model derived earlier. Therefore, except for the collusive model, we can test games by testing the statistical significance of the restrictions imposed by the game on the estimated CV parameters.

We follow Dixit (1986) to develop null hypotheses in testing nested models. Dixit (1986) shows that most pure strategy games can be nested in a CV model. As a result the CV approach provides a parsimonious way of describing different pure strategy games. Following Dixit (1986), CV parameters can be interpreted as fixed points that establish

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TABLE I.

STRATEGY PROFILES OF EACH BRAND

Brand		Pepsi				Mountain Dew			
		Stackelberg Leadership	Stackelberg Followship	Bertrand	Collusion	Stackelberg Leadership	Stackelberg Followship	Bertrand	Collusion
Coke	Stackelberg Leadership	*				*			
	Stackelberg Followship		*				*		
	Bertrand			*				*	
	Collusion				*				*
Sprite	Stackelberg Leadership	*				*			
	Stackelberg Followship		*				*		
	Bertrand			*				*	
	Collusion				*				*

(*) Represents brand strategies that are being analyzed in this paper. With four brands, note that the total number of pure strategies that can be generated is 256.

Game Set 1: Game estimated and tested against CV model using likelihood ratio test:

1 *Collusive Game:* Coke and Pepsi are the collusive brands. And Sprite and Mountain Dew use Bertrand conjecture.

2 *Full Bertrand Game:* Both the firms use Bertrand conjecture over all brands.

Game Set 2: To Test following strategic games we used Wald test procedure:

3 *Mixed Stackelberg and Bertrand Game 1:* Coke leads Pepsi in a Stackelberg game. Rest of the brand relationship is Bertrand.

4 *Mixed Stackelberg and Bertrand Game 2:* Coke leads Mountain Dew in a Stackelberg game. Rest of the brand relationship is Bertrand.

5 *Mixed Stackelberg and Bertrand Game 3:* Coke leads both Pepsi and Mountain Dew in a Stackelberg game. Rest of the brand relationship is Bertrand.

6 *Mixed Stackelberg and Bertrand Game 4:* Coke leads Pepsi and Mountain Dew, and Sprite leads Pepsi and Mountain Dew in a Stackelberg game.

7 *Mixed Stackelberg and Bertrand Game 5:* Coke leads Pepsi and Mountain Dew leads Sprite. Rest of the brand relationship is Bertrand.

8 *Mixed Stackelberg and Bertrand Game 7:* Sprite leads Mountain Dew in a Stackelberg game. Rest of the brand relationship is Bertrand.

9 *Mixed Stackelberg and Bertrand Game 9:* Pepsi leads Coke in a Stackelberg game. Rest of the brand relationship is Bertrand.

10 *Mixed Stackelberg and Bertrand Game 11:* Pepsi leads Coke and Mountain Dew leads Sprite in a Stackelberg game. Rest of the brand relationship is Bertrand.

11 *Mixed Stackelberg and Bertrand Game 15:* Mountain Dew leads Sprite in a Stackelberg game. Rest of the brand relationship is Bertrand.

12 *Mixed Stackelberg and Bertrand Game 15: Pepsi leads Coke and Sprite leads* Mountain Dew in a Stackelberg game. Rest of the brand relationship is Bertrand.

Note: This is the list of pure strategy pricing games analyzed in this paper.

consistency between the conjecture and the reaction function associated with a particular game. In this paper, we use our estimated CV model to test different market structures presented in Table I. For example, if all the estimated CV parameters were zero, then the appropriate game in the market would be Bertrand (game 2 in Table II). This generates the following null hypothesis (which can be tested using a Wald test),

$$[\eta_{C,P} \quad \eta_{C,MD} \quad \eta_{S,P} \quad \eta_{S,MD} \quad \eta_{P,C} \quad \eta_{P,S} \quad \eta_{MD,P} \quad \eta_{MD,S}]' = [0]'$$

where C stands for Coke, P for Pepsi, S for Sprite and MD for Mountain Dew.

In the case of any Stackelberg game, Dixit (1986) has shown that at equilibrium, the conjectural variation parameter of a Stackelberg leader should be equal to the slope of the reaction function of the follower, and followers' CV parameter should be equal to zero. Thus, in a game where Coca-Cola Company's brands lead PepsiCo.'s brands (i.e., game

6 in Table II: both Coke and Sprite leads Pepsi and Mountain Dew), parametric restrictions generate the following null hypothesis:

$$[\eta_{C,P} \ \ \eta_{C,MD} \ \ \eta_{S,P} \ \ \eta_{S,MD} \ \ \eta_{P,C} \ \ \eta_{P,S} \ \ \eta_{MD,P} \ \ \eta_{MD,S}]'$$
$$= [R_{P,C} \ \ R_{MD,C} \ \ R_{P,S} \ \ R_{MD,S} \ \ 0 \ \ 0 \ \ 0 \ \ 0]',$$

where $R_{i,j}$'s are estimated slope of the reaction function of brand i of the follower to a price change in j of the leader. For the rest of the games (as in Table II), we generate similar restrictions and test for them using a Wald test. We estimate the slope of the reaction functions by totally differentiating the estimated first-order conditions, where in the case of Coke's reaction to Pepsi's price change $R_{C,P}$ and $R_{S,P}$ can be stated as

$$
\begin{aligned}
R_{C,P} &= \frac{\varepsilon_{C,P}\frac{p_C}{p_P}(TR_C - TC_C) + \varepsilon_{S,P}\frac{p_S}{p_P}(TR_S - TC_S)}{\varepsilon_{C,C}(TR_C - TC_C) + \varepsilon_{S,C}(TR_S - TC_S) + TR_C} \\
R_{S,P} &= \frac{\varepsilon_{C,P}\frac{p_C}{p_P}(TR_C - TC_C) + \varepsilon_{S,P}\frac{p_S}{p_P}(TR_S - TC_S)}{\varepsilon_{S,S}(TR_S - TC_S) + \varepsilon_{C,S}(TR_C - TC_C) + TR_S}.
\end{aligned}
\tag{15}
$$

Similarly, we can derive the reaction function slopes for the rest of the brands.

We propose a sequence of tests in the following manner. First, we test our nonnested and partially nested models against each other using the Vuong test (1989). In the present paper, our collusive model and CV model are partially nested. One major advantage of the Vuong test is that it is directional. This implies that the test statistic not only tells us whether the models are significantly different from each other but also the sign of the test statistic indicates which model is appropriate. If we reject the collusive model, then the rest of the pure strategy models can be tested using Wald tests because they are nested in our CV model.

4. DATABASE

Table III provides brief descriptive statistics of all the variables used in the analysis. Figure 1 plots the prices of the four brands. During the period of our study, Mountain Dew was consistently the most expensive, followed by Coke, Pepsi, and Sprite. Figure 2 plots volume sales by brands. In terms of volume sales Coke and Pepsi were almost at the same level, Sprite and Mountain Dew's sales were significantly lower than Coke and Pepsi's sales.

TABLE III.
DESCRIPTIVE STATISTICS OF VARIABLES USED IN THE
ECONOMETRIC ANALYSIS

	Mean Purchase Characteristics				
Brands	Price ($/gal) ($p_i$)	Expend. Share (w_i)	Volume Per Unit (VPU_i)	Total Revenue ($Million/city)	Merchandizing (%) (MCH_i)
Coke	3.72 (0.09)	0.44 (0.12)	0.44 (0.07)	1.03 (0.93)	83.19 (7.53)
Mt. Dew	3.93 (0.15)	0.05 (0.04)	0.44 (0.07)	0.09 (0.07)	69.22 (14.41)
Pepsi	3.65 (0.09)	0.44 (0.13)	0.45 (0.07)	1.03 (0.95)	83.51 (7.66)
Sprite	3.63 (0.09)	0.07 (0.02)	0.42 (0.05)	0.17 (0.15)	78.79 (9.75)

Mean Values of Other Explanatory Variables

Variables	Units	Mean
Median age (*Demand Shift Variable* − [Z_{lt}])	Years	32.80 (2.4)
Median HH size (*Demand Shift Variable* − [Z_{lt}])	No.	2.6 (0.1)
% of HH less than $10k income (*Demand Shift Variable* − [Z_{lt}])	%	16.8 (3.3)
% of HH more than $50k income (*Demand Shift Variable* − [Z_{lt}])	%	20.8 (4.9)
Supermarket-to-grocery sales ratio (*Demand Shift Variable* − [Z_{lt}])	%	78.9 (5.8)
Concentration ratio (*Price Function: CR_{lt}^4*)	%	62.4 (13.8)
Per capita expenditure (M_{lt})	$	5.91 (1.22)
Median income (*Expenditure function: INC_{lt}*)	$	28374 (3445.3)

Note: Numbers in parenthesis are the standard deviations.

5. EMPIRICAL MODEL SPECIFICATION

As noted above, we modify the traditional AIDS specification with demographic translating. As a result, our AIDS model incorporates a set of regional dummy variables along with selected socio-demographic variables. Many previous studies using multi-market scanner data, including Cotterill (1994), Cotterill et al. (1996), and Hausman et al. (1994), use city-specific dummy variables to control for city-specific fixed effects for each brand. Here we control for regional differences by including nine regional dummy variables.[9]

Our AIDS specification incorporates five demand shifters, Z, capturing the effects of demographics across marketing areas. These variables are median household size, median household age, percentage of household earning less than $10,000, percentage of household earning more the $50,000, and supermarket-to-grocery sales ratio. In addition, to maintain theoretical consistency of the AIDS model, the following

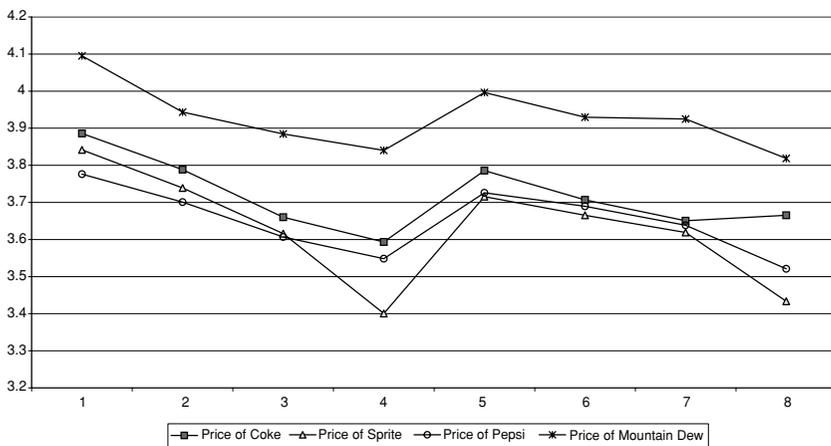9. Our region definitions are based on census definition of divisions.

FIGURE 1. BRAND PRICE.
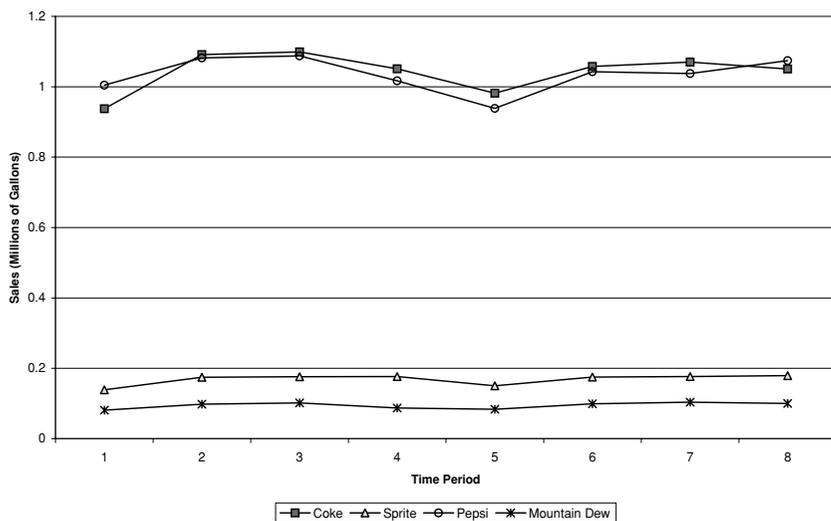
FIGURE 2. VOLUME SALES BY BRANDS (MILLIONS OF GALLONS).

restrictions based on (5) are applied to the demographic-translating parameter α_{0i},

$$\alpha_{0i} = d_{ir}D_r, \quad d_{ir} = 1, \quad i = 1, \ldots, N. \tag{16}$$

where d_{ir} is the parameter for the ith brand associated with the regional dummy variable D_r for the rth region. Note that as a result, our demand equations do not have intercept terms. We assume a constant linear

marginal cost specification. Such cost specification is quite common and performs reasonably well in structural market analysis (e.g., GLV, 1992; Kadiyali et al., 1996; Cotterill et al., 2000). The total cost function is

$$T\_Cost_{ilt} = U_i + MCost_{ilt} \times x_{ilt}, \tag{17}$$

where U_i is the brand-specific unobservable (by the econometrician) cost component and assumed not to vary at the mean of the variables. $MCost_{ilt}$ is the observable cost component and we specify it as

$$MCost_{ilt} = \theta_{i1} UPV_{ilt} + \theta_{i2} MCH_{ilt}, \tag{18}$$

where UPV_{ilt} is the unit per volume of the ith product in the lth city at time t and represents the average size of the purchase. For example, if a consumer purchases only one-gallon bottles of a brand, then unit per volume for that brand is one. Alternatively, if this consumer buys a half-gallon bottle then the unit per volume is 2. This variable captures packaging-related cost variations, as smaller package size per volume implies higher costs to produce, to distribute, and to shelve. The variable MCH_{ilt} measures percentage of a CSD brand i sold in a city l with any type of merchandising (e.g., buy one get one free, cross promotions with other products, etc.). This variable captures merchandising costs of selling a brand. For example, if a brand is sold through promotion such as: "buy one get one free," then the cost of providing the second unit will be reflected in this variable.

Following Blundell and Robin (2000), to control for expenditure endogeneity, the reduced form expenditure function in (14) is specified as

$$M_{lt} = Trend_t + \sum_{r=1}^{9} \delta_r D_r + \phi_1 INC_{lt} + \phi_2 INC_{lt}^2, \quad t = 1, \ldots, 8, \tag{19}$$

where $Trend_t$ in (19) is a linear trend, capturing any time-specific unobservable effect on consumer soft drink expenditure. The variables D_r's are the regional dummy variables defined above and capture region-specific variations in per capita expenditure. The variable INC_{lt} is the median household income in city l and is used to capture the effect of income differences on CSD purchases.

We estimate the system of three demand and four FOCs using FIML estimation procedure under normality.[10] One demand equation

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10. Although the demand specification involves budget shares, note that the consumption data used in our empirical analysis do not involve censored observations (i.e., the observed budget shares remain away from the boundaries of their feasible values). In this context, estimating the model under normality assumption does not appear unreasonable and it provides an empirically tractable way of estimating a highly nonlinear model while dealing with prevalent endogeneity issues.

drops out due to aggregation restrictions of AIDS. The variance–covariance matrix and the parameter vector are estimated by specifying the concentrated log-likelihood function of the system. The Jacobian of the concentrated log-likelihood function is derived based on the models with eight endogenous variables: 3 quantity-demanded variables (e.g., x_i's), 4 price variables (e.g., p_i's), and the expenditure variable (e.g., M). Note that in the process of estimation, we have one less quantity-demanded variable than price variables. This is due to the AIDS share equation adding-up condition. Because the sum of the brand shares is 1; one needs only estimate three share equations to obtain the parameter estimates of the fourth. We can express the demand for the fourth brand as a function of other endogenous variables, $x_4 = M - (p_1x_1 + p_2x_2 + p_3x_3)/p_4$.

6.   REGRESSION RESULTS AND TEST OF ALTERNATIVE MODELS

We estimate three alternative models: (1) collusive oligopoly where the two firms collude on the price of Coke and Pepsi, (2) the Bertrand model, and (3) the conjectural variation model.[11]

We assume that the demand shifters and the variables in the cost and expenditure specification are exogenous. In general, the reduced-form specifications (i.e., equations (17) and (18)) are always identified. The issue of parameter identification in nonlinear structural model is rather complex.[12] We checked the order condition for identification that would apply to a linearized version of the demand equation (4) and found it to be satisfied. Finally, we did not uncover numerical difficulties in implementing the FIML estimation and our estimated results are robust to the iterative process of estimation. As pointed out by Mittelhammer et al. (2000, pp. 474–475) in nonlinear full information maximum likelihood estimation, we interpret this as evidence that each of the demand equations is identified.

Table IV presents system R^2 based on McElroy (1977). In terms of goodness of fit the full CV model fits the best and collusive model gives the poorest fit. However, goodness-of-fit measure in nonlinear regression may not be the appropriate tool to choose among models. To test for an appropriate nesting structure and to select the best model we run further tests based on likelihood ratio and Wald test statistics.

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11. Detailed regression results of the estimated models are available from the authors upon request.

12. For a detailed discussion please refer to Mittelhammer et al. (2000, pp. 474–475).

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TABLE IV.
ESTIMATED SYSTEM R^2

</div>

Model	Estimate
Conjectural variation game	0.7182
Bertrand game	0.6079
Collusive game (collusion of Coke and Pepsi brand)	0.5242

As mentioned earlier, we estimate only one game with collusion. From the pure strategy profile in Table I if we eliminate collusive strategy then we will be left with 81 (i.e., four brands with three strategies each: 3^4) probable games.[13] These games include the full Bertrand model discussed above. Therefore, in this paper in total we test for 82 games, including a collusive game.

6.1 COLLUSION GAME OF COKE AND PEPSI (GAME 1 IN TABLE II)

Existing literature and anecdotal evidence do not suggest any significant level of collusion between Coca-Cola Company and PepsiCo. Our collusion model where Coca-Cola Company and PepsiCo. collude on pricing of the Coke and Pepsi brands is partially nested within our full CV model. Therefore, following GLV we use a modified likelihood ratio test based on Vuong (1989). The test statistic is -3.56. Under a standard normal distribution, the test statistic is highly significant. And the sign of the test provides strong evidence that the full CV model is more appropriate than the collusive model. Our estimation results confirm common industry knowledge. Coke and Pepsi do not collude on the brand pricing of the two leading brands.

6.2 BERTRAND GAME (GAME 2 IN TABLE II)

Nash–Bertrand games have been widely used in the NEIO literature for market power analysis (e.g., Werden, 1996). This motivated us to estimate this model separately so that we can test this model rigorously against alternative models. First we use our estimated full CV model to test for Nash–Bertrand conjectures. Under Nash–Bertrand conjectures all estimated CV parameters should be not significantly different from zero. At a 5% significance level, seven of eight CV parameter estimates

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13. A detailed list of all the games with three pure strategies is available from the authors upon request.

TABLE V.

ESTIMATED CONJECTURES AND SLOPE OF REACTION FUNCTIONS

Conjecture			Reaction Function		
Brand [*] Conjecture on	Brand [*]	Estimates	Brand [*]	Reaction to [*]'s Price Change	Estimate
Coke	Pepsi	0.4126 (0.0189)	Pepsi	Coke	−0.3599 (0.1665)
Coke	Mt. Dew	−0.4431 (0.3799)	Mt. Dew	Coke	1.3406 (0.07552)
Sprite	Pepsi	0.0368 (0.0028)	Pepsi	Sprite	1.69198 (0.11753)
Sprite	Mt. Dew	0.1674 (0.0771)	Mt. Dew	Sprite	−1.1259 (0.0526)
Pepsi	Coke	−0.3232 (0.1487)	Coke	Pepsi	1.3109 (0.16659)
Pepsi	Sprite	9.5276 (2.0698)	Coke	Mt. Dew	0.40856 (0.07552)
Mt. Dew	Coke	−0.3153 (0.1551)	Sprite	Pepsi	4.7133 (0.11753)
Mt. Dew	Sprite	4.9466 (2.1354)	Sprite	Mt. Dew	−2.3821 (0.0526)

Note: Numbers within the parenthesis (*) are the standard deviation of the estimates. Highlighted numbers are significant at the 5% level of significance.

are significantly different (Table V). Nash–Bertrand conduct is effectively rejected. To provide additional information, we first use a Wald test to investigate formally the null hypothesis that all the CV parameters are zero. The estimated Wald test statistic is 4211.24. Under a χ^2 distribution, we strongly reject the null hypothesis of Bertrand conjectures. Note that, unlike the likelihood ratio test, the Wald test can be specification sensitive (Mittelhammer et al., 2000). We also conduct a likelihood ratio test of the Bertrand model versus the full CV model. Testing the null hypothesis that restrictions based on Bertrand conjectures are valid, we also strongly reject this null hypothesis with a test statistic of 865.78. In conclusion, all our tests suggest overwhelmingly that the firms are not playing a Nash–Bertrand game.

6.3 TEST OF OTHER GAMES

We use our estimated CV model to test other games. In the case of Stackelberg games, only the leader forms conjectures. For Stackelberg leadership, such conjectures should be positive and consistent with the associated reaction functions, and follower's conjectures should be zero. In the case of estimated full CV model, we do not observe any such patterns of significance, where one brand's conjectures are positive and significant and the competing brand's conjectures are insignificant.

Table V presents estimated CV parameters and the estimated slopes of the reaction functions at the mean. For any two brands to have a

Stackelberg leader–follower relationship, the estimated CV parameters of the leader should be equal to the estimated reaction slope of the follower. For example, for Coke to be the Stackelberg leader over Pepsi, Coke's estimated conjecture over Pepsi's price (i.e., 0.41) should be equal to the estimated reaction function slope of Pepsi (i.e., −0.36). In addition, Pepsi's conjecture on Coke's price (i.e., −0.32) should be equal to zero. Assuming that other brand relationships are Bertrand our Wald test of the game investigates the empirical validity of these restrictions. The other games are tested in a similar fashion, using the restrictions on CV estimates and estimated reaction function slopes. We reject all the games at the 5% level of significance.[14] Using the Wald test, we fail to accept any of the other probable games.[15]

6.4 Consistency of Conjectures

We failed to accept any of the game with Stackelberg equilibrium. Therefore, we test for a less restrictive condition of Stackelberg leadership.

That is, we test for consistency of estimated conjectures. Consistency of conjectures implies that a firm behaves as if it is a Stackelberg leader even though there may not be any firm behaving as a Stackelberg follower. Results of the test of consistent conjectures are presented in Table VI. In general, our estimated reaction function slopes at the mean are quite different from the corresponding conjectures. This helps explain the overwhelming rejection of all the game scenarios with Stackelberg conjectures. Only Pepsi has a consistent conjecture with respect to Sprite at a 1% level of significance. One is left to the conclusion that the actual games being played are more complex than the relatively simple oligopoly games explained in the textbooks.

Failure to accept any specific nested games implies that the CV model is the most appropriate and general model. Of the estimated conjectures only one is insignificant and three out of eight estimated conjectures are negative. Interestingly, we find asymmetric price conjectures between the Coke and Pepsi brands. Coke has a positive price conjecture (0.4126) for Pepsi's price but Pepsi's conjecture for Coke's price (−0.3232) is negative. In terms of market conducts, this suggests that Coke, the market leader, would like to play a cooperative game, that is, expects Pepsi to follow its pricing. Pepsi, however, is pessimistic and expects rivalry from Coke, that is, it expects Coke to cut price when it increases price. In Table V, however, one observes a more general pattern of strategic interaction between the two soft drink companies.

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14. Detail test procedures and statistics are available from the authors upon request.
15. A list of probable games and detailed test statistics of all the games tested is available from the authors on request.

	Nature of Consistent Conjecture	Test Statistic
1	Pepsi has consistent conjecture over Sprite [1]	5.4634
2	Mt. Dew has consistent conjecture over Sprite [1]	11.2938
3	Pepsi and Mt. Dew have consistent conjecture over Sprite [1]	13.6508
4	Coke has consistent conjecture over Pepsi [1]	20.4324
5	Mt. Dew has consistent conjecture over Coke [1]	21.4919
6	Coke has consistent conjecture over Mt. Dew [1]	22.3875
7	Mt. Dew has consistent conjecture over Coke and Sprite [2]	27.5216
8	Coke has consistent conjecture over Pepsi and Mt. Dew [2]	38.8266
9	Pepsi has consistent conjecture over Coke [1]	84.2452
10	Pepsi and Mt. Dew have consistent conjecture over Coke [2]	94.6637
11	Sprite has consistent conjecture over Pepsi and Mt. Dew [2]	127.593
12	Pepsi has consistent conjecture over Coke and Sprite [2]	150.537
13	Pepsi and Mt. Dew have consistent conjecture over Coke and Sprite [4]	158.521
14	Sprite has consistent conjecture over Mt. Dew	175.028
15	Sprite has consistent conjecture over Pepsi	197.332
16	Coke and Sprite have consistent over conjecture over Mt. Dew	200.356
17	Coke and Sprite have consistent over conjecture over Pepsi	382.218
18	Coke and Sprite have consistent conjecture over Pepsi and Mt. Dew	587.856

Note: Number within the bracket [*] is the number of restrictions imposed for the test. Null hypothesis of each test is that conjectures are consistent. Highlighted numbers are significant at the 5% level of significance.

Note that three of Coke's price conjectures are significant and positive while the remaining is statistically zero. Coke effectively expects Pepsi to play a Nash-Bertrand game or cooperate on pricing. Pepsi, however, is quite different. It expects Coke to be somewhat aggressive when setting Coke prices and extremely cooperative when setting Sprite prices. Interestingly, we find large and significant conjectures by Pepsi and Mountain Dew on the price of Sprite. During the period of our study Coca-Cola Company was trying to find a brand to position directly against Mountain Dew. A high and positive value of conjectures can be due to such repositioning of Sprite to dampen the growth of Mountain Dew. And positive CV with Pepsi is the byproduct as anecdotal evidence and estimated price correlation matrix suggest that PepsiCo. tends to change price of Pepsi and Mountain Dew in tandem. In summary, Coke appears to be the leader, expecting Pepsi to stand pat or follow. Pepsi, however, expects Coke to follow its lead only with Sprite pricing.

Next, we explore the strategic implications of estimated elasticities and Lerner Index using alternative models. The Lerner Index is defined as (price–marginal cost)/price and calculated using the estimated FOCs. One of the main reasons for estimating a structural model is to estimate

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TABLE VII.

PRICE ELASTICITY MATRIX (CV MODEL)

</div>

	Coke	Sprite	Pepsi	Mountain Dew
Coke	−3.7948 (0.0591)	0.0016 (0.0051)	2.1814 (0.0538)	0.4311 (0.0108)
Sprite	0.1468 (0.0426)	−2.8400 (0.0707)	3.6776 (0.1242)	−1.8568 (0.0562)
Pepsi	2.3381 (0.0602)	0.5995 (0.0177)	−3.9384 (0.0583)	0.2529 (0.0108)
Mountain Dew	3.5060 (0.1468)	−2.7280 (0.0831)	1.7659 (0.1082)	−4.3877 (0.0734)

Notes: Numbers within the parenthesis (*) are the standard deviation of the estimates. Rows reflect percentage change in demand and column reflect percentage change in price. Highlighted numbers are significant at the 5% level of significance.

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TABLE VIII.

EXPENDITURE ELASTICITY
MATRIX (CV MODEL)

</div>

Brands	Estimate
Coke	1.1806 (0.0282)
Sprite	0.8725 (0.0773)
Pepsi	0.7478 (0.0340)
Mountain Dew	1.8438 (0.2102)

Note: Numbers within the parenthesis (*) are the standard deviation of the estimates. Highlighted numbers are significant at the 5% level of significance.

price and expenditure elasticities, and associated indicators of market power (e.g., Lerner Index). We evaluate the impact of alternative model specifications on elasticity and market power estimates. Tables VII and VIII present price and expenditure elasticity estimates for the full CV model.

Dhar et al. (2003) and Villas-Boas and Winer (1999) found that after controlling price and expenditure endogeneity, the efficiency of the elasticity estimates improves dramatically. This study also finds significant improvements in terms of the efficiency of our elasticity estimates.[16]

In our CV model, the estimated own-price elasticities have the anticipated signs, and own- and cross-price elasticities satisfy all the basic utility theory restrictions (namely symmetry, Cournot, and Engel aggregation). In addition, all the estimated cross- and own-price elasticities are highly significant suggesting rich strategic relationships between brands. Our estimated expenditure elasticities are all positive and vary

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16. Detailed results of models without controlling for endogeneity are available from the authors upon request.

TABLE IX.
LERNER INDEX

Strategic Game	Coke	Sprite	Pepsi	Mountain Dew
		Estimate		
Conjectural variation game [1]	0.3233	0.3795	0.3221	0.5197
Bertrand game [2]	0.2647	0.2991	0.2601	0.4625
Collusive game [5]	0.7274	0.1940	0.6726	0.6325

between 0.74 and 1.85, with Pepsi being the most inelastic and Mountain Dew being the most elastic brand. Interestingly, our elasticity estimates suggest that Mountain Dew and Sprite behave as complements. As mentioned before Mountain Dew is unique in the CSD market. In terms of taste it is similar to Sprite but on the other hand, in terms of caffeine content, it is positioned closer to Coke. It is probable that consumers with preference for lemon/lime-flavored drink use Mountain Dew as a complement to Sprite due to its caffeine content. In a study of the CSD market, Dubé (2004) also found that consumers tend to treat caffeine and non-caffeine CSD drinks as complements.

Table IX presents Lerner indices. Each is an estimate of price–cost margin for the entire soft drink marketing channel, that is, it includes margins of the manufacturers, distributors, and retailers. Using our CV model, Pepsi has the lowest price–cost margin and Mountain Dew has the highest. This is consistent with the fact that Mountain Dew is the fastest growing carbonated soft drink brand, with a higher reported profit margin than most brands.[17]

For the purpose of evaluating the impact of model specification, we also estimate the Lerner Index for the Bertrand and collusive games. In addition, note that Lerner Indices based on our CV model are higher than in the case of the Bertrand game. This is due to the fact that our estimated CV parameters are predominantly positive leading to higher markups for all the brands. To compare the three games, we calculated the average absolute percentage differences (APD) among the estimated Lerner Indices, where APD between any two estimates (ε^* and ε^{**}) is defined as

$$APD = \{100\,|\varepsilon^* - \varepsilon^{**}|\}/\{0.5\,|\varepsilon^* + \varepsilon^{**}|\}.$$

The average *APD* between Lerner Index estimates from the CV and the full Bertrand game is 19.14. Between the CV and the collusive model

17. According to Andrew Conway, a beverage analyst for Morgan Stanley & Company: "Mountain Dew gives PepsiCo. about 20% of its profits because it's heavily skewed toward the high-profit vending-machine and convenience markets. In these channels, Mountain Dew is rarely sold at a discount" (*New York Times*, Dec 16, 1996).

it is 57.92. Such large differences in an estimated Lerner Index across models indicate that appropriate model specification is important for empirical market power analysis.

7. Concluding Remarks

In this paper, we analyze the strategic behavior of Coca-Cola Company and PepsiCo. in the carbonated soft drink market. This is the first study to use the flexible nonlinear AIDS model within a structural econometric model of firm (brand) conduct. In addition, we derive generic first-order conditions under different profit-maximizing scenarios that can be used with most demand specifications and to test for strategic games. This approach avoids linear approximation of the demand and/or first-order conditions.

In this paper, we test for brand-level alternative games between firms. Most of the earlier studies in differentiated product oligopoly either tested for games at the aggregate level (i.e., Cotterill et al., 2000) or between two brands (Golan et al., 2000; and GLV, 1992). Given that most oligopolistic firms produce different brands, test of brand-level strategic competition is more realistic.

We first test a partially nested collusive model against a CV model. We find statistical evidence that the CV model is more appropriate than the collusive model. The remaining stylized games considered in this paper are in fact nested in the CV model. Our tests for specific stylized multi-brand multifirm market pure strategy models (relying on Wald tests) are attractive because of their simplicity. Treating each game as a null hypothesis, we reject all the null hypotheses. Our overall test results imply that the pricing game being played in this market is much more complex than the stylized games being tested.

It may well be that some complex game not considered in this paper conforms to the estimated CV model. As a result, if a researcher does not have out-of-sample information on the specific game being played then it is appropriate to estimate a CV model.

We use estimated parameters from different models to estimate elasticities and the Lerner Index. We find these estimates to be quite sensitive to model specifications. The empirical evidence suggests that the CV model is the most appropriate.

One of the shortcomings of this paper is that we do not consider mixed strategy games as in Golan et al. (2000). The pure strategy games considered here are degenerate mixed strategy games. It is possible that the actual game played is a game with mixed strategies. Additional research is needed to consider such models with flexible demand specification such as AIDS.

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