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An Econometric Analysis of Brand Level Strategic Pricing Between Coca Cola and Pepsi Inc.[Ψ]

by

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Abstract: Market structure and strategic pricing for leading brands sold by Coca Cola and Pepsi Inc. are investigated in the context of a flexible demand specification and structural price equations. This approach is more general than prior studies that rely upon linear approximations and interactions of an inherently nonlinear problem. We test for Bertrand equilibrium, Stackelberg equilibrium, collusion, and a general conjectural variation (CV) specification. This nonlinear Full Information Maximum Likelihood (FIML) estimation approach provides useful information on the nature of imperfect competition and the extent of market power.

Keywords: Market structure, strategic pricing, conjectural variations, price reaction, carbonated soft drinks.

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I. Introduction

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. The empirical implementation of these models can be complex due to highly non-linear nature of flexible demand and cost functions and the specification of strategic firm behavior. As a result, researchers have tended to simplify the structural model 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 strategic market analysis estimated demand parameters play a crucial role as the estimation of market power and strategic behavior depends crucially on the estimated price and expenditure elasticities. For example, Gasmi, Laffont and Vuong (1992) (hereafter GLV) and Golan, Karp and Perloff (2000) have used ad-hoc linear demand specifications. A major problem with ad-hoc demand specifications is that they do not satisfy all the restrictions of consumer theory. As a result estimated parameters may imply violation of basic tenets of economic rationality. Even under a correct specification of strategic game, 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, Leonard and Zona (1994) and Cotterill, Dhar and Putsis (2000) use a linear approximation to the Almost Ideal Demand System (LA-AIDS; see Deaton and Muellbauer, 1980a). The problem with LA-AIDS is that the validity of its elasticity estimates is subject to debate in the economic literature (e.g., Green and Alston 1990; Alston et al., 1994; Buse, 1994; Moschini, 1995). As a result, there is no clear consensus on the right way to estimate elasticities with LA-AIDS. For example, Hahn (1994) argues that LA-AIDS violates the symmetry restrictions of consumer demand.[1] This suggests that it is desirable to avoid approximation to the AIDS since such approximation imposes restrictions on price effects.

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 random utility model. Nevo (2000), Vilas-Boas and Zhao (2001) and others use characteristic-based demand system. Empirically this approach is appealing due to parsimonious description of the parameter space. However, the specification of random utility models often imposes restrictions that may not be implied by general utility theory. In a recent paper Bajari and Benkard (2001) 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 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.

In terms of specifying behavioral rules for a firm, two broad approaches can be found in the empirical literature. GLV (1992), Kadiyali, Vilcassim and Chintagunta (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 ad-hoc demand specifications. Cotterill, Putsis and Dhar (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 empirical literature, researchers have relied on instrumental variable estimation of the demand specification (e.g., Hausman, Leonard and Zona 1994; and Nevo, 2000). 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 (Warden, 1998).

In this paper we overcome some of these shortcomings by specifying a fully flexible 'representative consumer model' based nonlinear Almost Ideal Demand Specification (AIDS) and structural first-order conditions for profit maximization. Unlike Cotterill, Putsis and Dhar (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 empirical analysis of market, the correct strategic model specification is just as critical as the demand and cost specification. Until now most antitrust analysis of market power has tended to assume Bertrand conjectures (Cotterill, 1994a; Warden, 1998). One exception is Dhar, Putsis and Cotterill (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 game between two aggregate brands: private label and national brand. As a result, their analysis is based on 'two player game'. Similarly, GLV (1992) estimates and test for strategic behavior of Coke and Pepsi brands. In this paper, we consider games with multi firms and multi 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 needs to be tested increases greatly. To the best of our knowledge this is the first study to test for strategic brand level competition between 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, Chavas and Gould (2002) 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 four major brands marketed by Pepsi and Coca Cola Inc. GLV (1992) 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 effect on CSD demand. Also, we incorporate two other brands produced by Coca Cola and Pepsi Inc.: Sprite for Coca Cola, and Mountain Dew for Pepsi. Of the four brands, three are Caffeineted (Coke, Pepsi and Mt. Dew) and one is a clear non-caffeineted drink (Sprite). Characteristically, Mountain Dew is quite unique. In terms of taste it is closer to Sprite but due to caffeine content, consumers can derive alertness response similar to Coke and Pepsi.[2] These four brands dominate the respective portfolio of the two firms.

In the present study, unlike the GLV (1992) and Golan, Karp and Perloff (2000) study, we do not model strategic interactions of firms with respect to advertising. Due to lack of city and brand specific data on advertising we ignore 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 USA.[3]

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.

II. Model Specification

We specify a brand level non-linear Almost Ideal Demand System (AIDS) model. We then derive first-order conditions of profit maximization under alternative game theoretic assumptions using AIDS. Finally, we estimate the model using full information maximum likelihood procedure.

a. *Overview of the AIDS Demand Specification*

This is the first study to use nonlinear AIDS in analyzing strategic competition between firms. So in this section we describe the derivation of AIDS in details for interested readers.

The standard household utility maximization problem can be represented as:

$$V(p, M) = Max_x \{U(x): p' x \leq M\}, \tag{1a}$$

with its associated dual expenditure minimization problem:

$$E(p, u) = Min_x \{p' x: U(x) \geq u\}, \tag{1b}$$

where $x = (x_1, \ldots, x_N)'$ 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, $U(x)$ is the household direct utility function, and u is a reference utility level. The solution to (1a) gives the Marshallian demand functions $x^M(p, M)$, while the solution to (1b) gives the Hicksian demand functions $x^H(p, u)$. By duality, $E(p, V(p, M)) = M$ and $x^M(p, M) = x^H(p, V(p, M))$, where $x^H = \partial E/\partial p$ via Shephard's lemma.

Following Deaton and Muellbauer (1980b), assume that the expenditure function $E(p, u)$ takes the general form:

$$E(p, u) = exp[a(p) + u\ b(p)], \tag{2}$$

where $x = (x_1, \ldots, x_N)'$ 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, $U(x)$ is the household direct utility function, and 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 $b(p) = exp[\sum_{i=1}^{N} \beta_i ln(p_i)]$. Differentiating the log of expenditure function $ln(E)$ with respect to $ln(p)$ generates the AIDS specification:

$$w_{ilt} = \alpha_i + \sum_{j=1}^{N} \gamma_{ij} ln(p_{jlt}) + \beta_i ln(M_{lt}/P_{lt}), \tag{3}$$

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

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

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 k^{th} socio-demographic variable in the l^{th} 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 (3) becomes:

$$w_{ilt} = \alpha_{0i} + \sum_{k=1}^{K} \lambda_{ik} Z_{klt} + \sum_{j=1}^{N} \gamma_{ij} ln(p_{ijlt}) + \beta_i ln(M_{lt}) - \beta_i [\delta + \sum_{m=1}^{N} \alpha_{0m} ln(p_{mlt}) + \sum_{m=1}^{N} \sum_{k=1}^{K} \lambda_{mk} Z_{klt} ln(p_{mlt}) + 0.5 \sum_{m=1}^{N} \sum_{j=1}^{N} \gamma_{mj} ln(p_{mlt}) ln(p_{jlt})]. \tag{4}$$

The theoretical restrictions are composed of symmetry restrictions:

$$\gamma_{ij} = \gamma_{ji} \text{ for all } i \neq j, \tag{5a}$$

and homogeneity restrictions:

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

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, Moro and Green (1994) and set $\delta = 0$.

b. Derivation of the Profit Maximizing First-order Conditions

Here we explain our approach in deriving the estimable profit maximizing first-order conditions (FOC). We derive our base model FOC's, assuming firm forms conjectures on pricing behavior of competitors when it changes its own prices. 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 (Dixit, 1986; Genesove and Mullin, 1995). Since CV models nest most of the non-cooperative game that we investigate (see below), they will help to simplify the testing of different games.

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

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

$$\pi^2 = (p_3 - c_3)\, x_3 + (p_4 - c_4)\, x_4, \text{ for firm 2.} \qquad (6b)$$

The firms face demand functions $x_i = f_i(p_1, p_2, p_3, p_4)$, i = 1, …., 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). Assume that each firm anticipates the reaction of the other firm to its own pricing. In this paper, we assume that firms form conjecture such that each brand price is a function of the prices of competing brands price. The nature of this conjecture depends on the strategic games (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:

$$x_i = f_i(p_1(p_3, p_4), p_2(p_3, p_4), p_3(p_1, p_2), p_4(p_1, p_2)),\ \mathrm{i} = 1, \ldots, 4. \tag{7}$$

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

$$x_1 + (p_1 - c_1)\,[\partial f_1/\partial p_1 + (\partial f_1/\partial p_3)(\partial p_3/\partial p_1) + (\partial f_1/\partial p_4)(\partial p_4/\partial p_1)]$$
$$+ (p_2 - c_2)\,[\partial f_2/\partial p_1 + (\partial f_2/\partial p_3)(\partial p_3/\partial p_1) + (\partial f_2/\partial p_4)(\partial p_4/\partial p_1)] = 0, \tag{8a}$$

and

$$x_2 + (p_1 - c_1)\,[\partial f_1/\partial p_2 + (\partial f_1/\partial p_3)(\partial p_3/\partial p_2) + (\partial f_1/\partial p_4)(\partial p_4/\partial p_2)]$$
$$+ (p_2 - c_2)\,[\partial f_2/\partial p_2 + (\partial f_2/\partial p_3)(\partial p_3/\partial p_2) + (\partial f_2/\partial p_4)(\partial p_4/\partial p_2)] = 0. \tag{8b}$$

Similar first-order conditions can be derived for firm 2. Note that (8a) and (8b) can be alternatively expressed as:

$$TR_1 + (TR_1 - TC_1)\ \psi_{11} + (TR_2 - TC_2)\ \psi_{12} = 0, \tag{9a}$$

and

$$TR_1 + (TR_1 - TC_1)\psi_{21} + (TR_2 - TC_2)\ \psi_{22} = 0, \tag{9b}$$

where TR_i denotes revenue, TC_i is total variable cost, $\psi_{11} = [\varepsilon_{11} + \varepsilon_{13}\ \eta_{31}\ p_1/p_3 + \varepsilon_{14}\ \eta_{41}\ p_1/p_4]$, $\psi_{12} = [\varepsilon_{21} + \varepsilon_{23}\ \eta_{31}\ p_1/p_3 + \varepsilon_{24}\ \eta_{41}\ p_1/p_4],\ )\psi_{21} = [\varepsilon_{12} + \varepsilon_{13}\ \eta_{32}\ p_2/p_3 + \varepsilon_{14}\ \eta_{42}\ p_2/p_4]$, $\psi_{22} = [\varepsilon_{22} + \varepsilon_{23}\ \eta_{32}\ p_2/p_3 + \varepsilon_{24}\ \eta_{42}\ p_2/p_4]$, $\varepsilon_{ij} = \partial ln(f_i)/\partial ln(p_j)$ 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, …, 4. Combining these results with similar results for firm 2 gives

$$TR = (I + \Psi)^{-1} \Psi TC, \tag{10}$$

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 (10) 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 easily be estimated with complex demand specifications like AIDS or Translog.

As mentioned earlier our derived FOCs are generic and different structures of ψ matrix correspond to different strategic games. In the case of Nash game with Bertrand conjecture the ψ matrix becomes:

$$\Psi_B = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{21} & 0 & 0 \\ \varepsilon_{12} & \varepsilon_{22} & 0 & 0 \\ 0 & 0 & \varepsilon_{33} & \varepsilon_{43} \\ 0 & 0 & \varepsilon_{34} & \varepsilon_{44} \end{bmatrix} \tag{11}$$

A cursory comparison of ψ and ψ_B matrix implies that Bertrand game imposes restrictions that all η_{ij}'s are zero, in the CV model. So, the Bertrand game is nested in our CV model.

Finally, note that the case of fully collusive game would correspond to the following ψ matrix

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

Note that, when collusion is defined over all brands, then the $(I+\psi)$ matrix becomes singular due to Cournot aggregation condition. 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 Bertrand game. Given the historic rivalries between Coca Cola and Pepsi, such collusion may not be realistic. Below, we estimate this collusive model mainly for the purpose of test and comparison with other estimated models.

c. Reduced Form Expenditure Equation

Similar to Blundell and Robin (2000), we specify a reduced form expenditure equation where household expenditure in the l^{th} city at time t is a function of median household income and a time trend:

$$M_{lt} = f(\text{time trend, income}). \tag{13}$$

III. 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 cooperative and non-cooperative games. They use both likelihood ratio and Wald tests to evaluate different model specification. Of the two types of tests, the Wald test procedure is sensitive to functional form of the null hypothesis. Also, 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 non-nested likelihood ratio tests. In our view this is a suitable approach only in the case where the numbers of firms and products are few (preferably not more than two) and the demand and cost specification are not highly non-linear. 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 plays non-collusive Stackelberg or Bertrand games on other brands. For each brand, managers of Coca Cola and Pepsi can choose from four stylized pure strategies. These strategies are Stackelberg leadership, Stackelberg followship, non-cooperative Betrand and collusion. For each brand this implies four conceivable pure strategies in pricing against each of the competing brands. In Table 1, 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 equilibrium. Given the large numbers of pure strategy games and highly non-linear functional forms of our models, 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 models against the other. Out of sample information may help us to eliminate some of the games.

In Table 2, we present a sample of 12 representative games based on pure strategy pricing as described in Table 1. Of all the probable games, only the collusive game

[1] is not nested in our CV model derived earlier. So, except in the case of 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 hypothesis in testing nested models. Dixit (1986) shows that most pure strategy games can be nested in a CV model. As a result 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 consistency between the conjecture and the reaction function associated with a particular game. In this paper we use our estimated CV model to test the different market structures presented in Table 1. For example, if all the estimated CV parameters were zero, then the appropriate game in the market would be Bertrand (game 2 in Table 2). This generates the following null hypothesis (which can be tested using a Wald test):

$$[\eta_{C,P}\ \eta_{C,MD}\ \eta_{S,P}\ \eta_{S,MD}\ \eta_{P,C}\ \eta_{P,S}\ \eta_{MD,P}\ \eta_{MD,S}]' = [0]' \qquad (14)$$

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) have 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's brands leads Pepsi's brands (i.e., game 6 in Table 2: both Coke and Sprite leads Pepsi and Mountain Dew), corresponds to the following null hypothesis:

$$[\eta_{C,P}\ \eta_{C,MD}\ \eta_{S,P}\ \eta_{S,MD}\ \eta_{P,C}\ \eta_{P,S}\ \eta_{MD,P}\ \eta_{MD,S}]' = [\boldsymbol{R}_{P,C}\ \boldsymbol{R}_{MD,C}\ \boldsymbol{R}_{P,S}\ \boldsymbol{R}_{MD,S}\ 0\ 0\ 0\ 0]' \qquad (15)$$

where $\boldsymbol{R}_{i,j}$'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 2), we can generate similar restrictions and test for them using a Wald test. We estimate the slope of the reaction functions by totally differentiating the derived first order conditions.

We propose a sequence of test in the following manner. First we test our non-nested and partially nested models against each other using Vuong test (1989). In the present paper, our collusive model and CV model are partially nested. One major advantage of 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.

IV. Database

Table 3 provides brief descriptive statistics of all the variables used in the analysis. Figure 1 plots 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.

V. 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, Franklin and Ma (1996), and Hausman, Leonard and Zona (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.[4]

Our AIDS specification incorporates five demand shifters, Z, capturing the effects of demographics across marketing areas. These variables include: median household size, median household age, percent of household earning less than \$10,000, percentage of household earning more the \$50,000, and supermarket to grocery sales ratio. Also to maintain theoretical consistency of the AIDS model, the following restrictions based on (5) are applied to the demographic translating parameter α_{0i}:

$$\alpha_{0i} = \sum_{r=1}^{9} d_{ir} D_r, \; \sum_{r=1}^{9} d_{ir} = 1, \; i = 1, \ldots, N. \tag{16}$$

where d_{ir} is the parameter for the i^{th} brand associated with the regional dummy variable D_r for the r^{th} region. Note that as a result, our demand equations do not have intercept terms. We assume constant linear marginal cost specification. Such cost specification is quite common and performs reasonably well in structural market analysis (e.g., Kadiyali, Vilcussim and Chintagunta, 1996; GLV, 1992; Cotterill, Putsis and Dhar, 2000). The total cost function is:

$$T\_Cost = F_i + Mcost_{ilt} * x_{ilt} \tag{17}$$

Where F_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} in is the unit per volume of the i^{th} product in the l^{th} 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 units 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 (4) is specified as:

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

where $Trend_t$ in (13) 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. One demand equation 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 seven endogenous variablesl: 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 we have one less quantity demanded variables than price variables. This is due to the fact that we can express the demand for the fourth brand as function of rest of the endogenous variables: $x_4 = M - (p_1x_1 + p_2x_2 + p_3x_3) / p_4$.

VI. Regression Results and Test of Alternative Models

We estimate three alternative models: (1) collusive oligopoly where the two firms colludes on the price of Coke and Pepsi, (2) Bertrand model, and (3) the conjetctural variation model.[5]

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. equation (17) and (19)) are always identified. The issue of parameter identification in non-linear structural model is rather complex.[6] We checked the order condition for identification that would apply to a linearized version of the demand equations (4) and found it to be satisfied. Finally, we did not uncover numerical difficulties in implementing the FIML estimation. As pointed out by Mittelhammer, Judge and Miller (2000, pages 474-475) we interpret this as evidence that each of the demand equations is identified.[7]

Table 4 presents system R^2 based on McElroy (1977). In terms of goodness of fit the full CV model fits the best and collusive model fits the least. 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.

As mentioned earlier we estimate only one game with collusion. From the pure strategy profile in Table 1 if we eliminate collusive strategy then we will be left with eighty one (i.e., four brands with three strategies each: 3^4) probable games.[8] Of these games full Bertrand model discussed above is one of them. So, in this paper in total we test for eighty-two games, including a collusive game.

Collusion (game 1 in Table 2): As mentioned before we test only one game with collusion. Existing literature and anecdotal evidence do not suggest that collusion is pervasive. Our collusion model where Coca Cola and Pepsi Inc. collude on pricing of Coke and Pepsi is partially nested within our full CV model. So, 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.

Bertrand Game (game 2 in Table 2): Nash equilibrium with Bertrand conjectures has been widely used in the NEIO literature for market power analysis (e.g., Nevo, 2001). This motivated us to estimate this model separately so that we can test this model rigorously against our alternative estimated models. We first use our estimated full CV model to test for Bertrand conjecture. In the case of Nash equilibrium with Bertrand conjecture all the estimated CV parameters should be not significantly different from zero. At 95% significance level, 7 out of 8 CV parameter estimates are significant (Table 5). To provide additional information, we first used 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 chi-square 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, Judge and Miller, 2000). So, we also conducted 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 Bertrand conjecture is not a valid conjecture in this market.

Test of other Games: Except for the collusive and the full Bertrand model, we use our estimated CV model to test for rest of the game.

In the case of Stackelberg games, only the leader forms conjectures. Such conjectures should be consistent with the associated reaction functions and significant, 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 5 presents estimated CV parameters and estimated slope of the reaction functions at the mean. For any two brands to have Stackelberg leader-follower relationship 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, Cokes estimated conjecture over Pepsi's price (i.e., 0.4126) should be equal to the estimated reaction function slope of Pepsi (i.e. -0.3599). This is a sufficient condition. In addition, Pepsi's conjecture on Coke's price (i.e. –0.3232) should be equal to zero. Assuming that rest of the brand relationship is 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.[9] Using Wald test we fail to accept any of the game as described in Appendix Table A1.[10]

<u>Consistency of Conjectures:</u> We fail to accept any of the game with Stackelberg equilibrium. So, we test for less restrictive sufficient condition of Stackelber leadership. That is we test for consistency of estimated conjectures. Consistency of conjectures implies a firm behaves as if it is a Stackelberg leader even though there may not be any firm behaving as Stackelberg follower. Results of the test of consistent conjectures are presented in Table 6. 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 1% level of significance.

Failure to accept any specific nested games implies CV model is the most appropriate and general model. So, we focus our further analysis on our CV model. First, we explore the issue of estimating 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 to estimate a structural model is to estimate 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. Table 7 and 8 present price and expenditure elasticity estimates for the full CV model.

Dhar, Chavas and Gould (2001) and Vilas-Boas and Winer (1999) found that after controlling price and expenditure endogeneity, efficiency of the elasticity estimates improve dramatically. This study also finds significant improvements in terms of the efficiency of our elasticity estimates.[11]

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). Also, 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 between 0.74 to 1.85, with Pepsi being the most inelastic and Mountain Dew being the most elastic brand.

Table 9 presents Lerner indices. Each is an estimate of price-cost margin for the entire soft drink marketing channel, i.e. 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.[12]

For the purpose of evaluating the impact of model specification, we also estimate the Lerner Index for the Bertrand and collusive games. Our estimated Lerner Index from the CV model, Bertrand, and collusive games are quite different. To compare them, 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 it is 57.92. Such large differences in estimated Lerner Index across models indicate that appropriate model specification is very important for empirical market power analysis.

VII. Concluding Remarks

In this paper we analyze the strategic behavior of Coca Cola and Pepsi Inc. 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. Also, we derive generic first-order conditions under different profit maximizing scenario 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, Putsis and Dhar, 2000) or between two brands (Golan, Karp, and Perloff, 2000; and GLV, 1992). Given that most oligpolistic firms produces different brands, test of brand level strategic competition is more realistic.

We first test our partially nested collusive model against our 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 multi firm market pure strategy models (relying on Wald tests) are attractive because of its simplicity. Treating each game as a null hypothesis, we reject all 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.

However, we have not considered all possible games. It may well be that some complex game not considered in this paper would appear consistent with the CV model. As a result, if the researcher do not have any specific out of sample information on specific game being played then it is appropriate to estimate CV model.

We use estimated parameters from different models to estimate elasticities and 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, Karp and Perloff (2000). The pure strategy games considered here are degenerate mixed strategy games. It is possible that actual game involve games with mixed strategies. Additional research is needed to consider such models.

Table 1: Strategy Profiles of Each Brand

Brand		Pepsi				Mountain Dew			
		Stackelberg Leadership	Stackelberg Followship	Bertrand	Collusion	Stackelberg Leadership	Stackelberg Followship	Bertrand	Collusion
<u>Coke</u>	Stackelberg Leadership		*				*		
	Stackelberg Followship	*				*			
	Bertrand			*				*	
	Collusion				*				*
Sprite	Stackelberg Leadership		*				*		
	Stackelberg Followship	*				*			
	Bertrand			*				*	
	Collusion				*				*

(*) Represents brand strategy that is being considered. (*) implies probable pure strategy that can be considered. With four brands and four probable strategies, the number of pure game that can be generated is 256.

Table 2: Probable Pure Strategy Games[€]

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 uses 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 Stackelbarg 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 Moutain 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.

[€] A sample list of pure strategy pricing Games. A detailed list of pure strategy game with three strategy is presented in Appendix Table A1.

Table 3: 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)**	**% Merchandising [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}])*	#	**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^4_{lt})*	%	**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.

Table 4: Estimated System R^2

Model	Estimate
Conjectural Variation Game	0.7182
Bertrand Game	0.6079
Collusive Game (Collusion of Coke and Pepsi Brand)	0.5242

Table 5: Estimated Conjectures and Slope of Reaction Functions¶

Conjecture		**Estimates**	**Reaction Function**		**Estimate**
Brand [*] Conjecture on	Brand [*]		Brand [*]	Reaction to [*]'s Price Change	
[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)*

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

Table 6: Test of Consistency of conjectures for Stackelberg Game¶

	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**

¶*Number in 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.*

Table 7: Price Elasticity Matrix (CV Model) ¶±

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

¶*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.*

Table 8: Expenditure Elasticity Matrix (CV Model) ¶

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

¶*Numbers within the parenthesis (*) are the standard deviation of the estimates. Highlighted numbers are significant at the5% level of significance.*

Table 9: Lerner Index

Strategic Game	Estimate			
	Coke	**Sprite**	**Pepsi**	**Mountain Dew**
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

Figure 1: Brand Price

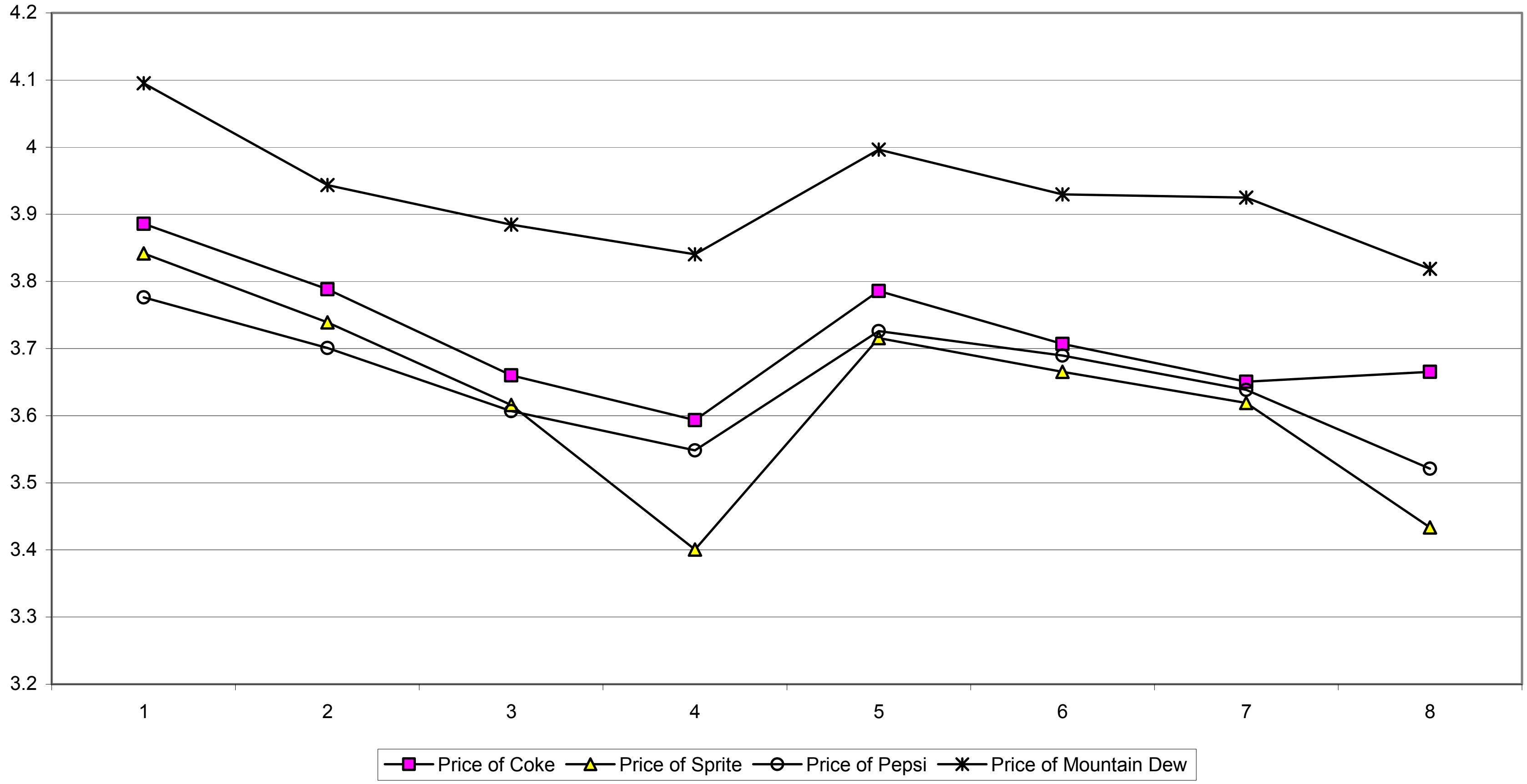

Figure 2: Volume Sales by Brands (Millions of Gallons)

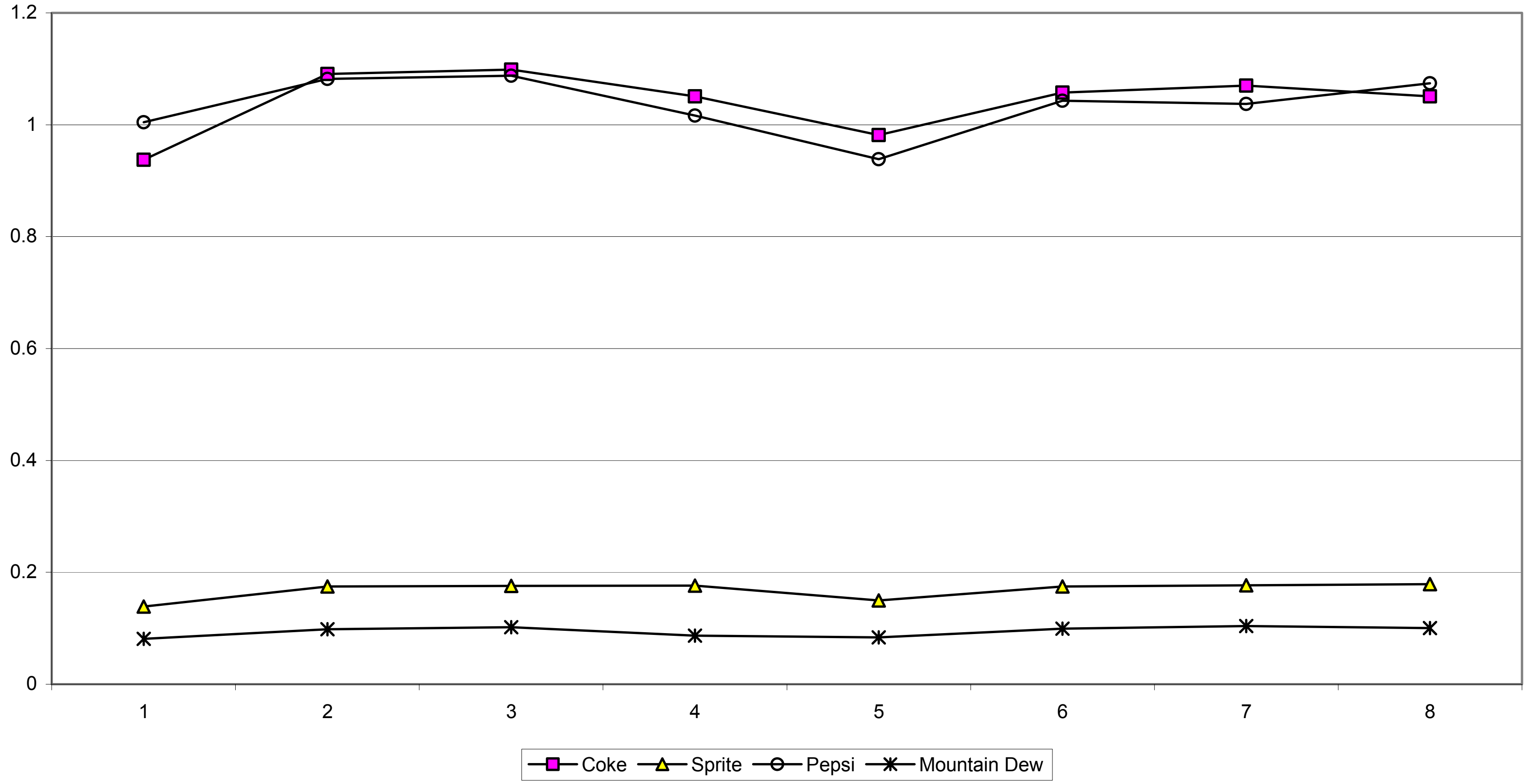

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Table A1: Probable Strategic Games with Three Pure Strategies (Stackelberg leadsership, Stackelberg followssship, Bertrand)

	Brand	R	Brand	Brand	R	Brand	Brand	R	Brand	Brand	R	Brand
1	Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
2	Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
3	Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
4	Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
5	Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
6	Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
7	Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
8	Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
9	Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
10	Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
11	Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
12	Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
13	Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
14	Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
15	Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
16	Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
17	Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
18	Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
19	Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
20	Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
21	Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
22	Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
23	Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
24	Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
25	Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew
26	Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
27	Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
28	Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
29	Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	leads	M. Dew

30 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	Bertrand	M. Dew
31 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	leads	M. Dew
32 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
33 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
34 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
35 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
36 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
37 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
38 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
39 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
40 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
41 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
42 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
43 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
44 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
45 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
46 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
47 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
48 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
49 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
50 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
51 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
52 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
53 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
54 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
55 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
56 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
57 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew
58 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
59 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
60 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
61 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	follows	M. Dew

62 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	Bertrand	M. Dew
63 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	follows	M. Dew
64 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Betrand	M. Dew
65 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
66 Coke	leads	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
67 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
68 Coke	leads	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
69 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
70 Coke	Bertrand	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
71 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
72 Coke	leads	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
73 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
74 Coke	Bertrand	Pepsi	Coke	follows	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
75 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
76 Coke	follows	Pepsi	Coke	leads	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
77 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
78 Coke	follows	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
79 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	leads	Pepsi	Sprite	follows	M. Dew
80 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	follows	Pepsi	Sprite	leads	M. Dew
81 Coke	Bertrand	Pepsi	Coke	Bertrand	M. Dew	Sprite	Bertrand	Pepsi	Sprite	Bertrand	M. Dew

Note: Here follows implies Stackelberb followssship; leads implies Stackelberg leadsership, Bertrand implies Bertrand Nash equilibrium.

Appendix Table A2: Regression Results (CV Model):

Variable	Value	Confidence Interval (95%)	
Coke		**Lower**	**Upper**
Region Binary 1	0.4449	0.5015	0.3882
Region Binary 2	0.3095	0.3549	0.2640
Region Binary 3	0.3926	0.4251	0.3601
Region Binary 4	0.3710	0.4145	0.3275
Region Binary 5	0.5511	0.5810	0.5211
Region Binary 6	0.5998	0.6410	0.5585
Region Binary 7	0.7025	0.7387	0.6663
Region Binary 8	0.3073	0.3692	0.2453
Region Binary 9	0.3793	0.4208	0.3377
Median Age	0.1464	0.5724	-0.2796
Median Household Size	0.8413	1.4682	0.2144
% of HH earning less than $10,000	0.0486	0.1018	-0.0046
% of HH earning more than $50,000	0.1068	0.1906	0.0230
Supermarket to grocery sales ratio	0.0573	0.2010	-0.0864
Total Expenditure on Softdrinks	0.0788	0.0545	0.1031
Price of Coke	-1.1842	-1.2316	-1.1369
Price of Sprite	0.0063	0.0019	0.0108
Price of Pepsi	-0.1314	-0.1413	-0.1215
Sprite			
Region Binary 1	0.0907	0.0808	0.1006
Region Binary 2	0.0632	0.0526	0.0739
Region Binary 3	0.0547	0.0477	0.0618
Region Binary 4	0.0458	0.0392	0.0525
Region Binary 5	0.0832	0.0762	0.0901
Region Binary 6	0.0915	0.0839	0.0991
Region Binary 7	0.1004	0.0943	0.1065
Region Binary 8	0.0661	0.0559	0.0762
Region Binary 9	0.0629	0.0537	0.0721
Median Age	0.1221	0.0347	0.2095
Median Household Size	0.2546	0.1255	0.3837
% of HH earning less than $10,000	-0.0024	-0.0156	0.0108
% of HH earning more than $50,000	0.0211	0.0063	0.0360
Supermarket to grocery sales ratio	0.0243	-0.0044	0.0530

Total Expenditure on Softdrinks	-0.0091	-0.0199	0.0018
Price of Coke			
Price of Sprite	0.9848	0.9376	1.0321
Price of Pepsi	0.2576	0.2415	0.2736
Sprite			
Region Binary 1	0.4220	0.3638	0.4802
Region Binary 2	0.5499	0.4938	0.6060
Region Binary 3	0.4567	0.4198	0.4936
Region Binary 4	0.5015	0.4528	0.5501
Region Binary 5	0.3099	0.2712	0.3486
Region Binary 6	0.2718	0.2101	0.3334
Region Binary 7	0.1812	0.1406	0.2219
Region Binary 8	0.5786	0.5071	0.6502
Region Binary 9	0.4942	0.4472	0.5412
Median Age	-0.3002	-0.7958	0.1955
Median Household Size	-1.1276	-1.8641	-0.3911
% of HH earning less than $10,000	-0.0435	-0.1092	0.0222
% of HH earning more than $50,000	-0.1025	-0.1985	-0.0066
Supermarket to grocery sales ratio	-0.0531	-0.2181	0.1118
Total Expenditure on Softdrinks	-0.1117	-0.1414	-0.0820
Price of Coke			
Price of Sprite			
Price of Pepsi	-1.3475	-1.3988	-1.2962
Cost Side Variables			
Coke			
Intercept	0.0984	0.0871	0.1098
Volume per Unit	3.9901	3.7042	4.2761
% Merchandising	0.2982	0.2783	0.3181
Sprite			
Intercept	0.0191	0.0172	0.0209
Volume per Unit	2.9059	2.5447	3.2672
% Merchandising	0.2663	0.2440	0.2887
Pepsi			
Intercept	0.1314	0.1247	0.1381
Volume per Unit	3.0537	2.8704	3.2371
% Merchandising	0.3287	0.3142	0.3431
Mountain Dew			
Intercept	0.0104	0.0077	0.0132
Volume per Unit	5.6314	4.8186	6.4442

% Merchandising	0.1742	0.1327	0.2157
Expenditure Equation			
Time Trend	-0.2971	-1.7706	1.1763
Region Binary 1	-2.3953	-5.0176	0.2271
Region Binary 2	-2.4676	-5.0721	0.1369
Region Binary 3	-2.1883	-4.8134	0.4368
Region Binary 4	-2.5114	-5.1515	0.1286
Region Binary 5	-2.2477	-4.7944	0.2991
Region Binary 6	-2.4061	-4.9739	0.1618
Region Binary 7	-1.9104	-4.4340	0.6133
Region Binary 8	-2.3797	-5.0293	0.2700
Region Binary 9	-2.2641	-4.9129	0.3847
Median HH Income	1.4355	-0.2691	3.1401
Square of Median HH Income	-0.1744	-0.4527	0.1039
Estimated Conjectural Slope Coefficients			
dP_{Pepsi}/dP_{Coke}	0.4126	0.3754	0.4497
$dP_{Mt.Dew}/dP_{Coke}$	-0.4431	-1.1909	0.3047
dP_{Pepsi}/dP_{Sprite}	0.0368	0.0313	0.0422
$dP_{Mt.Dew}/dP_{Sprite}$	0.1674	0.0157	0.3191
dP_{Coke}/dP_{Pepsi}	-0.3232	-0.6159	-0.0304
dP_{Sprite}/dP_{Pepsi}	9.5276	5.4537	13.6016
$dP_{Coke}/dP_{Mt.Dew}$	-0.3153	-0.6205	-0.0100
$dP_{Sprite}/dP_{Mt.Dew}$	4.9466	0.7435	9.1497

Footnotes

[1] For a detailed discussion on problems with LA-AIDS please refer to Chen (1998), Buse and Chan (2000).

[2] During the period of our study, Coca Cola Inc. 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.

[3] Information Resources Inc., collects data from supermarkets with more than $2 million in sales from major US cities. The size of supermarket accounts for 82% of grocery sales in the US.

[4] A list of the cities and definitions of the nine regions used in our analysis can be obtained from the authors upon request. Our region definitions are based on census definition of divisions.

[5] A regression result of the CV model is presented in the Appendix.

[6] For a detailed discussion please refer to Mittelhammer, Judge and Miller (2000, pages 474-475).

[7] Due to space limitations, we report only related econometric results. More complete reports of the results are available from the authors on request.

[8] A detailed lists of all the games with three pure strategies is presented in Appendix Table A1.

[9] Detail test procedures and statistics are available from the authors on request.

[10] Detailed test statistics of all the games tested is available from the authors on request.

[11] Detailed results of models without controlling for endogeneity are available from the authors on request.

[12] According to Andrew Conway, a beverage analyst for Morgan Stanley & Company: "Mountain Dew gives Pepsi about 20 percent 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).