Invited Presentation

Scanner Data: New Opportunities for Demand and Competitive Strategy Analysis

Ronald W. Cotterill

This paper reviews prior research by agricultural economists on the demand for food products using scanner data. Thereafter, a differentiated product's oligopoly model with Bertrand price competition is developed and used to specify brand level demand and oligopoly price reaction equations. The model has sufficient detail to estimate brand level price elasticities and price response elasticities which in turn can be used to estimate three indices of market power. The first index estimated is the familiar Rothschild Index. The paper develops estimates two new indexes, the observed index and the Chamberlin quotient for tacit collusion. It concludes with comments on how the proposed method for the measurement of market power in a differentiated oligopoly can be improved.

I. Introduction

During the 1980s scanning of grocery prices from the universal product codes on packages became common in the nation's supermarkets. With the wide scale adoption of computerized tracking of price and volume movement the food industry now operates in an entirely new and revolutionary marketing and distribution environment. Wal-Mart, for example, attributes a significant portion of its competitive advantage to its centralized inventory management and market analysis system. Checkout scanners in each Wall-Mart store instantaneously send point of sale information to the Bentonville headquarters. Wal-Mart cuts store and warehouse inventory levels to pipeline levels and evaluates marketing strategies on a weekly or even daily basis. They negotiate with suppliers and compete against competitors from a position of power based in part upon superior knowledge and low cost operation.

Food manufacturers also have garnered significant advances in the planning, implementation, and monitoring of their distribution and marketing strategies. Because there are real economies of scale and scope in data processing no individual retailer has sufficient incentive to process scanner data into a usable format for manufacturers. Two third party firms, A.C. Neilsen and Information Resources, Inc. (IRI) provide virtually all scanner based data services to food manufacturing firms. Neilsen and IRI provide food manufacturers with summary data, however, their primary output is on-line software that allows marketing managers access to proprietary IRI or A.C. Neilsen analytical programs as well as data to generate useful reports.

Each company offers two basic types of scanner data services. The first measures product flow through supermarkets. It is based upon a sample of several thousand supermarkets and projects product movement in physical units, market share, prices, and merchandising activities for local market areas, eg., Boston, and for the entire U.S. Merchandising activity includes the percent of a product sold on aisle end display, the percent sold that was featured in retailers' local newspaper ads, and the percent price reduction when a product is on special. These data allow manufacturers to monitor "retailer push" trade promotion activities that manufacturers offer as deals to retailers. A.C. Neilsen calls its supermarket movement data base Neilsen Scantrack. The IRI counterpart is the Infoscan data base that serves as the basis for a regular feature on product marketing in the *Wall Street Journal*.

The second general type of commercial scanner data base is the household panel. Both Neilsen and IRI maintain household panels with more than 15,000 participants. A panel allows food manufac-

Director, Food Marketing Policy Center. Department of Agricultural and Resource Economics, University of Connecticut. This research was supported by Special Research Grant No. 91-34178-6330 with the Cooperative State Research Service, USDA, and by the Storrs Agricultural Experiment Station. This report is Scientific Contribution No. 1568, Storrs Agricultural Experiment Station, Storrs, CT 06269.

turers or other market analysts to evaluate "consumer pull" as opposed to "retailer push" marketing programs. The most important consumer pull strategies are manufacturer advertising (TV, radio, and print) and manufacturer coupons that are distributed directly to consumers.

This paper will focus primarily upon aggregate supermarket movement data (IRI Infoscan) because it enables analysis of strategic interactions between brands and companies on a local market and/or national level.[1] Perhaps from a demand analysis perspective one would prefer the household level data, however, as we will see, the aggregate market level data do seem to allow estimation of demand curves for individual food products, and even brand level demand curves. For example, I will present brand level demand elasticities for carbonated soft drinks, including Coke and Pepsi, and Dr. Pepper.

The basic thesis of the paper is that the availability of these new commercial scanner data now allows significant advances in our understanding of food marketing because one can now estimate firm and brand level as well as market or commodity demand models. The analysis can be done within the framework of a differentiated product oligopoly model that incorporates "supply side" conduct that may not be competitive.

The paper is organized as follows. The next section reviews prior scanner based demand and industrial organization research to set the stage for the current research opportunities. Section three provides examples of the IRI Infoscan data for three products. They are from the University of Connecticut, Food Marketing Policy Center IRI Infoscan data set. It contains quarterly data for most branded and private label grocery products in local IRI market areas as well as the total U.S. for 1988–1992. The examples will illustrate possibilities for research including brand level demand analysis, the impact of a merger upon retail prices, and farm to retail price transmission analysis. Section Four will outline one approach to a detailed analysis of brand level demand and oligopoly price relationships. The approach provides brand level own and cross-price elasticities, supply side price reaction elasticities, and a new, more detailed measurement of market power. Currently, Lawrence Haller, Research Scientist, and Glenn Langan and Hong Wen, doctoral candidates, are working with me on a large scale project at the University of Connecticut Food Marketing Policy Center that uses IRI data to analyze several industries including soft drinks, beer, bottled water, catsup, cottage cheese, and cold breakfast cereal. The soft drink results reported here are provisional and as such should not be used for policy analyses because we are still developing our models and econometric methods. Nonetheless, they illustrate the type of new theories and empirical insights that scanner data will support.

II. Prior Research with Scanner Data

Demand Analysis

A.C. Neilsen, IRI, and their clients in the food industries have estimated brand and product category demand relationships; however, very few of these studies are public. Neilsen and IRI data have been systematically collected only since 1987 and they are available to public only for a fee if at all.[2] The Marketing Science Institute, Cambridge, Massachusetts has been a conduit for access to a limited amount of IRI panel data on coffee (Cooper and Nakanishi, 1988, p. 254).

Among agricultural economists, researchers at three different universities have collected raw scanner data from cooperating local supermarkets to estimate store level demand relationships. At Cornell, McLaughlin and Lesser (1986) studied potato sales in eight stores over a 42 week period. They report consumer response to price changes is relatively elastic.

At Texas A & M, Capps (1989) and Capps and Nayga (1991) estimate demand relationships for meat products. Capps analyzes weekly sales of steak, ground beef, roast beef, chicken, pork chops, ham and pork loin for all supermarkets of a leading chain store in the Houston market. There are 75 times series observations and the model is a single equation, double log, specification with pounds per customer as the dependent variable. It also is specified as a lagged explanatory variable to correct for autocorrelation and to account for habit persistence. Cross price effects are only captured by including an aggregate price for the other two meat categories. A non beef price, for example, is

[1] To date neither company has been able to construct a panel large enough to merge household level "consumer pull" information with the supermarket movement data. Thus, one cannot evaluate the impact of manufacturers' coupons upon product demand. IRI and Neilsen market area demographic and retail market structure variables are available on an annual basis from annual editions of Progressive Grocer, *Market Scope*.

[2] In addition the University of Connecticut purchase of quarterly Infoscan data for all major branded food products 1988–1992, the University of Vermont has purchased quadweekly Infoscan data for real and imitation maple syrup products for four IRI markets. Iskow et al. uses these data to analyze sales of maple syrup.

included in each specific beef product demand equation. Prices are assumed to be exogenous and Zellner's seemingly unrelated regression method is used to estimate parameters. Homogeneity or symmetry restrictions are not imposed or tested. There is no income variable; however, Capps notes that this chain targets high income consumers. The model contains demand shift variables including local advertising. Capps reports significant own price elasticities that are less than one except for roast beef. Given the review by Tellis (1988) of product (not commodity or industry) level demand studies, wherein own price elasticities are usually in the 1.5 to 2.5 range, the Capps result seems low to me. Most of Capps cross price elasticities are significant and positive.

At the University of Tennessee, Brooker and Eastman have produced several publications analyzing item movement and demand for products. They use weekly scanner data from five supermarkets of a chain store in a southeastern city. Brooker *et al.* (1994), for example, use a linear version of Capps and Nayga's model to estimate the demand for roast beef, steak, and ground beef. The data are aggregated across stores to produce 153 time series observations. In addition to own and cross price effects, they try to estimate own and cross elasticities for local TV advertising and feature newspaper advertisements for each product. Individual equations are estimated using ordinary least squares with some discussion of autocorrelation. Homogeneity and symmetry are not mentioned. Brooker *et al.* report significant own price elasticities ranging between -1.01 and -1.55, and significant negative, i.e., complementary, cross price elasticities for ground beef. No other cross price elasticities were significant. Own newspaper advertising effects are positive and significant as hypothesized but TV advertising only has a significant (positive) effect for roast beef. Cross advertising effects are generally not significant.

This is not the forum for critically assessing the contribution of these papers to demand analysis. They are to be credited for pioneering the use of scanner data. Yet, the advent and wide scale adoption of the Neilsen and IRI commercial data services by the industry is replacing *ad hoc* local market data collection efforts and allows much more precise and comprehensive analysis of marketing questions.

Iskow and others at the University of Vermont are currently using IRI Infoscan data to analyze demand for maple syrup (Iskow et al., 1994). They have purchased quadweekly data for a four year period (1988–1991) for four standard Metropolitan Statistical Areas in the Northeastern United States. It includes prices, quantities, and promotional activities for price and imitation maple syrup brands. Iskow et al. estimate price, income, and promotion elasticities for five leading brands. They use a double log specification and Zellners seemingly unrelated regression method with autoregressive disturbances. Prices are assumed to be exogenous, and homogeneity and symmetry restrictions are not considered. Iskow et al. report significant negative own price elasticities at the brand level and find that larger share brands have lower elasticities. They report positive and significant cross price and promotional effects.

Industrial Organization Analysis

Even less work on the firm strategies in oligopolistic markets has been done with scanner data, because such work requires information across several firms and/or markets as well as products. One can't use samples of a few supermarkets from one firm in one market. Using the IRI Infoscan Haller (1993, 1994) has analyzed the relationship between brand market share and price.[3] All brands are pooled across local markets and over quarters for 1988–1992. Given this panel data, a fixed effect estimation approach is used. For cottage cheese he reports that brands that have larger shares have significantly higher prices. For cooperative brands, however, there is no significant share price relationship and cooperative presence in a local market tends to lower proprietary cheese brand prices. Farmer cooperatives seem to be volume rather than profit oriented, possibly to move members' product and reduce milk surpluses.

Haller also has done work on the catsup industry (1994). Cotterill and Haller (1994) describe the local market structure and conduct of the ice cream, butter, margarine, cottage cheese, and fluid milk industries.

Chevalier (1993, 1994) uses IRI data in a very different and unique study. She develops a model of oligopoly that incorporates financial leverage. Depending on how leverage is modeled, she demonstrates in a duopoly framework that debt can transform a firm into a tough (lowers price) or soft (raises price) competitor. The actual outcome is an empirical question. Chevalier tests her theories on the supermarket industry where many leading firms underwent leveraged buyouts during the 1980s. As an MIT graduate student she was able,

[3] Although the data are retail data, note that the firms under analysis are food manufacturers. Control variables for retail markups are included in these models.

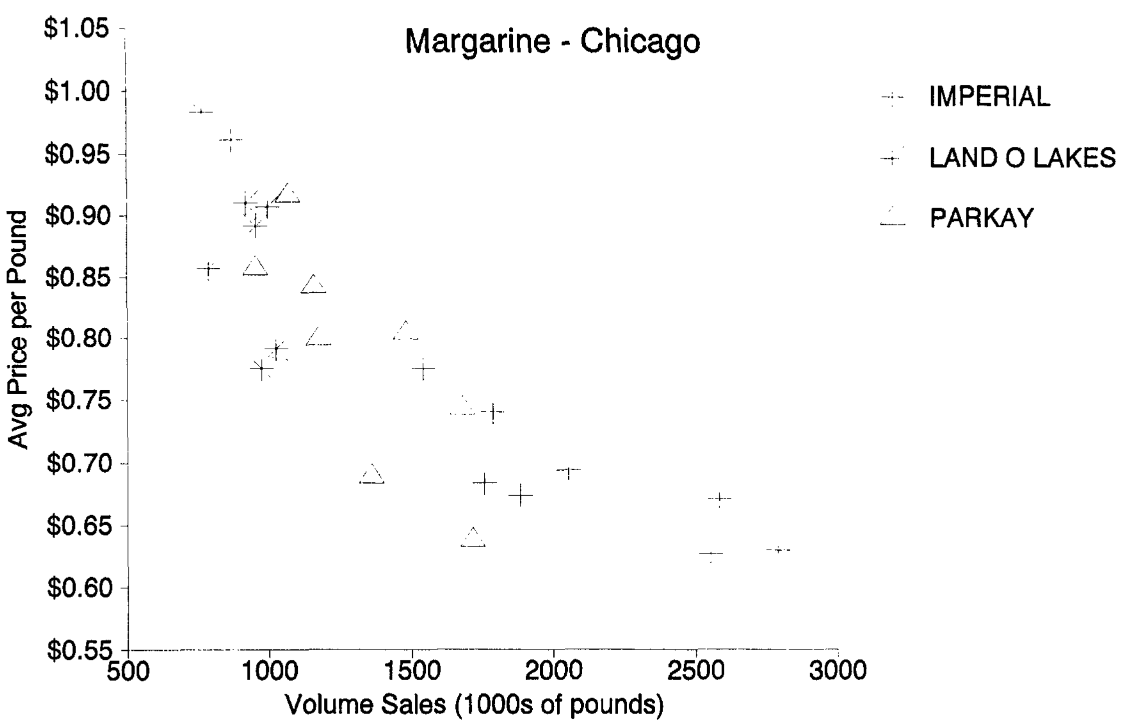
through an MIT professor who sits on the IRI Board of Directors, to obtain Infoscan data for individual chains in local IRI markets. Normally, IRI refuses to identify individual chains and provides only market area price for a particular product. Chevalier reports that leveraged supermarket chains did, *ceteris paribus*, charge significantly higher prices than non-leveraged chains in local markets. In fact she found that for 10 of the 17 local markets she analyzed all LBO chains were higher priced than non-LBO chains (1994, p. 23). Her model, however, does not include retail cost and market structure variables such as firm market share or retail concentration ratios. One wonders how their inclusion would affect her results.

III. Specific Examples of IRI Data

As the work by Haller and Chevalier suggest, the market level commercial scanner data bases, Neilsen Scantrak or IRI Infoscan, are the most appropriate to analyze both demand and strategic interactions. Often a chart that illustrates relatively simple relationships can communicate more about a topic than equations or words. This section contains a set of charts to illustrate different research topics that the IRI Infoscan data can address. Figure 1 displays the quarterly price and volume movement data for the three leading brands of margarine in Chicago for 1988–1991. The IRI Infoscan data base has 47 such local markets in 1988 and the number increases to 65 in 1992. These data for Chicago clearly seem to trace out demand relationships for each brand. If one ignores the fact that these three brands are being sold simultaneously and pools the data to estimate a demand curve for "branded" margarine, one clearly obtains a strong hyperbolic relationship.

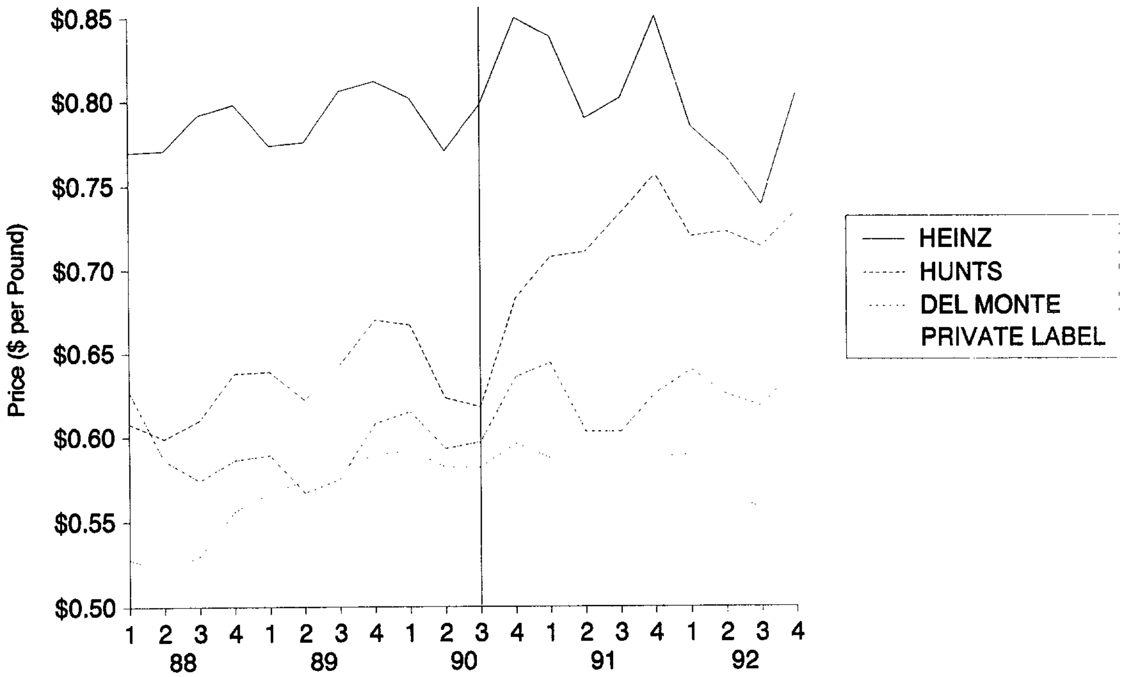
Since this is market and not household level data one probably should not assume price to be exogenous. In the next section we will endogenize price. Here, however, if one examines data for one city over time, the assumption of Capps and Nayga, Brooker and Eastman and Iskow et al. that prices are exogenous seems appropriate at least as a working assumption. Market demand may be rather stable and exogenous shocks to an unstable supply curve may identify a demand curve.

Figure 2 illustrates the impact of the ConAgra acquisition of Beatrice Foods upon Hunt's Catsup, a leading Beatrice brand. The vertical line in Figure 2 indicates the date of the merger. Prior to the merger, the pricing of Hunt's Catsup tended to follow industry and seasonal patterns. After the merger Hunt's Catsup follows a distinctly different



Source: Cotterill and Haller (1994), IRI Infoscan data, Food Marketing Policy Center, Univ. of Connecticut

Figure 1. Price and Volume Sales: Quarterly 1988–1989



Source: Haller (1994), IRI Infoscan data, Food Marketing Policy Center, Univ. of Connecticut

Figure 2. Catsup Prices: Total U.S.

and steadily increasing price trend. Data from Leading National Advertisers indicate advertising for Hunt's Catsup was cut, and Hunt's market share decreased from 22.2 percent in 1989 to 20.1 percent in 1992.[4] The merger seems to have triggered a unilateral exercise of market power; other firms, including the leader Heinz, did not follow Hunt's price lead.

Figure 3 tracks another major recent event in food markets. During late 1989 the Minnesota-Wisconsin price for manufacturing milk skyrocketed from $10.98 in May to $14.93 per hundredweight in December because of a temporary milk short fall. In 1990 it plummeted as farmers increased production rapidly and substantial milk surpluses reappeared. Figure 3 displays prices indices (quarter 1 1988 equals 100) for the Minnesota-Wisconsin milk price, private label and Kraft American Cheese. These indices allow us to examine how farm level price changes are transmitted to the retail level. Retail prices tend to lag farm prices by a quarter, and retail price increases are lower than milk prices prior to the peak Minnesota-Wisconsin price. This is to be expected since raw milk is only one cost factor in retail cheese prices and other cost factors tend to be less volatile.[5] With these caveats, farm and retail price changes seem to track each other quite closely prior to the peak in the Minnesota-Wisconsin price series. Thereafter, they diverge. Private label cheese price follow Minnesota-Wisconsin milk prices down with a distinct lag. The fact that they do not drop as much represents the converse of the fact that they do not increase as rapidly when raw milk prices rise.

Price conduct in Figure 3 for Kraft American Cheese, is distinctly different from private label conduct. Retail price continues to rise for several quarters after the Minnesota-Wisconsin milk price break in the fourth quarter of 1989. Kraft's conduct did not go unnoticed and resulted in congressional hearings on cheese prices. Since the data exist at the brand level and for major local markets as well as the total U.S., one can analyze geographic and brand or firm specific price transmission. Clearly, more detailed analysis of the IRI data can contribute to our understanding of the farm to retail price transmission process.

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[4] See Haller (1994a) for a detailed analysis of catsup pricing and Haller (1994b) for a detailed analysis of the impact of the ConAgra acquisition upon the price and advertising strategy of Beatrice's leading food brands.

[5] If raw milk costs account for only 50 percent of retail cheese price then a 20 percent increase in milk price, *ceteris paribus*, produces only a 10 percent increase in cheese price.

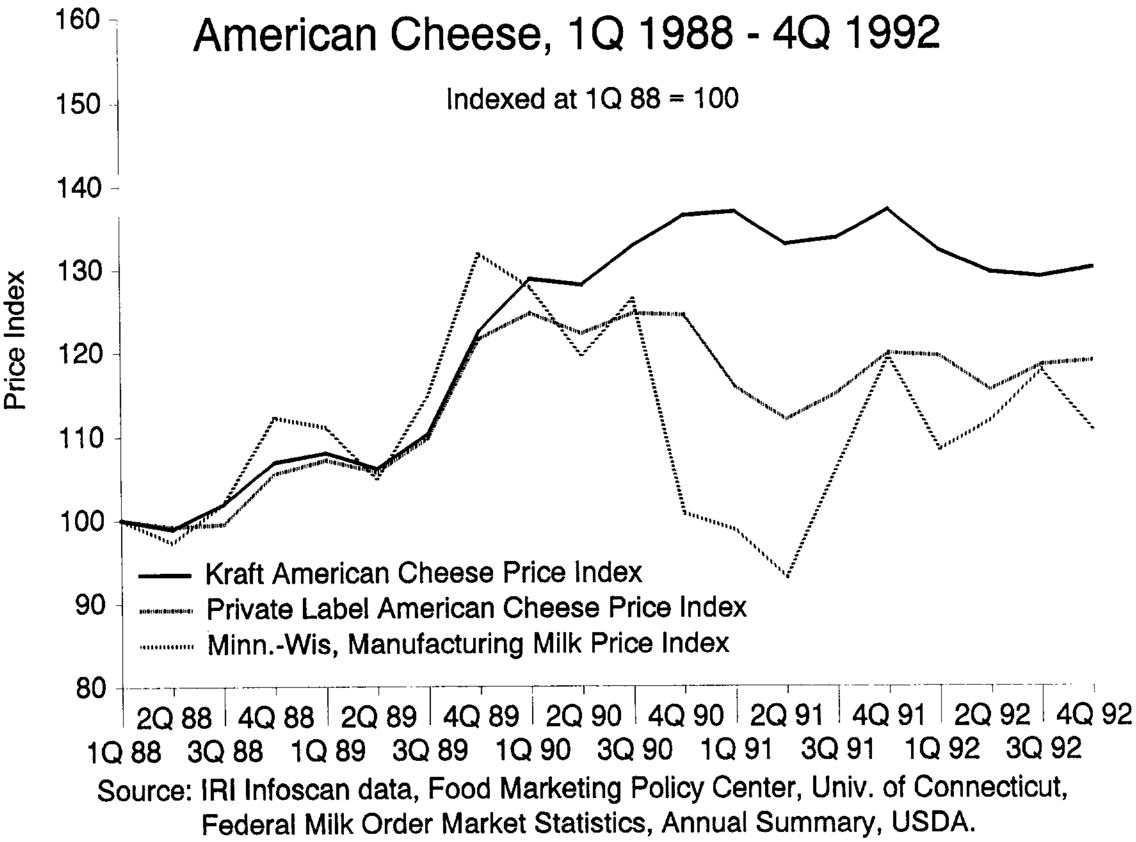

Figure 3. Price Index Trends: Total U.S.

IV. Brand Level Demand Analysis in a Differentiated Oligopoly

Neoclassical demand analysis usually focuses upon distinctly different commodities, for example, butter versus margarine or beef versus pork. Firm or brand level demand analysis introduces the organization of the industry in direct and unavoidable fashion. The demand estimation problem becomes particularly problematic when the industry is an oligopoly that sells differentiated products. Endogenizing prices is not sufficient. Price interdependence between brands complicates the specification of supply relationships. One cannot assume, for example, that the price of Pepsi remains constant when the price of Coke changes due to shift in a cost variable or a desire for a higher profit margin. Some degree of price followship or tacit collusion often exists among brands in concentrated oligopolies.

Baker and Breshnahan (1985) were the first industrial organization economists to consider carefully the potential benefits of combining demand and industrial organization concepts to analyze pricing in a differentiated oligopoly. Their approach, however, uses residual demand models that rely upon fairly restrictive supply side behavioral assumptions (Froeb and Werden 1991).

Brand level analysis of demand and market power can be based upon a more general theory, that I will present here. Assume that an industry is differentiated and that Bertrand competition, occurs, i.e. price is the strategic variable.[6] Then the demand for brand 1 in this industry of n brands is:

$$q_1 = q_1(p_1 \ldots p_n, D)$$

Where:

q_1 = the quantity of brand 1
p_1 = piece of brand $i = 1 \ldots n$
D = a vector of demand shift variables including income.

Taking the derivative of this equation, with respect to p_1, using the chain rule to account for oligopo-

[6] See, for example, Deneckere and Davidson (1985), Scherer and Ross (1990, p. 199–206).

listic price interdependence, and some algebraic manipulation yield the following formula for the observable price elasticity of demand.

$$\eta_1^0 = n_{11} + \sum_{i=2}^{N} \eta_{1i}\epsilon_{i1}$$

where:

η_1^0 = observable price elasticity for brand 1
η_{11} = partial own price elasticity of demand
η_{1i} = firm 1 cross price elasticity with respect to p_i
ϵ_{i1} = rivals' price response elasticity (the percent change in p_i when p_1 changes one percent).[7]

Baker and Breshnahan commence their analysis with a similar formula, however, they analyze perceived as opposed to actual observable demand elasticities because they consider ϵ_{i1} to be brand one manager's perceived or conjectured price response by rival i to a change in brand one's price. Later to estimate their model they implicitly assume conjectures are consistent, i.e., brand one manager's conjecture about a rival's price response is equal to the actual observed price reaction by that rival when brand one price changes. For clarity I make the assumption explicit and up front.

Note that a brand's observable own price elasticity has two general components. The first is the familiar partial own price elasticity. In industrial organization analysis we describe this as the nonfollowship demand elasticity because it quantifies the impact on brand demand when the price increases and no rival brands prices change. The nonfollowship price elasticity measures the unilateral market power of the brand (Federal Merger Guidelines, Section 2.11). The second component of the actual price elasticity measures the coordinated market power component of a brand's observable elasticity. If other brand managers behave in a tacitly collusive fashion and follow the elevation (or reduction) of brand one's price, then the ϵ_{i1} in equation 1 are positive. Assuming all products in the industry are substitutes, i.e., different brands compete with each other for customers, the cross price elasticities, ϵ_{i1}, are also positive. Thus to the extent that coordinated market power exists, it makes the observed own price elasticity less elastic than the partial own price elasticity.

Two special cases are worth mentioning. The first is when all ϵ_{i1} are zero and is the nonfollowship case discussed above. The second special case is when tacit collusion is perfect. Given the consistent conjunctures assumption, all ϵ_{i1} are one. When tacit collusion is perfect the observed own price elasticity is the partial price elasticity plus the sum of the cross price elasticities which is positive, so demand is less elastic.

Figure 4 illustrates these demand relationships for each individual brand. I have used the elasticities to draw a linear approximation at around point P_1 Q_1 of what may be nonlinear demand curves.[8] Assume the market is in equilibrium at P_1 Q_1 and the managers for brand 1 decide to raise price to P_2. In this example observed output decreases to Q_0. If there was perfect tacit collusion, it would have declined only to Q_F and if there was no tacit collusion output would have declined to Q_{NF}. One constructs a measure of the degree of unilateral market power by dividing the slope of the nonfollowship demand curve by the slope of the followship demand curve. This is the Rothschild Index (Greer p. 99). A more general definition that flows from my analysis is the ratio of the followship elasticity, η_1^F, to the nonfollowship elasticity, η_{11}.

$$\text{Rothschild Index (RI)} = \frac{\eta_1^F}{\eta_{11}}$$

$$\text{and O} \leq RI \leq 1$$

Under perfect competition the slope of the nonfollowship demand curve would be zero (η_{11} is infinitely negative) and the Rothschild Index is zero. If the nonfollowship demand curve is identical to the followship then all cross price elasticities of demand must be zero and the brand effectively has a monopoly position.

One can define a second measure of observed (i.e., combined unilateral and coordinated) market power, by dividing the slope of the observed demand by the followship demand. Again, a more general definition would be the ratio of the followship elasticity, η_1^F, to the observed elasticity, η_1^0. If there is no unilateral or coordinated power this index is zero and it ranges to one if observed demand equals followship demand. This index is new to the field and I chose to call it the O Index. Thus, we have:

$$\text{O Index (OI)} = \frac{\eta_1^F}{\eta_1^0}$$

$$\text{and O} \leq RI \leq OI \leq I$$

[7] In certain price reaction models it is possible to measure both conjectures about prices and actual price reactions and to test for consistent (Liang).

[8] Constant elasticity demand curves are nonlinear and other functional forms such as the double log and almost ideal demand system also produce nonlinear demand curves.

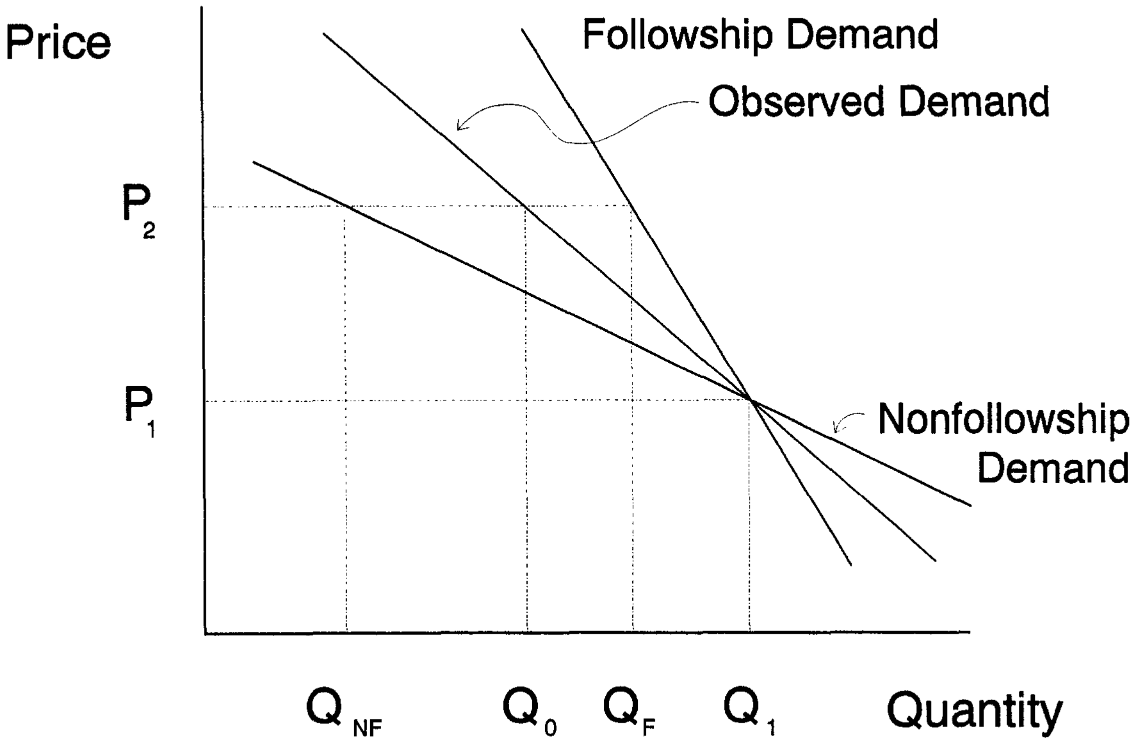

Figure 4. Theoretical Demand Relationships for a Brand in a Differentiated Oligopoly (linear approximation).

The O Index of observed market power is always greater than or equal to the Rothschild Index of unilateral market power because it includes coordinated market power.

Finally one can decompose the observed market power into the proportion that is due to coordinated market power. I define the Chamberlin Quotient (CQ) as:

$$CQ = 1 - \frac{\textit{Rothschild Index}}{\textit{O Index}} = 1 - \frac{\eta_{11}}{\eta_1^0}$$

$$0 \leq CQ \leq 1$$

It gives the proportion of observed market power that is due to tacit collusion. Again this index is new to the industrial organization field, and is named in recognition of Edwin Chamberlin, the economist who gave the English language the word "oligopoly" and who provided the first theoretical analysis of tacit collusion (1933).

When discussing the Rothschild Index Greer states:

> . . . the Rothschild Index provides only one answer to the question "How market power should be measured?" And it is not necessarily the best answer. Its greatest shortcoming is its purely theoretical nature. In practice it is not possible to estimate the index accurately . . . [Greer 1990 p. 101].

Since the Rothschild index provides only "one answer," there is need for additional measures such as the O and Chamberlin indices. Also, this paper demonstrates that the IRI or Neilsen brand level data now allow precise estimation of these indices.

To illustrate I will present provisional estimates of the own price, cross price and price response elasticities and the Rothschild, O, and Chamberlin Indices for a set of competing branded products. This work employs the linear approximate almost ideal demand system (LA/AIDS) as developed by Deaton and Muellbauer (1980) to model the regular soft drink brands.[9] In this paper I assume that the regular carbonated soft drink group is a relevant product market. Although I actually estimate a demand system for nine regular soft drink categories, for expository purposes assume the system

[9] Ultimately, regular and diet demand system estimates will be part of a two stage budget framework to estimate cross price effects between the two groups.

has only two brands. The LA/AIDS demand equations are:

$$s_1 = \partial_1 + \partial_{11}\ln p_1 + \partial_{12}\ln p_2 + \beta_1\log\left(\frac{X}{p}\right) + \beta_{12}D$$

$$s_2 = \partial_2 + \partial_{21}\ln p_1 + \partial_{22}\ln p_2 + \beta_2\log\left(\frac{X}{p}\right) + \beta_{22}D$$

where:

s_i = the market share of brand $i = 1, 2$
p_i = the price of brand $i = 1, 2$
X = the expenditures on the two brand category
$\ln p = s_1\ln p_1 + s_2\ln p_2$ (Stone's linear approximation price index)
D = a vector of demand shift variables

The LA/AIDS is a specific functional form for the general demand equations presented as equations 1 and 2. The linear approximate form substitutes Stone's price index for a more general weighted price index because that index requires non-linear estimation. Deaton and Muellbauer demonstrate that LA/AIDS model has desirable aggregation properties and is a preferred functional form for analyzing market level data. The homogeneity and symmetry restrictions of consumer demand theory can be readily imposed. In the two good models they are:

Homogeneity: $\partial_{11} + \partial_{12} = 0, \partial_{21} + \partial_{22} = 0$

Symmetry: $\partial_{21} = \partial_{12}$

Green and Alston (1990) provide an algorithm for computing own and cross price elasticities from the LA/AIDS model. Chalfant (1987) provides a method for computing standard errors for elasticities. Strictly speaking the vector of demand shift variables, D, should be introduced in a non linear fashion as part of a generalized expenditure index, however linear estimation is possible with the current specification so we retain it.

Turning now to the supply side of the model, each oligopolist seeks to maximize profits. We assume Bertrand competition, i.e., price not quantity is the strategic choice variable. In the duopoly example one has:

$$MAX\pi_i = p_iq_i = c_i(q_i, r_{-i})\ for\ i = 1, 2$$
$$wrt\ p_i$$

where:

$c_i(q_i, \underset{\rightarrow}{r}_{-i})$ the brand i total cost function
$(\underset{\rightarrow}{r}_{-i})$ is brand i input price vector

One can use the first order condition and the brand demand curve to solve for each brand's price reaction function. Liang (1989) provides a linear example that can readily be extended to the double log specification. Derivation of the exact functional form of the price reaction curves for the LA/AIDS model is not feasible, however Hong Wen, Lawrence Haller and I have made some progress for the AIDS model with its more general price index. Our basic results indicate that the following functional form is appropriate.

$$\ln p_1 = \epsilon_{10} + \epsilon_{12}\ln p_2 + \epsilon_{13}EXP + \epsilon_{14}s_1 + \underset{\rightarrow}{\epsilon}_{15}\underset{\rightarrow}{D} + \underset{\rightarrow}{\epsilon}_{16}\underset{\rightarrow}{r}_1$$

$$\ln p_2 = \epsilon_{20} + \epsilon_{21}\ln p_1 + \epsilon_{23}EXP + \epsilon_{24}s_2 + \underset{\rightarrow}{\epsilon}_{25}\underset{\rightarrow}{D} + \underset{\rightarrow}{\epsilon}_{26}\underset{\rightarrow}{r}_2$$

Since the price reaction functions are logarithmic in prices, the coefficients on the other brand's price, $\epsilon_{12}, \epsilon_{21}$, are the price response elasticities.

In the two brand example the two demand equations and the two price reaction equations seem to constitute a four equation simultaneous system with brand market shares, s_1 and s_2 and prices, p_1 and p_2, are endogenous variables. However, the adding up property of the LA/AIDS demand system means that for n demand equations one estimates $n - 1$, and recovers the parameter estimates for the n^{th} equation from them. Heuristically, since the market shares of the brands in our two brand example sum to 1, if one has an estimate of one share, one also knows the other. Thus, in the two brand example one actually estimates a three equation simultaneous system with three endogenous variables.

Let us now turn to an empirical example for regular soft drinks. The seven leading brands are Coke, Pepsi, Royal Crown Cola (RC), Sprite, Seven-Up (7-Up), Doctor Pepper (Dr Pep), Mountain Dew (Mt Dew). These brands plus private label regular soda (PrivLab) averaged 75 percent of regular soft drink sales in 1988–1990. All other soft drink brands are aggregated into a brand labeled *allother*. The resulting simultaneous equation system that is estimated includes (nine minus one) eight demand equations and nine price reaction equations with 17 endogenous share and price variables. Homogeneity and symmetry restrictions are imposed on the demand system.

Appendix Tables A1–A3 report the variables used in the analysis, system specification and descriptive statistics. The data set includes 12 quarterly observations (1988–1990) for 45 IRI local market areas. As such, it is a balanced panel data set with 540 observations. An error components

Table A1. System of Demand and Price Reaction Equations, Regular Carbonated Soft Drinks

$$
\begin{aligned}
Shr_{Coke} = \alpha_0 &+ \alpha_1 P_{Coke} + \alpha_2 P_{Pepsi} + \alpha_3 P_{RC} + \alpha_4 P_{Sprite} + \alpha_5 P_{7Up} + \alpha_6 P_{DrPep} \\
&+ \alpha_7 P_{MtDew} + \alpha_8 P_{PrivLab} + \alpha_9 P_{AllOther} + \alpha_{10} ExpenditureX + \alpha_{11} Feature_{Coke} \\
&+ \alpha_{12} Display_{Coke} + \alpha_{13} RelTVAdv_{Coke} + \alpha_{14} Temperature
\end{aligned}
$$

$$
\begin{aligned}
Shr_{Pepsi} = \beta_0 &+ \beta_1 P_{Coke} + \beta_2 P_{Pepsi} + \beta_3 P_{RC} + \beta_4 P_{Sprite} + \beta_5 P_{7Up} + \beta_6 P_{DrPep} \\
&+ \beta_7 P_{MtDew} + \beta_8 P_{PrivLab} + \beta_9 P_{AllOther} + \beta_{10} ExpenditureX + \beta_{11} Feature_{Pepsi} \\
&+ \beta_{12} Display_{Pepsi} + \beta_{13} RelTVAdv_{Pepsi} + \beta_{14} Temperature
\end{aligned}
$$

$$
\begin{aligned}
Shr_{RC} = \gamma_0 &+ \gamma_1 P_{Coke} + \gamma_2 P_{Pepsi} + \gamma_3 P_{RC} + \gamma_4 P_{Sprite} + \gamma_5 P_{7Up} + \gamma_6 P_{DrPep} \\
&+ \gamma_7 P_{MtDew} + \gamma_8 P_{PrivLab} + \gamma_9 P_{AllOther} + \gamma_{10} ExpenditureX + \gamma_{11} Feature_{RC} \\
&+ \gamma_{12} Display_{RC} + \gamma_{13} RelTVAdv_{RC} + \gamma_{14} Temperature
\end{aligned}
$$

$$\vdots$$

$$
\begin{aligned}
[Shr_{AllOther} = \delta_0 &+ \delta_1 P_{Coke} + \delta_2 P_{Pepsi} + \delta_3 P_{RC} + \delta_4 P_{Sprite} + \delta_5 P_{7Up} + \delta_6 P_{DrPep} \\
&+ \delta_7 P_{MtDew} + \delta_8 P_{PrivLab} + \delta_9 P_{AllOther} + \delta_{10} ExpenditureX + \delta_{11} Feature_{AllOther} \\
&+ \delta_{12} Display_{AllOther} + \delta_{13} RelTVAdv_{AllOther} + \delta_{14} Temperature]
\end{aligned}
$$

$$
\begin{aligned}
P_{Coke} = \kappa_0 &+ \kappa_1 Shr_{Coke} + \kappa_2 Pepsi + \kappa_3 P_{RC} + \kappa_4 P_{Sprite} + \kappa_5 P_{7Up} + \kappa_6 P_{DrPep} + \kappa_7 P_{MtDew} \\
&+ \kappa_8 P_{PrivLab} + \kappa_9 P_{AllOther} + \kappa_{10} ExpenditureX + \kappa_{11} Temperature + \kappa_{12} Feature_{Coke} \\
&+ \kappa_{13} Display_{Coke} + \kappa_{14} Unit/Vol_{Coke} + \kappa_{15} RelTVAdv_{Coke} + \kappa_{16} SupMkt/GrocSale \\
&+ \kappa_{17} MktCR4 + \kappa_{18} Population + \kappa_{19} Sweetner + \kappa_{20} CokeCaptive
\end{aligned}
$$

$$
\begin{aligned}
P_{Pepsi} = \lambda_0 &+ \lambda_1 Shr_{Pepsi} + \lambda_2 P_{Coke} + \lambda_3 P_{RC} + \lambda_4 P_{Sprite} + \lambda_5 P_{7Up} + \lambda_6 P_{DrPep} + \lambda_7 P_{MtDew} \\
&+ \lambda_8 P_{PrivLab} + \lambda_9 P_{AllOther} + \lambda_{10} ExpenditureX + \lambda_{11} Temperature + \lambda_{12} Feature_{Pepsi} \\
&+ \lambda_{13} Display_{Pepsi} + \lambda_{14} Unit/Vol_{Pepsi} + \lambda_{15} RelTVAdv_{Pepsi} + \lambda_{16} SupMkt/GrocSale \\
&+ \lambda_{17} MktCR4 + \lambda_{18} Population + \lambda_{19} Sweetner + \lambda_{20} PepsiCaptive
\end{aligned}
$$

$$
\begin{aligned}
P_{RC} = \psi_0 &+ \psi_1 Shr_{RC} + \psi_2 P_{Coke} + \psi_3 P_{Pepsi} + \psi_4 P_{Sprite} + \psi_5 P_{7Up} + \psi_6 P_{DrPep} + \psi_7 P_{MtDew} \\
&+ \psi_8 P_{PrivLab} + \psi_9 P_{AllOther} + \psi_{10} ExpenditureX + \psi_{11} Temperature + \psi_{12} Feature_{RC} \\
&+ \psi_{13} Display_{RC} + \psi_{14} Unit/Vol_{RC} + \psi_{15} RelTVAdv_{RC} + \psi_{16} SupMkt/GrocSale \\
&+ \psi_{17} MktCR4 + \psi_{18} Population + \psi_{19} Sweetner
\end{aligned}
$$

$$\vdots$$

$$
\begin{aligned}
P_{AllOther} = \omega_0 &+ \omega_1 Shr_{AllOther} + \omega_2 P_{Coke} + \omega_3 P_{Pepsi} + \omega_4 P_{RC} + \omega_5 P_{Sprite} + \omega_6 P_{7Up} + \omega_7 P_{DrPep} \\
&+ \omega_8 P_{MtDew} + \omega_9 P_{PrivLab} + \omega_{10} ExpenditureX + \omega_{11} Temperature + \omega_{12} Feature_{AllOther} \\
&+ \omega_{13} Display_{AllOther} + \omega_{14} Unit/Vol_{AllOther} + \omega_{15} RelTVAdv_{AllOther} + \omega_{16} SupMkt/GrocSale \\
&+ \omega_{17} MktCR4 + \omega_{18} Population + \omega_{19} Sweetner
\end{aligned}
$$

and three stage least squares estimation routine was used to estimate the model's parameters.[10]

Table 1 reports own and cross price elasticities and significance levels. Elasticities are computed from the LA/AIDS coefficient estimates using Green and Alston's formula *iii* (1990, p. 494). Significance levels are based upon standard errors computed using the Chalfont (1987) method. Coke's partial own price elasticity is -1.496. Pepsi is somewhat more elastic at -1.868. These measures of unilateral market power, i.e., nonfollowship demand, indicate that if Coke or Pepsi raise price and no other brand follows, their revenue declines. Such a price increase may however still be profitable. If profits are 10 percent of sales then increasing price 10 percent doubles the profit margin of an output that is only 14.9 percent lower for Coke or 18.6 percent lower for Pepsi.[11]

Note that the cross price elasticities for Coke and Pepsi are .35 and significant. The implication is if these brands tend to follow each other on price (tacitly collude) then the observed own price elasticity will be less than the nonfollowship elasticity reported in Table 1. For example, if there is fully collusive pricing between Coke and Pepsi (and all other brands do not follow their lead) then Coke's observed price elasticity would be $-1.496 + .355 = 1.141$. Pepsi's would be $-1.86 + .353 = -1.507$. A merger between these two brands is equivalent to establishing fully collusive pricing, so if they actually were practicing nonfollowship pricing before the merger, it clearly increases their market power.

Briefly examining some other brands, Royal

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[10] This is a random rather than fixed effects approach. Since many of our exogenous variables are essentially cross section variables, e.g., market area population, in Table A1, a fixed effects approach is not applicable. It wipes out all cross section variables (Hausman and Taylor 1981).

[11] See Langan and Cotterill (1994) for a more explicit example that uses actual company profit sales ratios. The basic point still holds.

Table A2. Description of Variables and Related Notes

SHR_{Coke}	the percent of regular carbonated soft drink expenditures spent on Coca Cola
Shr_{Pepsi}	the percent of regular carbonated soft drink expenditures spent on Pepsi
Shr_{RC}	the percent of regular carbonated soft drink expenditures spent on RC
Shr_{Sprite}	the percent of regular carbonated soft drink expenditures spent on Sprite
Shr_{7Up}	the percent of regular carbonated soft drink expenditures spent on 7Up
Shr_{Drpep}	the percent of regular carbonated soft drink expenditures spent on Dr Pepper
Shr_{MtDew}	the percent of regular carbonated soft drink expenditures spent on Mountain Dew
$Shr_{PrivLab}$	the percent of regular carbonated soft drink expenditures spent on Private Label
$Shr_{AllOther}$	the percent of regular carbonated soft drink expenditures spent on All Other Brands
P ___	natural log of price of ________ brand
ExpenditureX	natural log of (regular carbonated soft drink expenditures divided by a price index*)
Feature ___	percent of ________ brand's volume sold with feature advertising
Display ___	percent of ________ brand's volume sold with displays and point of purchase promotions
Unit/Vol ___	number of units ________ brand divided by the volume sold of ________ brand
RelTVAd ___	________ brand's national TV advertising as a percent of the leader
Temperature	mean temperature in local market for a given quarter
SupMkt/GrocSale	the percentage of all grocery sales in local market made by supermarkets
MktCR4	percentage of all grocery sales in local market made by top 4 grocery chains
Sweetner	price of most frequently used sweetner during study period (higher fructose corn syrup)
Population	population in local market
CokeCaptive	binary variable to indicate a Coca Cola Co.-owned bottler for the local market
PepsiCaptive	binary variable to indicate a Pepsi Co.-owned bottler for the local market

*Stone's linear approximate price index was used, i.e., (supra, p. 316)

Crown Cola which is priced significantly below the leading regular soft drink brands and marketed as a "value" brand (Duvall 1993, p. 60, 69) is the most elastic brand (−2.50). Private label regular soda performs in a very strange fashion. One would expect it also to be very elastic but it is the most inelastic brand, −.94. This seems to suggest that private label soda has more unilateral market power than all other brands and could increase both revenues and profits by increasing prices. Private label also has a fairly large negative cross price elasticity with RC and RC has a huge, −.758, cross price elasticity with private label.[12]

They clearly are strong complements. This suggests that they should be aggregated into a common "value brand" for the analysis of market power. The resulting own price elasticity probably could be more in line with the others.

Significant complements rather than substitute relationships also crop up elsewhere in Table 1. Sprite, a clear soda, for example, has a negative (complementary) cross price elasticity (−.090) in the Coke demand equation and Coke is a complement in the Sprite equation. Since these brands are both produced by the Coca Cola Company the results do provide some evidence on the extent to which companies position and market products as complements rather than substitutes. Mountain Dew, a Pepsico brand, however has a positive (substitute) cross price elasticity in the Pepsi demand equation (row 2 of Table 1).

Complementary demand relationships were not expected among these ostensibly competing regular soft drink products. Intuitively what seems to occur is that when Coke, for example, lowers its price shoppers are attracted to the aisle and pick up some Sprite as a complementary product to provide "variety" or a clear soda for the uncola crowd. Other strong complementary relationships exist for the following two pairs: Seven-Up and private label, and Mountain Dew and Dr. Pepper.

Table 2 presents estimates of the price reaction function elasticities for each brand. Reading across row one, one can see that a 1 percent increase in Pepsi price increases Coke price by .506 percent. A similar percentage point increase for RC only raises Coke price .079 percent; for Sprite, Coke price increases .177 percent; and for Seven-Up, Coke increases .129 percent.

Note that increases in Dr. Pepper, Mountain Dew and "all others" result in significantly lower Coke prices. Negative price reaction coefficients were not expected. In a linear demand and reaction

[12] The imposition of symmetry requires that the cross price coefficients in the LA/AIDS model be equal. Cross price elasticities can and do differ when brands have different market shares.

Table A3. Descriptive Statistics

Variable	Mean	St. Dev.	Variance	Min	Max	Variable	Mean	St. Dev	Variance	Min	Max
Share:						Displays:					
Coke	0.249	0.0831	0.0069	0.104	0.496	Coke	68.56	10.725	115.03	33.70	92.29
Pepsi	0.244	0.0616	0.0038	0.089	0.386	Pepsi	68.43	10.238	104.81	32.27	91.95
RC	0.020	0.0148	0.0002	0.001	0.085	RC	44.86	20.404	416.32	0.00	88.42
Sprite	0.040	0.0138	0.0002	0.015	0.095	Sprite	54.61	14.141	199.97	12.64	89.75
7-Up	0.052	0.0248	0.0006	0.015	0.141	7-Up	46.55	15.084	227.54	4.58	80.63
DrPep	0.038	0.0349	0.0012	0.003	0.217	DrPep	37.64	20.429	417.36	0.00	85.23
MtDew	0.031	0.0233	0.0005	0.005	0.111	MtDew	39.44	21.422	458.88	0.10	85.15
PrivLab	0.076	0.0464	0.0022	0.002	0.264	PrivLab	29.80	14.079	198.21	1.09	68.57
AllOthr	0.250	0.0702	0.0049	0.107	0.450	AllOthr	29.63	9.459	89.47	9.48	56.54
Price:						Relative National Advertising					
Coke	3.72	0.3072	0.0943	2.80	4.93	Coke	0.897	0.1515	0.0229	0.557	1.000
Pepsi	3.66	0.3826	0.1464	2.67	5.46	Pepsi	0.843	0.1962	0.0385	0.486	1.000
RC	3.30	0.4187	0.1753	2.25	5.14	RC	0.046	0.0426	0.0018	0.003	0.119
Sprite	3.63	0.3130	0.0980	2.79	4.92	Sprite	0.314	0.1488	0.0221	0.028	0.505
7-Up	3.79	0.3593	0.1291	2.85	5.05	7-Up	0.298	0.1644	0.0270	0.095	0.567
DrPep	3.99	0.4245	0.1802	2.85	5.36	DrPep	0.252	0.1348	0.0182	0.013	0.481
MtDew	3.93	0.4210	0.1773	2.86	5.32	MtDew	0.071	0.0536	0.0029	0.001	0.185
PrivLab	2.34	0.2516	0.0633	1.66	3.19	PrivLab	—	—	—	—	—
AllOthr	3.60	0.4019	0.1615	2.10	5.01	AllOthr	0.015	0.0075	0.0001	0.006	0.032
Feature Ads:						Units per Volume:					
Coke	6.99	4.999	24.987	0.26	31.84	Coke	2.26	0.330	0.1090	1.16	2.84
Pepsi	7.30	5.278	27.862	0.34	40.47	Pepsi	2.25	0.333	0.1107	1.10	2.87
RC	6.44	6.792	46.133	0.00	38.31	RC	2.47	0.363	0.1321	1.29	3.78
Sprite	12.08	7.253	52.606	0.61	44.23	Sprite	2.35	0.275	0.0756	1.43	3.35
7-Up	7.37	5.981	35.768	0.00	29.54	7-Up	2.52	0.250	0.0627	1.49	3.28
DrPep	8.48	7.476	55.897	0.00	41.98	DrPep	2.36	0.289	0.0838	1.27	2.82
MtDew	13.95	9.157	83.847	0.00	60.82	MtDew	2.28	0.342	0.1171	1.09	2.85
PrivLab	11.98	9.018	81.324	0.00	55.30	PrivLab	5.70	2.142	4.5894	2.73	13.24
AllOthr	12.63	6.395	40.894	0.91	42.48	AllOthr	3.61	0.836	0.6995	2.17	7.10
ExpenditureX	4.45	0.928	0.862	2.48	7.57	Sweetner	20.73	3.092	9.56	14.40	25.50
Temperature	58.09	15.605	243.52	18.80	91.64	Population:	3.1E+6	2.9E+6	8.4E+12	6.8E+5	1.6E+7
SpMkt/GrcSale:	77.17	5.977	35.72	64.50	95.30	CokeCaptive	0.437	0.496	0.246	0.0	1.0
Market CR4:	62.86	13.580	184.41	23.90	88.10	PepsiCaptive:	0.522	0.500	0.250	0.0	1.0

Table 1. Own and Cross Price Elasticities for Regular Carbonated Soft Drinks[1]

	Coke	Pepsi	RC	Sprite	7Up	DrPep	MtDew	PrivLab	AllOther
Coke	−1.496**	0.355**	0.063⁺	−0.090**	0.078⁺	−0.009	−0.021	0.031	0.016
Pepsi	0.353**	−1.868**	0.009	0.052⁺	0.120**	0.102**	0.076⁺	−0.002	0.049
RC	0.909*	0.251	−2.508**	0.205	0.457⁺	−0.121	0.394⁺	−0.758**	0.636**
Sprite	−0.555**	0.338⁺	0.095	−1.248**	0.051	−0.015	0.047	0.151*	0.108
7Up	0.440*	0.637**	0.172⁺	0.048	−1.881**	−0.015	−0.083	−0.190*	0.077
DrPep	−0.032	0.685**	−0.073	−0.013	−0.030	−1.453**	−0.313*	0.131	0.125
MtDew	−0.186	0.598⁺	0.247⁺	0.056	−0.158	−0.393*	−1.307**	0.183*	−0.179*
PrivLab	0.163	0.062	−0.207**	0.086*	−0.132*	0.071⁺	0.083**	−0.918**	−0.037
AllOther[2]	0.050	0.090*	0.044**	0.021⁺	0.009	0.020⁺	−0.016	−0.020	−1.134**

[1]Elasticities are read from left to right;
** = 1% significance level
* = 5% significance level
⁺ = 10% significance level
[2]t statistics for "All Other" are approximated in that covariances between expenditure and price coefficients are not accounted for in calculating standard errors of the elasticities. These approximations are reasonable because the covariances between expenditure and price coefficients for the other brands are quite small (the significance levels in these other equations do not change if these covariances are excluded in the calculation of the standard errors of the elasticities). Source: University of Connecticut, Food Marketing Policy Center; Computations from IRI Infoscan data base.

function system reaction coefficients are negative only if the associated cross price elasticity is negative (Liang 1989). Stated otherwise, positive cross price elasticities are sufficient to ensure positive corresponding price reaction coefficients. Our preliminary work with AIDS demand model suggests this constraint is not dependent upon the linear demand assumption. Perhaps it should be imposed upon to model along with the homogeneity and symmetry restrictions of demand theory.

A second way to interpret the reaction elasticities reported in Table 2 is to examine a column. Column one, for example, indicates how the prices of each soft drink change when Coke increases its price by one percent. Note that, except for Sprite, all other brands follow Coke's price increase. Similarly in column two all statistically significant reaction elasticities indicate that brands follow a Pepsi price increase. In contrast, every brand reactins in a significant negative fashion to a price increase by the "all other" brands. These results may be sensible in that the leading brands generate "respect and price followship" and the fringe is indeed competitive. However, I will question the reliability of these results until we develop less rigorous explanation for negative cross price elasticities and negative reaction elasticities or decide that a cross equation constraint equating the signs of cross price and reaction elasticities is appropriate. Note that in Table 2, all of the other cross price elasticities in the last column are negative and significant. Imposing a constraint that would require the same sign for corresponding cross price elasticities may produce very different results.

Table 3 provides computed values for the nonfollowship observed and fully collusive elasticities for each brand. The nonfollowship elasticities are the diagonal elements from Table 1. The fully col-

Table 2. Price Reaction Elasticities for Regular Carbonated Soft Drinks[1]

	Coke	Pepsi	RC	Sprite	7Up	DrPep	MtDew	PrivLab	AllOther
Coke	—	0.506**	0.079	0.177*	0.129*	−0.133*	−0.230*	0.005	−0.211**
Pepsi	0.555**	—	−0.035	−0.175†	0.121†	0.037	0.214*	0.004	−0.194**
RC	0.684**	−0.002	—	−0.188	0.131	0.076	−0.156	−0.017	−0.171**
Sprite	0.070	0.302*	−0.070	—	0.307**	−0.061	−0.082	0.046	−0.197**
7Up	−0.130	0.414**	0.111†	0.419**	—	−0.007	−0.350**	−0.077**	−0.083*
DrPep	0.432**	0.431**	0.103	−0.140	0.196**	—	−0.461**	0.009	−0.165**
MtDew	0.424**	0.177*	−0.041	−0.133	0.119†	0.142*	—	−0.041	−0.169**
PrivLab	0.082	0.120	0.213*	−0.087	−0.011	0.036	−0.044	—	−0.132**
AllOther	0.410**	−0.077	−0.031	−0.158†	0.208**	0.092	−0.009	−0.168**	—

[1]Elasticities are read from left to right;
** = 1% significance level
* = 5% significance level
† = 10% significance level
Source: University of Connecticut, Food Marketing Policy Center; Computations from IRI Infoscan data base.

Table 3. Brand Elasticity Measures and Market Indices

	Non-Followship Elasticity	Observed Elasticity	Fully Collusive Elasticity	Rothschild Index	O Index	Chamberlain Quotient
Coke	−1.496	−1.276	−1.073	0.717	0.841	0.147
Pepsi	−1.868	−1.571	−1.109	0.594	0.706	0.159
RC	−2.508	−2.618	−0.535	0.213	0.204	−0.044
Sprite	−1.248	−1.436	−1.028	0.824	0.716	−0.151
7Up	−1.881	−1.704	−0.794	0.422	0.466	0.094
DrPep	−1.453	−1.457	−0.974	0.670	0.669	−0.002
MtDew	−1.307	−0.950	−1.139	0.872	1.199	0.273
PrivLab	−0.918	−0.896	−0.828	0.902	0.924	0.024
AllOther	−1.134	−1.173	−0.937	0.826	0.799	−0.034

lusive (followship) elasticities are the sum of the rows in Table 1. The observed elasticity for a brand is computed using equation one and is the vector product of the brand's row of demand elasticities in Table 1 with its column of reaction elasticities in Table 2.[13] Table 3 also computes the Rothschild, O, and Chamberlin indices for each brand. For Coke, Pepsi, Seven-Up, and Private Label these indices behave as expected. Coke, for example, has a nonfollowship elasticity equal to − 1.496 and its fully collusive elasticity is − 1.073 so the Rothschild index is .71 and indicates a substantial amount of unilateral market power. The observed elasticity falls between the nonfollowship and fully collusive elasticity and produces in conjunction with the latter an O Index of unilateral and coordinated market power equal to .841. The Chamberlin Quotient indicates that 14.7 percent of Coke's market power is due to tacit collusion.

Other brands in Table 3 produce results that, quite frankly, were not expected and suggest the need for a broader conceptualization of competition and strategic interaction. Complementary (negative) cross price elasticities or negative price reaction elasticities combine to produce negative Chamberlin quotient for four brands (R.C., Sprite, Dr. Pepper and All Others). Also Mountain Dew generates an observed elasticity that is greater than the fully collusive value. Cross equation constraints on cross price and reaction elasticities do seem advisable. In conjunction with the symmetry constraint they would ensure that observed elasticities always fall between nonfollowship and fully collusive elasticities thereby eliminating these anomalies.

Note that even with the imposition of cross equation constraints one can still have negative cross price elasticities and negative corresponding reaction function elasticities. Since the product of two negatives is positive, the integrity of the rank ordering of the elasticities and market power indices reported in Table 3 is restored, but now one has complements in the formula. This leads me to suggest the following proposition, brands that are strategic complements behave in a fashion that enhances tacit coordination. For example, if Coke raises its price, and brand X is a strategic complement then brand X experiences lower demand for its product. Given the downward shift in its demand, brand X lowers its price to maximize profits (a negative price reaction to the change in Coke price). Due to symmetry brand X cross price elasticity in the Coke demand equation is also negative. Consequently, a decrease in brand X price increases demand for Coke and thereby lessens the loss of market share due to Coke's own price increase. In other words, the observed elasticity is less elastic than the nonfollowship elasticity.

V. Concluding Comments

If this paper raises more questions than it answers it has served its most basic purpose. This is a new area of theoretical and empirical inquiry. Both supermarket movement and household panel data collected by IRI and A.C. Neilsen are the core data for market research in the private sector. As these data become more accessible to the research public, they unquestionably will become the foundation for new theory and empirical science in marketing.

Demand modeling and empirical analysis of price, advertising retailer push, and consumer pull market strategies at the brand as well as product category or industry level will provide considerably more precise understanding of firm conduct and household behavior.

Scanner data and the analytical approach discussed in this paper may also contribute to the analysis of a wider range of topics including resource economic issues. The local market bottled water data, for example, provide an excellent base

[13] For purposes of this calculation Table 2 should also contain ones on the diagonal to include the own price practical elasticity.

for a defensive expenditure approach to the analysis of water contamination, or pollution incidents in particular cities or for particular brands such as the Benzine contamination of Perrier. Regarding the former one could collect municipal water quality ratings and use them plus public discussion of them as the stimulus variable. They may shift demand for bottled water. Similarly branded product recall due to contamination and changing food safety perceptions may be analyzed.

In closing, I think a fundamental issue is public access to IRI and Neilsen scanner data. To date public access has been very limited and usually quite expensive when approved. As this important lane of the "information superhighway" becomes so advanced that food marketers can micromarket to millions of individual households, one has to note the huge disparity in access by consumers, public researchers, and governmental oversight and operations staff vis a vis marketers in the private sector. Increasing access to scanner data need not damage or compromise strategic moves by firms, and it could improve the overall efficiency and performance of the food marketing system behavior. As this paper illustrates working at the interface of demand and industrial organizations theory may very well provide new theory and methods that will advance both fields. At some juncture this work may also make a significant contribution to the evolving quantitative focus of marketing research as taught in business schools.

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