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Market Share and Price Setting Behavior
For Private Labels and National Brands

By Ronald W. Cotterill,
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Contents

Tables and Charts

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Abstract

In this paper, we develop a framework for estimating market share and price reaction equations in an attempt to understand the nature of competitive interaction in the market for private label and branded grocery products. Specifically, we employ a Linear Approximate Almost Ideal Demand System (LA/AIDS, Deaton and Muellbauer 1980a), and specify the price reaction equations derived under the LA/AIDS demand specification. This enables us to consistently estimate share-price relationships, accounting for demand-side and competitive reactions simultaneously. The incorporation of LA/AIDS demands into a structural equation framework represents an important departure from previous demand specifications in competitive analysis. In addition to its rigorous foundation in utility theory, LA/AIDS demands are especially flexible for demand-side estimation, provide consistent reaction functions on the supply side, and have particularly nice aggregation properties.

In order to test the relative contribution of employing a flexible LA/AIDS functional form on the demand-side, and in a preliminary attempt to assess manufacturer-retailer interaction on the supply side, we compare our general framework (LA/AIDS demands with retailers following a proportional markup rule) to two alternative models of manufacturer-retailer interaction: Choi's (1991) Manufacturer-Stackelberg (M-S) model under linear demands, as well as Shubik demands under Stackelberg conduct (Raju, Sethuraman and Dhar 1995a, 1995b).

We first apply the proposed LA/AIDS framework to a sample pooled across 125 categories and 54 geographic markets in an attempt to produce result that generalize across the entire sample. We then estimate all three models using data on seven individual categories: bread, milk, pasta, yogurt, instant coffee, butter and margarine. We conclude that the LA/AIDS demand specification is preferred to the alternative linear demand specifications. Further, the empirical findings support our premise that consumer response to price and promotion decisions (demand) and the factors influencing firm pricing behavior (supply) jointly determine observed market prices and market shares. Most importantly, our specification with LA/AIDS demands produced excellent overall fits, as well as reasonable demand and price response elasticities.

Keywords: Competition; Competitive Strategy; Private Labels; Pricing

1. Introduction

The nature of competitive interaction between "national brand" and "private label" products has been a primary concern of marketing managers in the retail food industry for some time now. Over the past decade, understanding the different factors that influence the competitive interaction between national brands and private labels has taken on greater urgency. In this vein, in 1996, private label sales in food stores increased 6.3% versus manufacturer brand growth of just 1.3%, while retailer-controlled brands have outpaced manufacturer brands in 12 of the most recent 14 quarters (*Progressive Grocer*, November 1996). Overall, private label brands in U.S. supermarkets reached an all-time high unit market share of 20.8% in the third quarter of 1997, according to IRI (*BrandWeek*, 11/24/97). Alternatively, private label sales have declined in some categories as national brands have effectively responded to private label competition (*BrandWeek*, 5/29/95, *New York Times* 6/11/96). Yet, despite the increasingly intense competitive interaction between private labels and national brands, surprisingly little research has been conducted addressing this issue.

Previous research in marketing has focused on the *variation in market share* of private label products across categories (Sethuraman 1992; Sethuraman and Mittelstaedt 1992; Hoch and Banerji 1993; Narasimhan and Wilcox 1998). A number of factors have been identified in the literature to explain this variation. Sethuraman (1992), for example, identifies twelve marketplace factors as potential determinants of private label success. These factors include retail sales volume, average retail price, price differential between the private label and national brands, retail private label price promotion and brand promotion.

While the focus in marketing has primarily been on *market share* relationships, recent work in the economics and industrial organization literature has focused on the determinants of firm *price* setting behavior. Conceptually, the nature of manufacturer-retailer competition in any market will affect both the within channel power and the incentives for stocking and promoting store brands. The price setting behavior of both manufacturers and retailers will depend upon cost and demand considerations, as well as the nature of strategic interaction between competitors, including the potential use of market power by manufacturers and/or retailers. It is well established that factors that increase market power (such as increased concentration and market share) result in higher market prices (Deneckere and Davidson 1985, and Weiss 1989).

More recently, a number of studies have addressed competitive interaction in detail. One approach to estimating this interaction requires specifying, *a priori*, the various forms of competitive interaction to be considered (hence it is often referred to as a "menu" approach). Non-nested hypothesis tests are used to ascertain which type of competition best fits the data (see, e.g., Gasmi, Laffont and Vuong 1992, and Kadiyali, Vilcassim and Chintagunta 1996). Alternatively, a conjectural variations approach has been used to estimate the competitive interaction directly without the need to specify the interactions *a priori* (see, e.g., Putsis and Dhar 1997, and Kadiyali, Vilcassim and Chintagunta 1998). Other studies, such as those by Connor and Peterson (1992) and Slade (1995), have empirically addressed competition between private labels and national brands, but have not focused on the simultaneous determination of price and share.[1]

While previous work addressing the nature of competitive interaction has produced sophisticated models on the supply side, previous demand specifications used in much of the research on private label-national brand interaction have been rather restrictive in functional form. For example, models developed by Choi (1991) and by Raju, Sethuraman and Dhar (1995a, 1995b) employ restricted versions of a linear demand model.[2] While the restricted version of the Shubik model (Shubik and Levitan 1980) used by Raju, et al. is derived from an underlying consumer utility model, the model proposed by Choi is not. Neither demand structure allows for the imposition and testing of the symmetry and homogeneity restrictions from demand theory. Further, both impose Bertrand price competition (i.e., zero price conjectures) between manufacturers and Stackelberg behavior between manufacturers and retailers. Thus, while each of these models are important for the derivation of clean analytic results, estimation is not often easy and counter-intuitive restrictions on the demand-side parameters may need to be imposed. Further, recent theoretical work has suggested that that nature of vertical relationship depends upon the convexity of the demand structure (Lee and Staelin 1997).

Building on this research, we maintain that developing

1. Alternatively, other studies such as Kadiyali, Vilcassim and Chintagunta (1998) estimate demand and supply-side equations simultaneously, but do not address private label-national brand interaction, a focus of our study.

2. We note that Choi (1991) addresses nonlinear demand specification through numerical analysis. He does this since it is "extremely difficult to obtain analytical results" for a nonlinear specification (p. 279).

a complete understanding of the nature of the competitive interaction between national brands and private labels requires an understanding of the determinants of *both* demand and strategic pricing decisions by firms. As an example, recent price cuts in the ready-to-eat cereal category by Post and Nabisco in response to pressure from private label resulted in a consumer response that increased its market share from about 16 percent to over 20 percent, while decreasing private label shares. In response, Kellogg's announced a 20 percent across the board price cut due to declining shares of its major brands (*New York Times*, 6/11/96). General Mills and Quaker Oats also reduced prices. Clearly share responds to price, while the price setting behavior of firms depends upon the game being played by interdependent agents. Examining partial demand elasticity, i.e. the change in quantity due to a change in price *assuming all other prices remain constant*, gives at best an incomplete picture of the interaction between brands and private labels. Consumer response to price and promotion decisions (demand) and the factors influencing the pricing behavior of firms *jointly* determine observed market prices and quantities (market shares).[3]

In this paper, we expand on previous work by deriving a structural system of equations that allows for the simultaneous estimation of competitive interaction and demand parameters under a more flexible demand specification, the Linear Approximate Almost Ideal Demand System (LA/AIDS). The use of a flexible demand system empirically is consistent with the theoretical dependence of vertical relationships on demand convexity suggested by Lee and Staelin (1997). In order to assess the relative contribution of the proposed framework versus existing models, we derive and estimate a general linear system that nests two well-cited competing models of retailer-manufacturer interaction: a) the Choi (1991) Manufacturer-Stackelberg (MS) model, and b) the Raju, Sethuraman and Dhar (1995a)'s model of Stackelberg conduct with Shubik demands.

The paper proceeds as follows. In the next section, we describe the theoretical model that guides the empirical specification and the selection of variables. Using LA/AIDS demands, we are able to derive price reaction equations consistent with the LA/AIDS demand specification. We then derive the specific reaction equations for the models set forth by Choi (1991) and Raju, et al. (1995a). In the Empirical Analysis section that follows, we describe the methodology used in the empirical analysis in some detail. In the Results section, we first present estimates of model parameters for the LA/AIDS framework applied to a large cross-category panel data set that includes 125 categories in 54 local markets. We compare these results to those obtained by applying the proposed LA/AIDS framework to the data for seven individual categories: milk, butter, bread, yogurt, pasta, margarine and instant coffee. These results are then compared to those obtained for the Choi (1991) and Raju, et al. (1995a, 1995b) models. The paper concludes with a more detailed discussion of the LA/AIDS parameter estimates, relevant managerial implications and suggestions for future research.

2. Theoretical Framework

2.1 General Framework

Following work by Choi (1991) and Besanko, Gupta and Jain (1997), we begin with a category-level model of manufacturers operating in a duopoly, with one producing a national "branded" product and the other producing a "private label" product. Both products compete in a specific geographic area with price the sole strategic variable. The manufacturers sell to a local retailer by specifying a wholesale price, with the retailer setting the retail price. Following the rationale set forth by Besanko, Gupta and Jain (1997), we begin by assuming each retailer acts as a "local monopolist."[4]

We begin with a general framework and then discuss

3. It is well known that OLS applied equation by equation to jointly endogenous variables (e.g., price as a function of share and share a function of price as explained above) will produce inconsistent parameter estimates (see, e.g., Intriligator 1978 or Judge, 1985). Simultaneous equation approaches to estimation have a long history in marketing (Bass 1969; Schultz 1971; Hanssens, Parsons and Schultz 1990; Neslin 1990).

4. Besanko, Gupta and Jain (1997), p. 6, provide a strong rationale for this assumption, which is also made by Choi (1991). They cite the work of Slade (1995), who interviewed grocery chain managers "who reported that the vast majority of households (over 90%) *do not* engage in comparison shopping by visiting several stores" to seek out the best deal. This suggests that "competition takes place across brands *within* a store rather than *across* stores in a local market …" (italics added). Slade (1995), using data from the Saltine category, empirically demonstrates that sales within one chain are unaffected by prices at other chains, suggesting pricing *independence* across rival chains within a category. This is also consistent with the work of Walters and Mackenzie (1988), who use data across all grocery items sold by two retailers. We are able to relax this assumption in the empirical analysis below.

potential functional form specifications, focusing on the estimation of demands and price reactions under LA/AIDS demands. We begin by defining the following set of variables:

P^1_{ij} = the retail price per unit volume of the national brand in category i and city j.
P^2_{ij} = the retail price per unit volume of the private label brand in category i and city j.
Q^1_{ij} = the quantity of the national brand sold in category i and city j.
Q^2_{ij} = the quantity of the private label sold in category i and city j.
D_{ij} = demand shift variables for category i and city j.
C^1_{ij} = supply-side cost shift variables for the national brand in category i and city j.
C^2_{ij} = supply-side cost shift variables for the private label in category i and city j.

Define the general retail demand functions for national brand and private label products as:

$$Q^1_{ij} = Q^1(P^1_{ij},\ P^2_{ij};\ D_{ij}), \tag{1}$$

$$Q^2_{ij} = Q^2(P^1_{ij},\ P^2_{ij};\ D_{ij}). \tag{2}$$

The quantity of the national and private label products demanded are specified to be a function of prices and, following Hoch, Kim, Montgomery and Rossi (1995), a set of demand shift variables that will include per capita expenditures in category i and city j, the level of retail promotion in category i and city j, family income level in city j (reflecting the overall affluence of the geographic area), and median age in city j. Define the cost functions for branded and private label manufacturers as follows:

$$C^1(Q^1_{ij}, C^1_{ij}), \tag{3}$$

$$C^2(Q^2_{ij}, C^2_{ij}). \tag{4}$$

Thus, the total cost of producing Q^1_{ij} is a function of production, Q^1_{ij}, and a vector of supply side cost shift variables, C^1_{ij}. In a game where price is the strategic variable, the manufacturer chooses the wholesale price (w^1_{ij} and w^2_{ij}, respectively) and the profit maximizing problems for the two manufacturers are:

$$MAX\ \Pi_1 = [\ w^1_{ij}Q^1(P^1_{ij},P^2_{ij};D_{ij})-C^1(Q^1(P^1_{ij},P^2_{ij};D_{ij}))], \tag{5}$$

$$MAX\ \Pi_2 = [\ w^2_{ij}Q^2(P^1_{ij},P^2_{ij};D_{ij})-C^2(Q^2(P^1_{ij},P^2_{ij};D_{ij}))]. \tag{6}$$

Based upon the two wholesale prices, the retailer decides on the retail prices for both products that maximize its profits:

$$MAX\ \Pi_R = [(P^1_{ij} - w^1_{ij})Q^1(P^1_{ij},P^2_{ij};D_{ij}) + (P^2_{ij} - w^2_{ij})Q^2(P^1_{ij},P^2_{ij};D_{ij})]. \tag{7}$$

These maximization problems give rise to four first order conditions. When combined with the two retail demand equations, this produces six equations with six endogenous variables, P^1_{ij}, P^2_{ij}, Q^1_{ij}, Q^2_{ij}, w^1_{ij}, and w^2_{ij}. If data on w^1_{ij}, and w^2_{ij} were available, it would be possible to estimate the six structural equations above. However, since available scanner data does not generally provide information on wholesale prices, we can only reduce the structural equation estimation problem to four equations involving the four available endogenous variables (P^1_{ij}, P^2_{ij}, Q^1_{ij}, Q^2_{ij}) by imposing additional structure on the system. Following Narasimhan and Wilcox (1998), we will begin by assuming vertical Stackelberg conduct within the channel (with the manufacturer as the leader).[5] Since in a Stackelberg game, the manufacturer knows the retailer's best response function, $P^1_{ij}=P^1(w^1_{ij})$ and $P^2_{ij}=P^2(w^2_{ij})$, when the manufacturer sets w_1 , the retail price P_1 is chosen as well. Thus, one can invert the response functions for wholesale prices as a function of retail prices, substitute these in the manufacturers profit maximization equations (5 and 6) and maximize the manufacturer's profits with respect to its retail price. This gives two first order equations that can be solved for two reaction functions and two demand equations which are functions of the four observable variables, P^1_{ij}, P^2_{ij}, Q^1_{ij}, and Q^2_{ij} . The general form of the derived reaction functions is as follows:

$$P^1_{ij} = R_1(P^2_{ij}, D_{ij}, C^1_{ij}), \tag{8}$$

$$P^2_{ij} = R_2(P^1_{ij}, D_{ij}, C^2_{ij}). \tag{9}$$

Equations (8) and (9) represent the retail price reaction equations to be estimated. These equations, to be estimated simultaneously with the demand equations (1)

5 . In the LA/AIDS specification that follows, we also assume that retailers follow a proportionate markup rule. We derive tests for Stackelberg profit maximizing and proportional markup behavior and empirically test for these vertical pricing strategies in our analysis below. These results enable us to assess the appropriateness of the assumptions inherent in the proposed LA/AIDS framework.

and (2), provide an expression for the optimal retail price of P^k_{ij} (k=1, 2) given the rival's price, as well as exogenous demand and cost shift variables.[6] As will be shown in the next section, the specific functional form of the price reaction equations will depend upon the demand-side specification and upon the assumptions regarding the nature of manufacturer-retailer interaction.

2.2 Choice of Functional Form - LA/AIDS

Demand analysis and functional form specification has been well developed in the economics literature (see, e.g., Deaton and Muellbauer 1980a or Phlips 1983). Numerous forms have been proposed that are theoretically superior to a linear specification including the Linear Approximate Almost Ideal Demand System, or LA/AIDS (Deaton and Muellbauer 1980b). The reasons for its superiority include the fact that it is derived from the underlying choice axioms in utility theory, individual behavior can be aggregated to consistently estimate demand parameters from market level data, and that it gives a first-order approximation to any "true" demand system functional form (Deaton and Muellbauer, 1980b).[7]

We begin by presenting the general LA/AIDS demand specification and then derive the associated reaction functions. We then explore how LA/AIDS demands compare to the demand specification used in other models of manufacturer-retailer interaction, such as those used by Choi (1991) and Raju, Sethuraman and Dhar (1995a, 1995b). The general LA/AIDS functional form, originally introduced by Deaton and Muellbauer (1980b), is given by equation (10):

$$S^1_{ij} = \alpha_{10}+\alpha_{11}\, lnP^1_{ij} + \alpha_{12}\, lnP^2_{ij}+\alpha_{13}\, ln\,(E_{ij}) + \alpha_{14}D_{ij}\,. \quad \textbf{(10)}$$

where:

S^1_{ij} = the dollar market share of the national brand in category i and city j,

E_{ij} = total per capita expenditure on category i in city j, divided by Stone's price index = $S^1_{ij} \ln P^1_{ij} + S^2_{ij} \ln P^2_{ij}$.

The ratio of per capita expenditure is a deflated (real) measure of per capita expenditures.[8] Thus, its coefficient gives an estimate of the impact of changes in expenditures on demand for a given product. From the basic formulation in (10), the usual demand restrictions, symmetry, homogeneity, and adding up can be imposed. Further, all relevant demand elasticities can be recovered from the demand equation in (10).[9]

Given the complexity of the demand system

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6. In this formulation, and throughout the paper, we derive structural reaction functions for retail price setting behavior in each of the models. We note that this contrasts with the conjectural variations approach (e.g., Spiller and Favaro 1984, Gasmi, Laffont and Vuong 1992, and Putsis and Dhar 1997) and the menu-based equilibrium approach of Gasmi, Laffont and Vuong (1992) and Kadiyali, Vilcassim and Chintagunta (1998). One advantage of conjectural variation models is the estimation of price cost margins. We note that is also possible to estimate the price cost margin in our model. In order to do this, one first solves the two price reaction functions for the equilibrium price given the exogenous cost and demand shift variables. Then one substitutes these values into the demand equations to determine equilibrium quantities and computes the own price elasticities at equilibrium. Since a profit-maximizing manufacturer equates its price cost margin to the inverse of the own price elasticity, it is then possible to solve for the price cost margin.

7. The aggregation properties are especially important for our purposes. First, we note that the LA/AIDS is PIGLOG in form, which does not require the assumption of parallel linear Engel curves. This implies that we are able to consistently estimate expenditure effects using linearly aggregated data. In addition, under the assumption that prices change proportionately from period to period across retailers, taking the first difference of a LA/AIDS demand equation (see below) eliminates any linear response aggregation bias (Christen, Gupta, Porter, Staelin and Wittink 1997).

8. See Deaton and Muellbauer (1980a, 1980b) for an explanation of Stone's index. Its use allows the nonlinear AIDS model to be estimated linearly, hence the name LA/AIDS.

9. Following Green and Alston (1990), estimates of the national brand's own price and cross-price (here, with respect to private label price) elasticity of demand are:

$$\eta^{11} = -1+\frac{\alpha_{11}}{\bar{S}^1}+\alpha_{13} \qquad \eta^{12} = \frac{\alpha_{12}}{\bar{S}^1}+\alpha_{13}\frac{\bar{S}^2}{\bar{S}^1}\,,$$

respectively, where $\bar{S}^1$ and $\bar{S}^2$ are sample average market shares or any other market share value. Note that these demand elasticities vary as market shares vary. Thus they are local or point estimates of the elasticities. The expenditure elasticity and the elasticities for variables, d^k, in the vector of exogenous demand shift variables are:

$$\eta^{13} = 1+\frac{\alpha_{13}}{\bar{S}^1} \qquad e^k = \frac{\alpha^k_{14}}{\bar{S}^1}\bar{d}^k\,,$$

respectively, where $k = 1, \ldots, m$ is the index for the number of variables in the D vector and $\bar{d}^k$ is the average value of d^k. Note that, if some variables are expressed in logarithmic form, then this elasticity formula has the inverse of d^k rather than d^k on the right hand side. The price reaction elasticity for national brands, which gives the present change in brand price for a one percent change in private label price, is b_{11} in equation 14. The corresponding equations and elasticity formulae for private label are analogous to the branded equations presented above.

specification, it is not possible to directly derive the explicit functional form for the retailer's best response curves that determine the retail price, P^i, for a given level of w^i. Further, we typically don't observe w^i. If we assume, however, that retailers follow a (known) proportional markup rule for pricing decisions, then it becomes possible to derive price reaction curves in retail prices that capture manufacturer interactions. Under a proportional markup rule, we can write (focusing on the national brand):

$$P^1_{ij} = m^1 w^1_{ij}$$

or

$$w^1_{ij} = (1 / m^1)\, P^1_{ij} = k^1 P^1_{ij}. \qquad \textbf{(11)}$$

This enables us to express the profit maximization of the national brand manufacturer, for example, with P^1 as the choice variable (dropping the i and j subscripts for ease of presentation):

$$\underset{P^1}{MAX}\, \Pi_1 = k^1 P^1 Q^1 - C^1 Q^1 . \qquad \textbf{(12)}$$

Assuming, the firm faces a constant marginal cost schedule, the relevant first order condition for the national brand manufacturer is:

$$\frac{\partial \Pi_1}{\partial P_1} = k^1 \partial \frac{(P^1 \cdot Q^1)}{\partial P^1} - C^1 \frac{\partial Q^1}{\partial P^1} = 0 \qquad \textbf{(13)}$$

Note that this is the same first order condition one obtains for analysis of reactions between retail level prices except the constant k^1 is now in the first term of the expression. It is possible to divide equation (13) by k^1, and subsume the k^1 in a generalized marginal cost term, C^1 / k^1. This then leaves the standard problem of solving for the retail level price reaction equations.

As Choi (1991) notes, solving first order conditions with nonlinear demand models is generally not analytically tractable. He resorts to numerical analysis to derive qualitative results. Here, employing LA/AIDS demands as in equation (10), we solve the first order conditions for P^1 and P^2, respectively, using a Taylor series expansion to obtain a linear approximate retail reaction function that allows empirical analysis. This produces the following price reaction function for the national brand manufacturer:

$$\ln P^1 = \beta_{10} + \beta_{11} \ln P^2 + \beta_{12} D + \beta_{13} E_{ij} + \beta_{14} C^1_{ij} , \qquad \textbf{(14)}$$

where $\beta_{14} = \beta_{14} / k^1$, reflecting the influence of k^1 on price. The corresponding functional form for estimation of the private label reaction function is:

$$\ln P^2 = \beta_{20} + \beta_{21} \ln P^1 + \beta_{22} D_{ij} + \beta_{23} E_{ij} + \beta_{24} C^2_{ij} . \qquad \textbf{(15)}$$

The price reaction elasticity for national brands, β_{11} in equation 14, gives the percent change in brand price for a one-percent change in private label price. It does not depend on the retailer's proportional markup. Note, however, that the slope of the price reaction function does. Taking the anti-log of equation 14 gives the price reaction function for national brands:[10]

$$P^1_{ij} = (e^{\beta 10})\, (P^2_{ij})^{\beta 11}\, (D^1_{ij})^{\beta 12}\, (E_{ij})^{\beta 13}\, (C^1_{ij})^{\beta 14} . \qquad \textbf{(16)}$$

The slope of the price reaction function depends on the values of the exogenous variables in the system and their parameter estimates. Since all these variables are positive, the slope of the reaction is positive if and only if β_{11} is positive.[11] Also, we expect that national brand price will have a negative relationship with share in the brand demand equation, while the reverse relationship should occur in the price reaction curve capturing the power of brands *vis à vis* the private label sector (Weiss 1989).

The national brand demand function (10), and the logarithmic form of the reaction functions (equations 14 and 16) comprise the three-equation system to be estimated. The fourth equation in the system (the private label demand equation), and its associated demand elasticities, are recovered via the adding up property of the demand system.[12]

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10. The individual β parameters in equations (11) and (12) are complex functions of the demand and price conjecture elasticities. Based upon these relationships, cross-parameter and cross-equation restrictions are normally incorporated via parameter restrictions in estimation. However, the complexity of the demand parameters in the reaction functions under LA/AIDS demands prohibits a parsimonious set of parameter restrictions.

11. Note that this functional form accommodates the Bertrand zero price conjecture game or a generalized Bertrand game with nonzero price conjectures. If the model is a consistent conjecture model, then firm one's (two's) conjecture about changes in P^2 (P^1) when it changes P^1 (P^2) would be equal to the observed price reaction of P^2 (P^1) to P^1 (P^2). See Raju and Roy (1997) or Putsis and Dhar (1998) for a discussion of the various approaches taken for estimating competitive interaction.

12. Since the dependent variable is market share, if we estimate a model that predicts national brand share, private label share is

2.3 Choice of Functional Form–Alternative Specifications with Linear Demands

Modeling the interaction between national brands and private labels is especially challenging because, unlike competition between two national brands, there is a vertical relationship between national brand manufacturers and retailers. As a result, one needs to be particularly concerned about the vertical as well as the horizontal nature of competitive interaction. In the formulation above, we assumed that retailers behave passively by following a proportional mark-up rule. This assumption enabled us to focus on the manufacturer's price setting behavior and, consequently, to derive the retail level price reaction functions under LA/AIDS demands. However, it is not clear that such an assumption is reasonable *a priori*, and it is not clear how this form of manufacturer-retailer interaction compares to alternative characterizations. Consequently, we have derived estimable demand and price reaction systems for two alternative models of retailer-manufacturer interaction.

Choi (1991) analyzes linear demands under three different behavioral assumptions for the vertical pricing game: Manufacturer Stackelberg (M-S), Retailer Stackelberg (R-S) and Vertical Nash (V-N) behavior. These models assume that manufacturers act as Stackelberg leaders within the channel (M-S), retailers act as Stackelberg leaders within the channel (R-S), and retailers and manufacturers play a Nash game within the channel, respectively. Alternatively, Raju, et al. (1995a, 1995b) use a restricted version of Shubik's linear-form demand model and specify manufacturer Stackelberg conduct. In this section, we present the corresponding retail reaction functions for the Choi (1991) Manufacturer-Stackelberg, as well as the Raju, et al. (1995b) model.[13]

We begin with the Choi (1991) Manufacturer-Stackelberg model. Consistent with our framework above, Choi (1991) assumes that the vertical game has 3 players, a national brand manufacturer, a private label manufacturer, and a retailer that sells both the private label product and the national brand. Following in the tradition of McGuire and Staelin (1983) and Jeuland and Shugan (1988), Choi specifies linear demand that allow for product differentiation of the form:

$$Q^i = a - bP^i + \gamma P^j, \quad \forall \quad i, j = 1, 2, \quad j \neq i \qquad \textbf{(17)}$$

where Q^i is demand for brand *i* at price P^i given that the price of the other brand *j* is P^j. Consistent with our notation to this point, we designate brand 1 as the manufacturer brand and brand 2 as the private label. It can be shown that Manufacturer-Stackelberg behavior under linear demands, as specified by Choi (1991), implies the following reaction function for the national brand (with an analogous private label reaction):

$$P^1_{ij} = (\gamma / 2b)P^2_{ij} + (a/2b) + a/[4(b - \gamma)] + (C^1_{ij}/4), \qquad \textbf{(18)}$$

where a, b, and γ are the relevant demand response parameters from (14) above. We now have an empirically estimable model that consists of the two demand equations (14), and the two retail level brand price reaction functions equations (15). With appropriate cross equation restrictions, we can estimate the parameters, a, b, γ, in addition to the demand and price reaction elasticities. Finally, note that the price reactions in (15) are symmetric.[14]

Alternatively, Raju, Sethuraman and Dhar (1995a, 1995b) assume that private label manufacturers are competitive and that demand is characterized by a restricted form of Shubik demands (Shubik and Levitan 1980). It can be shown that in the two-good case, the relevant structural model consists of two demand

simply one minus national brand share. When national brand price, for example, increases and national brand share decreases we know how much private label share increased. Thus the national brand cross price coefficient in the private label demand equation is the negative of the national brand own price coefficient in the national brand equation. This property holds for all variables in the demand system.

13. We focus on the Choi (1991) Manufacturer-Stackelberg model since the reaction functions for the Vertical-Nash model are not identified, while there *are no* reaction functions for the Retailer-Stackelberg model. Consequently, the Manufacturer-Stackelberg framework represents the only *estimable* model. Detailed derivations for the Choi (1991) and the Raju, et al. (1995b) models are available upon request.

14. In the event that the private label manufacturer has no market power vis à vis the retailer (selling its product at a price equal to marginal cost), the reaction functions in (15) simplify considerably. In this case, the reaction functions are asymmetric: national brands react to private labels, while private label prices are exogenously determined. This provides a convenient (nested) test of competition and associated within-channel behavior for private labels.

equations (19a and 19b) and the asymmetric retail price reaction functions (20a and 20b) as follows:[15]

$$Q^1 = a_1 + b P^1 + g P^2, \qquad \textbf{(19a)}$$
$$Q^2 = a_2 + b P^2 + g P^1, \qquad \textbf{(19b)}$$

$$P^1 = \frac{g}{2b} P_2 + \frac{a_1}{2b} + \frac{ba_1 + ga_2}{4(b^2 - g^2)} + \frac{C^1}{4}, \qquad \textbf{(20a)}$$

$$P^2 = \frac{C^2}{2} + \frac{ga_1 + b_1 a_2}{b^2 - g^2}. \qquad \textbf{(20b)}$$

As with the Choi (1991) model presented above, the two reaction functions (equations 20a and 20b), together with the two demands (19a and 19b) constitute an estimable four equation simultaneous system. Note that the coefficient on private label price in the national brand price reaction equation (20a) is identical to the Choi (1991) price reaction coefficient in (15). Further, note that the principal difference between the Choi (1991) framework and the Raju, et al. (1995a) model with restricted Shubik demands is that the latter relaxes the identical intercept assumption and assumes that private label manufacturers are competitive. Letting $a_1 = a_2 = a$ in the Raju et al. (1995b) demand equations and relaxing the competitive private label assumption produces the Choi (1991) model. Relaxing only the competitive private label assumption transforms 20b into a reaction equation analogous to equation 20a.

This characterization suggests that we can nest the two models, producing a convenient test of the two alternative views of manufacturer-retailer interaction and demand. In Appendix A, we i) demonstrate how both the Choi (1991) Manufacturer-Stackelberg and the Raju, et al. (1995a) models can be represented as part of a more general class of mark-up models, and ii) derive tests for the demand and within-channel structure implied by these models. Specifically, we first present a test for whether the Choi (1991) or Raju et al. (1995a) demand structure provides a better fit to the data. We then derive tests to determine if Stackelberg profit maximizing and/or proportional markup behavior is consistent with the data. The results from these tests enable us to assess the appropriateness of the proportional markup and Stackelberg behavior assumption in the LA/AIDS specification.

15. We simplify the presentation of the restricted Shubik demands here to facilitate comparison with the Choi (1991) specification.

In summary, in the empirical section below, we attempt to answer the question "does the added flexibility of the LA/AIDS functional form presented above provide for improved empirical estimates of demand and price reaction elasticities?" In doing so, we estimate three potential models of demand and price response, using nested tests to compare the assumptions underlying each model, as well as the overall fit of each system:

- LA/AIDS demands with retailers following a proportional markup rule (equations 10, 12, and 13).
- Choi's (1991) Manufacturer-Stackelberg (M-S) model under linear demands (equations 14 and 15).
- Raju, Sethuraman and Dhar (1995b), specifying restricted Shubik demands and manufacturer Stackelberg conduct (equations 19 and 20).

3. Empirical Estimation–The Proposed LA/AIDS Framework

Since the primary contribution of this paper rests with the incorporation of LA/AIDS demands, we begin by discussing estimation of the proposed LA/AIDS framework in some detail. With any theory and empirical analysis, the transition from theoretical model to empirical specification entails the need for careful variable selection. It is important to choose the empirical model carefully, using the appropriate hypothesis tests to guide final model specification. A key is specifying the set of variables that are consistent with the theory and a set of control variables that remove extraneous variation. Consequently, we proceeded as follows. First, we specified three nested empirical models under LA/AIDS demands, as set out in equations (10), (12) and (13). Using nested hypothesis tests, we then selected the "best" of these specifications.[16] Chart 1 details the final set of variables used in the empirical analysis.[17]

16. The results from alternative nested model specifications are available from the authors in working paper form upon request (Cotterill, Dhar and Putsis 1996).

17. Consistent with some previous work on private labels (e.g., Slade 1995), aggregate private label and national brand variables were created for share, price and price reduction. Private label (national brand) share is sum of all private label (national) brands in the ith market, jth category. Private label (national brand) price is the volume-weighted average price of all private labels (national brands) in the ith market, jth category. The two price reduction variables are volume-weighted percent price reduction for all private label and branded products, respectively. Thus, for price and share, we have four aggregate

In moving from the general functional form specification of equations (10), (12) and (13) to the exact empirical specification, the LA/AIDS demands in (10) and the derived reaction functions in (12) and (13) dictate the choice and functional form of most of the variables to be included in the empirical specification. However, as with any empirical analysis, there are some important additional issues that need to be addressed in moving from the theory to the exact empirical specification. For example, note that the brand level Herfindahl index used in the empirical analysis is defined as the sum of the square of all individual brand market shares.[18] As such, when introduced jointly with national brand market share, it measures the size dispersion of brands. Thus, we use the brand Herfindahl as an imperfect, but readily available, instrument for segmentation and multiple brand strategies. To see this, note that branded share may sum to .80 (80 percent) with only two brands each with .40 share. In this case, the brand level Herfindahl index equals .32. However, if there are 80 brands each with .01 market share (much like the breakfast cereal category), then the brand Herfindahl is only .008. To the extent that the brand level Herfindahl index measures the degree of product differentiation via brand proliferation, we hypothesize that it will be negatively related to the prices of branded products. Segmentation and multiple brand strategies in a category tend to elevate the prices of all national brands (Willig 1991; Levy and Reitzes, 1993; Werden and Rozanski 1994, Putsis 1997).[19]

The relationship between the brand level Herfindahl and price is likely to be different for private label products, however. One might expect that elevated national brand prices in markets with low brand Herfindahls would also allow private labels to increase price. However, Schmalensee's (1978) analysis of brand proliferation as a barrier to entry suggests that the impact of the brand Herfindahl upon private label prices may be positive. As leading firms in these markets build portfolios of brands with small shares, it is harder for private labels to enter with a me-too brand. For example, many successful children's cereal brands capture only .006 (.6%) of the cereal market. A private label brand can hope at best to capture one third of this. The resulting volume is not sufficient to sustain production and distribution. Therefore, we hypothesize that private label price is positively related to the brand level Herfindahl index.

We also include a series of endogenous trade promotion variables in the price reaction equation.[20] These promotion variables consist of temporary percent price reduction, percent of volume sold on display, and percent of volume sold with a local newspaper feature ad. For example, percent price reduction for national brands (private label) are specified in the branded (private label) price reaction equation because reported prices are net of such reductions. The display and feature variables are specified as demand shift variables. As such, they appear in the demand equation, as well as the price reaction equations. This specification corresponds with the standard conceptualization of end-aisle displays and feature ads increasing sales even if there is no price promotion. Finally, since prior empirical work on the concentration-price relationship in grocery retailing suggests that the general level of the markup in a local market is related to retailer concentration (Marion 1979, Weiss 1989), we also specify the retail grocery four firm concentration ratio in

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variables: total branded share, total private label share, volume-weighted average price of national brands, and the volume-weighted average price of private label products. Also, note that the choice of variables was influenced by data availability. For example, no coupon or national advertising information was available, while average age, income and percent Hispanic were the only local demographic variables available.

18. Note that we use the brand Herfindahl, not the company Herfindahl (which are not available). The brand level Herfindahl in breakfast cereal, for example, is very low but the company level Herfindahl is very high because each of the top three companies sells many brands.

19. In many empirical settings, it is important to specify the Herfindahl index as endogenous - since the Herfindahl is a function of market share by definition, if share is endogenous, so must be the Herfindahl. Here, however, the situation is somewhat different. In our analysis, the primary cause of variation in the brand Herfindahl is *individual brand share* dispersion, which is not a function of aggregate national brand share (which is used in the empirical analysis). Given that the brand Herfindahl measures the share dispersion of the individual brands, we use it here as an imperfect but readily available instrument for segmentation and multiple brand strategies. Dropping the variable from the model had no appreciable effect on the estimation results for other variables in the model.

20. We address the endogeneity of the trade promotion variables through the use of instrumental variables. The principle is similar to the approach taken by Berry, Levinsohn and Pakes (1995). Specifically, each promotional vehicle for market i, category j, is expressed as a function of the promotional activity in each of the other j ($j \neq i$) markets, using the fitted value as the instrument. Note that in order for this approach to eliminate the endogeneity bias, the equation errors for each promotion instrument have to be independent. This requires that display and feature decisions, for example, are made on a market by market (or chain by chain) basis.

the price reaction curves to control for possible deviations from our monopoly retailer assumption (Besanko, Gupta and Jain 1997). Equation (21) presents the final form of the proposed LA/AIDS specification. Appendix B summarizes our key hypotheses.

$$\begin{aligned}
\text{BRSHARE} = {} & \alpha_{10} + \alpha_{11}\,\text{BRPRICE} + \alpha_{12}\,\text{PLPRICE} + \alpha_{13}\,\text{EXPENDITURE} + \alpha_{14}\,\text{BRFEATURE} + \alpha_{15}\,\text{BRDISPLAY} + \alpha_{16}\,\text{PLDISTN} + \alpha_{17}\,\text{PLFEATURE} + \alpha_{18}\,\text{PLDISPLAY} + \alpha_{19}\,\text{INCOME} + \alpha_{110}\,\text{HISPANIC} + \alpha_{111}\,\text{FAMAGE} + \varepsilon_1 \\
\text{PLSHARE} = {} & \alpha_{20} + \alpha_{21}\,\text{BRPRICE} + \alpha_{22}\,\text{PLPRICE} + \alpha_{23}\,\text{EXPENDITURE} + \alpha_{24}\,\text{BRFEATURE} + \alpha_{25}\,\text{BRDISPLAY} + \alpha_{26}\,\text{PLDISTN} + \alpha_{27}\,\text{PLFEATURE} + \alpha_{28}\,\text{PLDISPLAY} + \alpha_{29}\,\text{INCOME} + \alpha_{210}\,\text{HISPANIC} + \alpha_{211}\,\text{FAMAGE} + \varepsilon_2
\end{aligned} \quad \textbf{(21)}$$

$$\begin{aligned}
\text{BRPRICE} = {} & \beta_{10} + \beta_{11}\,\text{PLPRICE} + \beta_{12}\,\text{BRPRICEREDN} + \beta_{13}\,\text{BRVOLPUN} + \beta_{14}\,\text{HERFINDAHL} + \beta_{15}\,\text{GROCCR4} + \beta_{16}\,\text{EXPENDITURE} + \beta_{17}\,\text{BRFEATURE} + \beta_{18}\,\text{BRDISPLAY} + \beta_{19}\,\text{PLFEATURE} + \beta_{110}\,\text{PLDISPLAY} + \beta_{111}\,\text{PLDISTN} + \beta_{112}\,\text{INCOME} + \beta_{113}\,\text{HISPANIC} + \beta_{114}\,\text{FAMAGE} + \omega_1 \\
\text{PLPRICE} = {} & \beta_{20} + \beta_{21}\,\text{BRPRICE} + \beta_{22}\,\text{PLPRICEREDN} + \beta_{23}\,\text{PLVOLPUN} + \beta_{24}\,\text{HERFINDAHL} + \beta_{25}\,\text{GROCCR4} + \beta_{26}\,\text{EXPENDITURE} + \beta_{27}\,\text{BRFEATURE} + \beta_{28}\,\text{BRDISPLAY} + \beta_{29}\,\text{PLFEATUE} + \beta_{210}\,\text{PLDISPLAY} + \beta_{211}\,\text{PLDISTN} + \beta_{212}\,\text{INCOME} + \beta_{213}\,\text{HISPANIC} + \beta_{214}\,\text{FAMAGE} + \omega_2.
\end{aligned}$$

4. Empirical Estimation

4.1 Data

The data used in this study are IRI market-level data on food products across 59 geographic markets and 211 categories for 1991 and 1992. Categories were excluded from the analysis if they contained missing data, or if they were categories where private labels have not been introduced. This left 125 categories in the sample and 6,717 observations for an average coverage of 54 cities in a typical category. National brand volume (dollar) share averaged .721 (.775) in 1992.

These data were merged with independent data from *Progressive Grocer* on the demographic characteristics of the IRI geographic markets. Thus, we have two principal dimensions on which the data vary—across categories and across geographic markets. Consistent with previous work in the private label area (e.g., Sethuraman and Mittelstaedt 1992; Hoch and Banerji 1993; Slade 1995), aggregate branded and private label variables were created for the 125 product categories and 54 markets. Brand price, feature, display, and price reduction variables are volume as opposed to dollar market share weighted averages.

4.2 Methodology – LA/AIDS

The LA/AIDS system (equations 10, 12 and 13) was estimated directly using three stage least squares. Note that although our model has four equations, one of the demand equations is redundant for estimation purposes. Since the market shares of national brands and private labels sum to one, any loss of branded share due to changes in any variable, e.g. private label price, must go to private label share. This general adding up property of a demand system means that we can recover the estimated coefficients and standard errors (t-ratios) for the dropped equation. We drop the private label demand equation and estimate the remaining 3 equations with three stage least squares.

In an attempt to obtain results that generalize across all categories in the data set, we began by estimating the LA/AIDS system using a sample pooled across the 125 categories. It is important to note that cross-category analysis of this type precludes the use of price levels: one cannot compare the price of a pound of cheese to the price of canned soup. Thus, it would be inappropriate to conduct a cross-category analysis focusing on price relationships using data across multiple categories for a given time period (see, e.g., Kelton and Weiss 1989). Consequently, following Kelton and Weiss (1989), we estimated a first difference form on the pooled data.[21] Note that when conducting a cross-category study, estimating a first difference model is particularly attractive because it controls for first order fixed effects due to excluded local market and category variables in level regressions.[22]

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21. For example, in the first difference equations, BRSHARE is 1992 BRSHARE minus 1991 BRSHARE and BRPRICE is the 1992 LN(BRPRICE) minus the 1991 LN(BRPRICE). Changes in the natural logarithm of price from 1991 to 1992 are percent price changes that can be analyzed across categories.

22. Hausman and Taylor (1981) argue that excluded local market variables in panel data of this type can bias estimation results for level regressions. They show that this can be avoided by specifying a set of city binary variables. These drop out of the model when one takes the first difference. This is also true for

Further, to the extent that private label quality is constant from 1991 to 1992, estimating a first difference model eliminates the need for the inclusion of a private label quality measure for each category - an assumed constant level of quality drops out of the analysis when we difference. This is particularly important since quality measurement is such a difficult task (Hoch and Banerji 1993 and Narasimhan and Wilcox 1998).

In addition, in order to investigate differences that might exist across categories, we also estimated the proposed LA/AIDS framework using data for seven individual categories: milk, butter, bread, yogurt, pasta, margarine, and instant coffee. Since individual category-level analysis does not suffer from the same apples-to-oranges comparison that cross-category analysis does, we used the "level" data for each period for each individual category (we will refer to the data stacked from 1991 to 1992 data as the "level" data, and the data for 1992 minus 1991 as the "first difference" data). To summarize, the LA/AIDS specification was estimated using a first difference form applied to the sample pooled across all 125 categories, as well for seven individual categories using the level data.

4.3 Model Performance and Comparison with Alternative Functional Forms

In addition to the LA/AIDS specification, we estimated the Choi Manufacturer-Stackelberg model (equations 14 and 15) and the Raju, et al. model (equations 16 and 17) for each of the seven individual categories using three stage least squares. For each category, we estimated both models using the level data and used nested hypotheses tests to assess which of the two forms best fit the observed behavior in that specific category (as per the discussion above and Appendix A). In each instance, to facilitate comparisons, we used the same set of independent variables that were used in the LA/AIDS specification.

Thus, we make two sets of comparisons: i) individual-level category results across the Choi (1991) Manufacturer Stackelberg, Raju et al. (1995a) and the proposed LA/AIDS framework, and ii) the impact of pooling across categories on the parameter estimates (within the LA/AIDS specification). In doing so, we have attempted to assess the relative performance of the proposed LA/AIDS framework (versus two alternative model formulations), as well as the appropriate data to use when employing the LA/AIDS framework (individual category or pooled).

specifying a set of category binary variables in level regressions to control for excluded variables in individual categories.

5. Results

We begin by discussing the results obtained by estimating the LA/AIDS specification using the pooled sample and the first difference data, and then conclude by discussing the individual category results for all three models using the level data. Results are reported in Tables 1 through 4 (t-statistics in parentheses). Since traditional R^2 measures are not bounded between zero and one in three stage least squares, Carter and Nagar's (1977) multiple squared coefficient of correlation for simultaneous systems, R_w^2, was used.[23] All systems fit well, with the system-wide R_w^2 values ranging from a low of 0.9435 for bread under LA/AIDS to a high of 0.9997 for instant coffee and margarine in the linear specification.

5.1 LA/AIDS Estimation – Pooled Results

Tables1 and 2 present the results using the sample pooled across all 125 categories. Table 1 presents the full set of parameter estimates, while Table 2 presents the implied demand elasticities. The LA/AIDS specification applied to the pooled data performs extremely well. All of the coefficients have the hypothesized signs and are statistically significant, with the exception of the variables representing percent Hispanic and average family age (in the demand system) and private label feature and display (in the national brand price reaction equation).

In the price reaction equations, there is evidence of strategic interaction, but it is not particularly strong, and is only mildly asymmetric. For example, a 10 percent increase in national brand price leads to a mere 1.15 percent increase in private label price. Similarly, a 10 percent increase in private label price only leads to a 1 percent increase in national brand price. Note also that the four-firm retail concentration has a significant and positive impact on both branded and private labels prices. The coefficient is 50 percent higher for private label products (.06 versus .04 for national brands), suggesting that the price differential between private labels and national brands narrows in more concentrated local grocery markets. This is consistent with prior work on the relationship between concentration and price in grocery

23. R_w^2 has a usual R^2 interpretation. Specifically, it measures the percent of system-wide variation in the exogenous variables explained by all independent variables in the system. It is bounded by zero and one. However, we note that this statistic is frequently very high and should be interpreted with caution (see Berndt 1991, p.468).

retailing, but represents a significant advance due to the number of categories and markets studied here. Previous work relied on price indexes for only 96 products collected by in-store price surveys across only a few supermarket chains. Marion (1979), for example, analyzed prices for 3 chains in 35 major urban markets. Cotterill (1986) analyzed price indices using the same product set, but only for 2 chains in small towns in Vermont. In contrast, this study encompasses thousands of products and virtually all supermarkets in 54 major urban markets.

On the demand-side, the results in Table 2 suggest that the estimated own price elasticities for national brands (-1.078) and for private labels (-1.026) are highly significant, but lower than own price elasticities estimated at the category or product level. The cross-price elasticities are positive as hypothesized, but only the private label demand cross-price elasticity is statistically significant. Consistent with previous work by Blattberg and Wisniewski (1989) and Allenby and Rossi (1991), national brand price affects private label demand, but changes in the private label price do not significantly effect national brands.

5.2 Individual Category Results and Model Selection (LA/AIDS, Choi 1991, Raju, et al. 1995a)

Table 3 presents the estimated demand and price reaction elasticities for the LA/AIDS specification using the “level” data for seven categories, while Table 4a presents the corresponding estimated demand and reaction elasticities for the linear demand model. Table 4b presents the results from the hypotheses tests used to determine a) whether the Choi (1991) or Raju, et al. (1995a) demand model best fit the data, and b) whether the results are consistent with Stackelberg conduct and/or proportional mark-up pricing (Appendix A).

Examining Table 4b first, hypothesis tests favor the Choi (1991) model for the butter, bread, and margarine categories, while the Raju, et al. (1995a) modified Shubik demands are more consistent with the milk, yogurt, pasta, and instant coffee categories. Out of 14 tests for Stackelberg price reaction coefficients (7 for national brands and 7 for private labels), all but four are consistent with Stackelberg behavior within the channel. Out of 14 tests for proportional markup conduct, all but two (both for private labels) are consistent with proportional markup behavior within the channel. Note that the inability to reject Stackelberg and proportional mark-up behavior for almost all within channel pricing behavior (and for essentially all private label pricing) is consistent with the assumption of Stackelberg proportional mark-up behavior used in the derivation of the LA/AIDS reaction functions.

In comparing the LA/AIDS results in Table 3 to the linear demand results in Table 4a, we can not use traditional non-nested hypotheses tests to compare the models—note that the dependent variable in the LA/AIDS demand specification is expenditure share, while the dependent variable in the Choi (1991) and Raju, et al. (1995a) models is quantity. Since expenditure share cannot be represented as an appropriate transformation of quantity (see Balasubramanian and Jain 1994, pp. 56-57), even non-nested tests that can sometimes be used to compare models with different dependent variables (the Vuong and P-E tests), are not appropriate here.[24] Fortunately, more subjective measures of the relative performance of the different demand specifications paint a clear picture.

For the LA/AIDS parameter estimates in Table 3, the empirical estimation produced results with not only a great deal of face validity, but also results that were consistent with previous research on a number of dimensions. For example, Tellis (1988) in a meta-analysis of reported demand elasticities, found the mean price elasticity of demand to be -1.71, consistent with the national brand elasticities reported in the first row of Table 3. In addition, consistent with the pooled results, we find significant asymmetric price response - estimated private label own price elasticities are higher in most categories. However, this asymmetry is reversed in the butter category, which is consistent with recent work by Bronnenberg and Wathieu (1996). In terms of the price reaction elasticities, the price reactions of national brands were small in magnitude, with the highest price reaction by national brands occurring in the category with one of the highest private label shares (margarine). Overall, the reported price reactions are very close to those reported by Lambin (1976) and others (see, e.g., Hanssens, Parsons and Schultz 1990, pp. 201-210).

Alternatively, the results for the Choi (1991) and Raju, et al. (1995a) linear demand specifications show fewer significant coefficients, and a great deal more volatility in the parameter estimates. While there is some consistency between the magnitude of the *significant* demand elasticities for the linear and the LA/AIDS specifications, there are not many significant parameter estimates in Table 4a. For both the linear demand and price reaction elasticities, a number of parameter estimates are outside of the range reported in other studies. For example, estimated

24. We note, however, that since the demand and reaction elasticities in the LA/AIDS elasticities are calculated as quantity elasticities, they *are* directly comparable across the three models.

price reaction elasticities of 2.1 for private labels in the pasta and 1.9 for national brands in the yogurt categories (both significant at α = .01) not only *seem* high, they are inconsistent with previous research (e.g., Lambin 1976). We conjecture that the relative stability of the parameter estimates and the high number of significant coefficients in the LA/AIDS system is due in large part to the highly flexible form of the LA/AIDS specification.

6. Discussion

6.1 Methodological Issues

Despite some restrictive demand-side assumptions and a seemingly inflexible functional form, the Choi (1991) and Raju, et al. (1995a) models did not fare poorly. We were able to determine which of the two best fit the data and derive a number of statistically significant and reasonable elasticities. However, the volatility of the parameter estimates is disconcerting. The large number of insignificant coefficients leaves a researcher without information on key parameter values. Further, price reaction elasticities over 1.0 seem questionable even if statistically significant. In contrast, the LA/AIDS framework introduced above provides us with a flexible functional form that performs well on both individual categories and on a larger pooled sample. Further, the structural equation system provides clear and significant demand and supply-side results.

Perhaps most importantly, the PIGLOG form of the LA/AIDS model allows estimation at various levels of aggregation, minimizing the assumptions necessary to avoid linear aggregation bias. Christen, Gupta, Porter, Staelin and Wittink (1997) demonstrate that non-linear models estimated with linearly aggregated data can produce biased response parameters. The intuition behind this bias is similar to aggregation biases in advertising, (Leone 1995), diffusion (Putsis 1996) and demand analysis (Deaton and Muellbauer 1980a). However, the LA/AIDS model has especially nice aggregation properties. First, it does not necessitate the assumption of parallel linear Engel curves in order to achieve exact aggregation (see, e.g., Deaton and Muellbauer 1980b). This implies that estimated expenditure relationships are "representative" and do not contain the same bias as suggested by Christen, et al. (1997). Second, it is easy to demonstrate that any bias in marketing mix response estimates can be eliminated by taking the first difference, provided that *relative* store prices remain the same from one period to the next.[25]

We offer two arguments that suggest that this is a reasonable assumption. First, retail costs and manufacturer incentives are likely to vary similarly across stores over time in a given market, suggesting that retail prices in a given market should vary approximately by the same proportions over time. Second, Christen, et al. (1997) report that the magnitude of the bias can be severe, with the average error of over 100 percent for low frequency promotion items. Yet, despite this, our parameter estimates for own-demand response, cross-demand response and competitive reactions are consistent with a number of previous studies (see Results section above), suggesting to us that any aggregation bias, if present at all, is kept to a minimum.

In summary, we suggest that the level of data aggregation and concerns about aggregation biases (e.g., in instances where there is significant variance in pricing and promotional activity across stores) should play an important role in deciding whether the level or first difference form of the LA/AIDS formulation should be used. For higher levels of aggregation (both in terms of multiple categories and the use of market level data), one should consider using a difference formulation, whereas a level formulation would be preferred when looking at store level data for a single category, for example. For any pooled sample, one should *only* consider using the first difference formulation.

Finally, the variation from category to category in each of the parameter estimates suggests that while a pooled analysis might provide estimates of the demand and reaction elasticities that are correct *on average*, they are likely to provide inaccurate estimates of the response for any *specific* category. Although a pooled analysis provides some level of generalizability, the parameter estimates should be viewed as precisely that—general

25. This can be shown quite easily. Under a first difference model, all variables are expressed as the change from period t to t+1. Since the marketing mix response in a LA/AIDS specification of our model is log-log in share, first differencing expresses prices, for example, as the log of the ratio of prices in t and t-1. As long as the *relative* prices move together, the ratio of the prices is constant. Thus, if the percent *change* in prices is the same from store to store, the bias is eliminated (this is analogous to homogeneous marketing mix variables in the Christen, et. al. 1996 paper). Thus, it is not necessary that all consumers at all stores face the same prices. We would argue that assuming that the relative prices remain the same from one period to the next is much more tenable than assuming that all stores have the same prices.

results that may not hold for specific categories. Detailed information on the interaction that occurs for any specific category requires intra-category analysis (Bresnahan 1989).

6.2 Substantive Issues and Managerial Implications.

Once the methodological issues are resolved, there are a number of important substantive findings (we focus on the LA/AIDS parameter estimates in Tables 1 through 3 here). For example, retail concentration (measured by the local retail four-firm concentration ratio, GROCCR4) has a consistently positive impact on price for both national brands and private labels (see, e.g., the pooled results in Table 1). Thus, a more concentrated local retail environment results in a higher retail price across the board and the national brand private label price differential narrows. These results are more significant than prior studies of the retail concentration-price hypothesis (e.g. Marion 1979, Cotterill 1986) because they are based on a much larger sample of prices and chain supermarkets. At the brand level, we find that categories with many brands (i.e., a low Herfindahl) have higher national brand and lower private label prices. As suggested by Schmalensee (1978) and Putsis (1997), brand proliferation elevates all brand prices and makes it more difficult for private labels to compete.

Price response is decidedly asymmetric and idiosyncratic to the category. For example, in the bread category, a 1% increase in private label price elicits only a .322 percent increase in national brand price, while there is no evidence of a corresponding private label price response. Alternatively, a 1% increase in the national brand price in the instant coffee category elicits a .777 percent private label price response, this time without an accompanying *national brand* price response. In the price reaction equations, own feature and display have strong negative estimated coefficients for both private labels and national brands. It appears as though when price cuts occur, feature advertising and point of sale displays occur more frequently, advertising the price cuts. However, when national brand display and feature ads are active, private label prices are *lower*. This suggests to us that retailers often use price as a strategic weapon in categories where national brands use non-price promotion extensively. This is consistent with recent experience in the breakfast cereal industry (Gejdenson and Schumer 1999a, 1999b; Angrisani, 1996; Cotterill 1996).

In investigating some of the differences in price reactions across categories, we discovered that the price response is heavily dependent upon the existing private label share in the category. To illustrate this, we divided the sample into quartiles based upon private label share. Table 5 presents the estimated demand and price reaction elasticities across these quartiles. While there is little change in the own demand response across quartiles, we note that both the national brand demand response to private label price and the price reaction elasticities (national brand response to private label price in particular) increase substantially across quartiles. It appears as though price is not an important strategic weapon when private label share is low, but becomes increasingly important as private label share increases. Part of this, of course, is reflective of the endogeneity of share and the idiosyncratic nature of the individual categories. Nonetheless, this is consistent with previous work on competition using a conjectural variations approach (e.g., Gelfand and Spiller 1984), and it highlights the importance of an intra-industry analysis.

On the demand side (focusing on the results in Table 3), we find that the estimated own price demand elasticities ranged from -1.05 for instant coffee to -2.42 in the Yogurt category. All estimated elasticities are highly significant. In general, private label demand is more price elastic, although two exceptions are the bread and milk categories. Demand side responses to price changes, like supply side price reactions, are decidedly asymmetric: in general, private label demand is more responsive to changes in national brand price than was national brand demand to private label price. The one exception is in the butter category, a category where the national brand share is relatively low (.54). The expenditure elasticities are above 1.0 in all three models for national brands and below 1.0 in all three models for private labels. Household income elasticities (mean household income in 1992 was $39,358) in Table 2 indicate that an increase in household income has a small but significant *positive* impact on branded volume and a very but significant *negative* impact on private label volume. This suggests that higher income implies a lower level of private label consumption, i.e., it is an inferior good. The fact that both income elasticities are less than one implies that food is a necessity and, as income increases, a smaller portion of the budget is allocated to it.

7. Conclusions

Analysis of panel data such as the IRI Supermarket Review data studied here combined with consideration of both demand and supply side influences provide considerably more insight into competitive strategies than do single-equation cross sectional studies. In order to get a more complete view of the strategic implications and in an attempt to produce generalizable results, we have conducted our empirical analysis across a variety of categories and geographic markets. We felt it important to understand "the big picture" first, especially given the recent focus in marketing on generalizability, and given this is the first study to address the impact of competitive response on private label and national brand sales volume.

Based upon the discussion above, certain substantive implications become clear:

- Brand managers should expect to face traditional demand relationships regardless of whether they are managing a national brand or a private label - an increase in the price of a national brand (private label) lowers national brand (private label) share. There are no free lunches here—a higher price means a lower share, *ceteris paribus*.
- Both demand and supply-side reactions will vary by category, highlighting the importance of understanding the category-specific nature of competition and demand response.
- National brand prices are higher in categories with extensive product proliferation. Private labels have greater difficulty competing in these categories, and lower prices in an attempt to compete. However, the cross price elasticities suggest this is a meager way to capture volume from national brands.
- National brand private label price differential is lower when local retail concentration is high, suggesting that local retail concentration can afford retailers some degree of market power.
- Cross price elasticities are decidedly asymmetric with national brand price having a major impact on private label sales, whereas private label price has a considerably smaller impact on branded sales. This is consistent with the work on asymmetric competition and price tiers (Blattberg and Wisniewski 1989; Allenby and Rossi 1991). However, these asymmetries can be reversed, consistent with recent work by Bronnenberg and Wathieu (1996).
- Managers responsible for private labels operating in markets with higher per capita income or categories with a higher level of expenditure will have a more difficult time penetrating the market. More generally, we would expect private labels to suffer during stronger economic times.

Methodologically, the following conclusions are drawn:

- The linear demand specification supports Stackelberg proportional markup conduct. It produces demand estimates that are generally reasonable, but LA/AIDS demands produce more consistent demand side estimates.
- Estimated price reaction elasticities under the proposed LA/AIDS framework are not only statistically significant, but also consistent with previous studies. This is not true of the Choi (1991) or Raju, et al. (1995a) linear demand models.
- Within-category analysis should be used wherever possible—analysis of data pooled across categories is likely to be correct *on average*, but can lead to incorrect conclusions for any *specific* category.

Finally, as discussed in the introduction, insights into the effectiveness of competitive strategies for branded and private label grocery products entails an understanding of not only the effectiveness of various strategies on the demand side, but an understanding of the supply side competitive interaction between national brands and private labels as well. In order to assess the viability of such strategies, it is important to differentiate between the direct demand side effect and the likely response of rival firms. We encourage future research in this area, in particular, addressing competitive interaction on category-by-category basis with the use of disaggregate data.

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Appendix A – Testing Within-Channel Structure

i) Towards a More General Class of Mark-up Models

Although Choi (1991) and Raju, et al. (1995a) assume that retailers engage in explicit profit maximizing conduct, retailers may routinely use mark-up pricing to make retail pricing decision. Assuming that retailers use a generalized mark-up for a national brand:

$$P^1 = m_1^1 w^1 + m_o^1 \qquad \textbf{(A1)}$$

where: m_1 and m_o are proportional and fixed mark-up parameters respectively. Solving this "best response" price relation for w^1 gives:

$$w^1 = k_1^1 P^1 - k_o^1 \qquad \textbf{(A2)}$$

where: $k_1^1 = 1/m_1^1$ *and* $k_o^1 = m_o^1/m^1{}_1$.

Substituting (A2) into the manufacturers profit maximization problem, we can obtain the following retail level price reaction equation for the Choi (1991) Manufacturer-Stackelberg model:

$$P^1 = \frac{g}{2b}P^2 + \frac{a}{2b} + \frac{k^1{}_o}{ak^1{}_1} + \frac{C^1}{2k^1{}_1} \qquad \textbf{(A3)}$$

Comparing this to the Choi (15) and Raju, et al. (17a) reaction curves, note that the slope is identical to that of the Choi (1991) and Raju et al. models ($g/2b$).

It is possible to demonstrate that the characterization of profit maximizing conduct in the Choi Manufacturer-Stackelberg and Raju, et al. models are special cases of the generalized mark up rule, (i.e., for specific values of k_0^1 and k_1^1, it is possible to derive each model). For example, if m_0=0, then the markup is proportional and k_0^1 =0. In this case, the reaction function for the Raju, et al. specification reduces to:

$$P^1 = \frac{g}{2b}P^2 + \frac{a_1}{2b} + \frac{k^1{}_0}{2k^1{}_1} + \frac{C^1}{2k^1{}_1} \qquad \textbf{(A4)}$$

Note that if the intercept in the linear national brand reaction function is equal to $a_1 / 2b$, then the proportional mark-up model holds for the Raju demand specification. If the private label manufacturer has market power and enjoys a markup over costs then the test for proportional markup tests for the equality between the intercept coefficient from the private label price reaction equation and ($a_2 / 2b$). The same tests for proportional markup conduct are appropriate for the Choi model, where $a_1 = a_2$. We use these relationships in the next section to develop tests for assessing a) whether the demand structure observed is consistent with the Choi (1991) or Raju, et al. (1995a) specifications, and b) if the vertical relationship is characterized by Stackelberg, generalized mark-up, or proportional mark-up behavior. To these tests we now turn.

ii) Testing for Demand Structure and Within-Channel Behavior

Each of these relationships provide a convenient test of demand structure and within channel behavior. To demonstrate, note that one can estimate the following linear demand and price reaction system to test for demand structure and vertical conduct:

$$Q^1 = A_{10} - A_{11}P^1 + A_{12}P^2 \qquad \textbf{(A5)}$$

$$Q^2 = A_{20} - A_{21}P^2 + A_{22}P^1 \qquad \textbf{(A6)}$$

$$P^1 = R_{10} + R_{11}P^2 + R_{12}C^1 + R_{13}D^1 \qquad \textbf{(A7)}$$

$$P^2 = R_{20} - R_{21}P_1 + R_{22}C^2 + R_{23}D^2 \qquad \textbf{(A8)}$$

where all variables are defined earlier except C^1 and C^2, which are now instruments for unobserved marginal costs.[26]

To test whether the demand system is consistent with the Choi (1991) or Raju, et al. (1995a) demand specifications, the most straight forward approach is to test whether the intercepts A_{10} and A_{20} are equal. The hypothesis is:

H_o: $A_{10} - A_{20} = 0$ then the system is consistent with Choi demand, **(A9)**

H_a: $A_{10} - A_{20} \neq 0$ then it is consistent with Raju demand.

For the demand structure to be consistent with the Choi (1991) or Raju, et al. (1995) specification, the following must also hold (we note that it is possible that the estimated demand structure is consistent with neither the Raju, et al. or Choi specifications):

$$A_{11} - A_{21} = 0 \qquad \textbf{(A10)}$$

$$A_{12} - A_{22} = 0$$

To test for Stackelberg and proportional mark-up behavior, one needs to use the estimated coefficients on the reaction functions. For example, if conduct is consistent with Stackelberg behavior, then equations A11 and A13 should hold. If conduct is consistent with proportional markup behavior, then equations A12 and A14 should hold:

National Brands

$$R_{11} - \frac{A_{12}}{2A_{11}} = 0 \qquad \textbf{(A11)}$$

$$R_{10} - \frac{A_{10}}{2A_{11}} = 0 \qquad \textbf{(A12)}$$

Private Labels

$$R_{21} - \frac{A_{22}}{2A_{21}} = 0 \qquad \textbf{(A13)}$$

$$R_{20} - \frac{A_{20}}{2A_{21}} = 0 \qquad \textbf{(A14)}$$

Note that, as is assumed in the LA/AIDS derivation, it is possible for us to observe Stackelberg behavior concurrently

26 The demand shift variables D^1 and D^2 are necessary for empirical estimation and can be added to the linear demand specification by generalizing the intercept in those equations to be a function of an interception and demand shift variables.

with proportional mark-up conduct. Finally, if equations (A15) and (A16) hold, then the private label reaction function is consistent with (17b) and private label manufacturers sell to the retailer at competitive prices (i.e., at marginal cost):

$$R_{21} = 0 \tag{A15}$$

$$R_{20} = \frac{A_{20}}{2(A_{21} - A_{22})} \tag{A16}$$

Appendix B - A Summary of Maintained Hypotheses

H1: $a_{11}, a_{22} < 0; a_{12} a_{21} > 0$ Standard economic theory predicts negative own-price elasticities and positive cross-price elasticities for substitute goods. Further, effects should be asymmetric (Blattberg and Wisniewski 1989).

H2: $\alpha_{14},\alpha_{15},\alpha_{27},\alpha_{28} > 0$ Increased own promotions have a positive impact on own $\alpha_{17}, \alpha_{18}, \alpha_{24},\alpha_{25} < 0$ sales and a negative impact on the rival's sales

H3: $a_{19} > 0$ $a_{29} < 0$ As per capita income in a market increases, we expect that branded share increases and private label share decreases.

H4: $\alpha_{16} < 0$; $\alpha_{26} > 0$ As more supermarkets in a local market carry private $\beta_{111} < 0$; $\beta_{211} > 0$ labels (increased private label distribution), the share and price of national brands decrease (due to the increased competition), and the share and price of private labels increase.

H5: $b_{11}, b_{21} > 0$ The slope of the price reaction curves are positive (Deneckere and Davidson 1985).

H6: $b_{13}, b_{23} < 0$ Increasing average package size lowers cost, thereby lowering market price.

H7: $b_{14} < 0$; $b_{24} > 0$ Decreasing brand Herfindahl due to product proliferation increases the market power of incumbents by creating entry barriers, thereby raising national brand prices (Schmalensee 1978, Putsis 1997).

H8: b_{15}, $b_{25} > 0$ Increases in grocery firm local market concentration increase prices due to increased market power at the retail level (Weiss 1989).

Chart 1. Definitions for Variables Used in the Analysis[1]

BRSHARE	Aggregate share of category expenditure for branded products in the ith market, jth category
PLSHARE	Aggregate share of category expenditure for private label products, ith market, jth category
BRPRICE	Natural log of the price of the branded product in the ith market, jth category
PLPRICE	Natural log of the price of the private label product in the ith market, jth category
EXPENDITURE	Natural log of per capita category expenditures deflated by Stone's price index
BRFEATURE	Percent of branded products sold with feature advertising in the ith market, jth category
BRDISPLAY	Percent of branded products sold with displays and point-of-sale promotion, ith market, jth category
PLFEATURE	Percent of private label products sold with feature advertising in the ith market, jth category
PLDISPLAY	Percent of private label products sold with displays and point-of-sale promotion
INCOME	Natural log of the average household income in the local market
HISPANIC	Percent of population in the local market of Hispanic decent
AGE	Natural log of the average age of the local market population
PLDISTN	Private label average distribution in the ith market, jth category
BRPRICEREDN	Weighted percent average price reduction, branded products, ith market, jth category
PLPRICEREDN	Weighted percent average price reduction, private label products, ith market, jth category
BRVOLPUN	Natural log of average volume (weight) per package unit sold for branded product
PLVOLPUN	Natural log of average volume (weight) per package unit sold for private label
HERFINDAHL	Herfindahl index of brand concentration in the ith market, jth category
GROCCR4	Percentage of all grocery sales by the top four grocery chains in the ith market, jth category

1. Price rather than the natural log of price, and quantity rather than share, are used in the linear category models.

Table 1. Estimation Results for Pooled Data: LA/AIDS Model (First Difference)

	Demand Equations				Price Reaction Equations			
	Branded Share		Private Label Share		Branded Price		Private Label Price	
BR Price	-0.019	(-4.87)**	0.019	(4.87)**			0.115	(12.64)**
PL Price	0.018	(5.69)**	-0.018	(-5.70)**	0.100	(16.99)**		
BR Price Reduction					-0.104	(-6.29)**		
PL Price Reduction							-0.213	(-12.18)**
BR Volume/Unit					-0.857	(-146.00)**		
PL Volume/Unit							-0.843	(-106.50)**
BR Herfindahl					-0.161	(-8.80)**	0.433	(17.45)**
Grocery CR4					0.042	(3.10)**	0.064	(3.37)**
Expenditure	0.054	(15.54)**	-0.054	(-15.54)**	0.219	(35.74)**	0.145	(17.29)**
Br Feature	0.111	(6.35)**	-0.111	(-6.35)**	-0.209	(-7.15)**	-0.073	(-1.75)
Br Display	0.153	(12.95)**	-0.153	(-12.95)**	-0.413	(-20.65)**	-0.115	(-4.02)**
PL Feature	-0.022	(-2.09)*	0.022	(2.09)*	0.011	(0.610)	-0.151	(-5.90)**
PL Display	-0.085	(-12.13)**	0.085	(12.13)**	-0.013	(-1.11)	-0.234	(-13.99)**
PL Distribution	-0.187	(-36.06)**	0.187	(36.06)**	0.029	(3.23)**	0.027	(2.15)*
Income	0.021	(3.11)**	-0.021	(-3.11)**	0.121	(10.46)**	-0.065	(-3.94)**
Hispanic	-0.001	(-0.017)	0.001	(0.017)	-0.479	(-3.86)**	-0.210	(-1.18)
Family Age	-0.014	(-0.932)	0.014	(0.932)	-0.185	(-7.18)**	-0.107	(-2.91)**

BR = National Brand, PL = Private Label
Number of Observations = 6717
(t-statistics in parentheses)
** significant at the 1% level. * significant at the 5% level

Table 2. Estimated Demand Elasticities for Pooled Data:
LA/AIDS Model (First Difference)

	Branded Quantity	Private Label Quantity
BR Price	-1.078 (-175.78)**	0.270 (12.75)**
PL Price	0.007 (1.750)	-1.026 (-70.29)**
Expenditure	1.070 (237.86)**	0.759 (48.844)**
BR Feature	0.009 (6.347)**	-0.031 (-6.347)**
BR Display	0.022 (12.955)**	-0.076 (-12.96)**
PL Feature	-0.002 (-2.088)*	0.006 (2.088)*
PL Display	-0.013 (-12.13)**	0.043 (12.13)**
PL Distribution	-0.190 (-36.061)**	0.655 (36.06)**
Income	0.720e-06 (3.105)**	-0.249e-05 (3.105)**
Hispanic	-0.0001 (-0.017)	0.000 (0.017)
Family Age	-0.0005 (-0.932)	0.002 (0.932)

BR = National Brand, PL = Private Label
t-statistics in parentheses
** significant at the 1% level.
* significant at the 5% level

Table 3. Demand and Reaction Elasticities for Individual Product Categories, LA/AIDS Model (Level Data)

	Milk	Butter	Bread	Yogurt	Pasta	Margarine	Inst. Coffee
BR Own Price Elasticity	-1.63 (-4.20)**	-1.82 (-3.19)**	-1.80 (-9.66)**	-2.42 (-12.00)**	-1.48 (-13.90)**	-1.16 (-21.63)**	-1.05 (-47.06)**
PL Own Price Elasticity	-1.22 (-2.81)**	-2.93 (-4.47)**	-1.66 (-4.66)**	-4.85 (-5.11)**	-2.31 (-3.38)**	-5.86 (-6.60)**	-0.100 (-0.318)
BR Cross Price Elasticity	0.458 (0.513)	1.39 (2.94)**	0.234 (1.86)	0.795 (4.06)**	0.206 (1.91)	0.474 (5.47)**	-0.043 (-2.86)**
PL Cross Price Elasticity	0.308 (1.63)	1.14 (1.44)	2.26 (4.30)**	6.87 (7.04)**	3.04 (4.50)**	1.66 (3.01)**	1.05 (2.26)*
BR Price Reaction Elasticity	-0.600 (-1.64)	0.401 (3.40)**	0.322 (3.39)**	0.705 (3.99)**	1.25 (0.932)	1.06 (3.69)**	0.070 (1.07)
PL Price Reaction Elasticity	0.175 (2.10)*	0.777 (4.53)**	0.321 (0.84)	1.02 (2.05)*	1.01 (2.89)**	0.231 (0.776)	-0.083 (-0.518)
Average BR Share	.30	.54	.62	.77	.81	.84	.94
NOBS	116	112	118	114	118	118	108

BR = National Brand, PL = Private Label (t-statistics in parentheses)
** significant at the 1% level. * significant at the 5% level

Table 4a. Demand and Reaction Elasticities for Individual Product Categories, Linear Model (Selected Model, Choi or Raju)

	Milk	Butter	Bread	Yogurt	Pasta	Margarine	Inst. Coffee
Selected Demand Structure	Raju	Choi	Choi	Raju	Raju	Choi	Raju
BR Own Price Elasticity	-2.74 (-6.06)**	-0.453 (-0.676)	-0.415 (-0.925)	-1.99 (-7.38)**	-1.12 (-8.40)**	-1.31 (-12.95)**	-0.907 (-18.37)**
PL Own Price Elasticity	-0.831 (-1.62)	-0.245 (-0.245)	0.060 (0.084)	-3.03 (-2.21)*	-0.609 (-1.02)	-7.78 (-5.34)**	-0.009 (-0.028)
BR Cross Price Elasticity	-0.059 (-0.057)	-0.020 (-0.032)	-0.472 (-1.83)	0.391 (1.36)	-0.141 (-1.33)	0.564 (3.80)**	-0.135 (-3.91)**
PL Cross Price Elasticity	0.769 (3.40)**	-1.93 (-1.82)	-1.73 (-1.38)	4.001 (3.10)**	0.481 (0.641)	4.18 (3.95)**	1.17 (2.61)**
BR Price Reaction Elasticity	-0.361 (-1.42)	0.551 (5.16)**	0.307 (2.25)*	1.89 (2.96)**	1.19 (0.400)	1.44 (4.28)**	0.039 (0.603)
PL Price Reaction Elasticity	0.199 (2.39)*	0.731 (5.21)**	0.740 (2.48)*	-0.076 (-0.068)	2.101 (3.77)**	0.170 (0.545)	-0.077 (-0.484)
Average BR Share	.30	.54	.62	.77	.81	.84	.94
NOBS	116	112	118	114	118	118	108

BR = National Brand, PL = Private Label (t-statistics in parentheses)
** significant at the 1% level. * significant at the 5% level

Table 4b. Demand Structure, Manufacturer Stackelberg, and Proportional Markup Test Results for Individual Categories, Linear Model*

	Milk	Butter	Bread	Yogurt	Pasta	Margarine	Inst. Coffee
Demand Structure (A9 and A10 in Appendix A)	Raju p=.02	Choi p=.11	Choi p=.94	Raju p=.01	Raju p=.00	Choi p=.42	Raju p=.00
Manufacturer Stackelberg Conduct?							
i) National Brand (Equation A11)	Yes p=.17	Yes p=.94	Yes p=.35	No p=.01	Yes p=.67	No p=.00	No p=.06
ii) Private Label (Equation A13)	Yes p=.38	Yes p=.80	Yes p=.93	Yes p=.52	No p=.02	Yes p=.74	Yes p=.98
Proportional Markup Conduct?							
i) National Brand (Equation A12)	Yes p=.51	Yes p=.45	Yes P=.22	No p=.00	Yes p=.59	Yes p=.63	No p=.00
ii) Private Label (Equation A14)	Yes p=.09	Yes p=.67	Yes P=.94	Yes p=.99	Yes p=.73	Yes p=.17	Yes p=.98

* All tests use a 5% significance level criterion (p = test probability values).

Table 5. Demand and Reaction Elasticities for Subsets Sorted by Private Label Share: LA/AIDS Model (First Difference)

Quartile (Private Label Market Share)	Low Quartile (0 – 11.1%)	Mid Low Quartile (11.2 - 23.1%)	Mid High Quartile (23.2 - 39.9%)	High Quartile (> 39.9%)
BR Own Price Elasticity	-1.035 (-201.4)**	-1.057 (-147.1)**	-1.131 (-84.99)**	-1.285 (-38.78)**
PL Own Price Elasticity	-1.011 (-19.84)**	-0.907 (-22.05)**	-1.191 (-25.08)**	-1.413 (-23.77)**
BR Demand Cross Price Elasticity	0.0006 (0.220)	-0.013 (-2.26)**	0.056 (4.01)**	0.390 (6.95)**
PL Demand Cross Price Elasticity	0.715 (6.89)**	0.399 (7.98)**	0.417 (9.81)**	0.302 (8.59)**
BR Price Reaction Elasticity	0.075 (8.78)**	0.115 (9.19)**	0.096 (5.34)**	0.360 (11.15)**
PL Price Reaction Elasticity	0.173 (7.35)**	0.110 (7.03)**	0.103 (6.08)**	0.229 (11.78)**
NOBS	1680	1679	1681	1678

BR = National Brand, PL = Private Label
(t-statistics in parentheses)
** significant at the 1% level.
* significant at the 5% level

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