Spatial Competition in Private Labels

by

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Abstract

Private labels, or store brands, are an important part of non-price competitive strategy among multi-product retailers. Previous research into the rationale for private label products focuses on their ability to increase retailer's power over suppliers in the vertical channel, or to facilitate horizontal differentiation among retailers. This paper seeks to identify the relative importance of each role in retailers' positioning of private labels. This information is revealed through a novel empirical approach that considers the relative positioning of national brands and private labels in attribute space. In selecting attributes for private labels, retailers face a trade off between softening horizontal competition by differentiating their store brand from national brands, which facilitates inter-retailer differentiation, or increasing bargaining power over national brand manufacturers by designing products that closely mimic national brands. A spatial nested logit econometric model applied to the ice cream category shows that private labels tend to be positioned near national brand products in attribute space, allowing retailers to gain a greater share of the total marketing margin (manufacturer plus retailer margin). Differentiating through private labels allows a retailer to gain market share, but not necessarily increase retail margins.

keywords: multiproduct oligopoly, nested logit, private labels, retailing, spatial modeling.

Spatial Competition in Private Labels

Introduction

Over the past several years, the use of store brands, or private labels, has become a key component of retailer strategy. In the U.S., consumers spent a record $108.0 billion on private label products in 2005, an increase of 5.3% over 2004 (Datamonitor). Private labels now account for nearly one quarter of all consumer spending on food, beverages and personal care items. Both the trade press and academic research have documented several reasons for the popularity of private labels – building store loyalty, targeting specific market segments, generating higher margins, gaining strategic advantage over suppliers or maintaining control over the supply-chain. These reasons can be classified into two broad categories: (1) private labels that are similar to national brands increase retailers' bargaining power over manufacturers, thus raising retailers' share of the total (manufacturing plus retailing) margin, and (2) private labels provide a means of differentiating a retailer's product line from that of its rivals, increasing the total margin on all products sold. This paper designs and implements an empirical test to examine the relative importance of these two roles using a new approach that explicitly accounts for the strategic positioning of private labels, both in price and in attributes.

While offering important insights into the many potential explanations for the rise of private label products, the research to date considers their value in retailers' interaction with others in the vertical channel – consumers downstream or upstream suppliers – and not as strategic tools in horizontal rivalry with other stores. However, retailers now regard horizontal competition as perhaps their most pressing problem. Therefore, private labels almost certainly play an important role in store-differentiation, building market power, or in stealing others' loyal customers and building market share. Indeed, in industry surveys retailers often cite the strategic importance of private labels in competing with other stores (Food Institute). What is not clear is

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whether the strategic impact is through the "market power effect" (store differentiation) described above, or through the "market share effect" (attracting price sensitive consumers from other stores) (Dhar and Hoch 1997). Which effect dominates is an unresolved empirical question.

In this paper, we use a spatial econometric approach to study the positioning of private label products, specifically ice-cream. The strategic position of a store brand is typically defined in terms of its price point and revealed or "perceptual" substitutability with national brands (Sayman, Hoch and Raju, 2002; Bontemps, Orozco, and Requillart, 2005; Choi and Coughlan, 2006). However, because the degree of substitutability between any two pairs of products can derive from a number of potential sources, we consider how retailers (and retailer-manufacturers) position a product through the simultaneous choice of its attributes and its price. Consequently, a retailer's decision to introduce a private label is inherently spatial.

Although developed in the context of private label products, our model also represents a new way of thinking about the "demand for variety." Whereas Salop (1977), Dixit and Stiglitz (1977) and, more recently, Kim, Allenby and Rossi (2002), Watson (2004), and Draganska and Jain (2005) define variety in terms of the number of products, or number of variants of a product, variety is more appropriately defined in terms of the distance between products in characteristics space. Two examples help illustrate this concept. In automobiles, if General Motors introduces the Oldsmobile Alero, which is identical in nearly every respect but the nameplate to the Pontiac Grand Am, is there necessarily greater variety in vehicle choice? If Albertsons introduces a flakes-and-berries cereal in response to the popularity of Kellogg's "Red Berry Special K," then the number of stock-keeping-units (SKUs) offered by Albertsons increases by one, but does it represent more variety? Rather, our empirical description of variety refers to the span of attributes within a give category, or the size of the space occupied by its products.

The objective of this paper is to empirically determine the strategic role played by private label products among supermarket retailers. We consider both a horizontal role, as retailers compete for market share, and a vertical one, as retailers interact with imperfectly competitive suppliers. By taking both vertical and horizontal effects into account, we address a rationale for the introduction and proliferation of private label products that has not been considered previously in the empirical literature. We also contribute to the spatial econometrics literature by demonstrating how spatial dependence among substitute products can explain strategic choices by retailers who, in this case, also serve as manufacturers, or product designers.

The remainder of the paper is organized as follows. In the second section, we develop an econometric model of spatial competition among retailers offering private label products. The third section describes the data used to test this model and offers a detailed description of the estimation methods. The results are described in a fourth section, while the fifth provides some conclusions, some implications for the study of interaction among retailers and suggestions for future work in this area.

Econometric Model of Spatial Competition in Private Label Products

Overview

A retailer's decision to introduce a private label, or store brand, casts it in a rather unique position as a manufacturer and retailer both, competing with the suppliers that provide the national brands often thought necessary to attract brand-loyal consumers. Not surprisingly, the complex role of private labels has given rise to a number of alternative explanations for why retailers are increasingly choosing to compete with their own suppliers. First, the positioning of private labels has become an important tool in vertical competition with manufacturers (Sayman,

Hoch and Raju 2002; Chintagunta, Bonfrer and Song, 2002; Scott Morton and Zettelmeyer 2004; Choi and Coughlan, 2006). Both theoretical and empirical research shows that private labels can increase retailers' bargaining power with national brand manufacturers. Second, because private labels are essentially a means for retailers to vertically integrate, store brands tend to have higher margins that national brands because they reduce the double marginalization problem (Mills 1995, 1999; Bontemps, Monier and Requillart 1999; Sayman, Hoch and Raju, 2002). Third, store brands also allow retailers to maximize category revenue by discriminating between different consumer types, charging lower private-label prices to value conscious consumers and higher national-brand prices to brand loyal consumers in the same category (Gabrielsen, Steen and Sorgard 2002; Bontemps et al 2005), although the empirical evidence is mixed in this regard (Dhar and Hoch 1997; Ward, et al., 2002; Bonfrer and Chintagunta 2004). Fourth, others argue that retailers can increase their market power by differentiating themselves through high quality private labels or by building a large brand loyal consumer segment (Ward et al. 2002). The econometric model, therefore, must be able to distinguish each of these potential motivations.

On the demand side, we account for product differentiation in two ways. First, preferences are assumed to depend directly on the store, brand, flavor and whether a product is a private label or national brand. This assumption is uncontroversial as store and brand loyalty is well documented while Mills (1995) and Scott Morton and Zettelmeyer (2004) review the relevant literature on consumer's perceived bias against store brands. Second, consumers are assumed to possess a subjective assessment of product quality that depends on the distance between a product and all others in attribute space. Shelf-prices, therefore, are adjusted by each consumer's judgement regarding quality (Deaton and Muellbauer, 1980; Chiang, 1991; Nair, Dube and Chintagunta, 2005). Although others have incorporated distance in attribute space into econometric models of differentiated-product demand (Pinkse, Slade and Brett, 2002; Pinkse and

Slade, 2004; Slade, 2004b), we are the first to do so in the context of competition among retailers in a consumer-packaged good category. This "distance metric" (DM) approach not only allows us to differentiate between the demand for national brands and private labels, but also ensures that the "independence of irrelevant alternative (IIA)" attribute of discrete choice logit models does not apply.[2] On the supply side, retailers are assumed to price each product strategically, taking into the account the effect of private label pricing on the demand for their own national label products, and the competitive effect on store traffic *vis a vis* all other retailers in the market. Combining strategic pricing choices with an explicitly spatial demand model, the effect private labels have on the prices of national brands derives from the extent to which retailers choose to differentiate store brands from national brands, both horizontally and vertically. In this way, we are able to test each of the hypotheses regarding the economic rationale that underlies a private label strategy outlined above.

Nested Logit Model of Private Label Demand

Consumers are assumed to make hierarchical purchase decisions. Because shopping trips involve significant search and travel cost, consumers first choose whether to buy from a supermarket or some other outlet, then choose among available stores and, once in the store, choose from among the products that satisfy their various needs.[3] Therefore, we adopt a nested logit approach to model the demand for private labels and national brands (McFadden, 1978). A

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[2] Pinkse and Slade (2004) apply the DM approach of Pinkse, Slade and Brett (2002), but because they estimate demand directly, and not the best-reply function of Pinkse, Slade and Brett (2002), their estimating equation does not involve a spatial autoregressive term per se. Instead, the matrix of price responses consists of unspecified functions of distances in attribute space. Without a spatial autoregressive term, the estimation method is potentially much simpler.

[3] Our focus in this study is on competition among traditional supermarkets. Consequently, the outside option consists of convenience stores, warehouse stores, dollar stores and other outlets. There are no Wal-Marts nor other superstores in this market.

nested logit model provides both an intuitive way of describing the consumer's decision and analytical solutions for the retailer's profit maximizing positioning decision.[4] Partitioning products by retail store represents a natural choice because consumers are more likely to substitute among brands (in the same category) within a store than compare the same brand among stores. Although this assumption is common in the retail literature, and has ample empirical support (Slade, 1995; Sudhir, 2001), we test its validity using the empirical model of demand described next.[5]

The demand system implied by this nesting structure is represented using a DM extension of the variance component formulation of Cardell (1997), Berry (1994) and Currie and Park (2003). Formally, mean utility for consumer h from consuming good i purchased in store j is a function of a set of store and brand attributes (x_{ij}), its quality-adjusted price $(\hat{p}_{ijh})$ and unobservable factors. There are $i = 1, 2, ..., I_j$ products in each of the $j = 1, 2, ..., J$ stores. Utility, therefore, is written as:

$$ u_{ijh} = x'_{ij}\beta - \alpha\hat{p}_{ijh} + \xi_{1ij} + v_{hj} + (1-\sigma_J)v_{ih} + (1-\sigma_I)(1-\sigma_J)\varepsilon_{ijh}, \qquad (1) $$

where ξ_{1ij} is a random error that is unobserved by the econometrician, but reflects variables known to the firm that influence the product's price (for example, shelf space, supplier rebates, or anticipated shortages). The attribute vector x_{ij} includes binary private label (pl_i), store (st_j), brand (b_{ij}) and seasonal (se_k) indicators, as well as an indicator of whether the product is offered

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[4] Many authors use a nested logit approach to study various applied problems in differentiated product markets, particularly the automobile market. Fershtman and Gandal (1998) study the Arab boycott's impact on the Israeli automobile market, Goldberg (1995) estimates a model of the U.S. automobile market and Verboven (1996) the European car market. Many consumer goods can also be logically segmented into separable groups, or nests such as beer in the U.K. (Slade, 2004) or milk in the U.S. (Dhar and Cotterill, 2003).

[5] While the propensity to substitute among products within a store is assumed to be greater than among stores for each brand, this does not imply that there is no inter-store substitution. By allowing for an upper-level nest, we permit the data to determine the extent to which consumers shop among stores *ex ante.*

on a temporary discount (dc_{ij}), and an interaction term between the shelf price and the discount ($dc_{ij} p_{ij}$).[6]

Quality depends on a product's location in attribute space.[7] More precisely, each consumer forms a perception of the extent to which a product is differentiated from others based on its distance, $\boldsymbol{d_{ijh}}$, from all others.[8] Distance, or rather its analog in the spatial econometrics literature, proximity, is measured in a number of ways (Anselin, 1988; Kalnins, 1993). First, we use three discrete measures of contiguity that reflect whether or not two products are of the same brand, sell in the same store, or are of the same flavor. For example, if ice cream i is made by Ben and Jerry's, and l is also made by Ben and Jerry's then the il element of the "brand" distance matrix takes a value of 1.0. However, if i is the Chunky Monkey flavor, while l is Cherry Garcia, then the il element of the "flavor" distance matrix is assigned a 0. Second, we create a continuous measure of distance in nutritional attribute space. Defining the k nutritional attributes as grams of fat, carbohydrates, protein and sodium as well as total calories, the il element of the "nutrients" distance matrix is the inverse-Euclidean distance between the nutritional profile of item i and item l, or:

$$g_4(z_{il}) = \left(1 + 2\sqrt{\sum_k (z_{ik} - z_{lk})^2} \right)^{-1}. \tag{2}$$

Because (2) is defined it terms of inverse-distance, it represents a measure of how close the

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[6] Note that the discount variable is defined such that the price cut is temporary and not a permanent reduction in shelf price. The binary discount indicator assumes a value of 1.0 only if the price in the current week is at least 5% below the previous and following week.

[7] Our use of the term "quality" encompasses both horizontal and vertical differentiation as both dimensions are likely to be important in private label competition (Choi and Coughlan, 2006).

[8] Anderson, de Palma, and Thisse (1992) develop a similar argument in geographic space in the context of a spatial random utility model (P. 345).

products are in nutrient attribute space. We then create a linear quality index that consists of all four distance metrics and a constant term:

$$\psi_{ij}^{-1} = \psi_0 + \psi_1 g_1(st_{ij}) + \psi_2 g_2(b_{ij}) + \psi_3 g_3(f_{ij}) + \psi_4 g_4(z_{ij}), \tag{3}$$

where st_{ij}, b_{ij}, f_{ij}, and z_{ij} are elements of the store, brand, flavor and nutrient distance matrices, respectively. Next, we adjust all self prices by multiplying each by their respective quality index so that: $\hat{p}_{ij} = p_{ij}\psi_{ij}^{-1}$ where p_{ij} is the shelf price of product i in store j (Deaton and Muellbauer, 1980; Chiang, 1991). By adjusting shelf prices for variations in quality, we capture the expectation that consumers will respond differently to price changes for products nearer their preferred quality over others that are more distant.[9]

Perhaps more importantly, however, by adopting a DM approach, we relax the restriction imposed by the nested logit approach that "...the cross-price elasticity between [i,j] and [l,m] is independent of [i,j]" (Slade, 2004b) and the proportionate draw problem within nests commonly associated with the nested logit.[10] Synthesizing the DM and nested logit models in this way also creates a simple and parsimonious way of ameliorating the dimensionality problem associated with differentiated-products analysis by projecting the demand for goods into a smaller attribute space, while retaining the discrete-choice nature, but not the estimating difficulties, associated with the mixed logit model.

In our nested logit specification, the distribution of v_{ih} is defined so that the term (v_{ih} + (1

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[9] Following Slade (2004b), the main diagonal of the nutrient-distance matrix consists of own-nutrient content because the distance between a product and itself is, by definition, zero. This practice ensures non-degenerate results, and means that the own-nutrient measures are interpreted as hedonic values.

[10] Slade (2004b) compares a nested logit model with α_i defined as a function of product characteristics to a normalized quadratic DM model, but does not allow the price-response parameter to depend on the full matrix of distances between products. Not surprisingly, her model retains much of the inflexibility of a standard nested logit.

- $\sigma_I)\varepsilon_{ijh}$) is extreme-value distributed if the household specific error term ε_{ijh} is itself extreme-value distributed (Cardell, 1997). Extending this logic to a second nesting level implies that v_{hj} also possess the unique distribution that causes $v_{hj} + (1 - \sigma_J) v_{ih} + (1 - \sigma_I)(1 - \sigma_J)\varepsilon_{ijh}$ to be extreme-value distributed. The parameters σ_J and σ_I that measure utility-correlation within each nest are interpreted as measures of store and product heterogeneity – or more accurately the lack thereof – respectively such that $0 \le \sigma_I \le 1$ and $0 \le \sigma_J \le 1$. If $\sigma_J = 1$, then the correlation among stores goes to 1.0 and stores are regarded as perfect substitutes, or if $\sigma_I = 1$, then products within each store are perfect substitutes.[11] On the other hand, if these parameters each are zero, then the model collapses to a simple multinomial logit model, without store or product nests. The ability to estimate these parameters is a critical advantage of the nested logit model, because it ensures that the DM specification estimates the extent of differentiation due to product attributes and not to store or category heterogeneity. By including an outside option, the nested logit model also allows for general demand-expansion in addition to share-reallocation among stores and products.

Based on the random utility model in (1), define the level of mean utility for each choice of product i and store j as: $\delta_{ij} = x_{ij}\boldsymbol{\beta} - \alpha_{ij}p_{ij} + \xi_{1ij}$, where α_{ij} is the marginal utility of income multiplied by the quality index, ψ_{ij}. Following Berry (1994), the marginal share of good i purchased in store j is the product of the conditional share of good i given that a purchase was made from store j, the conditional share of store j given that the purchase was made from a supermarket, and the share of all supermarkets in the total market:

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[11] Ivaldi and Verboven (2005) derive a two-level version of the nested logit model that they apply to merger analysis in the European truck market. In their model, the heterogeneity parameters (σ_j) are allowed to vary by manufacturer. In the current study, we are less concerned with variation in substitutability within stores than arriving at a more general conclusion comparing inter- and intra-store substitution. Verboven (1996) provides additional detail on deriving a multi-product nested-logit equilibrium subject to binding output constrains.

$$s_{ij} = (s_{i|j})(s_{j|J})(s_J) = \frac{e^{\delta_{ij}/(1-\sigma_I)(1-\sigma_J)}}{E_{I_j}^{\sigma_I} D_J^{\sigma_J}(1 + \sum_J D_J^{1-\sigma_J})}, \quad i=1,2,...I, \quad j=1,2,...J. \tag{4}$$

where: $D_J = \sum_{j=1}^{J} E_{I_j}^{1-\sigma_I}$ is the inclusive value term for the conditional store choice and the

inclusive value term for the choice among products is: $E_{I_j} = \sum_{i=1}^{I_j} e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}$. Note that the

utility of the outside option, or no purchase, has been normalized to zero. Taking logs of both

sides of (4) leads to a share equation for product i in store j that is a function of the unobservable

inclusive values:

$$\ln s_{ij} = \delta_{ij}/(1-\sigma_I)(1-\sigma_J) - \sigma_I \ln(E_{I_j}) - \sigma_J(D_J) - \ln(1 + \sum_J D_J^{1-\sigma_J}), \tag{5}$$

and substitution parameters at the product and store-levels. Substituting expressions for the

aggregate supermarket share and the store (or supermarket chain) share into equation (5) and

simplifying gives the marginal share of product i in store j:

$$\ln s_{ij} = \ln s_0 + x_{ij}'\beta + \alpha_{ij}p_{ij} + \sigma_J \ln(s_{j|J}) + \sigma_I(1-\sigma_J)\ln(s_{i|j}) + \xi_{1ij}, \tag{6}$$

where ξ_{1ij} is the econometric error term described in (1) above.

In the linear-demand DM used by Pinkse and Slade (2004) and Slade (2004b), the

demand for each product is a function of all other prices. In this case, the flexibility of the matrix

of cross-price derivatives is clear. On the other hand, the DM / NML model still involves only a

single price vector, so it is perhaps less clear how cross-price elasticities vary within and among

groups. Because we project product demand into attribute distances rather than prices, however,

all cross-price elasticities must vary with the proximity of each product pair. Specifically, the

own-price elasticity is given by:

$$\eta_{ij,ij} = \left(\frac{\partial s_{ij}}{\partial p_{ij}} \right) \left(\frac{\bar{p}_{ij}}{\bar{s}_{ij}} \right)$$

$$= \bar{p}_{ij} \alpha_{ij} \left(\frac{1}{(1 - \sigma_I)(1 - \sigma_J)} \right) [1 - \sigma_I \bar{s}_{i|j} + \sigma_J (1 - \sigma_I) \bar{s}_{i|j} \bar{s}_{j|J} + (1 - \sigma_I)(1 - \sigma_J) \bar{s}_{ij}],$$ (7)

where the quality index now enters through the marginal utility of income, α_{ij}. Similarly, the

cross-price elasticity for products within-group (store) is:

$$\eta_{ij,lm} = \left(\frac{\partial s_{ij}}{\partial p_{lm}} \right) \left(\frac{\bar{p}_{lm}}{\bar{s}_{ij}} \right) = \bar{p}_{lm} \alpha_{ij} \left(\frac{1}{(1 - \sigma_I)(1 - \sigma_J)} \right) [-\sigma_I \bar{s}_{lm} - \sigma_J (1 - \sigma_I) \bar{s}_{l|m} \bar{s}_{m|J}],$$ (8)

for $i \neq l$ and $j = m$. The cross-price elasticity with respect to products in other stores is given by:

$$\eta_{ij,lm} = \left(\frac{\partial s_{ij}}{\partial p_{lm}} \right) \left(\frac{\bar{p}_{lm}}{\bar{s}_{ij}} \right) = \bar{p}_{lm} \alpha_{lm} \left(\frac{-\sigma_I \bar{s}_{lm}}{(1 - \sigma_I)(1 - \sigma_J)} \right),$$ (9)

for $i \neq l$ and $j \neq m$. The elasticity expression in (9) shows that the cross-price elasticity of each

product depends not only on the share of the other store, but on the specific attributes of the l

product in the m store. Thus, the DM extension to the NML model represents a simple,

parsimonious way of averting the well-known IIA problem of all fixed-coefficient logit models.

Of perhaps greater importance, however, are the implications that derive from incorporating

attribute-distances into retailers' supply decisions, particularly with respect to their positioning of

private labels.

The Supply of Private Label Products

There are two ways to model the supply decisions taken by retailers: (1) solve the first-order

conditions under an assumed game for the retail price as a function of market share and price-response elasticities, or (2) solve the first-order conditions for each retailer's multi-product best-reply function, or each of its prices as a function of all other prices in the game. We follow Sudhir (2001), Chintagunta, Bonfrer and Song (2002), Villas-Boas (2003), Villas-Boas and Zhao (2005), Slade (2004b) and many others in estimating a structural model of retailer conduct. Our innovation is to develop and estimate a supply model that is consistent with the DM/NML specification introduced above. Because price response depends on the distance between products in attribute space, the supply model takes into account the effect of product positioning on market power – both horizontally among stores and vertically with suppliers. The equilibrium concept is Bertrand-Nash, so retailers compete in prices, both of national brand products and their own store brands.

Supermarket retailers are assumed to maximize category profits within each store by choosing national brand and private label prices. Unlike Chintagunta, Bonfrer and Song (2002), who model retailer margins before and after the introduction of a private label product to determine its effect on market power in the vertical channel, the retailers in the current sample use private labels throughout the sample period. Therefore, pricing conduct is modeled as a function of distance in discrete private label, store, brand, flavor and continuous attribute space. More formally, the profit equation for retailer j selling in a particular category m is:

$$\Pi_{jm} = \sum_{i \in I} (p_{ijm} - r_{ijm} - c_{ijm}) s_{ijm} Q_m - F_{jm}, \tag{10}$$

where Q_m is the size of the total category, r_{ijm} is the wholesale price of item i in category m and store j, c_{ijm} is the marginal retailing cost, and F_{jm} is the fixed costs of operating the store that are allocated to category m. Unit retailing costs $C(q,w)$ are assumed to be of a Normalized Quadratic (NQ) form, with output vector q and input prices w so that the marginal cost function for

products in each category is written as:

$$c_{ijm} = \sum_l \gamma_l(w_{ml}/w_0),$$ (11)

for some normalizing input price vector, w_0. In (11), γ_l are parameters to be estimated and $c_{ijm} = \partial C_{ijm}/\partial q_{ijm}$. As is well understood, the regularity conditions for a well-behaved dual cost function can be tested and imposed during estimation for the NQ functional form.

Each retailer is assumed to maximize profits on a category-by-category basis, choosing the prices of all products in the category simultaneously. This is consistent with the practice of category management now used by a majority of supermarket retailers and implies that managers, at least implicitly, take into account all of the cross-price effects that are involved in setting the price for any single product. Adopting a portfolio approach to retail pricing decisions means that retail managers internalize any local monopoly power they may have over shoppers who do not shop for individual items (Bliss, 1988; Nevo, 2001). Consequently, the first order conditions for each product i in category m for the manager of store j are written as (suppressing the category index):

$$\frac{\partial \Pi_j}{\partial p_{ij}} = Qs_{ij} + Q\sum_{l=1}^{I_j} \Omega_{lj}\frac{\partial s_{lj}}{\partial p_{ij}}(p_{lj} - r_{lj} - c_{lj}) = 0, \quad \forall \quad i,j.$$ (12)

In this expression, the number of products can conceivably vary among stores, so there are a total of I_j items per store, and J stores. Assuming the number of products per store is a constant, I, and J stores in total, then define $\boldsymbol{\Omega}$ as an IJ x IJ matrix with $\Omega_{lj} = 1$ if i and l are two products sold by the same firm, and $\Omega_{lj} = 0$ if not (Nevo, 2001). In this way, (12) captures the essential multi-product nature of retailing while allowing for a general pattern of product interactions in $\partial s_{ij}/\partial p_{lm}$. Because retailers are assumed to solve the first order conditions in (12)

simultaneously, the solution is simplified considerably by using matrix notation such that:

$$Qs + Q(\Omega S_p)(p - r - c) = 0,$$ (13)

where p is a vector of prices, r is a vector of wholesale prices, c is a vector of marginal costs, and S_p is an IJ x IJ matrix of price derivatives with typical element: $\partial s_{ij}/\partial p_{lm}$. Solving for $(p - r - c)$ from (13) yields an estimable form of the structural model with margins as endogenous left-side variables and only the matrix of price-responses and market shares on the right-side:

$$(p - r - c) = -(\Omega S_p)^{-1}(s),$$ (14)

in the form of the familiar mark-up rule. The precise form of each element of S_p depends upon whether the products i and l are in the same store, different stores, or outside of the set of all products purchased at supermarkets in general.[12] Substituting these expressions into (14) provides an econometric model that is able to capture horizontal product-interactions within and among retailers, but not between retailers and manufacturers.

Our model of strategic behavior in private labels also includes their impact on vertical relationships with suppliers. Typically, research in this area considers highly simplified environments in which there is either a monopoly retailer (Chintagunta, Bonfrer and Song, 2002; Villas-Boas and Zhao, 2005) or a single, price-taking manufacturer (Besanko, Gupta and Jain, 1998). More realistically, however, competing manufacturers sell to retailers who also compete among themselves. Moreover, as private label suppliers, retailers also compete with their own manufacturers. Consequently, we develop a general model of vertical interaction for each retailer that subsumes both strategic pricing behavior and product design.

Assume each manufacturer is responsible for a single product, so there are $i = 1, 2, ... I_j$

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[12] The expressions are straightforward and are available from the authors.

firms in the market. We extend the single-retailer model of Villas-Boas and Zhao (2005) to include multiple retailers so that the profit of supplier i is given by:

$$\pi_i^m = \sum_{j=1}^{J} (r_{ij} - b_{ij}) s_{ij} Q - H_i, \quad \forall \ i = 1, 2, \ldots I_j, \tag{15}$$

where b_{ij} is the marginal cost of manufacturing product i, and H_i is the fixed cost of production. Manufacturers choose their selling prices and, given the maintained assumption that they compete vertically as Stackelberg leaders (Sudhir, 2001) must take retailer's pricing decisions into account: both for their own product and others' products. The first order conditions for this problem are:

$$\frac{\partial \pi_i^m}{\partial r_{ij}} = s_{ij} + (r_{ij} - b_{ij}) \sum_{m=1}^{J} \sum_{l=1}^{I} \left(\frac{\partial s_{ij}}{\partial p_{lm}} \right) \left(\frac{\partial p_{lm}}{\partial r_{ij}} \right) = 0, \quad \forall \ i = 1, 2, \ldots I_j, \tag{16}$$

which is then solved for the manufacturing margin as a function of the sensitivity of market share to price and of retail price to wholesale price (pass-through):

$$(r_{ij} - b_{ij}) = -s_{ij} \left(\sum_{m=1}^{J} \sum_{l=1}^{I_j} \left(\frac{\partial s_{ij}}{\partial p_{lm}} \right) \left(\frac{\partial p_{lm}}{\partial r_{ij}} \right) \right)^{-1}, \quad \forall \ i = 1, 2, \ldots, I_j. \tag{17}$$

The solution to equation (17), however, includes a parameter that is not provided in the data – the pass-through rate. Consequently, Sudhir (2001) and Villas-Boas and Zhao (2005) show that $\partial p_{ij} / \partial r_{ij}$ can be expressed in terms of estimated parameters by totally differentiating the first-order condition for the optimal retail price given by (12) above with respect to the wholesale price charged by each manufacturer. While they consider a single retailer, however, we extend their approach to allow for manufacturers that sell to multiple retailers. Consequently, suppliers

must take into account not only the impact of changes in their wholesale price on the retail price of other suppliers' products, but on the price of their own products set by other retailers. Formally, differentiating (12) with respect to the wholesale price of product i, the impact of a price change for each product i sold by retailer j is given by:

$$\sum_{m=1}^{J}\sum_{l=1}^{I}\frac{\partial s_{lm}}{\partial p_{lm}}\frac{\partial p_{lm}}{\partial r_{ij}} + \sum_{n=1}^{J}\sum_{l=1}^{I}\Omega_{ln}(p_{ln}-r_{ln}-c_{ln})\left(\frac{\partial^2 s_{ln}}{\partial p_{ln}\partial p_{lm}}\right)\left(\frac{\partial p_{lm}}{\partial r_{ij}}\right) = \frac{\partial s_{ij}}{\partial p_{lm}} \quad \forall \ i, j. \quad (18)$$

In matrix notation, define the gradient vectors $\nabla_r = \partial p_{lm}/\partial r_{ij}$, and $\nabla_p = \partial s_{ij}/\partial p_{lm}$ for each retailer j, and an IJ x IJ matrix G with typical (ij,lm) element given by:

$$g_{ij,lm} = \frac{\partial s_{ij}}{\partial p_{lm}} + \frac{\partial s_{lm}}{\partial p_{ij}} + \sum_{n=1}^{J}\sum_{h=1}^{I}\Omega_{hn}(p_{hn} - r_{hn} - c_{hn})\left(\frac{\partial^2 s_{hn}}{\partial p_{ij}\partial p_{lm}}\right) \quad (19)$$

then equation (18) is re-written: $G\nabla_r = \nabla_p$, where the IJ vector ∇_p on the right side of (18) describes how the share of product i in store j changes with the prices of all other products in all other stores.[13] We then solve for the unknown matrix of wholesale price responses as:

$\nabla_r = G^{-1}\nabla_p'$, so the supplier margin in equation (17) is re-written in matrix notation as:

$$(r - b) = -s(\nabla_p G^{-1}\nabla_p'). \quad (20)$$

With the wholesale price written in terms of estimable retail-demand parameters, the retail price in (14) can then be written in reduced form as:

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[13] To better understand the difference between ∇_p and S_p, the former represents column i of the latter, a vector that shows how the share of each product i changes with respect to the prices of all other products, in all other retailers. The specific form of the elements of G are straightforward and are available from the authors.

$$p - c = b - s(\nabla_p G^{-1} \nabla_p')^{-1} - (\Omega S_p)^{-1}(s). \tag{21}$$

so p - c represents an IJ x 1 vector of retail margins.

Without further modification, (21) describes the set of retailers as competing in a perfect Nash fashion. However, empirical evidence shows that this is not likely the case (Richards and Patterson, 2005). Therefore, we follow Villas-Boas and Zhao (2005) and Chintagunta, Bonfrer and Song (2002) and allow for departures from strict Nash behavior by interacting each element of the share-response matrix S_p with a conduct parameter $(1/\varphi_{ij})$.[14] The conduct parameter measures any deviation of retail-wholesale margins from the competitive benchmark. In this case, excess margins may be due to vertical interactions between retailers and suppliers that are not, in fact, Bertrand-Nash. Or, because our model has multiple retailers, non-zero conduct parameters may also be due to the nature of the game played among stores in the retail market.

Deviations from Bertrand-Nash behavior, however, are not likely to be constant across stores or products. Rather, if conduct is thought to depend on the extent of product and store differentiation as theoretical models of private label rivalry suggest, then it should be modeled as such (Choi and Coughlan, 2006). Therefore, each conduct parameter is written as a linear function of the set of discrete and continuous distance metrics defined above. Most importantly, by including a discrete private-label indicator among the distance metrics, we are able to determine whether or the pricing decision for a particular product depends upon whether it is a private label, or national brand. In this way, we not only estimate the presence or absence of

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[14] Note that our definition of a conduct parameter is not analogous to a conjectural variation in the sense of Bresnahan (1989) as applied by, for example, Kadiyali, Chintagunta and Vilcassim (2000) in a context similar to the current one. Rather, we maintain Bertrand-Nash behavior throughout so that tests of the significance of the conduct parameter are tests of the structure of the maintained model. Corts (1999), among others, criticizes the interpretation of conduct parameters as conjectural variations as a conjecture is a fundamentally dynamic concept while the model is static. Including these parameters in the econometric model, however, allows the researcher to avoid imposing a particularly restrictive form of the game being played on the model. In this way, the nature of the game is determined by the data.

market power, but also its source. Including the entire set of distance metrics, the conduct parameter in inter-store competition is written:

$$\varphi_{ij} = \varphi_0 + \varphi_1 g_1(pl_{ij}) + \varphi_2 g_2(b_{ij}) + \varphi_3 g_3(f_{ij}) + \varphi_4 g_4(st_j) + \varphi_5 g_5(z_{ij}), \tag{22}$$

where each of the $g_i(\ )$ functions are measures of contiguity or distance as defined above. Tests of overall retailer conduct thus depend on the entire φ_{ij} function and not an individual parameter. For example, if $\varphi_{ij} = 1.0$ for all products i in retailer j, then the retailer internalizes all pricing externalities associated with his or her own products (maximizes category profits), and those sold other stores (collusive oligopolist). If, on the other hand, $\varphi_{ij} > 1.0$, the retailer prices above Bertrand and is clearly playing some other, more cooperative game than the Nash equilibrium envisioned here. Given this insight, if the parameter φ_1 is greater than zero then a private label strategy allows the retailer to price above the Bertrand-Nash level. With only a single retailer, Chintagunta, Bonfrer and Song (2002) interpret a φ_{ij} less than 1.0 after a private label has been introduced as evidence of "softening" competitive interactions between the retailer and manufacturers. However, in the multiple-retailer case considered here a similar result implies that raising private label share raises margins due to greater store differentiation, customer loyalty, a better reputation for quality or any one of a number of other competitive rationales for using private labels.

Theoretical models of private label use also cite their impact on vertical competition with suppliers (Mills, 1995; Scott Morton and Zettelmeyer, 2004). In order to test the hypotheses that private label introduction increases retailer market power vis a vis suppliers and reduces the double-marginalization problem, we parameterize the departure of wholesale margins from a Bertrand-Nash benchmark. This is accomplished by introducing a second conduct function in the manufacturer-markup term in equation (21). As in the retailer-level case, the impact of private

label proliferation, individual store, brand, and flavor effects and the level of product differentiation (distance in attribute space) on manufacturer conduct is captured by allowing θ_{ij} to depend on each of the distance metrics defined above:

$$\theta_{ij} = \theta_0 + \theta_1 g_1(pl_{ij}) + \theta_2 g_2(b_{ij}) + \theta_3 g_3(f_{ij}) + \theta_4 g_4(st_{ij}) + \theta_5 g_5(z_{ij}). \tag{23}$$

Because manufacturers sell to a number of different retailers, we implicitly assume that manufacturer conduct varies by store and brand, and that flavor and nutritional attributes have an impact on their ability to charge higher wholesale prices. Further, we also assume that retailers' use of private labels has a different effect on each manufacturer. These are testable hypotheses.

Defining vectors of length NM of both conduct parameters, the estimated version of (21) then becomes:

$$\boldsymbol{p} - \boldsymbol{c} = \boldsymbol{b} - \boldsymbol{s}\theta(\nabla_p \boldsymbol{G}^{-1}\nabla_p')^{-1} - (\Omega(1/\varphi)\boldsymbol{S}_p)^{-1}\boldsymbol{s}. \tag{24}$$

Unlike the conjectural variations case, there is no direct interpretation of θ_{ij}. However, we can infer the degree of market power exercised by a wholesaler by comparing θ_{ij} to competitive and monopolistic bounds. Namely, if $\theta_{ij} = 1.0$, then the manufacturer of product i does indeed set its wholesale price to retailer j according to the hypothesized Nash solution. On the other hand, if $\theta_{ij} = 0$, then the manufacturer sets prices competitively as the elements of (23) apparently do not contribute to effective differentiation and, hence, upstream market power. If $\theta_{ij} < 1$, then we can conclude that the manufacturer of i prices below Nash. In fact, Villas-Boas and Zhao (2005) speculate that this may be due to long-term contracting incentives, but is more likely due to retailer market power. Most important for our objective of understanding the role of private label products, if the interaction parameter $\theta_1 > 0.0$, then private labels earn higher manufacturer margins (for the retailer-manufacturer) relative to national brands. If private labels earn greater

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upstream margins, then this provides evidence that manufacturer market power is lower when private label products are introduced in a given category.[15] A similar interpretation applies to each of the other elements of (23). For example, θ_5 measures the effect of product differentiation on manufacturer margins. Because z_{ij} is defined in terms of inverse distance (proximity), if $\theta_5 >$ 0.0 then the closer products are in attribute space, the higher are manufacturer margins. In the next section, we explain how each of the conduct parameters is identified in a relatively simple two-stage estimation procedure.

Estimation of the DM / NML Private-Label Model

Data Description

The data for this analysis were obtained from Fresh Look Marketing, Inc. (FLM) of Chicago, Illinois. FLM provided weekly price, volume and promotional information for all ice cream UPCs for all retail accounts in the Visalia, CA market for the two year (104 week) period from May 31, 2003 through June 1, 2005. Although our data set consists of similar scanner data for all categories in the store, we chose ice cream for a number of reasons. First, private label products play an important role in retailers' ice cream category strategies as ice cream ranks among the top five among all categories in terms of private label penetration (FMI). Second, the market includes two large national brand manufacturers who compete through a variety of mechanisms: product innovation, retail promotion, pricing, shelf placement and trade promotion and two premium brands that occupy a niche market decidedly above that of the national brands. Third,

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[15] The evidence on manufacturer market power is only indirect because the private label effect on upstream market power is defined relative to a national brand benchmark. Therefore, if private labels have a positive effect on upstream margins, they must have a negative effect on national brand margins, by definition.

ice cream manufacturers actively differentiate their products through a number of nutritional, ingredient, processing, packaging and labeling techniques. In most retail stores, differentiation means that the category consists of products with significantly different nutritional profiles, ingredient lists and production methods. Finally, the number of unique SKUs is relatively small, allowing for the specification of a DM model that captures the spatial dimension of ice cream rivalry in a parsimonious way.

There are also a number of reasons why Visalia, CA was chosen to serve as a test market for estimating the spatial private label model. First, selecting a small market is necessary in order to have store-level data from all major sources of ice cream supply in the market.[16] Second, there are no Wal-Mart stores in Visalia. This fact is important because Wal-Mart does not supply retail scanner data to data syndication firms such as FLM so our data set does not contain the "Wal-Mart gap" that is typical of other scanner-data studies. Third, the retailers in Visalia each follow a HI-LO pricing strategy wherein they maintain relatively high everyday shelf prices, but then periodically reduce prices in order to increase store traffic, feature a certain brand, introduce a new brand, or a number of other reasons. This is essential over a relatively short panel data set in order to have price variation at the brand level. Fourth, Visalia is relatively isolated, so geographic competition from supermarkets in other towns is likely to be limited. In demographic terms, Visalia is similar to the broader U.S. in terms of income, age distribution and education, but consists of a significantly greater proportion of Hispanic shoppers. Therefore, to the extent that Hispanic ice cream buying behavior differs from the general population, or results can only be generalized with significant caution.

When estimating a DM model, defining the set of product attributes and distance

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[16] Our retail scanner data coverage is complete for all traditional supermarket retailers. Other sources of ice cream supply include warehouse stores, convenience stores, food service outlets or shoppers who travel to other towns to shop. These sources of supply together form the outside option in the nested logit model of demand.

measures is critically important because they form the basis of our definition of how ice creams are differentiated. In order to capture the source of this differentiation, we chose from a set of macronutrients (fat, carbohydrates and protein), sub-components of the macronutrients (saturated fat, trans-fat, sugars), micronutrients (sodium and caffeine), the presence or absence of key ingredients (skim milk, whole milk, sugar, and flavoring), a brand identifier, and a flavor indicator. We also experiment with a number of different distance metrics, including inverse Euclidean distance (proximity), exponential distance, or whether two products are nearest neighbors or share a common boundary in attribute space. Pinkse, Slade and Brett (2002) provide a thorough discussion of how these metrics are defined. While the discrete measures of contiguity (brand, flavor, store, private label) were included on a priori grounds, we ultimately chose from among the possible attribute-distance specifications on the basis of a quasi-likelihood ratio (QLR) testing procedure (Gallant and Jorgenson, 1979).[17] In the final model, the set of attributes consists of total calories, fat (grams), carbohydrates (grams), protein (grams) and sodium (milligrams) per serving and proximity is defined as inverse Euclidean distance.[18]

On the supply side, the marginal cost function is estimated with input prices from the Bureau of Labor Statistics, including raw milk for manufacturing purposes, high-fructose corn syrup, milk-product manufacturing labor, an energy-price index and producer price indices for ice cream and chocolate production. Table 1 provides summary statistics for all of the major variables used in the study.

[table 1 in here]

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[17] Results from other DM specifications are available from the authors.

[18] Sodium is excluded from the list of nutrients on the main diagonal of the distance matrix because it was not statistically significant in preliminary specification tests.

Estimation Procedure

There are four complications that must be addressed prior to estimating the demand (6) and

pricing (24) equations. First, the share equation cannot be estimated using ordinary least squares

because prices are likely to be correlated with some of the elements of η_{1ij} – promotional

activities, in-store merchandising and other strategies cause price and market share to be jointly

endogenous. Second, the spatial nature of the demand equation in (6) means that successive

observations will be spatially correlated, a situation that gives rise to the same econometric

problems as autocorrelation in a time-series context (Slade, 2004a). Third, the richness of the

nested logit model means that the pricing block for individual brands is highly complex and non-

linear, requiring a non-linear estimator. The fourth complication is not necessarily endemic to

the problem, but is rather a preference – given that the pricing model is non-linear, it would be

desirable to use an estimation method that is not overly restrictive.

To develop tractable solutions to each of these estimation problems, we adopt two-stage

approach, estimating demand (6) in the first-stage and the pricing model in the second stage.

Although simultaneous estimation of demand and pricing is preferable on efficiency grounds, the

two-stage estimator is consistent and, most importantly, allows us to address the more serious

issues outlined above in a manner that is computationally feasible.[19] We address the first

complication (endogeneity) by using an instrumental variables estimator for the demand

equation. Specifically, we use a generalized methods of moment (GMM) estimator with

instruments constructed from input prices as well as attributes, prices and marketing activities

from products sold in other stores. While this approach is well accepted in the structural

modeling literature, it is much more intuitive in a DM context. Specifically, by defining spatial

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[19] Chintagunta, Bonfrer and Song (2002) take a similar two-stage approach, but use fundamentally different
methods. Specifically, they employ a random coefficients logit approach similar to Berry, Levinsohn and Pakes
(1995) to explicitly allow for unobserved consumer heterogeneity.

weight matrices formed from various distance metrics among items in each store, it is a simple matter to form instruments by interacting rival prices and exogenous variables with each weight matrix.[20] Kelejian and Prucha (1998) adopt this approach in deriving their spatial GMM estimator.

We address the likelihood that the demands for specific ice cream items are spatially correlated in two ways. First, as explained above, we allow embodied quality, ψ_{ij}, to depend on a set of distance metrics that reflect each product's proximity to others in terms of store, brand, flavor, private label and nutritional attributes. Second, given that the empirical model is inherently spatial, we allow the errors in the demand equation (6) to be spatially autocorrelated, with the strength of correlation dependent on each product's distance from all others in attribute space. Note that the spatial weight matrix constructed for this purpose does not necessarily have to be the same as that used to define the distance metrics in the demand equation itself. In fact, because the demand equation uses several weight matrices, doing so would not be feasible (Kalnins, 1993). Consequently, we assume that the attribute distance metric represents the most general definition and define M as the spatial weight matrix used to test for spatially autocorrelated errors.

Spatial autocorrelation implies that: $\xi_{ij} = \lambda M \xi_{ij}$, so a test of the null hypothesis, $\lambda = 0$, of no spatial autocorrelation consists of a test of the significance of λ. Although there are a number of alternative tests that are appropriate for this purpose, the Moran (I) statistic is widely used and generally accepted (Anselin, 1988). Moran's I is given in vector notation by: $I = \xi M \xi / \xi' \xi$, which is distributed standard normal after transforming according to:

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[20] The term "weight matrix" refers to a matrix with typical element, in the nutrient case, of the inverse Euclidean distance between a pair of products. For estimation purposes, the matrix is row-normalized to permit more intuitive interpretation of the spatial regression parameters.

$$Z_I = (I - tr(\boldsymbol{RM})/(n-k))[(1/m)(tr(\boldsymbol{RMRM}\,') + tr(\boldsymbol{RM})^2 + (tr(\boldsymbol{RM}))^2) - E(I)^2]^{-1/2}, \quad (26)$$

where: $\boldsymbol{R} = (\boldsymbol{I_n} - \boldsymbol{X}(\boldsymbol{X'X})^{-1}\boldsymbol{X'})$, X is a matrix of all explanatory variables in (6), n is the number

of observations, k is the number of regressors, and $m = (n - k)(n - k + 2)$. A failure to reject the

null in this case means that the spatial demand model must be estimated under the assumption

that each weekly observation is spatially independent of all others.

In the second stage, similar estimation concerns apply to the pricing model. Namely,

elements of both the retailer and manufacturer margin specifications are inherently endogenous

so least squares estimation will again yield biased estimates. Further, because both conduct

functions depend on the distance between all products in several dimensions, spatial dependence

arises here as well. Consequently, we adopt a similar GMM approach as in the demand side, but

define the set of instruments appropriate to the pricing equation. In particular, we choose a set of

instruments that consist of brand, flavor, store and private label indicators, continuous values of

each attribute, and spatially-weighted values of each discrete and continuous distance metric.

We also include non-linear functions of these distance metrics, again in a manner similar to

Kelejian and Prucha (1998). As on the demand side, we also test the pricing equation errors for

spatial autocorrelation given our implicit assumption that product pricing is likely to be

correlation across spatial dimensions.

Results and Discussion

The key hypotheses of this study are tested using the results of the pricing model. However,

because the demand estimates constitute critical input for the pricing equation, we begin the

presentation of results with a series of specification tests of the spatial demand model. Moreover, given the richness of the DM/NML specification, the first stage of the estimation procedure also provides many results that are likely to be of inherent interest, regardless of their implications for strategic pricing.

The first specification test concerns the presence or absence of spatial autocorrelation in the demand errors. Using the Moran *I* statistic introduced above, we find a test statistic value of 1.45. Given that the critical value from a standard normal distribution at a 5% level is 1.96, we fail to reject the null of no spatial autocorrelation. Consequently, all subsequent specification tests are performed with the GMM DM model uncorrected for spatial autocorrelation.

Next, we test whether our particular form of the nested logit model is an appropriate representation of ice cream demand. Draganska and Mazzeo (2003) estimate a single-retailer nested model of ice cream demand in which consumers choose brands and flavors in a hierarchical structure. Although they find that a brand-then-flavor model is preferred to the flavor-then-brand alternative, it is more likely the case that these two sources of differentiation are evaluated simultaneously.[21] In table 2, the significance of both $g(b)$ and $g(f)$ suggest that differences in brand and flavor are both important in determining choice probabilities. As a more direct test of the nesting structure used here, recall that if $\sigma_I = 0$ consumers do not substitute among products within a store, so a single-level store-based logit model is appropriate and if $\sigma_J = 0$ consumers do not substitute among stores, so a single-level product-based logit would be preferred. The results in table 2 show that neither of these cases apply. In the GMM estimates, both σ_I and σ_J are significantly different from zero so both the set of products and stores consist of viable, yet imperfect, substitutes.

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[21] Bresnahan, Stern and Trajtenberg (1997) develop a "principles of differentiation" model that accounts for such non-hierarchical discrete choices. In the current application, however, it is more likely the case that consumers choose stores for fundamentally different reasons from those used to select a brand of ice cream.

[table 2 in here]

The results in table 2 demonstrate the effect of defining product differentiation in explicitly spatial terms by comparing parameter estimates from spatial and non-spatial OLS specifications. Although there is a relatively small difference between the spatial and non-spatial price-response and heterogeneity parameters, failing to account for the spatial dependence in demand reverses the sign of the private label effect. Further, the non-spatial model understates the promotion effect and the degree of substitutability among stores – both important results from a managerial perspective.

The least squares estimates, however, are likely to be biased if retail prices and promotion strategies are endogenous. Villas-Boas and Winer (1999) describe a number of reasons why we may expect this to be the case *a priori* in a retail environment. Nonetheless, it is preferable to test before potentially applying an estimator that is less efficient than is necessary. Formally, we examine the data for price endogeneity using Hausman's (1978) general specification test. This test involves comparing the parameters of two models: one that is consistent under both the null and alternative hypotheses and one that is asymptotically efficient under the alternative hypothesis.[22] For current purposes, the efficient estimator is OLS and the consistent one is GMM. Based on the estimates in table 2, the calculated test statistic value is 284.01, while the critical chi-square value with 39 degrees of freedom at a 5% level is 54.29. Therefore, we can reject the null of no endogeneity and conclude that the GMM estimator is preferred. Comparing the spatial OLS and GMM estimates reveals the extent of endogeneity bias. Most importantly, the private label effect in the GMM model is nearly double the OLS estimate, and is significantly different from zero – unlike the OLS case. Further, the OLS brand and flavor distance

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[22] The test statistic is calculated as: $(\beta_1 - \beta_0)'(V_1 - V_0)^{-1}(\beta_1 - \beta_0) \sim \chi^2_K$, where β_1 is the vector of GMM parameters, β_0 is the vector of OLS parameters, V_1 is the GMM covariance matrix, V_0 is the OLS covariance matrix, and there are K degrees of freedom, where K is the number of parameters in the model.

parameters are insignificant, while they are strongly significant in the GMM model. Finally, demand is also much more sensitive to price, but less to temporary promotions, in the model that corrects for endogeneity. This is consistent with findings reported by Villas-Boas and Zhao (2005) and prior expectations.

The demand estimates in table 2 provide other parameters of interest. First, note that the nested logit scale parameters indicate a greater willingness to substitute among products within stores (σ_I) than among products in different stores (σ_J). While this outcome is, in fact, necessary for the nested logit model to be consistent with the random utility assumption (Anderson and de Palma, 1992) many authors assume that σ_J is equal to zero (Sudhir, 2001; Chintagunta, Bonfrer and Song, 2005). Assuming no substitution among stores justifies their use of single-retailer scanner data even in multi-retailer markets. Consequently, finding a value for σ_J significantly different from zero constitutes a valuable contribution to the literature.

Second, three of the four distance metrics are significantly different from zero. The distance metric parameters are interpreted as indicating the effect of proximity for the continuous measure and contiguity for the discrete. For example, a positive coefficient on the brand indicator suggests that carrying more of the same brand generates a positive market share effect. Further, controlling for brand proximity, carrying more items of the same flavor also causes market share to rise. This result is analogous to the descriptive finding of Draganska and Mazzeo (2003) who find that retailers tend not to sell two ice creams of the same flavor from different brands, avoiding the potential for cannibalism across product lines. While brand, flavor and store are likely dimensions of product differentiation, manufacturers regard the nutritional content of their product as the principal agent of product design. Therefore, the strongly negative coefficient on attribute distance is of critical importance, implying that the closer (farther) a product is to others in terms of its nutritional profile, the lower (higher) is market share. This is

the primary intent of differentiating one ice cream from another.

Third, the quality parameters indicate how price response varies with an ice cream's own nutritional attributes and its distance from all others. The parameter estimates in table 2 indicate that nutritional attributes are critical determinants of price-elasticity. In particular, high-calorie and high-protein ice creams are significantly more price-elastic than high-fat and high carbohydrate (sugar) ice creams, *ceteris paribus*. Evidence from the nutritional literature suggests that fat and sugar are highly addictive nutrients, so the relative inelasticity of high fat and sugar ice creams is perhaps to be expected.

Using these price-response estimates and the elasticity expressions given above, table 3 shows part of the demand elasticity matrix for one retailer. As in other attribute-based estimation methods (Berry, Levinsohn and Pakes, 1995), these results show that products of the same brand, flavor and, hence, nutritional profile, tend to be closer substitutes than those that are less contiguous. How this proximity influences pricing decisions, however, remains to be seen. [table 3 in here]

Two supply-side models were estimated, one assuming competitive upstream interactions and the other assuming a more general game. The precise nature of the general game is estimated as a parametric function of a set of distance metrics. Both models parameterize downstream conduct among retailers, with estimates of each appearing in table 4. In the first model, the fitted value of φ indicates the net effect of all influences on retail margins. If the null hypothesis is H_0: $\varphi = 0$, the test becomes a joint test of retailers' ability to manage the category so as to maximize profit (act as local monopolists over their own customers) *and* set prices in cooperation with other store owners. Given the estimate of 0.309, therefore, retailers appear to be either imperfect category managers or relatively non-cooperative price rivals. Disaggregating this parameter into its component parts provides more information in this regard. Because the

store effect (contiguity with other products in the same store) is strongly positive (3.184), this means that the value of φ for products sold in the same store is indeed very close to 1.0. Said differently, if we isolate the category management effect, retailers appear to maximize profit within their own store. Moreover, retailers tend to price products that are similar to others in attribute space in a cooperative way, charging higher margins on products that are similar to others. This is true even after controlling for any possible brand-contiguity effects as two premium ice creams will command high margins, no matter who the manufacturer. Somewhat surprisingly, private labels have no apparent impact on retailer pricing in this model. However, this may be due to the fact that this specification does not also account for their role in moderating upstream rivalry.

[table 4 in here]

Based on the quasi-likelihood ratio test reported in table 4, we reject a model that includes only downstream pricing in favor of one that includes both downstream and upstream pricing. Overall, manufacturers tend to earn significantly more than competitive margins, but less than if they had monopolized the upstream channel ($\hat{\theta} = 0.508$). Considering the individual determinants of upstream and downstream conduct, the downstream store and attribute effects remain qualitatively similar to the retail-margin model, but private labels appear to play a more important role. Specifically, retailers tend to take lower retail margins on private label products, but make much higher margins in their role as private label manufacturers (4.469 upstream vs -1.188 downstream). It is important to interpret this parameter carefully. While it is tempting to infer that this result means private label introduction raises all manufacturer margins (counter to orthodoxy), it implies instead that private label products provide their manufacturers higher margins relative to national brands. The explanation for why is straightforward and consistent with the theoretical literature. Because we account for private label design through the attribute

distance variable, much of the downstream margin premium is created by imitating successful national brands (Scott Morton and Zettelmeyer, 2004 and others). The mere fact that the product is a private label does not increase retail margins. Upstream, however, private labels earn their manufacturers high margins because: (1) to the extent that retailers are their own manufacturers, they earn greater share of the total margin, and (2) to the extent that they contract with others, they are able to extract better contract terms by selling their own brands. Although we cannot directly test the impact of private label usage on upstream market power, it is also likely that some of the private label margin premium is due to their ability to increase retailers' bargaining power with manufacturers of other products, or soften upstream competition in the terminology of Chintagunta, Bonfrer and Song (2002).

Among other important factors influencing upstream market power, if a retailer purchases a number of brands from the same manufacturer (brand contiguity), then upstream margins rise – perhaps due to opportunistic behavior on the part of manufacturers with customers who are clearly dependent upon their brand. More likely, this "brand effect" reflects a fundamental value of brand proliferation in the channel as multiple brands are able to internalize upstream pricing externalities that would otherwise go to competing brands. The opposite effect appears if a number of stores purchase from the same manufacturer. If a manufacturer has broad distribution, then the trade off it faces is through lower margins, reflecting the fact that retailers are more likely to be able to force lower wholesale prices if all are selling the same product. Interestingly, attribute distance does not play an important role in determining manufacturer margins.

The implications of these results go far beyond the private label ice cream case. In fact, ice cream is likely to be representative of the entire class of private label products given that the underlying economics depend little on the nature of the product. First, the growing trend toward private-label proliferation is easily explained by the impact of private label usage on upstream

margins (FMI). Second, manufacturers are fighting the growth in private labels by accelerating

the rate of product innovation, creating new products that they hope retailers cannot imitate

quickly and successfully. However, distancing new products from competitive private labels in

attribute space is only likely to attract market share, but not raise margins. In fact, margins on

these new products are ultimately going to be below more imitative versions. Third, our results

show that manufacturers have an incentive to focus distribution on individual retail clients, and

avoid selling the same brands and flavors to different accounts. Such "mass customization" is

common in many other categories and retail environments beyond the ice cream aisle in the

supermarket.

Conclusions and Implications

This study represents an empirical analysis of the role played by private label products in retail

demand and in retail and manufacturer pricing. By focusing on private label and national brands

of ice cream sold through all supermarkets in a single, relatively small, non-Wal Mart market, we

are able to estimate the effect of private label usage on competition among retail stores and in

vertical relationships between retailers and manufacturers. As such, this is the first empirical

study to explicitly consider the effect private labels on competition among stores.

The demand model is a distance metric nested logit model (DM / NML) in which prices

are adjusted to account for variations in quality, where quality is defined by the distance between

products in attribute space. In this way, we avoid the usual IIA criticism of the nested logit

model. Moreover, whereas most theoretical and empirical models of retail variety define variety

in terms of the number of distinct products, in this model we explicitly consider the distance

between products in attribute, flavor, brand and store space. The DM / NML model is estimated

using a GMM approach in order to account for the endogeneity of both prices and product attributes.

The empirical results provide a number of important insights. First, we answer the question raised in the introduction as to whether private labels are effective in increasing market share in horizontal competition, market power in vertical competition, both or neither. In short, private labels are most effective in stealing business from rivals, but can contribute to market power if they are located near to national brands in characteristic space. Second, as a corollary we find that differentiation *per se* is not effective in increasing margins – at either the manufacturer or retailer level. Rather, the pricing model results indicate that imitative ice creams tend to earn higher retail margins. Third, private label ice creams tend to earn lower retail margins due to their value-price positioning, but higher total margins because they increase retailers' vertical market power over contract manufacturers, and provide retailers a means of internalizing the manufacturing margin. Fourth, although we cannot test directly for the effect of private labels on national brand margins, part of the private label benefit may also be due to their impact on retailers' bargaining power with national brand manufacturers. Brands with wider retail distribution tend to earn lower manufacturer margins due to their ubiquity in the channel, but store-focused brands tend to be more profitable due to the importance retailers place on brand exclusivity. Brand-proliferation within single stores also appears to be a profitable means of combating retailers' private label strategies.

These results hold many implications for retailer and manufacturer strategy. While the incentives that are driving private label proliferation are clear, the rationality of manufacturers' response, that is creating new, differentiated products, is less obvious. New products may help build market share, but will earn below-average margins. The net effect may not justify high research and development expenditures. From a retailer's perspective, the upstream benefits to

introducing private label products are well understood, but their downstream role may be more complicated than is currently believed. Simply introducing a private label is not enough as its *design* is of critical importance. Namely, as other research has shown – using far different methods than used here – the closer private labels are to other products, the more profitable they will be.

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Table 1. Summary of Supermarket Data: Visalia, CA, May 31, 2003 - June 1, 2005

Variable	N	Mean	Std. Dev.	Minimum	Maximum
Product Sales ($ '000)	22032	$119.27	$457.35	$0.00	$6,038.90
Product Volume ('000 oz)	22032	1,997.80	7,000.20	0.00	102,470.00
Store Volume ('000 oz)	22032	71,921.00	26,888.00	18,536.00	174,460.00
Store Sales ($ '000)	22032	$4,293.80	$1,688.40	$1,232.50	$9,587.70
Market Volume ('000 oz)	22032	431,530.00	83,754.00	297,330.00	642,790.00
Market Sales ($ '000)	22032	$25,763.00	$4,589.20	$18,390.00	$35,785.00
Store Share	22032	0.03	0.26	0.00	0.59
Market Share	22032	0.00	0.08	0.00	0.16
Price ($/oz)	22032	$0.11	$0.08	$0.02	$0.27
Probability of Discount	22032	0.13	0.34	0.00	1.00
Milk Price ($ / gal.)	22032	$3.08	$0.25	$2.67	$3.57
Diesel Price ($ / gal.)	22032	$2.03	$0.40	$1.58	$3.00
HFCS Price (Index)	22032	131.81	0.67	130.60	133.50
Dairy Wage ($ / wk.)	22032	$680.34	$12.75	$653.66	$706.85
Chocolate PPI	22032	155.40	1.30	152.90	159.10
Ice Cream PPI (Index)	22032	164.84	3.21	160.30	168.20
Calories	22032	171.30	54.44	80.00	300.00
Total Fat (gms.)	22032	9.24	4.21	0.00	21.00
Sodium (mgms.)	22032	52.52	19.35	15.00	120.00
Carbohydrates (gms.)	22032	19.54	5.17	10.00	32.00
Sugars (gms.)	22032	15.34	5.24	3.00	30.00
Protein (gms.)	22032	2.91	1.08	1.00	5.00

Table 2. Nested Logit / Distance Metric (NML / DM) Model Results: OLS and GMM

Variable[a]	Non-Spatial OLS Estimates		Spatial OLS Estimates		Spatial GMM Estimates	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Albertsons	0.069*	7.893	-0.072*	-4.352	-0.087*	-9.237
Ralphs	-0.313*	-37.830	-0.088*	-3.996	-0.189*	-13.748
Vons	-0.114*	-13.700	-0.087*	-3.933	-0.093*	-11.602
SaveMart 1	-0.380*	-58.040	0.148*	6.069	0.157*	9.678
SaveMart 2	-0.267*	-41.320	0.071*	3.655	0.069*	6.244
Winter	-0.032*	-5.828	-1.391*	-20.854	-1.471*	-30.565
Spring	-0.093*	-16.920	-1.434*	-21.136	-1.520*	-31.677
Fall	-0.046*	-8.301	-1.424*	-21.608	-1.526*	-31.710
Albertsons: Private Label 1	-0.149*	-15.530	-0.002	-0.064	0.041*	3.726
Albertsons: Private Label 2	-0.372*	-29.490	-0.133*	-3.279	0.118*	3.668
Albertsons: Private Label 3	-0.413*	-33.930	-0.200*	-5.239	-0.029	-1.009
Breyers	-0.082*	-5.028	0.050	1.026	0.025	1.473
Dreyers	-0.093*	-5.527	-0.006	-0.120	-0.001	-0.054
Ben & Jerrys	0.021	1.251	0.117*	2.414	0.048*	2.699
Haagen Dazs	0.295*	19.770	0.426*	10.432	0.468*	27.116
Kroger: Private Label 1	-0.112*	-6.881	0.083	1.943	0.138*	8.284
Kroger: Private Label 2	-0.147*	-7.395	0.011	0.206	0.102*	4.518
Kroger: Private Label 3	0.001	0.069	0.096*	1.963	0.043*	2.612
Vons: Private Label 1	-0.232*	-14.030	-0.128*	-2.987	-0.235*	-11.520
Vons: Private Label 2	-0.159*	-9.695	-0.008	-0.165	-0.068*	-4.015
Vons: Private Label 3	-0.286*	-24.580	-0.173*	-5.021	-0.277*	-15.804
SaveMart: Private Label 1	-0.369*	-32.350	-0.201*	-5.917	-0.274*	-18.103
SaveMart: Private Label 2	0.009*	0.784	0.154*	4.970	0.126*	10.264
SaveMart: Private Label 3	0.718*	48.390	0.865*	25.395	1.050*	47.641
Any Private Label	-0.088*	-8.356	0.047	1.909	0.071*	6.658
Discount	0.055*	5.163	0.104*	8.079	0.069*	6.278
Discount*Price	-0.485*	-4.362	-0.765*	-5.927	-0.987*	-8.262
Store-Distance	N.A.	N.A.	-0.900	-1.200	-0.083	-0.339
Brand-Distance	N.A.	N.A.	0.059	0.677	1.412*	4.154
Flavor-Distance	N.A.	N.A.	-0.013	-0.182	0.593*	3.890
Nutrient-Distance	N.A.	N.A.	-3.312*	-5.340	-4.528*	-22.008
Own-Price	-1.259*	-15.630	-1.482*	-5.481	-6.472*	-11.578
Own-Calories	N.A.	N.A.	0.022*	3.921	0.041*	15.354
Own-Fat	N.A.	N.A.	-0.185*	-3.609	-0.346*	-13.117

Own-Protein	N.A.	N.A.	0.203*	3.516	0.326*	7.141
Own-Carbos	N.A.	N.A.	-0.122*	-4.667	-0.212*	-14.717
σ_I	0.782*	722.600	0.778*	338.660	0.730*	148.670
σ_J	0.445*	284.000	0.660*	17.802	0.623*	24.188
R^2 (psuedo-R^2 for GMM)	0.993		0.996		0.994	
GMM Function Value					3825.148	
QLR					102.489	

[a] In this table, a single asterisk indicates significance at a 5% level. The variables are defined as follows: *Discount* is a deal indicator value that assumes a value of 1.0 if the shelf price falls more than 10% in a given week and then rises back to its previous level (or greater) the following week, *Discount*Price* is an interaction term with shelf price, *Store, Brand, Flavor* and *Nutrient-Distance* are inverse Euclidean distances in discrete store, brand and flavor indicators and a continuous measure of total nutrient attribute inverse distance, σ_I is the nested logit scaling parameter and a measure of heterogeneity among ice cream products, σ_J is an equivalent measure among stores, *Own-Price* is a constant price-response parameter, and *Own-Calories, Own-Fat, Own-Protein*, and *Own-Carbos* show how price response varies with own-product attributes. QLR is a chi-square distributed quasi-likelihood ratio statistic with 38 degrees of freedom (critical value at 5% = 53.10) that compares the estimated GMM objective function to one calculated under a null-parameter assumption.

Table 3. GMM Estimates of Price Elasticity Matrix: First 18 Brand / Flavors, Albertsons

	Elasticity of Row with respect to Column Brand / Flavor:[a]																	
	b_1,f_1	b_1,f_2	b_1,f_3	b_1,f_4	b_1,f_5	b_2,f_1	b_2,f_2	b_2,f_3	b_2,f_4	b_2,f_5	b_3,f_1	b_3,f_2	b_3,f_3	b_3,f_4	b_3,f_5	b_4,f_1	b_4,f_2	b_4,f_3
b_1,f_1	-5.085	0.059	0.062	0.050	0.062	0.055	0.051	0.052	0.061	0.061	0.052	0.050	0.045	0.045	0.049	0.045	0.048	0.046
b_1,f_2	0.083	-5.431	0.071	0.062	0.080	0.066	0.063	0.064	0.071	0.071	0.064	0.061	0.057	0.056	0.061	0.057	0.059	0.058
b_1,f_3	0.121	0.109	-3.858	0.106	0.127	0.128	0.114	0.120	0.227	0.234	0.120	0.109	0.101	0.100	0.107	0.101	0.104	0.102
b_1,f_4	0.077	0.071	0.078	-5.559	0.074	0.086	0.083	0.079	0.077	0.077	0.081	0.093	0.070	0.068	0.108	0.071	0.089	0.073
b_1,f_5	0.067	0.062	0.072	0.052	-5.574	0.059	0.055	0.057	0.074	0.074	0.057	0.053	0.049	0.049	0.052	0.049	0.051	0.049
b_2,f_1	0.049	0.046	0.057	0.048	0.049	-5.202	0.058	0.060	0.055	0.055	0.066	0.051	0.044	0.043	0.049	0.044	0.046	0.044
b_2,f_2	0.048	0.046	0.052	0.050	0.048	0.063	-5.191	0.074	0.052	0.052	0.083	0.062	0.046	0.044	0.053	0.046	0.050	0.047
b_2,f_3	0.085	0.081	0.095	0.084	0.086	0.110	0.121	-5.100	0.095	0.095	0.200	0.092	0.079	0.078	0.087	0.079	0.084	0.081
b_2,f_4	0.089	0.083	0.143	0.082	0.094	0.090	0.085	0.088	-5.071	0.445	0.088	0.083	0.079	0.079	0.082	0.079	0.081	0.079
b_2,f_5	0.059	0.056	0.098	0.055	0.063	0.061	0.057	0.059	0.299	-5.290	0.059	0.055	0.053	0.053	0.055	0.053	0.054	0.053
b_3,f_1	0.031	0.030	0.035	0.031	0.031	0.043	0.047	0.068	0.034	0.034	-12.967	0.034	0.029	0.029	0.032	0.029	0.031	0.030
b_3,f_2	0.021	0.020	0.022	0.024	0.021	0.025	0.029	0.024	0.022	0.022	0.025	-13.284	0.020	0.019	0.034	0.020	0.026	0.021
b_3,f_3	0.017	0.017	0.018	0.019	0.017	0.018	0.019	0.019	0.018	0.018	0.019	0.020	-10.145	0.027	0.019	0.062	0.021	0.033
b_3,f_4	0.020	0.020	0.021	0.021	0.020	0.021	0.022	0.022	0.021	0.021	0.022	0.022	0.038	-10.734	0.022	0.037	0.023	0.029
b_3,f_5	0.026	0.024	0.026	0.035	0.025	0.029	0.030	0.028	0.026	0.026	0.029	0.043	0.025	0.024	-13.127	0.025	0.038	0.027
b_4,f_1	0.010	0.010	0.010	0.011	0.010	0.011	0.011	0.011	0.010	0.010	0.011	0.011	0.036	0.015	0.011	-9.556	0.012	0.020
b_4,f_2	0.015	0.014	0.015	0.019	0.014	0.016	0.017	0.016	0.015	0.015	0.016	0.022	0.016	0.015	0.026	0.016	-10.944	0.018
b_4,f_3	0.013	0.012	0.013	0.014	0.013	0.014	0.015	0.014	0.013	0.013	0.014	0.016	0.024	0.016	0.015	0.025	0.017	-10.851

[a] Elasticities represent the price elasticity of the row item with respect to a change in the price of the column item. This table represents half of the elasticity estimates for a single chain. All other elasticities are similar and are available from the authors upon request.

Table 4. GMM Estimates of Retail Ice Cream Supply: Retail and Mfg. Margins

Variable[a]	Parameter	Retailer Pricing Model		Retailer / Mfg. Pricing Model	
		Estimate	t-ratio	Estimate	t-ratio
Constant	θ_0	N.A.	N.A.	-0.022*	-2.144
Private Label	θ_1	N.A.	N.A.	4.469*	3.770
Store	θ_2	N.A.	N.A.	-0.769*	-4.541
Brand	θ_3	N.A.	N.A.	0.771*	4.554
Flavor	θ_4	N.A.	N.A.	0.002	0.270
Attributes	θ_5	N.A.	N.A.	0.013	0.885
Constant	φ_0	-5.272*	-8.130	-5.791*	-10.277
Private Label	φ_1	0.833	0.834	-1.188*	-2.975
Store	φ_2	3.184*	6.473	3.687*	7.461
Brand	φ_3	0.078	0.228	-0.208	-1.305
Flavor	φ_4	0.234	0.821	0.081	0.457
Attributes	φ_5	2.493*	4.603	1.800*	6.768
Constant	γ_0	0.006	1.600	0.004	1.187
Milk Price	γ_1	0.013*	5.586	0.009*	4.275
Diesel Price	γ_2	-0.001	-1.327	-0.001	-1.072
HFCS Price	γ_3	0.001*	-4.399	0.001*	-5.802
Dairy Wages	γ_4	0.003*	7.614	0.002*	5.111
Ice Cream PPI	γ_5	-0.003*	-7.229	-0.002*	-5.113
Chocolate PPI	γ_6	0.279*	2.286	0.297*	2.520
$\hat{\varphi}$		0.309*	7.887	0.474*	5.807
$\hat{\theta}$		N.A.	N.A.	0.508*	4.951
$\hat{C}$		0.114*	348.408	0.111*	346.704
GMM Function		2441.447		2413.267	
QLR				28.180	

[a] In this table, store indicator variables have been omitted for brevity. The entire set of parameter estimates are available from the authors. A single asterisk indicates significance at a 5% level. The parameters are defined as follows: φ_0 is the mean "conduct parameter" downstream, or among retailers, φ_1 is the private label effect, φ_2 is the brand effect, φ_3 is the flavor effect, φ_4 is the store effect, and φ_5 is the own-attribute effect. The θ parameters are defined similarly with respect to upstream conduct, or pricing relationships with ice cream manufacturers. The γ_i are parameters of the cost function. $\hat{C}$ is the fitted cost value, $\hat{\varphi}$ is the fitted value of the retail margin conduct parameter, and $\hat{\theta}$ is the fitted value of the manufacturing margin conduct parameter. Brand and store cost function effects are not presented due to space limitations, but are available from the authors. The QLR test statistic is chi-square distributed with 6 degrees of freedom (critical value = 12.59).