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Spatial Competition and Private Labels

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Private labels, also known as store brands, are an important component of competitive strategy among multi-product retailers, as they can increase retailers' power over suppliers in the vertical channel or facilitate horizontal differentiation among retailers. This paper seeks to identify the relative importance of each role, conditional on the location of both private labels and national brands of ice cream in attribute space. We find that retailers' share of the total margin (retail price less production cost) is higher for private labels than national brands when retailers choose to imitate national brands with their own offerings.

Key words: multi-product oligopoly, nested logit, private labels, retailing, spatial modeling

Introduction

Store brand or private label use has become a key component of retailer strategy. Consumers in the United States spent a record $108 billion on private label products in 2005, a 5.3% increase over 2004 (Datamonitor, 2006). Private labels now account for nearly one-quarter of all consumer spending on food, beverages, and personal care items. Although the literature documents several reasons for private label popularity, we focus on two and attempt to explain the relative importance of each in a category that relies heavily on store brands: ice cream. First, we hypothesize that positioning private labels near national brands provides retailers leverage over manufacturers, increasing retailers' shares of the total (retail plus manufacturing) margin. Second, private labels allow retailers to differentiate themselves from other stores, increasing the total margin on all products sold. This paper presents an empirical examination of each role using an approach that explicitly accounts for upstream and downstream strategic pricing of private labels.

Research on private labels to date has focused primarily on the value of private labels in retailers' interaction with others in the vertical channel and less on the role of private labels as strategic tools in horizontal rivalry with other stores. Producing private labels that closely mimic national brand characteristics helps retailers reduce the uncertainty of acceptance in the downstream market, but cannibalizes national brand sales (Sayman, Hoch, and Raju, 2002). The threat of market share losses to retailers' private labels forces national brand manufacturers to offer more favorable prices to retailers. However, private labels that are located near national brands in attribute space are likely less effective at differentiating the retailer from others. Because horizontal competition is one of retailers' most pressing problems, private

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labels may be regarded as important tools in differentiating a retailer from its rivals. Industry surveys show that retailers often cite the strategic importance of private labels in competing with other stores (Food Marketing Institute, 2006).

Our empirical approach considers the role of private labels as a tool to create both horizontal and vertical market power among retailers. We frame pricing decisions around spatial characteristics of national brands and private labels in a four-retailer oligopoly market. Specifically, we use spatial econometric methods to study how retailers price private label ice cream conditional on its perceived substitutability with national brands. Our approach assumes that product location in attribute space is determined in a prior, unobserved stage of the game. While this approach does not explicitly model the joint endogeneity of price and product line decisions considered by Draganska, Mazzeo, and Seim (2009), it allows for empirical analysis of pricing in attribute space.[1] By conditioning pricing decisions on a product's location in attribute space, we are able to estimate retail and wholesale margins for private labels in a way that controls for the effect of attribute differentiation on prices.

Modeling attribute space also suggests a new way of thinking about product variety. The standard approach in the product assortment literature follows Salop (1979); Dixit and Stiglitz (1977); Kim, Allenby, and Rossi (2002); Watson (2004); and Draganska and Jain (2005) in defining variety in terms of the number of variants, or flavors, offered by all brands in a store. An alternative and potentially useful definition is the distance between products in characteristics space, or the "size" of space spanned by all items stocked. For example, if a retailer stocks 20 different variants of vanilla, is this really variety? Compare the choices available in 20 vanillas to those available in five flavors ranging from non-fat, non-sugar vanilla to super-premium "Cherry Garcia." An explicitly spatial model better captures this latter interpretation of variety, which is akin to Lancaster's (1971) differentiation concepts and, more recently, in address-type models of product location by Anderson, dePalma, and Thisse (1992) and Feenstra and Levinsohn (1995).

Controlling for ice cream product attributes, we find that the vertical rationale for offering private labels dominates. Retailers tend to position private labels near national brands in attribute space, and thus raise their share of the total (manufacturer plus retailer) margin.

The remainder of the paper is organized as follows The next section describes the retail ice cream market and provides some descriptive statistics that reveal important pricing patterns for private labels and national brands, both within and among retailers. We then develop an econometric model of spatial competition among retailers offering private labels, followed by a detailed description of the methods used to estimate the econometric model. Results are presented in the next section, and the final section offers conclusions, implications for the study of interaction between retailers, and suggestions for future work in this area.

[1] There is a renewed interest in using discrete game methods to construct econometric models that explain firms' strategic choice of product location in both the marketing and economics literatures (Mazzeo, 2002; Thomadsen, 2005, 2007; Seim, 2006; Zhu and Singh, 2009; Orhun, 2006), retail pricing format (Ellickson and Misra, 2007), or the choice of a specific product assortment (Draganska, Mazzeo, and Seim, 2009). However, the problem is sufficiently complex that the empirical models are often restricted to consider only a subset of true competitive space, whether two firms in a multi-firm industry (Thomadsen, 2007) or a single flavor of ice cream among a broad assortment of possible flavors (Draganska, Mazzeo, and Seim, 2009). Endogenizing the choice of product location, these empirical models advance the methodological literature considerably, but are not able to test the detailed questions addressed in this paper, namely how the retail-cost margin is allocated among channel members.

The Ice Cream Market in Visalia, California

Data Description

Data for this analysis were obtained from Fresh Look Marketing, Inc. (FLM) of Chicago. 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.

We chose Visalia, CA, to serve as a test market for estimating the spatial private label model for a number of reasons. First, in order to obtain store-level data from all major sources of ice cream supply in the market, it is necessary to select a small market. Second, there are no Wal-Mart stores in Visalia; this is important because Wal-Mart does not supply retail scanner data to data syndication firms such as FLM. Our data set therefore does not contain the "Wal-Mart gap" typical of other scanner-data studies. Third, retailers in Visalia all 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 for other reasons. HI-LO pricing is convenient for econometric analysis because it provides price variation at the brand level in our comparatively short data set. Fourth, Visalia is relatively isolated, providing limited geographic competition from supermarkets in other towns.

Ice cream provides an appropriate and interesting case study of the role of private labels. First, ice cream is predominantly sold through retail supermarkets—fully 86% of all ice cream sold in the United States in 2003 [International Dairy Foods Association (IDFA), 2007]. Thus, retailing practices are important to the entire marketing channel. Second, the ice cream industry is highly concentrated, so strategic behavior among manufacturers is likely. In fact, the two leading manufacturers—Breyers, owned by Unilever, PLC, and Dreyer's, owned by Nestle—enjoyed nearly 44% of the U.S. market in 2004 through ownership of their indigenous brands as well as Ben & Jerry's by Unilever and Haagen Dazs by Nestle (Reich, Paun, and Davies, 2005). Third, private labels play an important role in the ice cream category as they hold nearly 49% of the market; relative to all categories, ice cream ranks among the top five in terms of private label penetration (Food Marketing Institute, 2006). Fourth, two large national brands (Breyers and Dreyer's) compete through a variety of mechanisms: product innovation, retail promotion, pricing, shelf placement, and trade promotion, as well as two premium brands (Ben & Jerry's and Haagen Dazs) which occupy a niche market decidedly above that of the national brands. Fifth, ice cream manufacturers actively differentiate their products through a number of nutritional, ingredient, processing, packaging, and labeling techniques. Consequently, the attribute space occupied by ice cream brands considered here is both large and relatively sparse, with low-calorie, low–carb, and low-fat brands selling alongside the most indulgent premium labels.

Although retailers typically sell hundreds of unique ice cream stock-keeping units (SKUs), we focus on an important subset of brands listed above and three private labels per store: a premium-quality label, a mid-tier label, and a value offering. The sample data include the top five flavors of each brand by category-share within each store. We also incorporate an "other" observation that includes all brands and flavors not present in this focus group. The flavors offered by each retailer, whether private label or national brand, tend to be very similar but not identical. Therefore, flavor samples vary somewhat by store depending on market preferences. Importantly, and unlike the bottled water market described by Bonnet, Dubois, and Simioni (2006), retailers generally manufacture at most one private label ice cream and purchase the remainder from contract manufacturers.

Each observation in the demand and pricing models described below represents a flavor, store, and week. Detailed price and category-share data for each brand and flavor in a representative store are summarized over the sample period in table 1. Table 2 provides data on relative ice cream price variability among flavors offered by one manufacturer (one brand), over all brands sold in the store, within each of three private-label tiers and within the same chain for the only multi-store chain in the market. Because we aggregate over different package sizes, volume is expressed in total ounces and prices on a per ounce basis.[2] These tables show that distinct price differences exist between brands, as expected, but different flavors of the same brand also have different prices.

All retailers in our sample offer three private label brands at price points that are close to, but still somewhat below, national brand prices. Retailers reach many different consumer types simultaneously by maintaining a "good/better/best" private label strategy. National brand ice creams tend to have larger market shares than all but the most popular private labels, despite the fact that private label flavors tend to closely mimic national brands. It is important to note (table 2) that stores within the same chain (SaveMart #1, #2, and #3) do not have identical prices for the same brand or flavor. Store managers have at least some latitude to promote individual items within the chain's overall pricing policy. Each store in the sample tends to follow sharply different pricing strategies for their private labels. For example, while Vons tends to keep premium private label prices constant, SaveMart frequently promotes both premium and mid-tier private labels. The fact that prices and market shares vary widely by flavor and brand suggests both perceived and real attributes are important competitive tools in the ice cream market.

Data on nutritional attributes of each brand and flavor are critical to our empirical model; we take them from manufacturer websites or directly from product labels. We assume ice creams are differentiated according to location in a multi-dimensional attribute space using the distance metric (DM) approach of Pinkse, Slade, and Brett (2002), Slade (2004a), and Pinkse and Slade (2004). Nutritional attributes such as fat, sugar, and protein are expressed in grams per serving (1/2 cup), and energy content is total calories per serving. On the supply side, the marginal manufacturing cost function is estimated with input prices from the Bureau of Labor Statistics, including raw milk for manufacturing purposes, high-fructose corn syrup (HFCS), milk-product manufacturing labor, an energy-price index, and producer price index for chocolate. Although Breyers and Ben & Jerry's do not use HFCS, the HFCS price is highly collinear with other sweetener prices, so we use HFCS as a proxy for all. Table 3 provides summary statistics for all major variables used in the study.

Econometric Model of Spatial Competition in Private Labels

Overview

A retailer's decision to introduce private labels, or store brands, casts it in a rather unique position as both manufacturer and retailer, competing with suppliers providing the national brands often thought necessary to attract brand-loyal consumers. Through private labels, retailers

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[2] Others in this literature (e.g., Villas-Boas and Zhao, 2005) treat different packages of the same brand and flavor as separate products. In the case of ice cream, however, there are too many variations in package size and type to make a similar approach practical. This is particularly true given that the sizes of the spatial weight matrices described below increase with the square of the number of products.

Table 1. Summary of Price and Market Share Data: Vons ($N = 104$)

Brand	Flavor	Mean Price	Std. Dev. Price	Mean Share	Std. Dev. Share
Lucerne	Chocolate	0.0409	0.0080	0.0040	0.0031
Lucerne	Mint Chocolate Chip	0.0407	0.0071	0.0040	0.0033
Lucerne	Neapolitan	0.0419	0.0080	0.0036	0.0025
Lucerne	Rocky Road	0.0417	0.0081	0.0061	0.0040
Lucerne	Vanilla	0.0430	0.0082	0.0104	0.0061
Jersey Maid	Chocolate	0.0464	0.0089	0.0104	0.0073
Jersey Maid	Cookies and Cream	0.0471	0.0092	0.0117	0.0094
Jersey Maid	French Vanilla	0.0469	0.0089	0.0227	0.0151
Jersey Maid	Real Vanilla	0.0471	0.0089	0.0225	0.0145
Jersey Maid	Rocky Road	0.0470	0.0082	0.0132	0.0086
Select	Chocolate Chip Cookie Dough	0.0505	0.0098	0.0066	0.0040
Select	French Vanilla	0.0493	0.0092	0.0061	0.0039
Select	Moose Tracks	0.0506	0.0102	0.0055	0.0039
Select	Rocky Road	0.0494	0.0093	0.0084	0.0045
Select	Vanilla	0.0505	0.0101	0.0146	0.0071
Breyers	Chocolate	0.0691	0.0181	0.0098	0.0079
Breyers	French Vanilla	0.0712	0.0183	0.0110	0.0070
Breyers	Natural Vanilla	0.0717	0.0181	0.0212	0.0104
Breyers	Rocky Road	0.0745	0.0208	0.0084	0.0066
Breyers	Strawberry	0.0695	0.0182	0.0085	0.0066
Dreyer's	French Vanilla	0.0788	0.0239	0.0084	0.0062
Dreyer's	Limited Edition	0.0775	0.0233	0.0101	0.0078
Dreyer's	Rocky Road	0.0789	0.0213	0.0128	0.0077
Dreyer's	Vanilla	0.0802	0.0218	0.0228	0.0131
Dreyer's	Vanilla Bean	0.0801	0.0233	0.0143	0.0080
Ben & Jerry's	Cherry Garcia	0.2153	0.0319	0.0047	0.0031
Ben & Jerry's	Chocolate Chip Cookie Dough	0.2120	0.0329	0.0039	0.0023
Ben & Jerry's	Chocolate Fudge Brownie	0.2098	0.0318	0.0031	0.0022
Ben & Jerry's	Chunky Monkey	0.2115	0.0309	0.0029	0.0022
Ben & Jerry's	Half Baked	0.2147	0.0304	0.0025	0.0018
Haagen Dazs	Chocolate	0.1950	0.0239	0.0049	0.0027
Haagen Dazs	Coffee	0.1958	0.0253	0.0060	0.0036
Haagen Dazs	Dulce de Leche Caramel	0.1988	0.0269	0.0033	0.0023
Haagen Dazs	Strawberry	0.1885	0.0203	0.0067	0.0039
Haagen Dazs	Vanilla	0.1836	0.0116	0.0130	0.0049
Other	Other	0.0606	0.0041	0.6720	0.0459

Note: Price is in terms of \$/ounce, and "share" refers to dollar share of the ice cream category.

create new contractual linkages in the vertical supply channel, which can consolidate wholesale and retail margins and expand the product range offered downstream. The econometric model, therefore, must account for potential motives for offering private labels—either in vertical competition with suppliers or horizontal competition with rival retailers.

Table 2. Ice Cream Price Variability by Store, Brand, and Flavor

Description	Albertsons Std. Dev.	Ralphs Std. Dev.	Vons Std. Dev.	SaveMart #1 Std. Dev.	SaveMart #2 Std. Dev.	SaveMart #3 Std. Dev.
Overall	$0.0648	$0.0699	$0.0678	$0.0671	$0.0671	$0.0672
By Flavor (same brand & store)	$0.0028 (4.33%)	$0.0040 (5.67%)	$0.0018 (2.69%)	$0.0019 (2.80%)	$0.0040 (6.01%)	$0.0033 (4.91%)
By Brand (same store)	$0.0689 (106.34%)	$0.0742 (106.51%)	$0.0721 (106.39%)	$0.0711 (106.01%)	$0.0711 (106.04%)	$0.0713 (106.08%)
By Value Private Label (same store)	$0.0004 (0.57%)	$0.0044 (6.30%)	$0.0009 (1.33%)	$0.0002 (0.28%)	$0.0010 (1.54%)	$0.0003 (0.51%)
By Mid-Tier Private Label (same store)	$0.0003 (0.41%)	$0.0011 (1.57%)	$0.0003 (0.44%)	$0.0068 (10.06%)	$0.0071 (10.61%)	$0.0072 (10.78%)
By Premium Private Label (same store)	$0.0017 (2.60%)	$0.0015 (2.11%)	$0.0006 (0.91%)	$0.0125 (18.65%)	$0.0110 (16.39%)	$0.0109 (16.16%)
By Chain (same brand & flavor)						$0.0124 (18.39%)

Note: Values in parentheses are standard deviations expressed as a percentage of the overall (category) variability.

Table 3. Summary of Supermarket Data: Visalia, CA, May 31, 2003 to June 1, 2005 (*N* = 22,032)

Variable	Mean	Std. Dev.	Minimum	Maximum
Product Sales ($000s)	$119.27	$457.35	$0.00	$6,038.90
Product Volume (000 ozs.)	1,997.80	7,000.20	0.00	102,470.00
Store Volume (000 ozs.)	71,921.00	26,888.00	18,536.00	174,460.00
Store Sales ($000s)	$4,293.80	$1,688.40	$1,232.50	$9,587.70
Market Volume (000 ozs.)	431,530.00	83,754.00	297,330.00	642,790.00
Market Sales ($000s)	$25,763.00	$4,589.20	$18,390.00	$35,785.00
Store Share	0.03	0.26	0.00	0.59
Market Share	0.001	0.08	0.00	0.16
Price ($/oz.)	$0.11	$0.08	$0.02	$0.27
Probability of Discount	0.13	0.34	0.00	1.00
Milk Price ($/gal.)	$3.08	$0.25	$2.67	$3.57
Diesel Price ($/gal.)	$2.03	$0.40	$1.58	$3.00
HFCS Price (index)	131.81	0.67	130.60	133.50
Dairy Wage ($/wk.)	$680.34	$12.75	$653.66	$706.85
Chocolate PPI	155.40	1.30	152.90	159.10
Ice Cream PPI (index)	164.84	3.21	160.30	168.20
Calories (per ½ cup serving)	171.30	54.44	80.00	300.00
Total Fat (gms)	9.24	4.21	0.00	21.00
Sodium (mgms)	52.52	19.35	15.00	120.00
Carbohydrates (gms)	19.54	5.17	10.00	32.00
Sugars (gms)	15.34	5.24	3.00	30.00
Protein (gms)	2.91	1.08	1.00	5.00

We account for product differentiation on the demand side in two ways. First, we assume preferences for a particular flavor depend directly on flavor identity, the store in which it was purchased, its brand, and whether it is a private label or national brand.[3] Store and brand loyalty is well documented, while Mills (1995) and Scott-Morton and Zettelmeyer (2004) review relevant literature on perceived bias against store brands. Second, we assume consumers possess a subjective assessment of product differentiation that depends on the distance between a flavor and all others in attribute space. Consequently, shelf prices are adjusted by each consumer's judgment regarding the extent to which a product is differentiated from others (Deaton and Muellbauer, 1980; Chiang, 1991; Nair, Dube, and Chintagunta, 2005). The DM approach not only allows us to differentiate between demand for private label and national brand flavors, but also ensures that the "independence of irrelevant alternative" (IIA) attribute of discrete choice logit models does not apply.

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 among brands and flavors that satisfy their various needs once in the store.[4] Therefore, we adopt a nested logit approach to model demand for private labels and national brands (McFadden, 1978). A nested logit model provides an intuitive way to describe consumers' decisions and analytical solutions for retailers' profit-maximizing positioning decisions. Partitioning brands and flavors by retail store represents a natural choice because consumers are more likely to substitute among flavors (in the same category) within a store than compare the same flavor among stores.[5] Although this assumption is common in the retailing literature and has ample empirical support (Slade, 1995; Sudhir, 2001), we test its validity using an empirical demand model.

The demand system implied by this nesting structure is represented using a DM extension of Cardell's (1997) variance component formulation of the nested logit (also used by Berry, 1994; Currie and Park, 2002). Formally, mean utility for consumer h from consuming flavor i purchased in store j in week t (the time subscript is suppressed below) is a function of a set of store and flavor attributes ($\mathbf{x}_{ij}$), the flavor's adjusted price ($\hat{p}_{ij}$), and unobservable factors. There are $i = 1, 2, ..., I$ flavors in each of the $j = 1, 2, ..., J$ stores. Therefore, utility is written as:

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

where ξ_{1ij} is a random error unobserved by the econometrician but reflecting variables known to retailers that influence the flavor's price (e.g., shelf space, supplier rebates, or anticipated shortages). Prices are adjusted according to the degree of perceived quality relative to all other flavors using the DM approach described below. The attribute vector $\mathbf{x}_{ij}$ includes binary

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[3] To avoid confusion, an individual SKU is hereafter referred to as a "flavor" and is indexed by either i or l, while the manufacturer is referred to as a "brand." Flavors are sold through stores, which are indexed by either j or m. Because each unit of observation is a flavor/store/week, there is no need to index by brand.

[4] Our focus in this study is on competition among traditional supermarkets. Consequently, outside options consist of specialized ice cream stores, convenience stores, warehouse stores, dollar stores, and other outlets. There are no Wal-Marts or other superstores in this market.

[5] While McFadden and Train (2000) demonstrate that a mixed logit model provides a more general description of such discrete-choice situations, identifying the hierarchical choice in which we are interested requires either household-level data, which we do not have, or assumptions about the distribution of unobserved heterogeneity (Nevo, 2001), which we are not willing to make.

private label (pl_{ij}), store (st_{ij}), brand (b_{ij}), and seasonal (se_k) indicators, as well as an indicator of whether the flavor is offered on a temporary discount (dc_{ij}), and interaction terms between the shelf price and the discount ($dc_{ij}p_{ij}$).[6] Further, the distribution of v_{ih} is defined so that $(v_{ih} + (1 - \sigma_I)\,\varepsilon_{ijh})$ is extreme-value distributed if the household-specific error term ε_{ijh} is also extreme-value distributed (Cardell, 1997). Extending this logic to a second nesting level implies v_{jh} also possesses the unique distribution that causes $v_{jh} + (1 - \sigma_J)\,v_{ih} + (1 - \sigma_I)\,(1 - \sigma_J)\,\varepsilon_{ijh}$ to be extreme-value distributed. The parameters σ_J and σ_I measure utility correlation within each nest and are interpreted as inverse measures of store and product heterogeneity, respectively. Both parameters lie between 0 and 1. If $\sigma_J = 1$, then correlation among stores goes to 1.0 and stores are regarded as perfect substitutes; if $\sigma_I = 1$, then flavors within each store are perfect substitutes.

Degree of differentiation depends on a flavor's location in attribute space in a manner similar to Pinkse and Slade (2004) and Pofahl and Richards (2009). More precisely, each consumer forms a perception of the extent to which a flavor is differentiated from others based on its distance from all others. Distance, or rather its analog in the spatial econometrics literature (Anselin, 1988; Kalnins, 2003), proximity, is measured in four ways: (*a*) brand contiguity (two flavors belong to the same brand); (*b*) store contiguity (two flavors are sold in the same store); (*c*) flavor contiguity (two flavors produced by different manufacturers, or sold in different stores, are the same); and (*d*) nutrient proximity (how far or near two flavors are defined in terms of Euclidean distance in a multi-attribute nutrient space). While the three contiguity metrics are discrete, assuming a value of 1 if true and 0 if not, the inverse Euclidean distance measure is continuous. We define a separate distance matrix for each of these measures, $\mathbf{G}_d$, for $d = 2$ (brand), 3 (store), 4 (flavor), and 5 (nutrients). Because we consider the distance between each product pair in the data set, the distance matrices consist of $(IJ) \times (IJ)$ elements with typical element $g_{d,ij,lm}$ for each pair of flavors i and l in stores j and m. As an example of the brand contiguity metric, if ice cream i is made by Ben & Jerry's and l is also made by Ben & Jerry's but they are sold in different stores, then the ij,lm element of the "brand" distance matrix takes a value of 1. However, if i is the Chunky Monkey flavor, while l is Cherry Garcia, then the ij,lm element of the "flavor" distance matrix is assigned a value of 0.

We define relevant ice cream attributes to include calories, fat, carbohydrates, protein, and sugar. Because two products are differentiated if their nutrient contents differ for any of these five, we need a multi-dimensional measure of distance. Euclidean distance is a logical choice in this regard, although others exist (Pinkse and Slade, 2004). Formally, the inverse Euclidean distance ($zn_{ij,lm}$) between the nutritional profile of item i and item l in stores j and m is calculated as:

$$g_s(zn_{ij,lm}) = \left(1 + 2\sqrt{\sum_k (n_{ij,k} - n_{lm,k})^2}\right)^{-1}. \tag{2}$$

Because (2) is defined in terms of inverse distance, it represents a measure of how close the flavors are in nutrient attribute space. For example, we consider two products (1 and 3) sold in two stores (2 and 4) and two nutrients (fat and protein); if one flavor has 9 grams of fat and 8 grams of protein, while the other has 2 grams of fat and 6 grams of protein, the inverse Euclidean distance between these two is given by:

[6] Note that the discount variable is defined whereby 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 weeks. Alternative discount levels of 10% and 20% produced no qualitative difference in results. Hosken and Reiffen (2007) use a similar discount definition.

$$g_s(zn_{12,34}) = \frac{1}{1+2\sqrt{(9-2)^2+(8-6)^2}} = 0.064.$$

Slade (2004b) allows the marginal utility of income in a nested logit framework to vary with the distance between product attributes. While this approach creates a more flexible version of the nested logit, marginal utility of income cannot logically vary between products. Consequently, we create a vector of differentiation-adjusted prices by multiplying the shelf-price vector by each row-normalized (rows sum to 1.0) distance matrix and forming a linear sum. In this way, adjusted prices are spatially weighted averages of all other prices and ψ_d parameters are interpreted as spatial-autoregressive coefficients (Pinkse, Slade, and Brett, 2002; Pinkse and Slade, 2004). Adding a constant term to account for direct own-price effects, the adjusted price for flavor i in store j is written in matrix notation as:

(3) $$\hat{\mathbf{p}} = \psi_1\mathbf{G}_1\mathbf{p} + \psi_2\mathbf{G}_2\mathbf{p} + \psi_3\mathbf{G}_3\mathbf{p} + \psi_4\mathbf{G}_4\mathbf{p} + \psi_5\mathbf{G}_5\mathbf{p} = \mathbf{\Psi p},$$

where $\mathbf{G}_1$ is an identity matrix and $\mathbf{\Psi} = \psi_1\mathbf{G}_1 + \psi_2\mathbf{G}_2 + \psi_3\mathbf{G}_3 + \psi_4\mathbf{G}_4 + \psi_5\mathbf{G}_5$ is the "differentiation matrix" with typical element $\psi_{ij,lm}$. Expressed in terms of a typical element in each distance matrix, the price index becomes:

(4) $$\hat{\mathbf{p}}_{ij} = \psi_1\sum_l\sum_m g_1(I_{lm})p_{lm} + \psi_2\sum_l\sum_m g_2(zst_{ij,lm})p_{lm} + \psi_3\sum_l\sum_m g_3(zb_{ij,lm})p_{lm} + \psi_4\sum_l\sum_m g_4(zf_{ij,lm})p_{lm} + \psi_5\sum_l\sum_m g_5(zn_{ij,lm})p_{lm},$$

where $zst_{ij,lm}$, $zb_{ij,lm}$, $zf_{ij,lm}$, and $zn_{ij,lm}$ are elements of the store, brand, flavor, and nutrient distance matrices, respectively.[7] The set of nutrient attributes consists of total calories (per ½ cup serving), fat (grams), carbohydrates (grams), protein (grams), and sodium (milligrams) per serving, and proximity is defined as inverse Euclidean distance.

It is no longer the case that "... the cross-price elasticity between [*i, j*] and [*l, m*] is independent of [*i, j*]" (Slade, 2004b), which means the matrix of price elasticities does not reflect the proportionate-draw problem typical of other nested-logit models. To show why, we define the level of mean utility for each choice of flavor i and store j as: $\delta_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta} - \alpha\hat{\mathbf{p}}_{ij} + \xi_{1ij}$. Because marginal utility of income (α) is not separately identified from differentiation index parameters (ψ_d), we estimate the product of α and each ψ_d parameter. Although these parameters are fixed values, the marginal effect of variations in shelf price depends on the distance each flavor lies from all others through the differentiation matrix, $\mathbf{\Psi}$. This logic is captured by writing $\boldsymbol{\alpha}_{ij}$ as the product of α and the ijth row of $\mathbf{\Psi}$, or $\boldsymbol{\alpha}_{ij} = \alpha\mathbf{\Psi}_{ij}$. Because $\boldsymbol{\alpha}_{ij}$ depends on the distance between all flavors through the differentiation index, our demand model provides a more flexible pattern of price responses than typical with a logit or nested logit approach.

The market share of good i purchased in store j in the DM/nested multinomial logit (DM/NML) model 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 (Currie and Park, 2002):

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[7] 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 nondegenerate results, and means that the own-nutrient measures are interpreted as hedonic values.

$$(5) \qquad s_{ij} = (s_{i|j})(s_{j|J})(s_J) = \frac{e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}}{E_I^{\sigma_I} D_J^{\sigma_J}\left(1+\sum_J D_J^{1-\sigma_J}\right)}, \quad i = 1, 2, ..., I;\; j = 1, 2, ..., J.$$

In this expression, there are I flavors in store j, and

$$D_J = \sum_{j=1}^{J} E_I^{1-\sigma_I}$$

is the inclusive value term for the conditional store choice, and the inclusive value term for the choice among flavors is

$$E_I = \sum_{i=1}^{I} e^{\delta_{ij}/(1-\sigma_J)(1-\sigma_I)}.$$

Taking logs of both sides of (5) and simplifying gives the market share of product i in store j:

$$(6) \qquad \ln(s_{ij}) = \ln(s_0) + \mathbf{x}_{ij}'\boldsymbol{\beta} - \alpha\hat{\mathbf{p}}_{ij} + \sigma_J \ln(s_{j|J}) + \sigma_I(1-\sigma_J)\ln(s_{i|j}) + \xi_{1ij},$$

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

Pinkse and Slade (2004) and Slade (2004b) use a linear DM demand model in which demand for each product is a function of all other prices and the flexibility of the cross-price derivative matrix is clear. On the other hand, the DM/NML model still involves a single price vector, and so it may be less clear how cross-price elasticities vary within and among groups. Because we project demand for each flavor into attribute distances rather than prices, however, all cross-price elasticities must vary with the proximity of each flavor pair. The DM extension to the NML model therefore represents a simple, parsimonious way of averting the well-known IIA problem of all fixed-coefficient logit models.[8]

Private Label Supply

We describe private label supply using a structural model of retailer and manufacturer conduct (similar to Sudhir, 2001; Chintagunta, Bonfrer, and Song, 2002; Villas-Boas and Zhao, 2005; Bonnet, Dubois, and Simioni, 2006; and Berto Villas-Boas, 2007). The supply model takes into account how each flavor's location influences its price, both horizontally among stores and vertically with suppliers. The equilibrium concept is Nash in prices (Bertrand-Nash).

Supermarket retailers are assumed to maximize category profits within each store by choosing national brand and private label prices.[9] 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 is:

$$(7) \qquad \pi_j^r = \sum_{i=1}^{I_j} (p_{ij} - r_{ij} - cr_{ij}) s_{ij} Q - R_j,$$

[8] Expressions for all own- and cross-price elasticities are available from the authors upon request.

[9] Each of the retailers in our sample set prices on a metropolitan statistical area (MSA) basis from head office. Therefore, prices are not set by managers in individual stores, but do reflect local market and competitive conditions. As evidence, prices for similar brands/flavors differ significantly among chains.

where π_j^r is the profit of retailer *j*, I_j is the subset of flavors sold by retailer *j*, *Q* is total market size (including the outside option, meaning all ice cream sold in Visalia, CA), r_{ij} is the wholesale price of flavor *i* in store *j*, cr_{ij} is marginal retailing cost, and R_j denotes the fixed costs of operating the store. Marginal retailing costs are assumed to vary only by brand and retailer and are estimated using a set of brand and store fixed effects.

We assume each retailer maximizes ice cream profits by simultaneously setting prices for the entire subset of flavors sold. Adopting a portfolio approach to retail pricing decisions means that retail managers internalize any local monopoly power they may have over consumers who do not shop for individual flavors (Nevo, 2001). Consequently, the first-order conditions for each flavor *i* in store *j* are written as:

$$\text{(8)} \qquad \frac{\partial \pi_j^r}{\partial p_{ij}} = Qs_{ij} + Q\sum_{i=1}^{I_j}(p_{lj} - r_{lj} - cr_{lj})\frac{\partial s_{lj}}{\partial p_{ij}} = 0, \quad i = 1, 2, ..., I; \; j = 1, 2, ..., J.$$

There are a total of I_j flavors per store, so (8) captures the multi-product nature of retailing while allowing for a general pattern of interactions in partial $\partial s_{lj}/\partial p_{lm}$. Because retailers are assumed to solve the first-order conditions in (8) simultaneously, the solution for all *J* retailers is simplified considerably by using matrix notation such that:

$$\text{(9)} \qquad Q\mathbf{s} + Q(\mathbf{\Omega}^r * \mathbf{S}_p)(\mathbf{p} - \mathbf{r} - \mathbf{cr}) = 0,$$

where **p** is a price vector, **r** is a wholesale price vector, **cr** is a marginal retailing cost vector, $\mathbf{S}_p$ is an $IJ \times IJ$ matrix of price derivatives with typical element $\partial s_{lj}/\partial p_{lm}$, $\mathbf{\Omega}^r$ is an $IJ \times IJ$ matrix with $\Omega_{lj}^r = 1$ if *i* and *l* are two flavors sold by the same retailer and $\Omega_{lj}^r = 0$ if not (Nevo, 2001), and $*$ denotes element-by-element multiplication. Solving for ($\mathbf{p} - \mathbf{r} - \mathbf{cr}$) from (9) yields an estimable form of the structural model with margins as endogenous left-hand-side variables and only the matrix of price responses and market shares on the right-hand side:

$$\text{(10)} \qquad (\mathbf{p} - \mathbf{r} - \mathbf{cr}) = -(\mathbf{\Omega}^r * \mathbf{S}_p)^{-1}(\mathbf{s}),$$

in the form of the familiar mark-up rule. The precise form of $\mathbf{S}_p$ elements depends on whether flavors *i* and *l* are in the same store, different stores, or outside of the set of all flavors purchased at supermarkets in general. Substituting these expressions into (10) provides an econometric model that captures horizontal flavor interactions within and among retailers, but not between retailers and manufacturers.

We also model private label impact on retailers' vertical relationships with suppliers. We allow for a general case where each brand manufacturer sets prices for each brand flavor and for each store to which it is sold. Therefore, we model all *IJ* unique pricing decisions by all *F* manufacturers.[10] As in Berto Villas-Boas (2007), the same flavor can be sold for a different wholesale price to different retailers. The profit of manufacturer *f* is assumed to be given by:

[10] There are 16 total brands in the data set, plus an "other" category. Of these 16 brands, Unilever owns two (Breyers and Ben & Jerry's) and Nestle owns two (Dreyer's and Haagen Dazs). However, phone interviews with brand managers led us to believe that each of the brands is managed separately. Of the private labels, each retailer manufactures, at most, one of their own brands. The remainder are produced by contract manufacturers, none of which are the national brand manufacturers. Therefore, we treat the manufacturer brands as 16 economically independent entities. As shown by the data reported in table 2, price variation among flavors is much smaller than among brands.

$$\pi_f^m = \sum_{i=1}^{I_f}\sum_{j=1}^{J} (r_{ij} - cm_f)s_{ij}Q - M_f\,, \quad \forall f = 1, 2, ..., F, \tag{11}$$

where cm_f is the marginal cost of manufacturing flavor *i,* which is assumed to be constant over all flavors produced by manufacturer f; M_f is the fixed cost of production for manufacturer f; and I_f is the subset of flavors produced by manufacturer f. Unit manufacturing costs $CM(\mathbf{q}, \mathbf{w})$ are assumed to be of a normalized quadratic (NQ) form, with output vector **q** and input prices **w** so that the marginal cost of producing flavor i by manufacturer f is written:

$$cm_f = \gamma_{0f} + \gamma_1\left(\frac{w_1}{w_0}\right) + \gamma_2\left(\frac{w_2}{w_0}\right) + \gamma_3\left(\frac{w_3}{w_0}\right) + \gamma_4\left(\frac{w_4}{w_0}\right) + \gamma_5\left(\frac{w_5}{w_0}\right) + \gamma_6\left(\frac{w_6}{w_0}\right), \tag{12}$$

for some normalizing input price w_0, where γ_{0f} is a manufacturer-specific constant term, γ_k are parameters to be estimated, and $cm_i = \partial CM_i / \partial q_i$. We also include a set of brand fixed effects to reflect our assumption that cost varies by manufacturer.

Manufacturers choose their selling prices and, given the assumption that they compete vertically as Stackelberg leaders (Sudhir, 2001), must take retailers' pricing decisions into account—both for their own flavor and other manufacturers' flavors. Following Berto Villas-Boas (2007), the first-order conditions for this problem are:

$$\frac{\partial \pi_f^m}{\partial r_{ij}} = s_{ij} + \sum_{l=1}^{I_f}\sum_{m=1}^{J} (r_{lm} - cm_l)\left(\frac{\partial s_{lm}}{\partial r_{ij}}\right) = 0, \quad i = 1, 2, ..., I_f\,;\; f = 1, 2, ..., F, \tag{13}$$

which is then solved for the manufacturing margin as a function of market share sensitivity to wholesale price:

$$(r_{lm} - cm_l) = -s_{ij}\left(\sum_{m=1}^{J}\sum_{l=1}^{I_f}\left(\frac{\partial s_{lm}}{\partial r_{ij}}\right)\right)^{-1}, \quad i = 1, 2, ..., I_f\,;\; f = 1, 2, ..., F, \tag{14}$$

where

$$\frac{\partial s_{lm}}{\partial r_{ij}} = \left(\frac{\partial s_{lm}}{\partial p_{l'm'}}\right)\left(\frac{\partial p_{l'm'}}{\partial r_{ij}}\right)$$

for all other flavors l' and retailers m'. The solution to equation (14), however, includes a parameter that is not provided in the data—the pass-through rate, or $(\partial p_{l'm'} / \partial r_{ij})$. Consequently, we derive an expression for the pass-through rate by totally differentiating the first-order condition in (8) with respect to the wholesale price charged by each manufacturer (Sudhir, 2001; Villas-Boas and Zhao, 2005; Bonnet, Dubois, and Simioni, 2006; Berto Villas-Boas, 2007; Draganska and Klapper, 2007).[11] Manufacturers must take into account the impact of wholesale price changes on the retail price of their own flavors and on the prices of other flavors. In matrix notation, we define gradient vectors as

$$\nabla_r = \left(\frac{\partial p_{lm}}{\partial r_{ij}}\right) \text{ and } \nabla_p = \left(\frac{\partial s_{ij}}{\partial p_{lm}}\right)$$

[11] Details of this derivation can be found in Villas-Boas and Zhao (2005) and are available from the authors for the specific notation used here.

of length IJ, and an $IJ \times IJ$ matrix $\mathbf{H}$ that reflects the second-order effects of changes in retail prices on the shape of each flavor's demand curve. We also define a manufacturer ownership matrix $\mathbf{\Omega}^m$ analogous to the retail ownership matrix above. We then solve for the unknown matrix of wholesale price responses as $\nabla_r = \mathbf{H}^{-1}\nabla'_p$; the manufacturer margin in equation (14) is rewritten in matrix notation as:

$$(15) \qquad (\mathbf{r} - \mathbf{cm}) = -\mathbf{s}(\mathbf{\Omega}^m * \nabla_p \mathbf{H}^{-1}\nabla'_p).$$

The retail price in (10) is written in reduced form as:

$$(16) \qquad \mathbf{p} - \mathbf{cr} = \mathbf{cm} - \mathbf{s}(\mathbf{\Omega}^m * \nabla_p \mathbf{H}^{-1}\nabla'_p) - (\mathbf{\Omega}^r * \mathbf{S}_p)^{-1}(\mathbf{s}),$$

when $\mathbf{p} - \mathbf{cr}$ represents an $IJ \times 1$ vector of retail margins.[12] In deriving this expression, we do not assume private labels have zero manufacturing margins as in Bonnet, Dubois, and Simioni (2006). Unlike their bottled water example, many private label ice creams are purchased from contract manufacturers and are not fully vertically integrated.

Without further modification, (16) describes retailers and wholesalers competing among themselves in a Bertrand-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 Bertrand-Nash behavior by interacting each element of the share-response matrix $\mathbf{S}_p$ with a conduct parameter ($1/\varphi_{ij}$). The conduct parameter measures any retail-wholesale margin deviation from the competitive benchmark. Excess margins may be due to vertical interactions between retailers and suppliers that are not Bertrand-Nash.

Deviations from Bertrand-Nash behavior are not likely to be constant across stores or flavors. Rather, if conduct is thought to depend on flavor and store differentiation, as theoretical models of private label rivalry suggest, then it should be modeled as such (Choi and Coughlan, 2006). Hence, 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 determine whether pricing decisions for particular flavors depend upon their status as private label or national brand. We not only estimate the presence or absence of market power, but also relate market power to factors such as attribute proximity, whether the flavor is a private label, and the other distance metrics described above. Including the entire set of distance metrics, the conduct parameter in inter-store competition is written:

$$(17) \qquad \begin{aligned} \varphi_{ij} &= \varphi_0 + \varphi_1 g_1(zpl_{ij,lm}) + \varphi_2 g_2(zb_{ij,lm}) + \varphi_3 g_3(zf_{ij,lm}) \\ &\quad + \varphi_4 g_4(zst_{ij,lm}) + \varphi_5 g_5(zn_{ij,lm}), \end{aligned}$$

where each of the $g_d(\cdot)$ functions are measures of contiguity or distance as defined above. Tests of overall retailer conduct depend on the entire φ_{ij} function and not individual parameters.

[12] Bonnet, Dubois, and Simioni (2006) consider the more general case where manufacturers use nonlinear pricing (two-part tariffs) and resale price maintenance. However, Villas-Boas and Zhao (2005) offer compelling logical arguments for why linear wholesale prices are likely better reflections of true "... economic marginal wholesale cost..." than if real prices were available (which included nonlinear elements), because they regard many aspects of nonlinear supply contracts, such as promotional allowances or slotting fees, as not indicative of the true marginal cost. Although Bonnet, Dubois, and Simioni describe a more general form of upstream contracting, Berto Villas-Boas (2007) explains why nonlinear pricing terms are not identified without more data than are available here.

For example, if $\varphi_{ij} = 1$, the retailer internalizes all pricing externalities associated with his or her own flavors (maximizing category profits). If $\varphi_{ij} > 1$, the retailer prices above Bertrand and is clearly playing a more cooperative game than the Nash equilibrium. 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 after a private label introduction as evidence of "softening" competitive interactions between retailer and manufacturers. However, in the multiple-retailer case considered here, a similar result implies that raising private label share increases margins due to greater store differentiation, customer loyalty, better reputation for quality, or any one of a number of other competitive rationales for using private labels.

We test the hypotheses that private label introduction is associated with higher retailer market power vis-à-vis manufacturers by introducing a second conduct function in the manufacturer-markup term in equation (16) (Mills, 1995; Scott-Morton and Zettelmeyer, 2004). Draganska and Klapper (2007) employ a similar technique to test whether retail market attributes impact competitive intensity among suppliers. As in the retail-margin case, the impact on manufacturer conduct of private label proliferation; individual store, brand, and flavor effects; and the level of product differentiation (distance in attribute space) is captured by allowing θ_{ij} to depend on each of the distance metrics defined above:

(18)
$$\theta_{ij} = \theta_0 + \theta_1 g_1(zpl_{ij,lm}) + \theta_2 g_2(zb_{ij,lm}) + \theta_3 g_3(zf_{ij,lm}) + \theta_4 g_4(zst_{ij,lm}) + \theta_5 g_5(zn_{ij,lm}).$$

Because manufacturers sell to different retailers, we implicitly assume that manufacturer conduct varies by store and brand, and that flavor and nutritional attributes are related to their ability to charge higher wholesale prices.[13]

Defining vectors of length NM of both conduct parameters, we then substitute equations (17) and (18) into (16) and write the estimated version of (16) as:

(19)
$$\mathbf{p} - \mathbf{c} = \mathbf{b} - \mathbf{s}\theta(\boldsymbol{\Omega}^m * \nabla_p \mathbf{H}^{-1} \nabla_p')^{-1} - \left(\left(\frac{1}{\varphi}\right)\boldsymbol{\Omega}^r * \mathbf{s}_p\right)^{-1} \mathbf{s} + \boldsymbol{\xi}_2 ,$$

where $\boldsymbol{\xi}_2$ is an error term with typical element ξ_{2ij}. Unlike the conjectural variations case, there is no direct interpretation of θ. However, we can infer the degree of market power exercised by a wholesaler by comparing θ_{ij} to competitive and noncompetitive benchmarks. Specifically, if $\theta_{ij} = 1.0$, then manufacturers do indeed set wholesale prices according to the hypothesized Bertrand-Nash solution. On the other hand, if $\theta_{ij} = 0$, then manufacturers set prices competitively as the elements of (18) apparently do not contribute to effective differentiation and upstream market power. If $\theta_{ij} < 1$, then we can conclude that manufacturers price below Nash. Most important for understanding the role of private labels, if the interaction parameter $\theta_1 > 0$, then private labels earn higher manufacturer margins (for the retailer-manufacturer) relative to national brands. If private labels earn greater upstream margins, then this provides evidence that manufacturer market power is lower when private labels are introduced in a given category. A similar interpretation applies to each of the other elements of (18). Next, we explain how each of the conduct parameters is identified in a relatively simple two-stage estimation procedure.

[13] As Berto Villas-Boas and Hellerstein (2006) show, wholesale margins depend upon departures from Nash behavior by retailers, so tests of wholesaler contact are necessarily joint tests of conduct at both the wholesale and retail levels.

Estimation of the DM/NML Private-Label Model

Estimation Procedure

Several complications must be addressed prior to estimating the demand (6) and pricing (19) 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 the error term, ξ_{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 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 the pricing block for individual flavors is highly complex and nonlinear, requiring a nonlinear estimator.

We adopt a two-stage approach in which we estimate demand (6) in the first stage and the pricing model in the second stage in order to provide a tractable solution to each of these estimation problems. Although simultaneous demand and pricing estimation is preferable on efficiency grounds, the two-stage estimator is consistent and allows us to address the more serious issues outlined above in a computationally feasible manner.

Endogeneity of prices, discounts, *Price*Discount* interaction terms, and conditional shares in (6) are addressed using an instrumental variable generalized methods of moment (GMM) estimator. Our identification strategy is simple and intuitive. The goal is to find two sets of instruments: one that is correlated with prices (and discounts), but not the unobserved error in the demand model (ξ_{1ij}), and another that is correlated with the conditional share terms in the demand model, but not unobserved errors.

The first set of instruments are constructed by interacting input prices (milk for manufacturing purposes, high-fructose corn syrup, and milk-manufacturing wages) with brand and store dummy variables (Chintagunta, Bonfrer, and Song, 2002; Berto Villas-Boas, 2007). Input prices vary over time, and input contents vary by brand and store; the interaction between the two exhibits sufficient variation to identify the demand parameters. Further, because the demand model includes store and brand fixed effects, instruments will not be correlated with the unobservable errors for each demand equation because store and brand effects have been removed (Berto Villas-Boas, 2007). Second, we follow Berry, Levinsohn, and Pakes (1995) in constructing instruments that reflect attributes of flavors sold in other stores. More specifically, weighted averages of the nutritional attributes of all other flavors in the market are created by multiplying each variable by the inverse Euclidean distance weight matrix ($\mathbf{G}_4$) described above. This procedure is used by Pinkse and Slade (2004) and Slade (2004b), and is also suggested by Kelejian and Prucha (1998), who include nonlinear spatial-interaction terms in developing their spatial GMM estimator. Weighted average ice cream attributes from other brands and stores are likely to be valid instruments because the remaining unobservables in the demand equation are decisions like shelf placement, in-store advertising, and display activity—all of which are independent of design decisions made in a previous, unmodeled product-design game (Chintagunta, Bonfrer, and Song, 2002). Moreover, rival product attributes vary due to differences in the product portfolio sold by each store (Berry, Levinsohn, and Pakes, 1995; Draganska, Mazzeo, and Seim, 2009).[14]

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[14] Hausman (1997) uses prices in other markets as instruments for endogenous cereal prices. However, an analogous strategy here, using prices in other stores, is not valid for the reason described in the comment on Hausman by Bresnahan (1997), namely that shocks to demand will not be independent across stores if they are market-wide.

We address the likelihood that the demands for specific ice cream items are spatially correlated in two ways. First, differentiation strength depends 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.[15] 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, 2003). Consequently, we assume that the nutrient attribute distance metric represents the most general definition and define $\mathbf{G}_4$ as the spatial weight matrix used to test for spatially autocorrelated errors.

Spatial autocorrelation implies that $\xi_{1ij} = \lambda \mathbf{G}_4 \xi_{1ij}$, so a test of the null hypothesis ($\lambda = 0$) consists of a test of the significance of λ. Although a number of appropriate alternative tests exist for this purpose, we apply the Moran (I) statistic (Anselin, 1988). Failure to reject the null in this case indicates the spatial demand model must be estimated assuming each observation is spatially independent of all others.

Similar estimation concerns apply to the pricing model—i.e., because elements of both the retailer and manufacturer margin specifications are inherently endogenous, least squares estimation will again yield biased estimates. Further, because both conduct functions depend on the distance between all flavors in several dimensions, spatial dependence arises here as well. Consequently, we adopt a GMM approach as in the demand side, but define the set of instruments appropriate to the pricing equation. Specifically, we require a set of instruments that shift demand and markup terms in a way that is exogenous to retailers' and manufacturers' pricing decisions. Factors that are predetermined to the pricing decision in a relatively short panel data set include brand, flavor, store, and private label indicators, continuous values of each own nutritional attribute, and spatially weighted values of other brand and flavor nutrient attributes. Seasonal indicator variables also capture variation in temperature, which is understood to be a critical driver of ice cream demand. Tables 1, 2, and 7 document the inherent time-series and cross-sectional variation in both observed retail price and estimated marginal cost data, variation that is more than sufficient to identify differences in pricing behavior both upstream and downstream. 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 correlate across spatial dimensions.

Results and Discussion

We test the key hypotheses of this study 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 spatial demand model specification tests.

Table 4 presents the results for three different demand models, from the most simple to a comprehensive model that takes into account all hypothesized features of retail ice cream demand:

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[15] Note that if the data are indeed spatially autocorrelated, then the i.i.d. assumption necessary for the random utility assumption to be valid is violated. This is the nature of criticisms of the "mother logit" model in which the utility of each choice is a function of both own- and cross-attributes (McFadden and Train, 2000). In our spatial model, we remove any dependence of utility across choices to ensure that the remaining errors are i.i.d., and hence consistent with random utility maximization.

Table 4. Nested Logit/Distance Metric (NML/DM) Model Results: OLS and GMM

	Nonspatial OLS Estimates		Spatial OLS Estimates		Spatial GMM Estimates	
Variable	Estimate	*t*-Ratio	Estimate	*t*-Ratio	Estimate	*t*-Ratio
Albertsons	0.069*	7.893	−0.072*	−4.352	−0.079*	−8.694
Ralphs	−0.313*	−37.830	−0.088*	−3.996	−0.089*	−8.002
Vons	−0.114*	−13.700	−0.087*	−3.933	−0.090*	−10.871
SaveMart 1	−0.380*	−58.040	0.148*	6.069	0.161*	11.226
SaveMart 2	−0.267*	−41.320	0.071*	3.655	0.077*	7.739
Winter	−0.032*	−5.828	−1.391*	−20.854	−1.356*	−29.717
Spring	−0.093*	−16.920	−1.434*	−21.136	−1.410*	−30.952
Fall	−0.046*	−8.301	−1.424*	−21.608	−1.389*	−30.718
Albertsons: Private Label 1	−0.149*	−15.530	−0.002	−0.064	−0.055*	−2.877
Albertsons: Private Label 2	−0.372*	−29.490	−0.133*	−3.279	−0.018	−0.591
Albertsons: Private Lavel 3	−0.413*	−33.930	−0.200*	−5.239	−0.129*	−4.403
Breyers	−0.082*	−5.028	0.050	1.026	−0.012	−0.532
Dreyer's	−0.093*	−5.527	−0.006	−0.120	−0.003	−0.098
Ben & Jerry's	0.021	1.251	0.117*	2.414	0.054*	2.162
Haagen Dazs	0.295*	19.770	0.426*	10.432	0.351*	15.530
Ralphs: Private Label 1	−0.112*	−6.881	0.083	1.943	0.037	1.758
Ralphs: Private Label 2	−0.147*	−7.395	0.011	0.206	0.032	1.027
Ralphs: Private Label 3	0.001	0.069	0.096*	1.963	0.023	1.016
Vons: Private Label 1	−0.232*	−14.030	−0.128*	−2.987	−0.218*	−8.888
Vons: Private Label 2	−0.159*	−9.695	−0.008	−0.165	−0.071*	−3.228
Vons: Private Label 3	−0.286*	−24.580	−0.173*	−5.021	−0.257*	−11.783
SaveMart: Private Label 1	−0.369*	−32.350	−0.201*	−5.917	−0.254*	−12.475
SaveMart: Private Label 2	0.009*	0.784	0.154*	4.970	0.087*	4.413
SaveMart: Private Label 3	0.718*	48.390	0.865*	25.395	0.832*	36.051
Any Private Label	−0.088*	−8.356	0.047	1.909	0.043*	4.463
Discount	0.055*	5.163	0.104*	8.079	0.522*	5.219
Discount ∗ *Price*	−0.485*	−4.362	−0.765*	−5.927	−0.625*	−5.703
Store-Distance	NA	NA	−0.900	−1.200	−1.207*	−4.549
Brand-Distance	NA	NA	0.059	0.677	0.187*	2.596
Flavor-Distance	NA	NA	−0.013	−0.182	0.072*	3.503
Nutrient-Distance	NA	NA	−3.312*	−5.340	−3.574*	−19.361
Price	−1.259*	−15.630	−1.482*	−5.481	−1.700*	−13.464
Price-Calories	NA	NA	0.022*	3.921	0.033*	11.652
Price-Fat	NA	NA	−0.185*	−3.609	−0.302*	−11.204
Price-Protein	NA	NA	0.203*	3.516	0.320*	6.925
Price-Carbs	NA	NA	−0.122*	−4.667	−0.205*	−14.587
σ_I	0.782*	722.600	0.778*	338.660	0.774*	236.730
σ_J	0.445*	284.000	0.660*	17.802	0.624*	27.829
R^2 (pseudo-R^2 for GMM)	0.993		0.996		0.993	
GMM Function Value					3,650.278	
QLR					100.438	

Notes: An asterisk (*) denotes 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-Distance*, *Brand-Distance*, and *Flavor-Distance* are binary contiguity metrics (1 = same, 0 = different), while *Nutrient-Distance* is an inverse Euclidean distance measure in nutrient attributes; 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; *Price* is a constant price-response parameter; and *Price-Calories*, *Price-Fat*, *Price-Protein*, and *Price-Carbs* 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. The *J*-statistic value for this model has a critical χ^2 value of 74.468 with 56 over-identifying restrictions.

(*a*) nonspatial OLS, (*b*) spatial OLS, and (*c*) spatial GMM. We first evaluate whether the form of the nested logit model used here (i.e., store choice, then brand and flavor choice) is an appropriate representation of ice cream demand. Although the significance of both the brand and flavor distance parameters suggests that differences in brand and flavor are both important in determining choice probabilities, a more direct test of the nesting structure used here involves testing whether $\sigma_I = \sigma_J = 0$. If this is the case, consumers do not substitute among either flavors or stores, so a simple logit would be preferred. The results reported in table 4 show that neither of these cases apply. Both σ_I and σ_J are significantly different from zero. Thus, both the set of flavors and stores consist of viable, imperfect substitutes.

Second, we evaluate the importance of defining product differentiation in explicitly spatial terms by comparing parameter estimates from spatial and nonspatial OLS specifications. Although a relatively small difference exists between the spatial and nonspatial price-response and heterogeneity parameters, failing to account for the spatial dependence in demand reverses the sign of the private label effect. Further, the nonspatial model understates the promotion effect and the degree of substitutability among stores—both important results from a managerial perspective.

Third, we test for the endogeneity of retail prices and market shares using Hausman's (1978) general specification test. The calculated test statistic value is 272.91, 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, private label effect is significantly different from zero—unlike the OLS case. Further, the OLS brand and flavor distance parameters are insignificant, while they are strongly significant in the GMM model. Finally, demand is slightly more sensitive to price and to temporary promotions in the model that corrects for endogeneity; this result is consistent with findings reported by Villas-Boas and Zhao (2005). Using the GMM model, we also test for presence or absence of spatial autocorrelation in the demand errors. Using the Moran *I*-statistic introduced above, we find a test statistic value of 1.23. 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 results are obtained using the GMM DM/NML model uncorrected for spatial autocorrelation.

Among other demand parameters, the nested logit scale parameters indicate a greater willingness to substitute among flavors within stores (σ_I) than among flavors in different stores (σ_J). This outcome is necessary for the nested logit model to be consistent with the random utility assumption (Anderson and de Palma, 1992). Although many authors assume σ_J is equal to zero (Sudhir, 2001; Chintagunta, Bonfrer, and Song, 2002), more recent studies assume a more general, multi-retailer environment (Bonnet, Dubois, and Simioni, 2006; Berto Villas-Boas, 2007; Draganska and Klapper, 2007). While assuming retailers behave as local monopolists may be an analytical convenience and justifies the use of single-retailer scanner data, this assumption may lead to erroneous conclusions.

All four spatial autoregressive parameters in table 4 (*Store-Distance*, *Brand-Distance*, *Flavor-Distance*, and *Nutrient-Distance*) are significantly different from zero. We interpret these parameters as indicating the effect of proximity for the continuous measures and contiguity for the discrete measures on perceived quality of each product and market share. For example, a positive coefficient on brand indicator suggests that carrying more of the same brand is associated with a positive market share effect. Further, controlling for brand proximity, market share is higher when retailers carry flavors within the same brand. While brand, flavor, and store are likely dimensions of product differentiation, manufacturers regard the nutrient content of their product as the principal embodiment of product design. Therefore, the strongly negative coefficient on nutrient-attribute distance is of critical importance, implying that the closer (farther) an item is to others in terms of its nutritional profile—conditional on price, brand, store, and flavor effects—the lower (higher) its market share.

The other attribute parameters show how market share varies by store, brand, flavor, season, and private label status. Because SaveMart 3 is the excluded store variable, the results in this table show that if a particular ice cream is sold in Albertsons it will have a 7.9% lower market share than if it were sold in SaveMart 3. Holding store, flavor, and season constant, a private label ice cream will have a 4.3% higher market share than a national brand. Clearly, private labels tend to sell in high volume, no matter the category.

Price response varies with an ice cream's own nutritional attributes and its distance from all others. In general, price-response estimates indicate that nutritional attributes and price elasticity tend to be closely related. 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. While this may seem somewhat counterintuitive, it is likely that the price responsiveness of high-calorie ice creams reflects the high elasticity we would expect from relatively indulgent high-sugar and high-fat ice creams. Using these price-response estimates, table 5 shows part of the demand elasticity matrix for one retailer (Albertsons) at the brand-flavor level. As in other attribute-based estimation methods (Berry, Levinsohn, and Pakes, 1995), these results reveal that products of the same brand, flavor, and nutritional profile tend to be closer substitutes than those that are less contiguous.

We estimate two supply-side models, one assuming competitive upstream interactions (zero upstream margins) and the other assuming a more general game. Based on the quasi-likelihood ratio test reported in table 6, we reject the model that includes only downstream pricing in favor of one that includes both downstream and upstream pricing. In terms of retailer, or downstream behavior, the fitted value of $\hat{\varphi} = 0.572$ reflects both internal and external effects. Disaggregating this parameter into its component parts shows that the store effect (contiguity with other flavors in the same store) is greater than 0 but less than 1; retailers do not maximize category profit entirely.[16] Moreover, retailers tend to earn higher margins on flavors that are alike nutritionally. Retailers provide manufacturers an incentive to reduce wholesale prices on their brands by locating private label products near national brands in attribute space, increasing retail margins. This effect is true even after controlling for any possible brand-contiguity effects, as two premium ice creams will command high margins. Further, private labels have a negative effect on retailer margins in this model. This result is also to be expected given the strength of *Flavor* and *Attributes* effects, but counter to accepted wisdom that private labels generate higher retail margins than national brands. Controlling for the proximity of one flavor to another in attribute space, retail margins on private labels are lower than would otherwise be the case because retailers must credibly price-discriminate in order to create the necessary market power over national brand manufacturers. This may be the primary motivation for introducing private labels given the magnitude of the effects shown here.

[16] Because prices for each market are set by retailers from their respective head offices, it is possible that a portion of the departure from profit-maximizing levels could be due to pricing errors rather than the strategic considerations that we describe.

Table 5. 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_1, f_1	−3.996	0.056	0.059	0.044	0.059	0.051	0.045	0.047	0.057
b_1, f_2	0.082	−4.368	0.067	0.056	0.078	0.061	0.057	0.058	0.067
b_1, f_3	0.112	0.095	−2.974	0.092	0.120	0.120	0.100	0.108	0.252
b_1, f_4	0.061	0.055	0.062	−3.800	0.057	0.069	0.067	0.063	0.061
b_1, f_5	0.056	0.051	0.061	0.041	−3.927	0.047	0.043	0.046	0.063
b_2, f_1	0.041	0.037	0.049	0.040	0.040	−3.869	0.051	0.053	0.047
b_2, f_2	0.039	0.036	0.043	0.040	0.039	0.055	−3.790	0.066	0.043
b_2, f_3	0.073	0.069	0.085	0.072	0.075	0.103	0.115	−3.936	0.085
b_2, f_4	0.075	0.068	0.138	0.066	0.081	0.077	0.070	0.074	−3.810
b_2, f_5	0.048	0.044	0.092	0.043	0.052	0.050	0.046	0.048	0.317
b_3, f_1	0.010	0.009	0.011	0.010	0.010	0.015	0.017	0.027	0.011
b_3, f_2	0.007	0.007	0.007	0.009	0.007	0.009	0.011	0.009	0.007
b_3, f_3	0.005	0.005	0.006	0.006	0.005	0.006	0.006	0.006	0.006
b_3, f_4	0.006	0.006	0.007	0.007	0.006	0.007	0.007	0.007	0.007
b_3, f_5	0.008	0.008	0.009	0.013	0.008	0.010	0.011	0.010	0.009
b_4, f_1	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.003	0.003
b_4, f_2	0.005	0.005	0.005	0.007	0.005	0.006	0.006	0.006	0.005
b_4, f_3	0.004	0.004	0.005	0.005	0.004	0.005	0.005	0.005	0.005

[a] Elasticities represent 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.

(extended . . . →)

Keeping in mind that the test for manufacturer deviation from Nash is a joint test of retailer and manufacturer behavior (Berto Villas-Boas and Hellerstein, 2006), the results show that manufacturers tend to earn significantly more than competitive margins, but less than if they had monopolized the upstream channel ($\hat{\theta} = 0.312$). However, our estimates imply retailers make higher margins in their role as private label manufacturers than do national brand suppliers. While it is tempting to infer that manufacturer margins are higher for private labels, the correct implication is rather that private labels provide their manufacturers higher margins relative to national brands. The explanation for why this is the case 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 fact that the product is a private label does not increase retail margins. Upstream, however, private labels earn their manufacturers high margins because: (*a*) to the extent that retailers are their own manufacturers, they earn all of the margin between retail price and manufacturing cost (Bontems, Monier, and Requillart, 1999), and (*b*) to the extent that they contract

Table 5. Extended

	Elasticity of Row with Respect to Column Brand/Flavor:[a]								
	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	0.057	0.047	0.044	0.039	0.038	0.043	0.039	0.041	0.039
b_1, f_2	0.067	0.058	0.055	0.050	0.049	0.055	0.050	0.053	0.051
b_1, f_3	0.261	0.109	0.094	0.084	0.082	0.091	0.084	0.088	0.085
b_1, f_4	0.061	0.065	0.077	0.054	0.051	0.092	0.054	0.073	0.057
b_1, f_5	0.063	0.046	0.041	0.037	0.037	0.041	0.037	0.039	0.038
b_2, f_1	0.047	0.059	0.043	0.035	0.034	0.041	0.035	0.038	0.036
b_2, f_2	0.043	0.075	0.053	0.036	0.035	0.044	0.036	0.040	0.037
b_2, f_3	0.085	0.206	0.081	0.067	0.065	0.075	0.066	0.071	0.068
b_2, f_4	0.493	0.074	0.067	0.063	0.063	0.066	0.063	0.065	0.064
b_2, f_5	−3.898	0.048	0.044	0.041	0.041	0.043	0.041	0.042	0.042
b_3, f_1	0.011	−3.655	0.011	0.009	0.009	0.010	0.009	0.010	0.009
b_3, f_2	0.007	0.009	−3.994	0.007	0.006	0.013	0.007	0.010	0.007
b_3, f_3	0.006	0.006	0.007	−2.794	0.010	0.006	0.026	0.007	0.013
b_3, f_4	0.007	0.007	0.008	0.015	−2.954	0.007	0.014	0.008	0.011
b_3, f_5	0.009	0.010	0.017	0.008	0.008	−3.825	0.008	0.014	0.009
b_4, f_1	0.003	0.003	0.004	0.016	0.006	0.004	−2.594	0.004	0.008
b_4, f_2	0.005	0.006	0.008	0.006	0.005	0.010	0.006	−3.192	0.007
b_4, f_3	0.005	0.005	0.006	0.010	0.006	0.006	0.010	0.006	−3.200

with others, they are able to extract better contract terms by selling their own brands (Chintagunta, Bonfrer, and Song, 2002). Although our results are not a direct test of the impact of private label usage on upstream market power, they do provide indirect evidence of the behavior we expect if this spatial aspect of private label introduction indeed exists.

We resolve this issue by simulating the impact of each effect on retail and manufacturing margins. These results are reported in table 7. Specifically, the values in this table represent average retail and manufacturing margins for each national brand and private-label tier (i.e., premium, mid-tier, and value) over the six stores (in four chains) in the sample data. As observed from table 7, the total margins for private labels are indeed generally higher than for national labels. These results also show that the proportion of total margin accounted for by the difference between wholesale prices and production cost is greater than the retail margin. Therefore, the competing retail margin effects shown in table 6—lower margins due to the private label effect and higher margins due to the attribute-proximity effect—appear to result in net lower retail margins, while the wholesale margin effects dominate.

The implications of these results go far beyond the private label ice cream case. First, the growing trend toward private-label proliferation is easily explained by the impact of private label usage on upstream margins (Food Marketing Institute, 2006). Second, manufacturers are fighting private label growth by accelerating product innovation rate, creating new products they hope retailers cannot imitate quickly and successfully. However, distancing new products

Table 6. GMM Estimates of Retail Ice Cream Supply: Retail and Manufacturing Margins

		Retailer Pricing Model		Retailer/Mfg. Pricing Model	
Variable	Parameter	Estimate	t-Ratio	Estimate	t-Ratio
Constant	θ_0	NA	NA	5.844*	17.420
Private Label	θ_1	NA	NA	0.092*	3.216
Store	θ_2	NA	NA	−4.023*	−8.797
Brand	θ_3	NA	NA	1.600*	4.777
Flavor	θ_4	NA	NA	−0.899*	−23.241
Attributes	θ_5	NA	NA	−1.052*	−15.159
Constant	φ_0	−0.975*	−19.778	−4.707*	−49.587
Private Label	φ_1	−0.087*	−2.871	−0.283*	−4.194
Store	φ_2	0.666*	14.672	2.358*	29.781
Brand	φ_3	−0.070*	−5.533	−0.333*	−11.154
Flavor	φ_4	0.087*	3.737	0.615*	15.976
Attributes	φ_5	0.214*	8.340	0.870*	15.670
Milk Price	γ_1	−0.428*	−2.722	−1.856*	−7.346
Diesel Price	γ_2	0.075*	0.443	−0.009	−1.045
HFCS Price	γ_3	0.095*	1.010	0.047*	2.423
Dairy Wages	γ_4	−0.026*	−4.093	−0.030*	−4.258
Packaging Price	γ_5	0.179*	3.596	0.225*	4.385
Chocolate PPI	γ_6	0.004*	0.282	0.043*	2.694
$\hat{\varphi}$		0.472*	7.047	0.572*	4.036
$\hat{\theta}$		NA		0.312*	3.184
c_m		0.057*	9.177	0.056*	112.563
GMM Function		1,849.448		1,237.993	
QLR				594.382	

Notes: An asterisk (*) denotes significance at a 5% level. In this table, store and brand indicator variables have been omitted for brevity. (The entire set of parameter estimates is available from the authors upon request.) 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 marginal cost of manufacturing function. (Store- and flavor-specific estimates are available from the authors upon request, as are brand intercepts and store retailing costs.) The QLR test statistic is chi-square distributed with 6 degrees of freedom (critical value = 12.59). GMM estimates are obtained using a Newey-West (1987) estimator and the standard errors are bootstrapped to account for the presence of an estimated regressor (Cameron and Trivedi, 2005). The J-statistic value for this model has a critical χ^2 value of 89.391 with 69 overidentifying restrictions.

from competitive private labels in attribute space is only likely to attract market share, not raise margins. Margins on these new products are ultimately going to be below more imitative versions.

Conclusions and Implications

This study represents an empirical analysis of the role played by private labels in retail demand and in pricing by retailers and manufacturers. We estimate the relationship between private label usage and the nature of competition among retail stores and vertical relationships between retailers and manufacturers using data on private label and national brand sales of ice cream sold through all supermarkets in a single, relatively small, urban market.

Table 7. Estimated Margins by Brand and Private Label (PL) Tier

Description	Breyers	Dreyer's	Ben & Jerry's	Haagen Dazs	Premium PL	Mid-Tier PL	Value PL
Average of All Retailers:							
Price	$0.078	$0.086	$0.210	$0.214	$0.103	$0.061	$0.050
	($0.044)	($0.028)	($0.045)	($0.038)	($0.089)	($0.067)	($0.038)
Marginal Cost	$0.037	$0.048	$0.121	$0.125	$0.029	$0.019	$0.009
	($0.026)	($0.023)	($0.026)	($0.024)	($0.017)	($0.002)	($0.005)
Total Margin	0.532	0.440	0.422	0.416	0.721	0.680	0.815
Retail Margin	0.336	0.376	0.386	0.390	0.192	0.242	0.234
Mfg. Margin	0.196	0.065	0.036	0.026	0.528	0.437	0.581
Representative Retailer—Vons:							
Total Margin	0.642	0.518	0.550	0.503	0.980	0.718	0.907
Retail Margin	0.408	0.477	0.448	0.496	0.110	0.354	0.307
Mfg. Margin	0.234	0.041	0.102	0.007	0.869	0.364	0.600

Notes: Margins are estimated based on the nature of the equilibrium shown in table 6. All brand and private-label margins are averages calculated over the six stores (four chains) in the sample data set. Prices and costs are in $/oz. and margins are expressed as a percentage of the retail price. Values in parentheses are standard deviations.

The demand model is a distance metric nested logit model (DM/NML) in which prices are adjusted to account for variations in the extent to which a product is differentiated from all others, where differentiation is defined by the distance between products in attribute space. We avoid the usual IIA criticism of the nested logit model with this approach. 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 to account for endogeneity of prices and market share.

The empirical results provide a number of important insights. First, we answer the question as to how private label usage is related to higher market share in horizontal competition, greater market power in vertical competition, both, or neither. In short, using private labels appears to be most strongly associated with the former, business-stealing effect, but can correlate with higher margins if they are located near national brands in characteristic space. Second, as a corollary, we find that differentiation per se is not associated with 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—perhaps 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 relationship between private label usage and national brand margins, part of the private label benefit may also be due to the relationship between private label usage and retailers' influence with national brand manufacturers.

These results hold many implications for retailer and manufacturer strategy. While the incentives that drive private label proliferation are clear, the rationality of manufacturers' response—creating new, differentiated products—is less obvious. New products may help build market share, but will earn below-average margins; net effect may not justify the necessary product-development expenditures. From a retailer's perspective, upstream (with respect to suppliers) benefits to introducing private label products are well understood, but their downstream (with respect to consumers) role may be more complicated than is currently believed. Simply introducing a private label is not enough, as its design is of critical importance. As other research has shown (employing different methods than used here), the closer private labels are to other products, the more profitable they will be.

One important limitation of our study is the implicit assumption that the location of each product in attribute space—its design—is determined in a previous, unobserved game. Studying the nature of that game and how its results interact with the pricing strategy described here may be a promising avenue for future research. Second, while our market-specific data are useful in avoiding the "Wal-Mart gap" typical of other retail competition studies, if pricing decisions are made at the chain level, our empirical results may be measuring something other than variation in market power. Our demand specification may also be useful in future research for evaluating the competitive and welfare effects of introducing new products with different attributes from existing products.

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