Selected Paper 78

Why Store Brand Penetration Varies by Retailer

Sanjay K. Dhar
Stephen J. Hoch

April 1997

Abstract

Store brands are the only brand for which the retailer must take on all responsibility—from development, sourcing, and warehousing to merchandising and marketing. Manufacturers' actions largely drive the decisions retailers take about national brands, but the retailer plays a more determinant role in the success or failure of its own label. Based on data from 34 food categories for 106 major supermarket chains operating in the largest 50 retail markets in the U.S., we show that variation in store brand penetration across retailers is related systematically to underlying consumer, retailer, and manufacturer factors. Store brand market shares are influenced by trading area demographics; retailer economies of scale and scope; retailer pricing, promotion, and assortment tactics; retailer category expertise; local retail competition; within category brand competition; and manufacturer promotion (push) and advertising strategies (pull) efforts. We argue that private label brands threaten national brands most in categories when there is high variance in share across categories (as opposed to high average share per se). In high variance categories, store brand share could increase dramatically if the poor performing retailers imitate best practices.

Why Store Brand Penetration Varies by Retailer

In the packaged goods world, store brands (or private labels) behave much the same as any other brand. They face downward sloping demand with respect to price and upward sloping demand with respect to quality. Promotional price elasticities are greater than everyday price elasticities. And display and feature activity magnify the effects of temporary price reductions. But store brands also are different (Hoch 1996). They are the only brand for which the retailer takes on all responsibility—from development, sourcing, and warehousing to merchandising and marketing. While the actions of the manufacturers in large measure determine the decisions retailers take about national brands or regional players, the retailer plays a bigger role in the success or failure of its own label.

Although retailers have lots to gain by better understanding the determinants of successful store brand programs, this knowledge may be more valuable to manufacturers. Lessons learned from competing with other national brands may not transfer one-to-one to the store brand case because, quite simply, a popular private label program changes the status of the retailer from being solely a customer to also a competitor. When customers are competitors, standard predatory tactics may not be appropriate; instead there is a premium on creating a successful basis for coexistence.

This paper explains the across-retailer variation in store brand performance shown in Table 1. We utilize sales data from 50 U.S. markets to identify key determinants of retailer performance and draw implications for channel interactions.[1] Previous research has focused on explaining across category variation, illustrated in the table by the differences between edible grocery and dairy (Hoch and Banerji 1993; Sethuraman 1992; Raju, Sethuraman, and Dhar 1995a,b). We have a good understanding, for example, of why store brands constitute 65 percent of sales of canned green beans but only 1 percent of deodorants. But no research has considered across retailer variation in private label sales within a category, a more relevant issue to national manufacturers interested in their own brands.

Based on data from 34 food categories for 106 major supermarket chains operating in the largest 50 retail markets in the U.S., Table 1 shows private label performance in five key markets broken down by three potential sources of variance—geographic market, retail chain within a market, and broad category groups within a chain within a market. We see substantial variation in aggregate performance across major metropolitan markets; for the entire data set, not just that portion shown in Table 1, private label share ranges from a low of 15 percent in Chicago to a high of 32 percent in Portland. Similarly, there are large differences between retailers; the average difference in private label performance between the best and worst retailer within a market is 11 percent, the narrowest range is 1 percent in Baltimore, and the widest range 36 percent in New Orleans. Finally,

1. U.S. store brands usually are not quite up to the quality standards of the top national brands and always are priced at a discount; our findings may be less applicable to countries where these same conditions do not hold.

Table 1:

Variation in Store Brand Share Across Markets, Retailers, and Category Groups

Market	*Share*	*Retailer*	*Share*	*Category Group*	*Share*
Atlanta	23.74%	A & P	11.15%	Dairy	15.78%
				Edible Grocery	9.32
		Kroger	21.41	Dairy	29.47
				Edible Grocery	20.23
		Publix	18.45	Dairy	24.67
				Edible Grocery	11.93
		Winn-Dixie	29.03	Dairy	35.16
				Edible Grocery	22.36
Chicago	15.29	Dominick's	20.58	Dairy	32.84
				Edible Grocery	9.81
		Eagle	10.49	Dairy	16.10
				Edible Grocery	7.50
		Jewel	16.32	Dairy	18.79
				Edible Grocery	11.45
		Omni	5.30	Dairy	8.35
				Edible Grocery	4.29
Los Angeles	16.31	Albertson's	20.41	Dairy	32.64
				Edible Grocery	11.45
		Alpha-Beta	7.36	Dairy	7.90
				Edible Grocery	8.06
		Boys/Viva	9.64	Dairy	8.75
				Edible Grocery	13.32
		Hughes	9.08	Dairy	19.05
				Edible Grocery	1.24
		Lucky	17.79	Dairy	26.50
				Edible Grocery	11.45
		Ralphs	16.77	Dairy	28.38
				Edible Grocery	7.68
		Vons	14.48	Dairy	24.77
				Edible Grocery	7.09
New York	17.06	A & P	13.98	Dairy	17.36
				Edible Grocery	10.73
		Grand Union	11.07	Dairy	13.46
				Edible Grocery	8.76
		Pathmark	17.36	Dairy	24.88
				Edible Grocery	12.37
		Shoprite	20.52	Dairy	26.54
				Edible Grocery	15.37
		Waldbaum's	17.05	Dairy	23.27
				Edible Grocery	10.53
Portland	32.28	Albertson's	32.29	Dairy	49.42
				Edible Grocery	14.21
		Fred Meyer	29.28	Dairy	40.62
				Edible Grocery	15.17
		Safeway	33.60	Dairy	50.84
				Edible Grocery	13.69

although there are stable differences at the retailer-market level, some retailers achieve quite different levels of store brand performance depending on commodity type. For instance, Omni has a weak program across the board while Winn-Dixie has a strong program. On the other hand, Dominick's is very strong in dairy but weak in edible grocery.

We carried out a more formal analysis of the complete data underlying Table 1: private label market shares for each of three years broken down by the top 106 retailer/market combinations in 34 food categories (3x34x106=10,812 observations). We estimated a series of hierarchical models by regressing store brand market share onto subsets of intercept terms representing categories, markets, retailers, and retailer x market interactions. The results appear in Table 2.

Table 2:
Hierarchical Analysis of Category, Market, and Retailer Determinants of Store Brand Penetration

Intercepts	*Variance Explained (R^2)*
Category	40.2%
Category + Market	44.3
Category + Retailer	56.7
Category + Market + Retailer	57.1
Category + Market + Retailer + M*R Interactions	57.2

Not surprisingly, most of the explainable variance is due to differences between categories. Differences between markets explain an additional 4 percent of the variance. Differences between retailers account for almost 17 percent of the variance and in fact subsume local market effects because most retailers operate in single regions. Our empirical work focuses on this 17 percent variance. We ask the following question: After controlling for category differences, what are the key determinants of store brand market share for a specific retailer? We also show that coefficients differ depending on whether the average quality of store brand alternatives in a category is high or low relative to the national brands.

The rest of the paper is organized as follows. The next section lays out a conceptual scheme that attributes the factors that might influence store brand performance to one of three parties—consumers, retailers, and national manufacturers (Hoch and Banerji 1993). We then describe the dataset, predictor variables, and results. We report directional results and then average coefficients across all 34 categories. To recognize the heterogeneity that exists across categories, we utilize a random coefficient approach and pool the categories into high and low quality types. Fortunately, the analyses offer a clean picture of the major issues. The concluding section draws implications for both retailers and manufacturers.

Background

We would prefer that a parsimonious theory could explain the across-retailer variation in Table 1, but previous cross-category research suggests that this is unlikely (Hoch and Banerji 1993; Raju et al. 1995a). The story is more complicated because store brands sit right in the middle of the manufacturer-retailer-consumer vertical relationship. Unlike the typical national brand, where consumer demand results from response to the pull tactics of the manufacturer, U.S. store brands are the prototypical push product. If the retailer decides to push the product, consumers will be exposed and respond accordingly depending on underlying quality and other retailer actions, as well as whatever actions national manufacturers coincidentally pursue.

Following Hoch and Banerji (1993), we localize the drivers of store brand performance with the three parties that make up the retail channel: consumers, retailers, and manufacturers. In a cross-sectional analysis of 185 grocery categories, Hoch and Banerji found that six variables could explain 70 percent of the variance in market shares.
Store brands obtained higher market share when:

- quality relative to the national brands was high,
- quality variability of store brands was low,
- the product category was large in absolute terms ($ sales),
- percent gross margins were high,
- there were fewer national manufacturers operating in the category,
- national advertising expenditures were low.

The first two variables show that, all else equal, consumers are more likely to buy private labels that provide parity quality. The middle two factors reflect the retailer's scarce resource allocation problem. Because retailers must draw on internal funds for the branding, packaging, production, and advertising of their store brands, they invest more heavily in large categories offering high profit margins so as to maximize their return. The last two variables demonstrate the influence of manufacturers and show that private labels can be crowded out of the market when national brand competition is high and when those brands invest advertising resources into the consumer franchise. The differences between dairy and edible grocery in Table 1 are consistent with this story—dairy has high quality store brands (regulated by the USDA), huge sales volume and big margins, and few national brands who spend little on advertising.

Determinants of performance in a cross-category analysis, however, are not necessarily the ones that explain performance across retailers within a category. For example, quality, size of the market, and gross margins vary more across categories than across retailers within a category. Alternatively, demographic characteristics, level of promotion, and pricing policy vary more across retailers than across categories. Conceptually, however, it is possible to localize the responsibility with the consumer, the retailer, or the manufacturer—and so we will organize our discussion of the drivers of store brand penetration in this manner.

Consumer Factors

In order for consumers to influence retailer specific store brand performance, not only must demographics matter but also differ by retailer. For economists, the typical store brand sold in the U.S. is an inferior good and as such should be purchased more frequently by price sensitive shoppers. Becker (1965) argues that systematic differences in price sensitivity should emerge due to differences in opportunity costs of time associated with demographic characteristics (Blattberg, Eppen, and Lieberman 1978). Starzynski (1993) found that heavy private label users had lower incomes and larger blue collar households with part time female heads of household. In a study of micromarket differences in demand for private labels, Hoch (1996) found that stores with larger category price elasticities had higher private label share; moreover, there were systematic differences due to the demographic characteristics of a store's trading area. Store brands obtained higher share when the trading area contained more elderly people, lower housing values and lower incomes, more large families, more working women, and higher education levels. Each of these demographic relations is consistent with Becker's opportunity cost story except education.

Even though store-level sales of private label can be linked to consumer characteristics, it is an empirical question whether these distinctions emerge when aggregating up to the chain level. Do supermarket chains serve and attract sufficiently distinct clienteles? Demographics could vary across retailers because of differences in targeting, positioning, and real estate. Our data reveal wide disparities in demography by geographic region. Compared to Los Angeles, Philadelphia has a larger elderly population (23 percent vs 17 percent) and significantly lower housing values (19 percent vs 41 percent of homes worth more than $250,000). Demographic profiles also vary by retailer within a market. In New Orleans, A&P serves a better educated clientele than Winn Dixie (21 percent vs 16 percent college educated), while Schwegmann's trading area contains more blacks and hispanics (37 percent) than Delchamps (23 percent).

Retailer Factors

There are a large number of retailer characteristics that position some supermarket chains to better develop and exploit a store brand program than others. First, we discuss those factors largely fixed across categories and then address those that vary from category to category.

Retail Competition. Retailers face different levels of competition depending on: (a) the number of retail competitors; and (b) the heterogeneity in their market shares. More competitors and a uniform distribution of shares leads to greater competition (Waterson 1984). Facing a large set of competitors increases uncertainty; witness Los Angeles retailers who must think about the potential actions of ten other major players versus Chicago where Jewel (35 percent share) is the long term price setter and Dominick's (21 percent) the price follower. Retailers operating in markets with lots of competitors have smaller market shares on average and must focus on stealing customers and defending their own turf. Retailers could use their store brand program to help in this effort, but more likely will leverage national brand resources to build store traffic. In contrast, with few competitors retailers have larger shares on average and plenty to gain by exploiting existing store traffic, an objective that private label is particularly well suited to achieve because of higher margins. Heterogeneity in market shares moderates the effect of a fixed number of competitors; when a few chains dominate a market, the retailer can safely focus attention on the major players and not worry about the minor competitors. In the highly concentrated European food retailing scene, retailers use store brands to differentiate themselves from the few big competitors they face.

Economies of Scale and Scope. Large retailers are better positioned to build scale economies than smaller chains. Higher sales volumes bring down unit costs through: (a) lower printing and holding costs for package labels; (b) better prices from suppliers due to longer production runs and negotiating clout; and (c) lower inventory holding costs through more continuous supply. These scale economies allow the retailer to provide better value for the money.

Retailers achieve economies of scope when corporate brand programs extend across more of the 350 categories that full-service supermarkets typically carry. Presence in more categories increases salience of the store brand concept and justifies investment in resources dedicated to private label, such as in-house quality assurance, unique promotion events, and a premium store brand program (e.g., Safeway Select). Retailers also signal commitment through naming of the store brand—placing the chain name prominently on 1,000-plus items makes the relation to the parent firm transparent. This reduces consumer risk in trying products with unknown manufacturing origins and increases motivation of employees responsible for merchandising the product. These scope factors serve as surrogates for retailer effort and commitment to a store brand program.

EDLP and Breadth of Assortment. Consider the effect of EDLP (everyday low pricing) versus Hi-Lo pricing on store brand performance (Hoch, Drèze and Purk 1994). With less promotion activity and simpler merchandising tactics, EDLP makes the normal price difference between the national brands and private label more apparent and facilitates parity comparisons. EDLP's value orientation also is consistent with typical store brand positioning. Depth of assortment also influences private label performance. Retailers committed to a full service look offer more variety and deeper assortments, including more slow moving items as they sacrifice efficiency for satisfying customer needs. Narrow assortments favor the store brand; specialty items are more likely to be eliminated, not private labels positioned against the leading national brands, sizes, and flavors.

Category Expertise. Retailers may develop special expertise in particular categories. Some retailers excel in their presentation of meat and produce, while others have expertise in better serving the eating needs of particular ethnic groups. Category expertise develops in response to the demand side, but once developed, it becomes part of the organization's intellectual capital. The expert retail buyer is less dependent on national brands to provide category knowledge and may use private labels to enhance margin mix for an already high performance (in unit sales) category.

Price Gaps and Promotion. Category level pricing and promotion strategies could influence store brand performance. The bigger the price gap between national brands and private labels, the bigger is the incentive for the consumer to trade down to the private label. Despite obvious economic arguments, evidence is mixed as to the importance of relative price. In the cross category work of Raju et al. (1995b; Mills 1995; Sethuraman 1992), price differential actually is negatively related to private label performance—categories with big gaps have lower private label penetration than those with smaller gaps. Raju et al. (1995a) argue that this result is due to cross-sectional aggregation. In equilibrium, differences in price sensitivity across categories lead to bigger gaps in price insensitive categories (analgesics) and smaller gaps in price sensitive categories (canned vegetables) where demand for private label is high. Hoch (1996) conducted single retailer pricing experiments where the price gap varied from 10 to 35 percent. Private labels were twice as sensitive to the gap as national brands, but price elasticities generally were low, and so a profit maximizing retailer was better off with larger than smaller gaps. If category price elasticities vary across retailers, however, different optimal price gaps may emerge and within-category differences in price differentials may prove an important predictor of store brand performance.

Just as the everyday pricing tactics of the retailer can influence private label performance, so can the manner in which they promote products. Some markets and retailers engage in aggressive week-to-week promotion battles; retailers use national brands as loss leaders to build store traffic (Drèze 1995). Store brands lose their comparative advantage when national brands are heavily promoted, especially amongst more price sensitive buyers and heavy users who stockpile promoted product. Other retailers could elect to aggressively promote private label—using shallow deals to help maintain a good margin mix across products. But research on asymmetric cross-price elasticities between high and low quality brands suggests that such tactics will be less effective for store brands (Allenby and Rossi 1991) because they are more vulnerable to national brand promotion and their own promotional efforts have less clout (Kamakura and Russell 1989).

Retailer Summary. All retailer factors are to some degree endogenous, even retail competition and chain size. For econometric purposes, however, we assume that only price gap, promotion, and assortment decisions are short term and endogenous enough to require special treatment. Retailers can change chainwide policies (e.g., quality level) but only in the long-run.

Manufacturer Factors

Brand Competition. National brands influence store brand performance directly with various consumer pull tactics and indirectly through push tactics offered to the retail channel. Probably the biggest influence on store brands is competition in the category. As with retail competition, we follow the IO literature, which characterizes brand competition as higher when: (a) there are a large number of national brands; and (b) market shares are evenly distributed amongst the different brands (Waterson 1984). When retailers carry many brands, there is a pure crowding out effect; on average, each brand (including the store brand) will command a smaller share of a fixed pie (Raju et al. 1995b). Further, for a fixed number of national brands, higher concentration in market shares among a few brands indicates less heterogeneity in tastes and possibly a price umbrella, both conditions that are attractive to the store brand. When competing against a couple of large share brands that may benefit from a price umbrella, store brands can pursue a focused positioning strategy and offer an attractive alternative at a lower, but still quite profitable, price. Alternatively, a store brand facing numerous same-size competitive brands requires diffuse marketing effort in response to multiple fronts. Greater brand competition hurts the store brand. Clearly the retailer has the final say over how many brands they carry; we deal with this endogeneity in our econometrics.

Pull Promotion. A highly fragmented category is more sustainable for a national brand than a private label because national brands benefit from the substantial economies of scale in production and advertising that accrue to national distribution (Schmalensee 1978). Consider the RTE (ready-to-eat) cereal category, where about 200 brands are alive at any point in time and 120 of them are actively marketed. Only a handful of brands obtain more than 1 percent of the market and a majority have less than .5 percent. But .5 percent of an $8 billion market is still an economically viable $40 million brand. The problem for the store brand in a differentiated category is that the only way for the retailer to grab significant share is to enter with multiple brands in disparate locations in the product space, a practice that is self-limited by insufficient scale economies. In the long run most manufacturer pull tactics serve to increase differentiation, reduce price sensitivity, and increase top-of-mind awareness, each of which increase demand for national brands and hurt store brands. To the extent that advertising (TV, newsprint, and magazine) and consumer promotion (coupons, sweepstakes, etc.) differ by markets, pull promotion spending should limit store brand penetration.

Push Promotion. Trade promotion activity varies dramatically by geographic market. Although manufacturers legally must offer identical terms of trade to resellers competing in the same market, national brands can and do allocate trade dollars disproportionately across markets depending on category development (consumption rate); brand development (market share); and presence or absence of regional competition. Trade promotion dollars take many forms but eventually are expressed at retail as reductions in everyday prices, temporary price reductions, or feature advertising and display. Because manufacturers cannot directly set prices, these decisions are partly endogenous to the retailer. At the same time, higher levels of trade spending do result in lower prices, and manufacturers can contractually mandate performance requirements for feature advertising and display. Greater levels of national brand promotion should limit private label performance (Lal 1990).

Summary

Table 3 shows the predicted impact of each variable on store brand performance.

Understanding the determinants of store brand performance requires a recognition that consumers, retailers, and manufacturers all influence the process. We localized the source of influence at one level of the distribution channel, but clearly interdependencies between the supply side and demand side make some of these distinctions fuzzy. For example, manufacturers and retailers jointly determine retail pricing and promotion. The next section describes the empirical work.

Table 3:
Predicted Impact of Key Determinants of Store Brand Share

Key Determinants	*Expected Sign*
Consumer Factors	
Wealthy People in Customer Base	-
Elderly People in Customer Base	+
Higher Education Level in Customer Base	+
Ethnic Composition of Customer Base	+
Retailer Factors	
Retail Competition	
Number of Retailers	-
Heterogeneity in Market Shares	+
Economies of Scale (Chain Size)	+
Economies of Scope	
Private Label Stock-keeping Units (SKUs) as Fraction of Total	+
Quality Commitment (In-House Quality Assurance)	+
Chain Name for Private Label	+
Premium Store Brand Program	+
EDLP Strategy	+
Depth of Assortment	-
Category Expertise	+
National Brand - Private Label Price Gap	+
Promotion Intensity for Private Label	+
Manufacturer Factors	
Brand Competition	
Number of Brands	-
Heterogeneity in Market Shares	+
Pull Promotion	-
Push Promotion	-

The Study

We utilized four different data sources. A large packaged goods firm provided us with the main database—syndicated sales data from A. C. Nielsen for all of their major product categories and key retail accounts. Before reporting the results we present a detailed description of the data sources and measures developed. We estimate individual category regressions and then use a random coefficient approach to pool categories into two quality types. Both analyses produce convergent findings about what drives variation in store brand performance across retailers.

Data Sources

1. We use account data for 106 major U.S. grocery retail chains in the 50 Nielsen SCANTRACK markets.[2] This includes all retailers with average annual store sales of $2 million plus. These retail chains account for 60 percent of total supermarket sales in the markets they serve. For each retail account, the dataset includes monthly brand level information for 34 categories over three calendar years. The categories represent a wide range of both edible grocery and dairy products including major categories such as RTE cereal, coffee, and cheese and more minor ones like rice, marshmallows, and mustard. Nielsen brand totals are used, aggregating all sizes and forms of each brand name. Separate brand totals are reported for each distinct variant; for example, in cereal Kellogg's Corn Flakes and Kellogg's Raisin Bran are reported as separate brands. Due to confidentiality agreements all private label variants are aggregated into one brand total even in cases where the retailer carries more than one label (e.g., President's Choice).

The data provide detailed brand level information on both total equivalent unit sales and dollar sales that is further subdivided into different components. Separate subtotals are reported for sales accompanied with different forms of retail promotion including the use of feature advertising, display, and temporary price reductions. Print media expenditures (newspapers and magazines) are reported for all 50 markets but TV advertising for only 23 major metropolitan markets. The database also includes information on brand level consumer promotion offers.

2. We obtained detailed annual demographic data for each retailer from a syndicated data service that overlay the trading area of each store onto the underlying census tracts. This provided distributional information on age, income, ethnicity, education, and home value.

3. Two published secondary data sources provide additional information on characteristics of the retail chains and the markets served. For each SCANTRACK market, *Market Scope* and *Marketing Guidebook* report each retailer's (chains and independents) overall market share, the number of stores operated, the average floor area, and the names of the store brand lines carried to determine whether the chain uses its own name or carries a premium store brand line. Both publications are well-known sources published annually by Trade Dimensions, a unit of the Progressive Grocer Data Center.

2. Each SCANTRACK area covers a designated number of countries, with an average of 30 and a range from 1 to 68. All markets include central city, suburban, and rural areas.

4. We also surveyed each of the retail accounts in the database. Retailers were asked for information on their private label strategy, specifically for each of the three years: (a) an estimate of the total number of private label SKUs and the number of categories where they carried a private label; (b) whether or not they had a quality assurance program for their private labels; and (c) names of key private label lines they carried. Retailers also provided us with information on whether they followed an EDLP or Hi-Lo pricing strategy. Multiple calls were made to the retail accounts leading to 93 of the 106 retailers completing the questionnaire.

Measures Used in the Analysis

We developed all measures at the retailer-market level. This means that Winn-Dixie in Tampa is treated as a separate entity from Winn-Dixie in Dallas. We created yearly aggregates for each measure resulting in three data points per retailer per category. We do so for purposes of stability and the fact that about half of our measures are only available at the annual level. This allows us to use the time series nature of our data to address certain endogeneity issues.

Private Label Share (PLSHARE). To normalize for differences in package size and facilitate comparisons across categories, the dependent measure is the equivalent unit (pounds) share of private labels (normal and premium variants) in a category for a retail market account. Share is calculated as the ratio of total pound sales for the private label to total pound sales for the whole category. For exposition, share is expressed in percentage terms. Using dollar sales instead of equivalent unit sales or a logit transformation of these market shares led to similar insights.

Home Value (HOMEVAL). This variable measures the extent to which the customer base for a retail account is comprised of wealthier individuals. HOMEVAL measures the fraction of total number of households for a retail account owning homes with value higher than $250,000; it is highly correlated (r=.79) with income (percent greater than $50,000). We expect a negative coefficient because wealthier consumers are less price sensitive due to higher opportunity costs.

Elderly (ELDERLY). This variable is operationalized as the fraction of a retailer's customer base that is older than 55 years. Because the elderly have lower opportunity costs and more severe budget constraints, the coefficient should be positive.

Education (EDUC). This variable is given by the fraction of households in a retail account's customer base with a four-year college degree. Despite obvious income effects, we predict a positive coefficient (Hoch 1996). If educated consumers have greater shopping expertise, they may rely less on brand name as an indicator of product performance.

Ethnic (ETHNIC). The extent to which a retail account serves minority groups is measured by the fraction of black and hispanic households. Although conventional industry wisdom suggests that blacks and hispanics are more likely to buy well known brand names, we predict a positive coefficient as found by Hoch (1996).

Retail Competition (#RETAIL, RETVAR). Two measures capture the extent of retail competition in a local market: the number of retail competitors (#RETAIL) and the heterogeneity in shares across these retailers (RETVAR). #RETAIL is directly measured from *Market Scope*. Heterogeneity is captured as the variance (σ^2) in market shares. Retail competition is higher with lots of competitors and is lower when heterogeneity in shares is greater, implying a negative coefficient for #RETAIL and a positive one for RETVAR.

Chain Size (SIZE). Size of the chain is captured by the number of stores that each retailer operates in a particular market. Conceptually, it represents the potential for a retailer to benefit from economies of scale and should be positively related to private label share. Using total square footage of the chain (number of stores times average square footage) produced similar results.

Private Label SKUs (PLSKU). This variable is the total number of private label sku's expressed as a fraction of the total number of SKUs across all categories in the store and represents the potential for economies of scope. As with SIZE, the coefficient should be positive.

Quality Assurance for Private Labels (QUAL). This is an indicator variable, where QUAL=1 if the retail account has a quality program and QUAL=0 otherwise. This variable represents a signal about the retailer's commitment to private label quality and to some extent may capture actual quality differences across retailers. The coefficient should be positive.

Own Name Label (PLNAME). Using information on private label names provided in the *Marketing Guidebook* and cross verifying through the survey, we create an indicator variable PLNAME=1 when the chain uses its own label and 0 otherwise. It should have a positive sign.

EDLP/Hi-Lo Pricing Strategy (EDLP). EDLP=1 when chains use an everyday low pricing strategy and 0 when they go Hi-Lo. Retailers initially were classified based on their answers to the survey, and corroborated through a search of trade press. The regular price gap between national and store brands was 36 percent in EDLP chains vs 44 percent in Hi-Lo chains. EDLP chains also sold less product on deal, 20 percent of private label and 25 percent of national brands compared to 24 percent and 30 percent respectively in Hi-Lo chains. We expect EDLP to have a positive sign.

Premium Label (PREMIUM). Using information from the manufacturer's sales force, the retailer survey, and published secondary sources, we determined that PREMIUM=1 when a retailer stocks a higher quality and premium price label (e.g., President's Choice) in addition to their normal store brands. We would prefer to examine premium private labels separately but confidentiality agreements require Nielsen to aggregate across store brand types when providing syndicated data to manufacturers. The premium variable probably captures both the effect of a larger number and likely greater differentiation of store brands in any one category (normal plus premium) and may serve as a surrogate for retailer commitment to the whole idea of a store brand program. The expected sign is positive.

Depth of Assortment (AVGSKU). The extent of category-specific item proliferation is measured by the average number of stock-keeping units (SKUs) carried in that category averaged across stores in a particular retail chain. This measure was created from another database providing more detailed item level information. Because we account for the number of national brands separately, this variable measures the level of variety that the retailer offers for the average national brand. We endogenize this variable because the retailer has final say. AVGSKU should have a negative sign.

Category Development Index (CDI). The CDI for a retail account is an index measuring the account's category share of total equivalent unit sales volume in a market relative to its total size (measured by all commodity volume, or ACV$) in the market. By normalizing for the relative size of the retail account, the measure captures the extent to which the retailer does well in a specific category relative to performance across all categories. This is given by,

$$\text{CDI} = \frac{\text{Account Eqvt. Unit Volume for Category}}{\text{Market Eqvt. Unit Volume for Category}} \times \frac{\text{Market ACV\$}}{\text{Account ACV\$}}$$

Normalizing retailer volume by the total U.S. leads to the same results. Categories with a high CDI are relatively more important to that retailer and therefore likely to draw more attention. We view CDI as a long-run surrogate for category expertise, though we recognize the likely recursive relationship between expertise and the demand side. Although we are unaware of any studies showing that heavy category users buy a disproportionate amount of private label, this could lead to a contemporaneous correlation between CDI and private label share, and so we endogenize the variable. The CDI coefficient should be positive.

National Brand-Private Label Price Differential (PRDIFF). The price gap is measured as the price difference per equivalent unit between the average national brand and the private label divided by the average national brand price. We compute both the shelf price differential and the regular price differential using information on total and nonpromoted sales, respectively. Sales (in equivalent units) weighted as well as unweighted average brand prices were computed. Since alternate measures—weighted or unweighted, shelf or regular price differentials—led to the same insights, we report results only for the unweighted regular price differential measure. Larger price gaps should lead to better store brand performance. Since national brand and private label cross-price effects can influence the setting of the price differential and store brand share, we endogenize this variable.

Percentage Private Label Volume Sold on Deal (PLPROMO). This variable measures the average retail promotion intensity for the store brand and is given by the fraction of total equivalent unit volume sold when accompanied by any kind of retail promotion including temporary price reductions, feature advertising, and display. Collinearity precluded use of more detailed breakups. The coefficient should be positive.

Percentage National Brand Volume Sold on Deal (NBPROMO). Promotion intensity of national brands is measured by the fraction of its total equivalent unit sales volume sold with any kind of retail promotion. The coefficient should be negative. Conceptually both PLPROMO and NBPROMO are equivalent to promotion elasticity times frequency of promotion. For reasons cited for PRDIFF, we endogenize both PLPROMO and NBPROMO.

Brand Competition (#BRANDS, BRNDVAR). As with retailer competition, we measure brand competition using two variables: the number of brands carried by the retailer (#BRANDS) and heterogeneity in brand market shares (BRNDVAR) as captured by the variance (σ^2) in shares. Since we are interested in the degree of national brand competition, we compute the variance in shares after dropping the store brand and renormalizing the remaining brand shares to sum to 1. Because retailers ultimately control the number of brands they let on their shelves, we endogenize both #BRANDS and BRNDVAR. #BRANDS should have a negative coefficient because of crowding out. BRNDVAR should dampen the number of brands effect (+ sign); a lumpy distribution of shares means that store brands can concentrate their efforts on the big players, ignore the minor brands, and still appeal to a large percentage of the market.

Consumer Advertising (ADVPROMO). Print and magazine advertising and consumer promotion information is available for all 50 markets. TV advertising, however, is available for only 23 of the major metropolitan markets but is highly correlated (.88) with print media spending in those markets. Because consumer promotions typically focus on price whereas advertising focuses on attributes, we initially separated these two promotions. Unfortunately because of multicollinearity (r=.92) and the fact that consumer promotions make only 14 percent of spending, we could not estimate separate effects. Consequently, we combined advertising and promotion into a common ADVPROMO measure equal to the sum of the number of all newsprint and magazine impressions and consumer promotion offers. This measure is computed for each national brand, averaged across them, and then normalized by the number of households in the market. ADVPROMO should have a negative sign.

Model Estimation

We postulate a regression relationship between private label share and these measures. Individual category level regressions were estimated across the 93 retail market accounts for which we had information on all measures. Retailers are included only if they stock a store brand in that category. We use the time series nature of the data to address possible endogeneity problems. Specifically, underlying retailer-specific characteristics may simultaneously determine private label share and the setting of NB-PL price gaps, promotional intensity of both national and store brands, CDI, assortment size, number of brands, and heterogeneity in shares. Since this results in a contemporaneous correlation of the endogenous explanatory variables with the error term, we endogenize PRDIFF, NBPROMO, PLPROMO, CDI, AVGSKU, #BRANDS, and BRNDVAR and replace them with instruments. We created instruments using the standard two-stage least squares approach, first regressing the current values of the endogenous variables versus

3. Hausmann's (1978; Johnson 1984) test procedure was used to show that we need to endogenize these variables. Furthermore, in order to show that appropriate instruments were chosen, we selected alternate instruments for the endogenous variables. Since the planning horizon for promotions (PLPROMO and NBPROMO), price differential (PRDIFF), and product stocking (#BRANDS, AVGSKU, BRNDVAR) are likely to be well within a year, the further we go back in time to select alternate instruments, the less likely they are to be contemporaneously related with the current error term. Since two years is the maximum that our dataset allows us to go back to, we use two-stage least squares to create alternate instruments using two-year lagged values. Two-year lag instruments are not significant in a regression containing one-year lags (Spencer and Berk 1981), and so we feel comfortable using one-year lagged instruments.

the one-year lags and then using the predicted values.[3] The instrumented variables do not remain constant from year to year. We also checked for a first order autoregressive process by assuming the same serial coefficient across retailers. We estimated the serial correlation using the data for all retailers by regressing the estimated error for a year against the preceding year's estimated error. We lost one year of data due to the instrumented variables. Our analysis indicated no serial correlation in the data.[4]

For each category, we regress account level private label share against the corresponding explanatory variables for a two year period since we lose the first year of data when computing the instruments. Pooling tests show no differences in the value of the estimated coefficients across the two years in any of the category regressions. Therefore, we run individual category level regressions by pooling the data across the two years.

To avoid overwhelming the reader with all the minutiae inherent in considering the influence of 20 predictor variables in 34 product categories, we adopt an analysis plan that goes from more general to more specific. First, we estimate a separate regression relationship for each of the 34 categories and examine whether the coefficients generally are of the same predicted sign across categories. The third column of Table 4 shows the number of positive/negative coefficients out of 34 total that are statistically significant ($p<.05$). To get a handle on the overall pattern of results, we average the coefficients from the individual category regressions, test whether they are statistically significant from zero, and compute a measure of substantive importance by determining the impact of each variable on store brand share (columns four through seven). Finally, although considerable commonality in coefficients exists across categories, we consider various pooling methods to deal with category heterogeneity. Specifically, we find systematic differences in slope coefficients for categories that ex ante are known to contain higher quality store brand alternatives (Table 5).

Category Level Results

The predictor variables explained a substantial amount of the variability in private label share across retail accounts in all 34 categories. The regressions have an average adjusted R^2 of 0.67 (median=0.75) ranging from a low of 0.39 to a high of 0.90. Variance inflation factors (VIF) for each independent variable, ranging from 1.6 to 2.8, indicated no serious multicollinearity. Since cross-sectional analysis is used, errors could be heteroskedastic over retail accounts in the same category. Examination of the errors (White's test 1980) revealed no heteroskedasticity.

Table 4 provides several different measures of the impact of the independent variables on store brand share. Before discussing the table in detail, we offer the following stylized facts as summary. Clearly the main take-away should be that the retailer has a big impact on penetration level of their own store brands. When categories are uncrowded, both in terms of number of brands and assortment, and to a lesser extent when heterogeneity in brand shares is high, store brands can do very well. They also do well when attractively priced and promoted compared to the national brand. And although each of

4. In addition, we also estimate the serial correlation coefficient using the three full years of data. This analysis also supports our earlier findings.

these variables is influenced by national brand policies, the final decision rests with the retailer. The only variable totally controlled by the manufacturer is local advertising and consumer promotion, and while statistically significant, it does not have as much impact. Retailers also control their own destiny through a variety of chainwide policies, including quality control, store brand naming, and a premium line. Although greater

Table 4:
Substantive Impact of Predictor Variables (34 Categories)

Variable	Predicted Sign	Significant Coefficients #+/#-	Average Coefficient	Average Category Std Deviation	Market Share Effect 1 Std. Dev. Around Mean	Standardized Coefficient
Consumer Factors						
HOMEVAL	-	3/11	-5.62[a]	14.83	-1.67%	-0.071
ELDERLY	+	7/0	4.50	3.72	0.33	0.023
EDUC	+	5/5	-4.90	4.67	-0.45	-0.023
ETHNIC	+	2/6	0.21	8.83	0.04	0.011
Retailer Factors						
#RETAIL	-	3/7	-0.05[a]	16.24	-1.62	-0.042
RETVAR	+	8/1	9.10[a]	0.04	0.73	0.051
SIZE	+	8/2	0.01[b]	40.25	0.81	0.007
PLSKU	+	10/2	6.10[b]	7.71	0.94	0.042
QUAL (0-1)	+	11/1	2.31[a]	na	2.31	0.061
PLNAME (0-1)	+	12/2	2.10[a]	na	2.10	0.082
EDLP (0-1)	+	8/3	1.40[b]	na	1.40	0.041
PREMIUM (0-1)	+	13/2	2.51[a]	na	2.51	0.096
AVGSKU	-	5/12	-0.20[a]	10.36	-4.14	-0.043
CDI	+	12/4	3.23[a]	0.22	1.42	0.063
PRDIFF	+	14/2	8.21[a]	14.12	2.32	0.082
NBPROMO	-	1/12	-9.40[a]	8.74	-1.64	-0.064
PLPROMO	+	9/1	9.48[a]	16.98	3.22	0.128
Manufacturer Factors						
#BRANDS	-	0/31	-0.72[a]	10.26	-14.77	-0.387
BRNDVAR	+	21/5	51.30[a]	0.06	6.16	0.270
ADVPROMO	-	2/9	-0.20[a]	0.58	-0.23	-0.012

[a]: $p<.01$

[b]: $p<.05$

[c]: $p<.10$

retail competition does reduce store brand penetration, it is much less important than brand competition. Finally, most consumer characteristics, except wealth, do not have much impact at all. We are not arguing that the demand side is unimportant but the direct impact is small. Possibly retailers have already adjusted their policies to consumer behavior and so the effect of demographics is partially subsumed in other variables. The remainder of this section describes the more detailed results.

The third column of Table 4 reports the number of statistically significant ($p<.05$) positive and negative coefficients. In the average category 8 out of 20 coefficients were statistically significant, 6.5 with the "right" sign and 1.5 with the "wrong" sign. The maximum number of statistically significant wrong signs in an individual category was 3, indicating deviations from theoretical expectations were not systematic or isolated to a few outlying categories.

To get a better idea about the substantive impact of each variable, the fourth column shows the value of each coefficient averaged across the individual category regressions along with t-test significance levels.[5] For example, looking at the average coefficients for the four dichotomous variables indicates that store brands gain 2.3 share points when the retailer has a quality assurance program, 2.1 points when the private label carries the retailer's own name, 1.4 points when the retailer follows an EDLP strategy, and 2.5 points when they merchandise a premium store brand in addition to their regular private label. Adding all of these effects together imply a 8.3 percent difference in share points. It is more difficult to interpret the other variables, either because the scale is unfamiliar (BRNDVAR) or the likely extent of variation in the variable is unknown. Therefore, we calculated the average standard deviation of each variable in each category across categories (column 5), and for each of the nondichotomous variables, we report the market share difference for a variation of one standard deviation on both sides of the variable's mean (column 6). This is like comparing retailers in the bottom third to the top third on that variable. In the seventh column, we report standardized beta coefficients (averaged across categories) for each of the variables. In summary:

1. Brand competition, represented by #BRANDS and BRNDVAR, has the highest substantive impact among all the predictor variables, in fact more than the combined impact of PRDIFF, NBPROMO, and ADVPROMO. Both PRDIFF and NBPROMO are in the top half in terms of impact and more important than ADVPROMO. Combined, factors over which manufacturers have partial or complete control have about the same impact as the retailer factors.

2. AVGSKU, PLPROMO, QUAL, PLNAME, and PREMIUM are the most important retailer factors closely followed by CDI and EDLP. A more detailed comparison of the different factors reveals that PLPROMO has a higher substantive impact than NBPROMO, suggesting that private label promotions are quite effective in leading to higher market share for private labels. Also, the extent of competition among national and private label brands is a much more important determinant of private label share than is the extent of retail competition, #RETAIL and RETVAR.

5. This also provides an alternative estimation for pooling coefficients across categories when the random coefficient approach cannot be used, either due to violation of underlying assumptions or data limitations (Bass and Wittink 1978).

3. Finally, consumer factors have a much lower impact on private label share performance than either the manufacturer or retailer factors; HOMEVAL is the only demographic variable having a substantial impact.

Pooled Analysis across Categories

It is unrealistic to expect that the slope coefficients are homogeneous across all 34 categories, and so in the next section we consider methods of pooling information across categories. This will not only help get precise estimates of the common pattern but also better summarize central tendencies in the data. We specify the system of category regressions as part of a multivariate regression system making the following error assumptions and using the following notation:

$$ms_c = X\beta_c + \epsilon_c; \quad c=1, 2, \ldots 34.$$

We assume that $\epsilon' = (\epsilon_1', \epsilon_2', \ldots \epsilon_c') \sim MVN(0, \Lambda \otimes I_n)$; $\Lambda = \mathrm{Diag}(\sigma^2{}_1, \ldots, \sigma^2{}_c)$. ms^c is the vector of private label shares for the c^{th} category expressed in terms of deviations from the mean category share across the retail accounts. *X* is the *Nxk* matrix of values for the *k* independent variables, each variable being expressed in terms of deviations from the within-category mean across retailer accounts. *N* is the number of retail accounts. β_c is the c^{th} category slope coefficient vector and ϵ_c is the *Nx1* vector of error terms for the c^{th} category. Mean centering by category of both the dependent and independent variables is equivalent to removing the main effect (category intercepts) of category. Consequently, our pooled analysis seeks to explain the variation in private label share across retail accounts as opposed to identifying factors that might explain differences in mean private label share across categories.

We also assume that (a) the error terms are independent across retail accounts within a given category, i.e., $\epsilon_c \sim MVN(0, \sigma^2{}_c I_n)$; and (b) that the errors across categories for the same retail account are independent. Our careful selection of the relevant independent variables justifies the first assumption. The second assumption is justified by an analysis of the correlation matrix of the errors across individual category level regressions.

Formal testing of the pooling restriction assuming that the slope coefficients are the same across the category regressions is rejected. This is not surprising given large differences in within-category variance in private label share between categories. Therefore, we searched for a partitioning variable that satisfied two criteria: (a) it led to a substantial reduction in within-group heterogeneity; and (b) it was theoretically justified so as to facilitate interpretation of any differences in slope coefficients that might emerge. Past research suggests that actual quality of the store brand is an important determinant of store brand performance (Hoch and Banerji 1993). In categories offering lower quality store brands, the price gap and demographic factors influencing consumer price sensitivity may be more influential in explaining retailer performance. In contrast, factors related to the retailers' reputation and ability to differentiate themselves from competition may be more important in categories with higher quality store brands. To complete this analysis, we took recent category quality estimates from Hoch and Banerji (1993). They elicited category level estimates of store brand quality from 25 quality assurance managers at leading U.S. supermarket chains and wholesalers. We utilized their rankings, rank-ordered the 34 categories, and performed a median split into higher and lower quality types. Although this ex ante quality measure is not perfect, it was the best available to us.

We use a random coefficient regression procedure in order to estimate the mean coefficients for the two quality groups. Our procedure is similar to that used in the pooling literature (Bass and Wittink 1975, 1978; Hoch, Kim, Montgomery, and Rossi 1995). We assume that the category coefficient vectors for the high quality categories are draws from a super-population distribution with mean $ß^h$ and variance $V_{ßh}$. Similarly, the coefficient vectors for the low categories are draws from a super-population distribution with mean $ß^l$ and variance $V_{ßl}$. That is, within the high and low quality category groups, the category coefficient vectors are distributed i.i.d. with means $ß^h$ and $ß^l$ and corresponding variances of $V_{ßh}$ and $V_{ßl}$. To characterize the central tendency or commonality among the categories within each quality type, we would like to infer the means for each of the quality types. Using the procedure in Hoch et al. (1995), we use the entire dataset to obtain consistent estimates of the mean slope coefficient vector for the low quality categories and the differences in the mean slope coefficients between the two quality types. This is used to compute the mean slope coefficient vector for the high quality categories. Asymptotically justified estimates of the variance-covariance matrix are used to determine the significance level of the two mean slope coefficient vectors.

Table 5 presents the mean slope coefficient vector for the two quality types. We also report the interaction terms testing the differences in the mean slope coefficients between the high and low quality categories. The pooled analysis presents quite a clean picture, one that generally reinforces the conclusions from the individual category regressions. Only the EDUC variable is not statistically significant for either the high or low quality groups or both. The 3.16 intercept difference between the two quality types indicates that even after controlling for all the other variables, higher quality categories have higher store brand penetration than lower quality categories. For 4 of the 20 predictor variables, the slope coefficients do not differ by quality level: PRDIFF, NBPROMO, PLPROMO, and ADVPROMO. Several of the variables have more impact (i.e., absolute value) in the low quality categories. For example, the fact that low quality categories have larger coefficients (in absolute value) for HOMEVAL, ELDERLY, and EDLP suggests that price and consumers' reaction to it are more important when store brand quality is not up to the standards of the national brands, that is when the store brand truly is an inferior good in the economic sense. CDI also is more important in lower quality categories, a finding that might indicate that category expertise is more important when it is difficult to offer a top-quality store brand.

The remaining coefficients have larger slopes in the high quality categories. Degree of competition, at both the brand and retail level (#RETAIL, RETVAR, #BRANDS, BRNDVAR), and economies of scale and scope (SIZE, QUAL, PLSKU, PLNAME, PREMIUM) are more important when category quality is higher. The larger coefficients for the scale and scope variables may indicate the greater importance of retailer reputation in categories where the consumer does not have to make a price-quality tradeoff when buying the store brand. Finally, the coefficients for ETHNIC flips signs and are statistically significant; we have no ready explanation for this.

Table 5:

Pooled Analysis Across Categories

Variable	Average Coefficient Low Quality Categories	Average Coefficient High Quality Categories	Difference Between Low and High Quality Categories
Consumer Factors			
HOMEVAL	-8.08[a]	-3.29[b]	4.79[b]
ELDERLY	8.21[a]	3.37[c]	-4.84[c]
EDUC	-6.25	8.45	14.70[b]
ETHNIC	7.65[a]	-6.34	-13.99[a]
Retailer Factors			
#RETAIL	-0.03[a]	-0.08[a]	-0.05[a]
RETVAR	5.03[b]	9.99[b]	4.96[c]
SIZE	0.007	0.023[c]	0.016[b]
PLSKU	5.00[b]	7.00[b]	2.00[c]
QUAL (0-1)	0.30	2.14[a]	1.84[a]
PLNAME (0-1)	1.34[a]	3.01[a]	1.67[c]
EDLP (0-1)	5.43[b]	0.21	-5.22[c]
PREMIUM (0-1)	2.39[a]	3.71[a]	1.32[a]
AVGSKU	-0.21[a]	-0.14[b]	0.07[b]
CDI	6.99[a]	0.80	-6.19[a]
PRDIFF	8.96[a]	6.25[b]	-2.71
NBPROMO	-6.58[a]	-11.55[a]	-4.97
PLPROMO	9.28[a]	11.67[a]	2.39
Manufacturer Factors			
#BRANDS	-0.29[a]	-0.95[a]	-0.66[a]
BRNDVAR	13.51[b]	87.22[a]	73.71[a]
ADVPROMO	-0.21[b]	-0.13	0.08

[a]: p<.01
[b]: p<.05
[c]: p<.10

Conclusions

This study shows how and why the performance of private label programs systematically vary across retailers. Although our analysis shows that the pull and push tactics of the national brands exert an important influence on store brand performance, we find that a substantial part of the variation in market share comes about from actions taken by the retailer, either independently as part of their overall marketing strategy or in response to manufacturer actions. Key insights are as follows:

1. Overall chain strategy in the use of EDLP pricing, commitment to quality, breadth of private label offerings, use of own name for private label, a premium store brand offering, and number of stores consistently enhance the retailer's private label share performance in all categories. Also, the extent to which the retailer serves a customer base containing less wealthy and more elderly households and operates in less competitive markets improves the performance of the store brand.

2. Although an EDLP positioning (and the concomitant lower level of national brand promotion) helps the store brand, there are countervailing effects. A lower price gap and less private label promotion accompanying EDLP work in the opposite direction. Furthermore, the EDLP positioning benefits the store brand only in lower quality categories where the value positioning of the store may be better aligned with the price advantage of the store brand. Our regression models suggest, however, that the net result is quite positive for the average EDPL store. By plugging in the average values for all the other variables into the equations, we find that the average predicted EDPL store captures 3.8 more store brand share points when compared to the average Hi-Lo competitor.

3. Recent statements in the popular press document an increased use of merchandising activities by retailers. Our analysis suggests that retailer promotional support can significantly enhance private label share performance.

4. Retailers often use national brands to draw customers to their stores. Retailers who pursue this traffic building strategy usually carry more national brands and broader assortments and offer better everyday (lower price gap) and promotional prices on national brands. Each of these actions work against the retailer's own store brands, highlighting the important balancing act the retailer must perform to profitably manage the sales revenue and margin mix in each of their categories. At the same time, adding a higher quality premium store brand program may mitigate this trade-off.

5. Unlike cross-category studies, our within-category across-retailer analysis shows that the national brand-private label price differential exerts an important positive influence on store brand performance. Across all categories, the average gap is about 40 percent (range 20 to 60 percent). Our data show that a 10 percent change in the price gap fraction results in a 0.8 percent change in store brand share (average ß=8.2). This supports the contention that the negative sign for price gap observed in previous research probably results from cross-category aggregation problems (Raju et al. 1995b).[6]

6. A cross-category analysis for the current dataset also leads to a similar result for the price gap.

6. When retailers obtain more than their fair share of a category (high CDI), they also do much better with private label. On average a retailer performing 10 percent better than the norm (CDI=110 vs 100) will have a store brand with 3 percent higher market share.

7. From the national brand's perspective, encouraging the retailer to carry more brands (#BRANDS) and deeper assortments (AVGSKU) may be the most effective ways to keep store brands in check. And although an even distribution of brands also works against the store brand, it is unclear how manufacturers can influence BRNDVAR. The importance of these variables, however, may depend on the national brand's market position. For example, a category leader may be glad to see a rise in store brand share if it comes at the expense of one of its secondary national brand competitors. For instance, although P&G's efforts to streamline assortment appear aimed at creating marketing and operating efficiencies, the end result may be an increase in store brand sales at the expense of minor brands. Low share underdogs are extremely vulnerable to assortment reductions.

8. The exact impact of most of the variables depends on the underlying quality of store brands in a category. When store brand quality is high, competition at the retail and brand level is more important, as are variables capturing economies of scale and scope enjoyed by the retailer. In contrast, demographics associated with consumer price sensitivity and EDPL pricing matter more in low quality categories.

9. Finally, premium store brands may offer the retailer an avenue for responding to the national brand's ability to cater to heterogeneous preferences. This appears more likely in categories where store brands already offer high quality comparable to the national brands.

Appreciating what separates the best from the worst retailers is important for both retailers and manufacturers. Although understanding "best practices" is generically important no matter the industry, we would argue that it is even more important in retailing. The reason is that retailers can easily observe each others actions, assess the impact of those actions, and quickly imitate successful strategies. For retailers, arguably the most important practices are those that successfully build store traffic (e.g., new store formats, store appearance, perimeter departments, advertising) and produce significant shifts in market share.[7] Leading manufacturers must be alert to these changing practices, but in general will get their fair share of category sales irrespective of which retailer makes the sale. On the other hand, retailer imitation of successful store brand programs is more threatening to national manufacturers because within-store loss of share to the retailer's store brand (or for that matter to another national brand) is not likely to be made up with a sale at a different retailer. As European retailers with high powered corporate branding programs (e.g., Sainsbury) continue to acquire regional chains in the U.S., the threat to national brands becomes more immediate.

The foregoing implies that national manufacturers need to: (a) identify which categories in their product portfolio are most vulnerable to retailer investments in private

7. We do not mean to downplay the importance of practices that increase operational efficiency such as improved logistics, but for present purposes we contend that these practices are less observable and therefore more difficult to imitate (witness K-Mart vis-a-vis WalMart).

label; and (b) understand what actions they can take to limit store brand encroachment in key retail accounts. The usual starting point for answering the first question is to focus on categories where store brands already have achieved high share. This type of analysis, however, only identifies categories that are already a problem. It does not distinguish problem categories that national brands can do nothing about (e.g., salt and other commodities) from those problems that could get worse, nor does it suggest which categories could turn into bigger problems in the future.

Consider the 2x2 matrix in Figure 1 where we classify the 34 categories into one of four cells formed by jointly considering "average private label share across retailers" and "variance in private label share across retailers." Each cell can be labeled as categories in which private labels pose: (A) *no problem*—low average share and low variation; (B) *possible future threat*—low average share and higher variation; (C) *little hope* without a major product innovation—high average share and low variation; and (D) *biggest threat*—high average share and high variation. Due to confidentiality restrictions, we report the names of only a couple of categories for each cell.

National brands are most vulnerable in high variance categories (cells B and D)—it is here that imitation of best practices could result in substantial increases in store brand share. When average private label share also is high, these categories pose big current threats if low share retailers start doing as well as the best performers. When average private label share is low, categories pose a future threat, mainly because poor performers are starting from scratch and will imitate in the high threat categories before allocating resources here. National brands should spend less time worrying about how retailers manage their store brands in categories where there is little variation across retailers (cells A and C). In cell A, manufacturers can take comfort in knowing that no retailer has

Figure 1

Classification of Categories: Average and Variation in Store Brand Performance across Retailers

Average PL Share across Retailers	Variation in PL Share across Retailers: Low	Variation in PL Share across Retailers: High
Low	A No Problem *coffee* *syrup* $\bar{x}$=9.4% sd=7.9%	B Future Threat? *bagels* *pizza* $\bar{x}$=11.4% sd=14.6
High	C Little Hope *cream cheese* *dried rice* $\bar{x}$=28.1% sd=10.8%	D Biggest Threat *cottage cheese* *marshmallows* $\bar{x}$=27.0% sd=20.7%

figured out how to sell store brands in these categories, and therefore allocate resources against their national competitors. Cell C represents categories where private label share growth probably has peaked, having reached a natural asymptote. And instead of overspending on push promotions that the retailer can arbitrage through forward buying and diversion or pull tactics that do not work anymore, manufacturers (at least the leading brands) may get higher returns by investing in the type of product innovations that got them where they were in the first place. Although the above analysis may serve as a useful decision support tool for national brand manufacturers, it is important to note that our analysis assumes that private label quality will remain comparable to that in the existing market. However, discontinuous increases in store brand quality can occur. Witness the successful introduction of quality cola to the soft drink market by COTT, which posed an immediate threat to national brands in an otherwise low share, low variation “no problem” category.

Table 6 contrasts the substantive impact of each of the independent variables for the following three category groups: all categories (same as in Table 4); biggest threat (cell D); and little hope (cell C). Store brands have an important position in both the “big threat” and “little hope” categories; the difference is that variation in performance across retailers is about four times greater in the “big threat” categories (average σ^2 of .047 vs .012). Because of greater variation in the dependent variable, it is not surprising that most of the independent variables have a greater impact on performance in the high variance categories. Table 6 shows that brand competition variables (#BRANDS, BRNDVAR, AVGSKU) have about two times the impact in the “high threat” categories, suggesting that reductions in assortment could lead to big increases in store brand share. Most of the retailer variables (SIZE, PLSKU, QUAL, PLNAME, EDLP, PREMIUM, PRDIFF) also have substantially more impact in the “big threat” categories compared to either the “all” category or “little” averages. In contrast, manufacturer pull tactics (ADVPROMO) make more of a difference in the “little hope” categories, a finding for which we do not have a ready explanation.

Although our study provides a number of interesting insights, its limitations suggest several issues for future research. First, we could not obtain a direct measure of the quality of each retailers’ store brands, a variable the previous research has shown is very important. Our two quality-type random coefficient pooling approach provides us with an overall picture of how a large set of characteristics influence store brand performance; but we have not systematically modelled how these underlying relationships (represented by the slope coefficients) might vary with other category distinctions. However, given the large number of characteristics we consider (many of which are themselves category descriptors) and lack of a theoretical framework for how the slopes might vary by category, we feel that more could be gained by supplanting our rich but admittedly descriptive approach with a more elemental structural model (e.g., Allenby and Rossi, 1991). Finally, although we have adjusted our econometrics to deal with endogeneity whenever we could clearly identify it, data on about half of our variables was available on an annual level for

Table 6:

Comparison of Market Share Difference Two Standard Deviations Around Mean

Variable	*All Categories*	*Biggest Threat Categories*	*Little Hope Categories*
Consumer Factors			
HOMEVAL	-1.67%	-3.02%	-1.52%
ELDERLY	0.33	1.21	0.18
EDUC	-0.45	-2.10	-1.74
ETHNIC	0.04	-0.97	1.30
Retailer Factors			
#RETAIL	-1.62	-2.59	-3.25
RETVAR	0.73	0.70	1.91
SIZE	0.81	2.69	0.53
PLSKU	0.94	2.32	1.68
QUAL (0-1)	2.31	4.14	2.30
PLNAME (0-1)	2.10	3.80	2.01
EDLP (0-1)	1.40	1.92	0.30
PREMIUM (0-1)	2.51	4.10	1.50
AVGSKU	-4.14	-7.14	-3.29
CDI	1.42	2.48	0.73
PRDIFF	2.32	3.57	1.08
NBPROMO	-1.64	-1.87	-1.17
PLPROMO	3.22	1.64	3.17
Manufacturer Factors			
#BRANDS	-14.77	-24.37	-6.37
BRNDVAR	6.16	19.27	4.49
ADVPROMO	-0.23	-0.14	-1.22

three years. Consequently, this limited our ability to fully utilize the procedures recommended by Boulding et al. (1994).

There also are substantive findings worth pursuing. We found that private label promotions had more impact on private label share than opposing national brand promotions. This could be due to recent improvements in quality that place private labels in the same tier as some national brands or an increase in the intensity of private label merchandising activities by retailers. Separating premium from standard private labels may be a potentially fruitful topic to pursue, something that we could not completely address with the current data.[8] The positive impact of using the chain name for private labels

8. We did run separate regressions after dividing the sample of retailers into two groups, those with and without a premium store brand line. We found no differences in the signs of the coefficients across the two groups. The pattern of differences in magnitudes between coefficients for premium and nonpremium retailers was similar to what we found in our high vs low quality category analysis.

across categories warrants further investigation into the individual cross-category purchasing behavior of consumers and the impact on retailers' image. The importance of the #BRANDS and the AVGSKU variable suggests that national manufacturers could benefit from a more detailed examination of the economics of using brand-extension and flanker strategies versus line-extension strategies. Future research at an individual store and category level needs to investigate the impact of changing the price gap between national brands and the private label.

Finally, our results are decidedly bound to the U.S. grocery market. It is well-known that store brands play a more dominant role is several European markets and Canada. For example, store brands have 45 percent share in Switzerland, 37 percent in the UK, and 22 percent in Canada. Moreover, store brands in many European markets are reputed to be of much higher quality than in U.S., and so some might argue that the regularities we found in the U.S. are less relevant to other markets. We have no problem accepting the fact that the rules are not exactly the same as in the U.S. For example, retail concentration is much higher in Europe (three firm concentration ratio ranging from 45 to 80 percent vs 17 percent in the U.S.). At the same time, however, the extent of variation in store brand performance across countries is not that different in magnitude from what we observe within the U.S. We look forward to examining these issues in other markets as data become available.

Our research shows that the substantial differences that exist across retailers systematically affect the success of a chain's private label program. Not controlling for this in empirical studies can lead to biased conclusions (e.g., effect of national brand-private label price differential on private label share). The study also identifies a set of basic factors describing the retailers' strategy that account for the differential success of their private label programs. Our research ser ves as the starting point for future inquiry that formally recognizes the leading role of the retailer in the store brand equation.

References

Allenby, Greg M., and Peter E. Rossi. 1991. "Quality Perceptions and Asymmetric Switching Between Brands," *Marketing Science,* 10 (3), 185–204.

Bass, Frank M., and Dick R. Wittink. 1975. "Pooling Issues and Methods in Regression Analysis with Examples in Marketing Research," *Journal of Marketing Research,* 12 (4), 414–25.

———. 1978. "Pooling Issues and Methods in Regression Analysis with Examples in Marketing Research: Some Further Reflections," *Journal of Marketing Research,* 15 (2), 277–9.

Becker, Gary. 1965. "A Theory of the Allocation of Time," *Economic Journal,* 75, 493–517.

Blattberg, Robert C., Gary D. Eppen, and Joshua Lieberman. 1978. "A Theoretical and Empirical Evaluation of Price Deals for Consumer Nondurables," *Journal of Marketing,* 45 (1), 116–29.

Boulding, William, and Richard Staelin. 1995. "Identifying Generalized Effects of Strategic Actions on Firm Performance: The Case of Demand-side Returns to R&D Spending," *Marketing Science,* 14 (3), G222–G236.

Drèze, Xavier. 1995. "Loss Leaders and Cherry Picking: A Theoretical and Empirical Analysis," Unpublished Dissertation, University of Chicago, Graduate School of Business.

Hausmann, J. A. 1978. "Specification Tests in Econometrics," *Econometrica,* 46 (6), 1251–71.

Hoch, Stephen J. 1996. "How Should National Brands Think about Private Labels?" *Sloan Management Review,* 37 (Winter), 89–102.

Hoch, Stephen J., and Shumeet Banerji. 1993. "When Do Private Labels Succeed?" *Sloan Management Review*, 34 (Summer), 57–68.

Hoch, Stephen J., Xavier Drèze, and Mary E. Purk. 1994. "EDLP, Hi-Lo, and Margin Arithmetic," *Journal of Marketing,* 58 (4), 16–29.

Hoch, Stephen J., Byung-Do Kim, Alan L. Montgomery, and Peter E. Rossi. 1995. "Determinants of Store-Level Price Elasticity," *Journal of Marketing Research,* 32 (1), 17–29.

Johnston, Jack. 1984. *Econometric Methods,* New York: McGraw-Hill.

Judge, George, et al. 1985. *The Theory and Practice of Econometrics,* New York: Wiley and Sons.

Kamakura, Wagner A., and Gary J. Russell. 1989. "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research,* 26 (November), 379–90.

Lal, Rajiv. 1990. "Manufacturer Trade Deals and Retail Price Promotions," *Journal of Marketing Research,* 27 (4), 428–44.

Mills, David E. 1995. "Why Do Retailers Sell Private Label?" *Journal of Economics and Management Strategy,* 4 (3), 509–28.

Raju, Jagmohan S., Raj K. Sethuraman, and Sanjay K. Dhar. 1995a. "The Introduction and Performance of Store Brands," *Management Science,* 41 (June), 957–78.

———. 1995b. "National-Store Brand Price Differential and Store Brand Market Share," *Pricing Theory & Practice,* 3 (2), 17–24.

Schmalensee, Richard. 1978. "Entry-Deterrence in the Ready to Eat Breakfast Cereals Industry," *Bell Journal of Economics,* 9, 305–27.

Sethuraman, Raj. 1992. "The Effect of Marketplace Factors on Private Label Penetration in Grocery Products," Marketing Science Institute, Report #92-128.

Spencer, David E., and Kenneth N. Berk. 1981. "A Limited Information Specification Test," *Econometrica,* 49 (4), 1079–1086.

Starzynski, Greg. 1993. *The Private Label Consumer: Is There One?* Northbrook, IL: A. C. Nielsen.

Waterson, Michael. 1984. *Economic Theory of the Industry,* Cambridge: Cambridge University Press.

White, Hal 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica,* 50, 483–99.