Long-Term Growth Trends in Private Label Market Shares

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Abstract

Previous research has shown that most consumer product markets are in long-run competitive equilibrium. In most categories, a given brand's market share is stationary, showing remarkable stability over long time horizons (10 years). This empirical generalization has been attributed to both consumer inertia and competitive reaction elasticities that lead to offsetting marketing spending which nullifies attempts by one brand to take unilateral action to increase share. Despite consumer inertia and competitive matching, we find that during the period 1987-94 one brand consistently showed positive market share evolution — the retailer's own brand, the private label. In 225 consumer packaged goods categories, private labels trended upward 86% of the time. To provide some insight into these empirical findings we develop an analytic explanation for how private labels can grow even though national brands exhibit no growth on average. We argue that this can occur because unlike its national brand competitors, the retailer through its private label is the only brand that not only controls its own marketing spending but also exerts some influence over the ultimate marketplace spending of their national brand competitors.

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A marketing manager observes that unit sales were flat but market share decreased by 2% in the third quarter. Was it seasonality, bad luck, quarterly accounting concerns, problems with a leading retailer, or was it a more systemic downward trend in the performance of the business? Was the competition doing anything different and if so, what? An academic looks at the same numbers and then asks to see prior quarterly results which show market share changes of +2%, -0.5%, +0.5%, +1%, -1%, +0.5%, and -0.5% over the previous seven quarters. The academic concludes that there is a sufficient amount of noise in the system and that the market looks stable and stationary. The manager sees that while market share was up 3% in the prior year, it is down 3% in the latest 12 month period and decides that quick and decisive marketing actions must be taken to reverse the negative trend.

So who is right? The correct answer may not be knowable. Small market share (or sales) changes may be nothing more than random error with no systematic drift, but as they say 1-2% of a big number is also a big number and therefore demands managerial attention and action. If nothing else, it is difficult to defend doing nothing in such a situation, especially if competitors seem to be doing something different, like spending more on promotion or lowering wholesale prices. We would argue that both academic and practitioner are partially right; but more importantly, their disagreement has more to do with the fact that they are not looking at the problem in the same way. And in fact, it may be because the practitioner reacts so quickly to small changes in performance that many consumer product markets display the stationarity documented by virtually all studies of long-term market share performance (Bass and Pilon 1980; Ehrenberg 1988; Lal and Padmanabhan 1995).

The main purpose of paper, however, is neither to demonstrate once again that market shares are remarkably stable nor to provide evidence that the stability is due to consumer inertia and rapid competitive reactions that nullify one competitor's unilateral marketing actions. We find the nullifying competitive reaction story very compelling. Instead, we demonstrate that while most brands in a product category do show market share stationarity, there is one brand that does not. And it is the retailer's own brand, the private label. We find that in 86% of consumer packaged goods categories the private label trends upward, on average about 1% per year during the period 1987-1994. We argue that the reason for the anomalous behavior of the private label is due to the fact that it is the only brand that not only controls its own marketing mix decisions, but it also exerts a substantial measure of control over many of the marketing mix decisions made by its competitors. This is due to the special status of the retailer as both a customer and competitor of all the national brands.

Consumer Inertia

A number of different analyses, both theoretical and empirical, suggest that a majority of consumer packaged goods markets are more or less mature and long-run brand shares are approximately stationary. For example, Ehrenberg and numerous colleagues (1988; Ehrenberg, Goodhardt, and Barwise 1990; Goodhardt, Ehrenberg, and Chatfield 1984) repeatedly have demonstrated the remarkable fit of the Dirichlet model to consumer repeat purchase data. Strictly, the model applies to markets that are stationary (no trends short or long run), not segmented (no homogeneous subgroups of consumers or brands), and where purchase behavior is zero-order (no learning or purchase feedback). On the surface these assumptions appear somewhat heroic, but in practice discrepancies from Dirichlet model predictions have been small and not all that common. Fader and Schmittlein (1993) have shown that high market share brands exhibit repeat purchase rates (brand loyalty) that are excessive compared to that predicted by Dirichlet model. Kahn, Kalwani, and Morrison (1986) have found outlying instances of niche brands (low share brands with high repeat rates) and change-of-pace brands (higher share brands with repeat rates that are too low).

Despite these anomalies, the overwhelming conclusion is that the Dirichlet model fits the data very well, suggesting that its assumptions of stationarity, lack of segmentation, and zero-order purchase behavior cannot be too far off. According to Ehrenberg, this is because of the consumer inertia that results from the steady-state stochastic process that describes brand switching behavior over time (Bass 1974). Brand specific characteristics and idiosyncracies clearly exist and although changes in marketing mix decisions (price, advertising, promotion) may cause short-term perturbations in brand performance, apparently they wash out in the long-run as category shares generally attain a long-run equilibrium (Bass and Pilon 1980). Dikempe and Hanssens (1995) in a meta-analysis of 400 prior analyses find that unit sales and marketing spending usually (68% of the time) evolve (i.e., move in one direction or another). In contrast, a similar analysis of market shares showed that 78% of the time series were stationary. Lal and Padmanabhan (1995) found that less than 1/3 of all brand level time series showed a statistically significant trend.

Institutional Inertia

Although consumer inertia may explain some of the stationarity that characterizes consumer packaged goods markets, it is difficult to imagine that it is the full story. There is plenty of evidence that consumer tastes change over time and new brands and entirely new product categories that better satisfy consumer needs hit the market every year. And so it seems likely that some other forces also are operating. Specifically, Bass has argued that besides a healthy dose of consumer inertia, there is also plenty of institutional inertia. Let us go back to the brand manager mentioned earlier. He knows that when he increases promotional spending that his brand gets a significant short-term lift in sales performance. He probably believes that own-price elasticities are substantial. Chances are that he also believes that sales of competitive brands are influenced by his promotional spending. And the story suggests that he believes that his brand has been adversely affected by competitive promotions. Therefore, cross-price elasticities also are substantial. With these beliefs, what does he do? He reacts to the competition and his competitors react to his actions. Therefore, reaction elasticities also are substantial. If he and/or his competitors overestimate own and cross elasticities, then what may result is marketplace inertia due to aggressive reactions to competitors that essentially cancel each other out. This is exactly the conjecture of Bass et al. (1984) — offsetting promotional activities contribute to the long-run equilibrium of market share.

Institutional inertia is probably of greater magnitude than consumer inertia since the firms have so much to lose if they get forced out of the market. What would they do with all those fixed assets that they have employed to bring their products to market? The natural tendency is to do whatever it takes to ensure survival. Some firms may be willing to spend more than others but willingness to spend has to be closely linked to current market share since market share is a surrogate for what the firm potentially might lose by not matching. In support of this view, Lal and Padmanabhan (1995) found no trend in relative promotional expenditures over time. Even in categories that displayed non-stationarity market shares, firms reacted quickly to changes in the promotional spending of their competitors. In essence these matching reactions nullify short-term changes in performance that might accompany a change in promotional spending by the competition. The result is long-term stationarity in shares.

Private Label Gains while National Brands Stagnate

The data used in this research come from the Marketing Factbook published annually by Information Resources, Inc., a syndicated data provider to the consumer packaged goods industry. The database contained most of the product categories sold by supermarkets in the

United States during the time period 1987-1994[1]. The data used in our analyses represent an aggregation of the purchases of about 35,000 individual households, from 26 markets shopping in 180 different food stores. IRI states that the sample has demonstrated itself to be representative of national buyer behavior and overall consumer purchasing dynamics. The categories range from dry grocery (both food and non-food), frozen and refrigerated foods, health and beauty aids, and some general merchandise. There were 300 categories for which we had complete data for all 8 years. In 225 of these categories, there was a private label alternative available. To our knowledge this is the first analysis to use data from the entire Factbook, and not simply samples of specific categories[2].

The basic finding of this paper is that private labels have shown consistent long-term growth while national brands have been relatively stable. The average annual percentage change for the top three national brands is -0.20%. In contrast, the average annual percentage change for private labels is +1.12%. In other words, the private labels have shown solid growth during this time period while the national brands have been stagnant. To illustrate the distribution of these changes we construct probability density estimates of the annual percentage changes for the national brands and private labels across the 225 product categories as shown in Figure 1. Notice that there is a substantial amount of variation in annual growth rate for all brands, but a dominating finding is that the distribution of private labels is shifted to the right which indicates an average tendency for private labels to grow at the expense of the national brands.

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[1] Although the Factbook goes back to 1982, we elected not to use the earlier years due to potential problems that could arise from a change in the sampling frame. During the first 5 years, the sample was largely composed of the small-town BehaviorScan markets, whereas in later years the data includes major metropolitan supermarket chains.

[2] This dataset is available through the Wharton Research Data Services. For more information see http://wrds.wharton.upenn.edu.

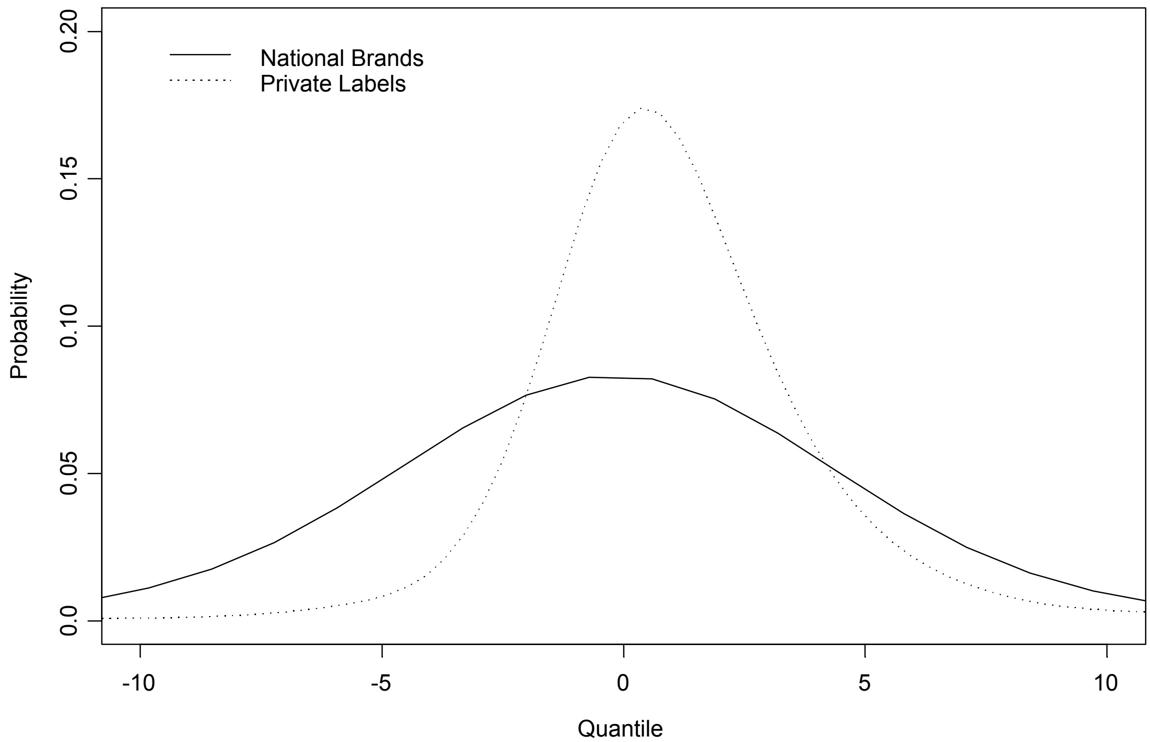

Figure 1. Empirical distribution of change in annual market share for the national brands and private labels.

In the remainder of this section we offer a simple analytic framework that can explain why these patterns may exist. We do not claim that ours is the only explanation for this phenomenon, but it is a simple and robust result that is consistent with our findings and offers some insight into why private labels may grow while other brands decline at a very slow rate. At the heart of this framework is an assumption that retailers target their private labels at the most successful brand(s) in the category (Sayman, Hoch, and Raju 1998), using similar product ingredients, packaging, and shelf positioning. Moreover, we presume that the targeted brand(s) are growing in relative and/or absolute terms. It is difficult to imagine a retailer allocating scarce resources toward developing a private label that targets a brand whose share of the market is contracting. The crux of our argument is that since the retailer is selectively targeting growing brands, and can continue to do this each year by retargeting, private labels will exhibit growth even in a stagnant marketplace.

Let us suppose that a retailer sells M brands, and the absolute change in sales growth for each brand is denoted by x_i. For simplicity let's assume that the x_i's are independently and identically distributed, where $F_X(x_i)$ and $f_X(x_i)$ denote the probability distribution and density functions of x_i. Furthermore, we presume that national brand market shares are stable, i.e., $E[x_i]=0$. We can arrange our M national brands in the following manner: $x_{(1)}, x_{(2)}, ..., x_{(M)}$, where $x_{(1)}$ is the national brand with the lowest growth, $x_{(2)}$ is the national brand with the next highest growth, and finally $x_{(M)}$ is the brand with the highest growth. Our assumption is that the retailer will target $x_{(M)}$, which we will denote as $t=x_{(M)}$. Fortunately, the exact probability density of this leading national brand (t) can be calculated as:

$$pr_T[t] = M F_X[t]^{M-1} f_X(t).$$

To illustrate this relationship, let's assume that x_i follows a normal distribution, $x_i \sim N(0,F^2)$. The probability density of the growth of each national brand and the leading national brand can be constructed for a market with three national brands. Notice that the mean of the distribution for growth of the leading national brand is positive, even though the individual brands have a zero mean, e.g., they have no expectation of growth. As the number of brands in the market increases (assuming the national brands are symmetric), the expected sales growth for the leading national brand becomes even more pronounced. Following Johnson, Kotz, and

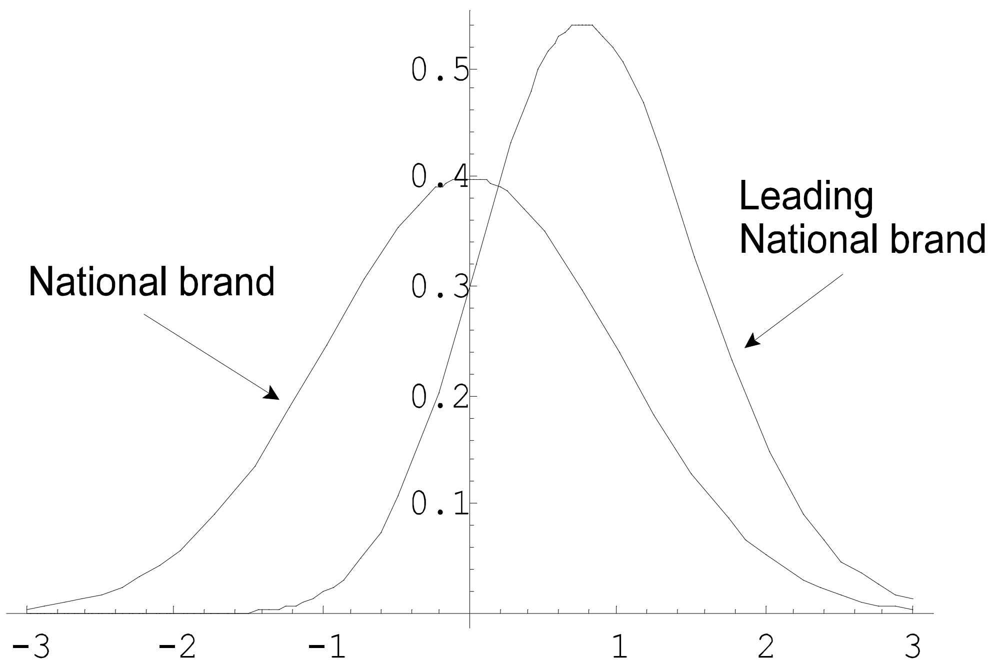

Figure 2. Probability distribution of growth for the leading national brand vs the rest of the national brands

Balakrishnan (1994, pp. 93-94), we can show that expected growth of the private label (i.e., the maximum of normal variates) is .56F, .85F, 1.03F, and 1.16F for a market of 2, 3, 4, and 5 national brands. The reason for this increase in expected growth is that as more brands are added the variability of the market increases yielding new potential targets.

The importance of these calculations is that the private label will inherit the properties of the leading national brand (t). The simplest assumption about sales growth of private labels is that its change is proportional to that of the leading national brand. Specifically, assume that the change in sales for the private label (s) will attract g% of the new market that the leading national brand has created, i.e., $s = gt$. Therefore the distribution of the change in sales of the private label will be the same of the leading national brand depicted in the previous graph. This structure presumes that no sales are lost by retargeting the leading national brand. However, this is not a limiting assumption since we could complicate the sales structure of the private label further and assume that the private label will only retarget when the potential market of the national brand exceeds its current market. It is straightforward to prove that E[s]$0 for this case.

Our framework has shown that private label will grow even while the sales of the national brands are stagnant. The critical assumption is that the private label can quickly target the leading national brand in every period. However, even this assumption can be relaxed further, so that as long as the retailer has some ability that is better than chance at predicting the leading national brand its expected sales will increase. Let us assume that the retailer's probability of correctly targeting the leading brand is p (i.e., $t=x_{(M)}$ with probability p) and the probability of incorrectly targeting each of the remaining brands is q (i.e., $t=x_{(i)}$ with probability q where $i \neq M$), where $p + (M\text{-}1)q = 1$. For simplicity if we again assume that sales growth of the private label is proportional to the growth of the targeted brand, then expected sales growth of the private label is:

$$
\begin{aligned}
E[s] &= g\big(pE[x_{(M)}] + qE[x_{(M-1)}] + \cdots + qE[x_{(1)}]\big) \\
&= g\big((p-q)E[x_{(M)}] + qE[x_{(M)}] + qE[x_{(M-1)}] + qE[x_{(1)}]\big) \\
&= g(p-q)E[x_{(M)}] \;=\; g(p-q)E[t]\,.
\end{aligned}
$$

This simplification comes by substituting in the fact that the sum of the expectation of the ordered brands equals the sum of the expectation of the original data, which both equal zero:

$$E[x_M] + E[x_{M-1}] + \cdots + E[x_1] \;=\; E[x_{(M)}] + E[x_{(M-1)}] + \cdots + E[x_{(1)}] \;=\; 0\,.$$

Notice, that as long as p exceeds q, the expected sales growth of the private label will be greater than zero, i.e., E[s] = g (p-q) E[t]>0 since each of the components is greater than 0. In other words, as long as the retailer has better than even odds of predicting the leading national brand, the growth rate of the private label will exceed the growth rate of the average national brand.

Clearly this is a fairly simplistic framework, but it is also one that is consistent with our findings, our intuition about how private labels operate, and represents a parsimonious argument about why private labels may exhibit growth while national brands are relatively stable. Moreover, this framework is robust, and does not require normality or specific distributional assumptions as we have used in our illustration. The only critical assumption is that the sales of the private label depends upon the sales of a targeted national brand which the retailer expects to grow. Hence, changes to our assumptions may lessen the growth of the private label, but what we find most interesting is that the expected sales growth of the private label will always exceed that of the national brands.

We believe that these assumptions are supported well by what we know about private label strategies employed by retailers. The most direct way that private labels target national brands is developing new private labels that have similar product attributes. At the same time, there are less drastic and less expensive ways that retailers can retarget national brands that still may allow the retailer to appropriate some of the chosen national brand's growth. First, the retailer can quickly change the shelf placement of the private label. Second, in some circumstances the retailer may decide to introduce more than one private label. Sayman (1997) showed both analytically and empirically that in a product category with two leading national brands (e.g., Miracle Whip and Hellman's Mayonnaise), a retailer is more likely to maintain multiple store brands. Additionally, the retailer may choose to target multiple national brand's by introducing a premium store brand (like President's Choice or Safeway Select). Finally, there are numerous ways that the retailer can piggy-back onto the demand generating activities of the fastest growing national brands. For example, when a national brand spends trade promotion dollars to secure in-store display space, retailers can display their store brands in close proximity. Similarly the retailer can use national brand advertising (both retailer-initiated feature advertising and national brand's own direct-to-consumer advertising) to build store traffic and then re-route that traffic toward its own brand once customers are inside the store. Some retailers engage in a practice called price shielding; whenever a leading national brand engages in a price promotion, the store brand also goes on deal in order to maintain its price advantage. Note that price shielding is not a game that national brand's can play against each other unless the retailer cooperates.

The Study

The purpose of the study was to analyze trends in the market share performance of private labels and compare them with trends observed for national brands. In addition, after demonstrating robust trends for the private label, we were interested in understanding which of the competitive brands are most likely to lose out to the private label. Finally, we tried to better understand what factors predispose a private label to grow faster. We considered both category level buying characteristics and the marketing spending patterns of national brands and private labels.

Database Description

At the overall category level, IRI provides the 13 pieces of information in the Marketing Factbook as shown in Table 1 along with total category volume expressed in units appropriate to the category (ounces, pounds, rolls, tablets). In addition the same set of facts are reported for a number of manufacturers, some individual brands, and for private labels. The private label totals represent an aggregation across all individual retailers' store brand alternatives. The level of disaggregate brand detail varies greatly from category to category. To maintain consistency across all categories, we aggregated up to the manufacturer level and formed five brand level aggregates: the leading national brand (NB_1), the second largest national brand (NB_2), the third largest national brand (NB_3), the private label (PL), and all the rest of the brands (Other). National brand market share status was determined by a manufacturer's rank in the first year of the data, 1987.

Table 1

Description of the Database

Variable	Description
Category Volume	Percent of total category volume in units
% Households Buying	Percent of households who made at least one purchase during the year
Volume/Purchase	Average volume of the item bought on a single shopping trip
Purchases/Buyer	Average number of times the item was purchased by buyers during the year
Purchase Cycle (Days)	Average number of days between consecutive purchases among repeat buyers of the item
Price/Volume	Average price paid per equivalent category-specific volume
Any Trade Deal	Percent of volume sold with any form of promotion
Print Ad Feature	Percent of volume sold with any newspaper or store flyer advertising
In-Store Display	Percent of volume sold with any off-shelf display
Shelf Price Reduction	Percent of volume sold with any short-term reduction in price of 5%
Store Coupon	Percent of volume sold with a coupon issued by the store. All coupons for private labels are store coupons.
Manufacturer Coupon	Percent of volume sold with a manufacturer's coupon
% Off Deal Prices	Average percent discounts on price deals

Results

For each of the 225 categories with complete data and a private label alternative, we estimated a simple linear time trend by regressing market share onto time for each of the five brand aggregates (NB_1-NB_3, PL and Other). A logistic transformation of the market share data produced identical results. We also conducted two other nonparametric tests: a standard run test and the so-called r test. The r test compares the sum of squared deviations of successive observations to the sample variance; a trend is present when $r = \frac{1}{2}(n-1)\sum_{t=1}^{n-1}(x_{t+1} - x_t)^2 / S^2$ is small. Both the run test and the r test are omnibus tests that can detect more than simple linear trends. However, the omnibus properties of these tests also result in lower statistical power against simple linear trends, and therefore provide more conservative criteria for declaring a trend. The results are summarized in Tables 2a-2b.

Table 2a: Overall Trends and Regression of Market Shares onto Time

Brand	**Overall Trends**		**Average**	**Average**	**Significant Trends (p<.05)**	
	Positive	**Negative**	**Market Share Change/Year**	**Estimated Slope (S.E.)**	**Positive**	**Negative**
PL	86%	5%	+1.12	+ .92 (.08)	68%	5%
NB_1	40	60	-.36	-.02 (.01)	20	37
NB_2	41	59	-.12	-.01 (.02)	17	32
NB_3	48	52	-.10	-.03 (.03)	28	24
Other	28	72	-.54	-.13 (.04)	14	43

Table 2b: **r Test and Run Test for Randomness**

Brand	**r Test (p<.05)**		**Run Test (p<.05)**	
	Positive	**Negative**	**Positive**	**Negative**
PL	61%	4%	44%	3%
NB_1	17	32	12	24
NB_2	16	26	9	20
NB_3	23	22	14	19
Other	12	39	10	24

Across the five brand aggregates, 57% of the series displayed a significant trend, half positive and half negative. Using the same data source but a different time frame (1983-92) and a somewhat different brand aggregation scheme, Lal and Padmanabhan (1995) found that 33% of the categories showed significant trends ($p<.05$).[3] The most striking feature of the data is the overwhelming tendency for positive (86%) and statistically significant (68%) trends in private label shares. The average annual change in private label share is +1.12 share points. With an average β coefficient of +0.92 for the time variable, this implies an estimated increase in private label share of 7.84 share points over the 1987-94 time period. This does not strike us as evidence for stationarity. Instead store brands appear to be systematically gaining ground at the expense of national brand competitors. For the four national brand aggregates, we see that about half of the time series display significant trends, somewhat more negative (34%) than positive (20%) trends. Clearly, however, there is more noise in the national brand trend data as only the trends for NB_1 and Other are statistically significant.

Category Growth Analyses. We conducted the same set of analyses conditional upon the overall category growth pattern. Specifically, we estimated category growth by regressing overall category unit volume onto time. The 225 categories were then divided into growing or declining categories depending on whether the trend coefficient was statistically significant ($p<.05$), or flat otherwise. Table 3 shows the percent of categories displaying a positive trend for each of the brand aggregates.

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[3] Lal and Padmanabhan do not report whether they included private labels in their analysis.

Table 3 : Positive and Negative Trends Dependent on Category Growth

Variable	Category Growth Pattern: Growing		Flat		Declining	
#of Categories	80		85		60	
	+ Trend	- Trend	+ Trend	- Trend	+ Trend	- Trend
PL	69%*	7%	64%	6%	72%	2%
NB_1	19	43	18	32	23	38
NB_2	11	41	19	26	23	30
NB_3	31	24	26	29	27	18
Other	25	36	9	49	7	43

* Percent of categories with statistically significant trends ($p<.05$)

A priori, we expected that private labels would gain more share in declining categories, where due to category commoditization, national brands reduce category investments because they foresee limited upside potential. Instead the results for all of the brand aggregates are robust to category growth. As can be seen in Table 3, private labels show significant positive trends irrespective of category growth.

Proportional Draw Analysis. The previous analyses provide clear evidence that private labels are gaining share. Moreover, the generally negative trends for the rest of the brands in the category suggest that private label is gaining some share from all of its competitors. A more penetrating question, however, is whether the store brand is gaining at the expense of some brands more than others. In order to address this issue, we need to compare the empirically observed share loses to what might be expected given an appropriate null model. The naive model we employed was proportional draw which is consistent with a logit choice model formulation. Specifically, in the first year of the time series (1987), for each of the four brand aggregates (NB_1, NB_2, NB_3, Other) we calculated each brand's share of the market exclusive of the private label. For example, let us say that the private label had 20% market share and NB_1

had 30%. Moreover, let us say that the PL gained 10 share points to rose to 30% market share in 1994. Then NB_1's expected share lose would be calculated as NB_1/(100%-PL)=30/80=37.5% x (10% PL share gain)=-3.75%.

Previous research suggests that proportional draw is a fairly compelling naive model. At the same time, research on price tiers and asymmetric price competition (Blattberg and Wisnewski 1989; Hoch 1996) has shown that higher quality leading national brands may be less affected by store brand policies than secondary national brands. For example, retailers probably are more likely to drop a weak national or regional brand than a similarly weak SKU from a leading national brand. Table 4 displays the results of the proportional draw analysis.

Table 4

Loss of Share Analysis: Observed vs Expected Under Proportional Draw

	1987-1994 Market Share Loss		**Observed-Predicted**
Brand	**Observed**	**Proportional Draw**	**t-test**
NB_1	2.52	3.34	<-1
NB_2	.84	1.38	<-1
NB_3	.70	1.28	-1.50
Other	3.78	1.85	3.53

As can be seen, private labels gain disproportionate market share from the smaller brands in a category. Although the top three brands on average lose share, the share loses all are less tan predicted according to a proportional draw analysis. Only the Other category losses more than expected given its starting market position. There are a number of possible reasons for this. First, consumers may perceive private labels as more similar to these smaller share brands. Second, as retailers make attempts to reduce supply chain costs through assortment reductions, they may be more likely to eliminate smaller regional brands who have less clout and with whom the retailer has a more limited relationship in other product categories.

Category Level Analyses

The previous analyses have shown that the uptrend in private label market share is a robust finding. In 86% of the categories private labels show a positive trend, and in 68% of the categories the uptrends are statistically significant. Moreover, store brands trend upward irrespective of overall category growth. In contrast, the top three national brands (and the catch all Other) show much weaker downward trends. Private labels appear to gain a little bit of market share from all of their competitors, though a proportional draw analysis indicates that the smallest brands in each category (Other) lose more than their fair share. In the remaining set of analyses, we attempt to better understand in which categories private labels show the largest share growth and why.

Penetration-Frequency Analysis. A key tenet of category management is that the retailer must decide on the role each category plays in the overall store portfolio and then execute towards those goals. With distinctive strategies, the retailer avoids dissipation of scarce resources that accompanies trying to be all things to all people with all categories. Retailers can influence category volume by taking marketing actions that either: (1) increase store traffic; or (2) use in-store activities to increase the probability of category purchase by consumers who already are in the store anyway. One popular method of classifying categories (FMI Category Management Guide #1, 1995) utilizes consumer-based category roles which rely on information on whether most households buy the category every week and spend a large part of their shopping budget on it (e.g., bread, carbonated beverages), or if only a few interested consumers make infrequent purchases in the category (e.g., vinegar, yeast). Each of the 225 categories were classified as either high or low penetration (% Households Buying) and high or low frequency (the reciprocal of Purchase Cycle) based on a simple median split of both variables. With a 2x2 crossing of penetration and frequency, each category falls into one of four groups: (1) *staples* (high penetration/high frequency); (2) *niches* (low penetration/high frequency); (3) *necessities* (high penetration/low frequency); and (4) *fill-ins* (low penetration/low frequency). Because higher penetration and frequency categories are more likely to be in a shopper's market basket, retailers tend to use staples as lower margin traffic builders and fill-ins as profit builders.

Previous research has found that private labels historically have obtained higher share in larger categories (high penetration and high reach); Hoch and Banerji (1993) reason that retailers are more likely to invest their resources here due to a better return on investment. The current data also reveal that private labels in higher penetration categories have higher share. Averaged across the 8 year time series, private labels have 18.7% shares in high penetration categories and 16.5% shares in low penetration categories. The results are different when considering private label trends. An analysis of the estimated time series b's indicates that store brands are growing much faster in low penetration categories (β=1.26 vs .59, p=.0003) which are purchased less frequently (β=1.17 vs .67, p=.05). There are a couple of reasons why this might be the case. First, it could be that there is a "soft" ceiling on the larger higher penetration/frequency categories. Private labels in these categories tends to be well developed and so retailers may invest less resources as they move forward. Second, the national brands in the smaller low penetration, low frequency categories may be significantly weaker competitors who can not invest enough in marketing spending or new product development and therefore became more vulnerable to the retailer's own investments in private label. Whatever the reason, the differences in growth are substantial.

Determinants of Private Label Trends. In the last set of analyses we attempt to take advantage of both the time series and cross-sectional character of our data to better understand how category buying behavior and the market mix decisions of both the national brands and the retailer influence trends in private label market share. The basic structure of the analysis is as follows. First, the market shares were transformed using the logit function. Analyses of the untransformed data yielded the same results. Second, since we are interested in understanding trends in share across categories, the share data were mean-centered separately by category. This is equivalent to including an intercept for each of the categories. We then estimated the following model:

$$PL_{t+1} = f[PL_t,\ \Delta_{(t+1)-t}(\text{Category Buying Characteristics}),$$
$$\Delta_{(t+1)-t}(\text{NB and PL Marketing Mix Decisions})]$$

That is, we regress the logit transformed market shares onto the lagged market shares, contemporaneous changes in the buying characteristics of the category, and changes in the marketing mix decisions of both the national brands in aggregate and the private label. Although the resultant OLS estimates are consistent, with heteroskedasticity introduced either through autocorrelation in the errors or violations of across category pooling assumptions, the standard errors tend to be biased downward. We therefore used White's Asymptotic Covariance procedure to recompute corrected standard errors which are asymptotically consistent under these types of specifications. The results are displayed in Table 5.

Table 5: Determinants of Trends in Private Label Market Share

Variable	Parameter Estimate	Standard Error	t-statistic	p value
PL_t	.6352	.0356	17.83	0.000
Δ(Category Volume)	3.57x10^{-6}	3.70x10^{-6}	0.96	0.336
Δ(Category Penetration Rate)	-.0093	.0046	-1.99	0.047
Δ(Volume/Purchase)	.0001	.0167	0.08	0.937
Δ(Category Purchase Cycle)	.0022	.0020	1.12	0.261
Δ(NB Price)	.0429	.0523	0.82	0.412
Δ(NB Trade Deals)	.0007	.0020	0.36	0.723
Δ(NB Print Ad Feature)	-.0073	.0034	-2.15	0.032
Δ(NB In-Store Display)	-.0082	.0027	-3.00	0.003
Δ(NB Coupons)	-.0091	0.0019	-4.69	0.000
Δ(PL Price)	-.0465	.0353	-1.32	0.188
Δ(PL Trade Deals)	.0006	.0018	0.31	0.757
Δ(PL Print Ad Feature)	.0033	.0024	1.38	0.167
Δ(PL In-Store Display)	.0058	.0022	2.61	0.009
Δ(PL Coupons)	.0089	.0106	0.84	0.404

The adjusted R^2 of the model was 0.48. The statistically significant variables are shaded in the table.

There is a negative relationship between changes in category penetration and changes in private label share. This indicates that private labels tend to grab more share in categories where fewer new consumers are entering the category. This result is consistent with two previous analyses, first where we found that private labels trended upward slightly more in categories experiencing declining volume and also in the penetration-frequency analysis which indicated greater private label growth in lower penetration categories. This result may be symptomatic of category maturity. Private labels tend to do better in mature categories because the national brands introduce fewer new products, and as a consequence the private label manufacturers have a better opportunity to close the all-important quality gap with the national brands (Hoch and Banerji 1993).

Marketing mix decisions also play a role in private label growth. Increases in national brand feature advertising, in-store display, and coupons all retard private label growth. In contrast, when retailers elect to display their own brands in their stores, private labels show greater increases in share. In terms of the competitive promotion spending equilibria that might lead to market share stationarity, it is interesting to think about who actually makes these marketing mix decisions. Two of the decisions seem straightforward. The retailer clearly has complete control over the decision to display their own brands in their own stores. In addition, the national brands have virtually complete control over their direct-to-consumer couponing activities. National brands, however, have only partial control (at best) of the feature advertising and display activities of the retailer. Witness the less than 50% pass-through of the trade-deals that they offer to the retailer. It is true that national brands sometimes can negotiate advertising and display guarantees as a precondition to providing the retailer with trade promotion monies. But the retailer still has the final say.

The retailer faces an interesting trade-off. Increases in national brand feature advertising, paid for one way or another by the national brands, clearly benefit the retailer both by increasing store traffic and nonplanned in-store purchases. At the same time, these activities work against the growth of the retailers' own brands. The main point still is that by virtue of its intermediary position in the channel, the retailer can blunt the competitive reactions of the national brands to the performance and promotional spending for their own private labels. Moreover, there are limits to the reactions of NB's to the unilateral actions the retailer takes for the private label. Yes the NB's can increase non-feature advertising (TV, magazine, etc.) and couponing but only with considerable delay. Quick tactical reactions are more limited unless the retailer sees it in their best interests to cooperate. It would seem that retailers are more likely to support one NB's reactions against another NB since by playing NB against NB the retailer accrues the benefits from an escalation of category promotional spending.

Discussion

Clearly, there are exogenous events that may disturb the stability that characterizes most consumer product markets. For example, a product recall or health scare may lead to a shift in market power, e.g. the Tylenol tampering episode or Coca Cola's recent problems in Europe. In addition, genuinely new product ideas can shake up an established category. For example, in 1984 when P&G introduced gel technology into its disposable diapers, Pampers gained 12 share point in one year. Of course, because the new product innovation involved unpatented technology imported from Japan, the next year P&G's competitors reformulated their products and regained much of the lost share. What else might perturb the institutional inertia that keeps any one competitor in check? Any one brand controls its own spending but has little if any control over what its competitors do. In essence each firm is one player in an n-firm prisoner's dilemma where tit-for-tat rules the day. Every brand that is except for one–the retailer's own private label brand. This brand is much like any other brand. It faces downward sloping demand with respect to price and upward sloping demand with respect to quality (Dhar and Hoch 1997). But unlike other firms, the private label occupies a special role because the firm that owns it and stands the most to gain and lose from its performance is the very same firm (the retailer) that ultimately has some measure of control over a variety of marketing mix decisions that get made for other brands in the category. For example, although the wholesale prices and trade promotion spending of the national brands have an undeniable influence on the ultimate price and promotion decisions made by the retailer, the retailer still has the final say and more control over the competition, at least relative to the control exerted by one national brand over another.

Therefore, unlike the national brand case, the substantial reaction elasticities that may keep national brand shares relatively constant over time may not exert as strong an influence over the market share performance of private labels. For example, consider the case of price competition in a product category without a substantial private label presence. Generally when one national brand (NB) lowers its wholesale price, other national brand competitors follow suit quickly and the retailer passes those price changes onto the consumer. In contrast, when the retailer has a private label in the category, it is not clear how they will react to the NB's price decrease. Before passing the price decrease onto the consumer, the retailer must decide whether this is in their best interests (Hoch and Lodish 1998). Not only must they anticipate the change in demand for the NB, but also the impact of the smaller price gap on demand for their own private label if they hold their price or the increase in category demand if they decide to match the NB's price decrease with one of their own. In the end they may decide to pocket the national brand's lower price in the form of higher margins and there is little that the NB can do about it.

Conclusion

In this paper we have shown that in a high percentage of categories private labels have exhibited substantial long-term positive growth trends. This contrasts with national brands who have grown in far fewer categories and also show negative growth in many other categories. To the best of our knowledge our dataset is the most extensive that has been brought to bear on this problem in terms of the number of categories analyzed and length of time considered. Clearly, these results indicate private labels exhibit unique growth characteristics.

Besides the empirical findings about the growth of private labels, we have also presented an analytic framework that may explain why private labels can grow while the average national brand is stable. Unfortunately, even with our extensive dataset, a deficiency of this study is that the data is very aggregate in nature, and we believe a better understanding of private labels requires a knowledge of the behavior of individual markets. The private labels analyzed in this paper are not those of a single retailer, but aggregates of private labels across all retailers. We know that local markets are very heterogeneous and that there are huge differences in the performance of store brands both across retailers (Dhar and Hoch 1997) and across categories (Hoch and Banerji 1993). The leading national brand is not the same across all geographic markets or even within the same market. For example, in the Chicago market, the leading laundry detergent at Jewel may be Wisk, while the leading brand at Dominick's may be Tide. If each retailer targets the leading national brand in its chain, the aggregate consumer segments reached by the private labels are very different. This heterogeneity in appeal for private labels means that the class of private labels will draw from a very diverse set of consumer segments, even though individual retailers may be narrowly targeting segments served by the leading national brands.

The importance of this heterogeneity is that actions taken by a national brand to defend against encroachment by private labels will have spillover effects in all consumer segments, since the private label is not a unique brand, but an agglomeration across many markets. In sum, national brands are not competing against a single private label, but the family of private labels. Therefore defensive marketing strategies for national brands against encroachment by private labels cannot be narrowly targeted at a single consumer segment, and hence traditional strategies used to compete against other national brands may prove very ineffective. We hope the findings of this paper will encourage other researchers to continue empirical and theoretical research into the unique behavior of private labels.

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