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Distribution and Market Share

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Abstract

This paper presents findings from a census of more than 79,000 stock-keeping units (SKUs) in 37 consumer packaged goods categories totaling $55 billion in annual revenue. It shows that, in 86 percent of product categories, the relationship between market share and retail distribution is increasing and convex at the SKU level. The degree of convexity is greater in categories with higher revenues and more concentration in market shares. The relationship is also typically convex within leading brands' SKU portfolios, showing that the "double jeopardy" phenomenon of low share and distribution not only affects small brands competing against market leaders, it also affects low-share SKUs within a category leader's product line. Holdout evidence shows that the distribution/share relationship within a brand's portfolio of existing SKUs usually holds for new SKUs as well. We explain how knowledge of the distribution/share relationship can help to improve a brand's go-to-market decisions for new SKUs.

Keywords: Consumer package goods; Empirical generalizations; Market share; Distribution; New products

Introduction

Retail distribution plays a critical role in determining market shares: a product must be offered for sale before it can be purchased. Distribution also contributes to sales in less obvious ways. It can generate consumer awareness, change the set of competitors facing the product and alter the consumer's perception of the retailer and the brand.

Given this critical role of distribution in determining market outcomes, a large empirical literature has examined the interplay between distribution and market share. For example, Ailawadi (2001) reviewed a stream of literature that showed that manufacturers exercise substantial influence over their retailers. Nijs et al. (2010) substantiated this recently by estimating a mean distribution channel pass-through elasticity of 0.41. Bucklin, Siddarth, and Silva-Russo (2008) exploited variation in consumers' proximity to auto dealers to construct household-level measures of distribution intensity, estimating the elasticity of sales with respect to distribution to be 0.6 in the automotive industry. Ataman, van Heerde, and Mela (2009) found that the sales elasticity of distribution is 0.74 in packaged goods categories, about six times larger than the advertising elasticity.

A particularly important and robust finding within the literature on distribution is the "double jeopardy" phenomenon that high-share brands tend to sell more "per point" of retail distribution than small-share brands. This relationship has been observed using cross-sectional brand data in several categories (Farris, Olver, and de Kluyver, 1989; Reibstein and Farris, 1995) and over time for a single brand that rapidly gained and lost share and distribution (Farris et al., 1989). Convex relationships have also been documented in the UK (Nuttal, 1965), Japan (Borin, Van Vranken, and Farris, 1991) and the Netherlands (Verbeke, Clement, and Farris, 1994).

The largest-scale confirmation of this convex relationship was offered by Kruger and Harper (2006). These authors investigated brand-level data on 143,356 brands in 263 product categories. They found that the cross-sectional relationship between brands' market share and distribution levels was convex 95 percent of the time, with exceptions mainly occurring in categories that were ancillary to larger categories or evolving over time.

The "double jeopardy" problem faced by small brands has been attributed to three related factors: consumer preferences, retailer assortment strategies and retailer expectations. Manufacturers with strong consumer preference can "pull" consumer traffic into the store. The strongest form of

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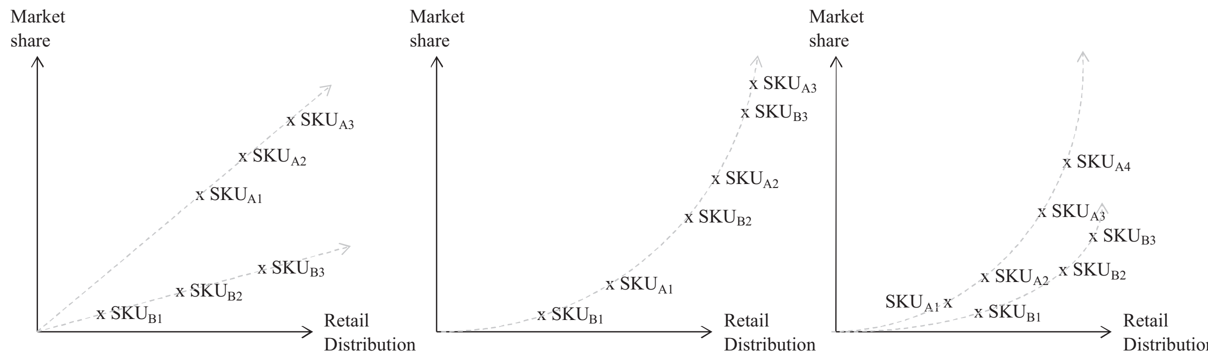

Letters indicate brands, numbers indicate SKUs offered by a brand

Fig. 1. Conceptual explanations for brand-level double jeopardy findings.

preference might include search loyalty or switching stores when a particular brand or stock-keeping unit (SKU) is not available (Ailawadi, Harlam, Cesar, and Trounce, 2006). Meanwhile, many retailers strategically limit their assortments. Therefore, a limited-assortment retailer is disproportionately likely to stock a strong brand in order to minimize customer traffic lost to competing retailers. Limited-assortment retailers offer manufacturers less competition within the store and therefore yield greater sales per point of distribution. As a brand's market share and distribution increase, it tends to enter into progressively less competitive retail environments (Farris et al., 1989; Reibstein and Farris, 1995). These assortment decisions are based on retailer expectations of consumer behavior, therefore those expectations may become self-fulfilling, especially for small brands.

Despite all this work, much remains unknown about the relationship between distribution and market share at the level of the individual stock-keeping unit (SKU). Yet this is the level at which many marketing decisions (go-to-market, pricing, trade promotions, etc.) are actually made and implemented.

For example, it remains unknown whether "double jeopardy" is exclusively a brand-level phenomenon. The brand-level measurements could be implied by phenomena that exists at either the brand level alone, at the SKU level alone, or both. A purely brand-level phenomenon is illustrated in the first panel of Fig. 1, which shows a setting in which market share per point of distribution is constant across SKUs but varies across brands A and B. However, a different explanation for the same brand-level pattern is illustrated in the second panel. This diagram shows a single convex relationship at the SKU level where variation only occurs in the locations of competing brands' SKUs. Such variation could occur if, for example, Brand A entered the market first; Bronnenberg, Dhar, and Dube (2007) provided compelling evidence that the order of entry of consumer package goods (CPG) brands into local geographic markets created competitive advantages over rivals that lasted for generations. When aggregating over these SKUs to brand-level phenomena, a researcher would find that brand A has both more distribution and more share per point of distribution, even though the relationship between distribution and market share really occurred at the SKU level. The analysis below finds that the reality is closest to the illustration in the third panel, in which there is a convex relationship across SKUs within a brand, and that relationship varies across brands within the category.

To the best of our knowledge, this article offers the first evidence that the relationship between market share and distribution is increasing and convex at the SKU level; all prior evidence used brand-level data. We also uncover the product category characteristics which influence the shape of the relationship. The degree of convexity increases with category revenues and concentration in category market shares. Finally, we show that the relationship varies across brands within a category, and that SKU portfolios offered by bigger brands more frequently exhibit convex distribution/share relationships.

We also show how this relationship can be useful to a manufacturer. We consider a manufacturer seeking to detect and avoid unprofitable go-to-market decisions for new SKUs. Holdout evidence shows that the relationship between distribution and market share estimated using a brand's existing SKUs is normally a good predictor of patterns displayed by new SKUs introduced in future periods. However, in the exceptions when the current brand-specific relationship is not a good predictor for new SKUs, new SKUs tend to perform very badly. In other words, the relationship among a brand's existing SKUs never under-predicts new SKUs' performance. Therefore, the relationship exhibited by a brand's existing SKUs can serve as a useful check on managers' pre-launch distribution assumptions for potential new SKUs.

Before proceeding, it is important to emphasize what this paper does not seek to do. The goal here is to establish empirical generalizations about the nature of share–distribution relationships using data from many categories, but we do not attempt to estimate any causal effect of retail distribution on market share. Any such estimate would need to rely on a plausibly exogenous source of variation to disentangle the effect of distribution on sales from the effect of sales on distribution or to eliminate other unobserved factors.[2] Such effects are interesting and important

[2] One might initially think that past distribution could serve as an instrument to identify the direct impact of current distribution on market share, as distribution is strongly autocorrelated. However, there is ample reason to believe that there are other current determinants of market share (e.g., consumer preferences, prices

but they have been estimated by numerous previous studies and are not the focus of this paper.

Data

The data used in this study include quarterly national sales and distribution for 37 consumer packaged goods categories. For each SKU, we observe the brand, product category, quarterly sales revenues, and retail distribution from 2003 to 2005. These 37 categories totaled about $55 billion in annual sales from over 79,000 SKUs. The average category contained about 2,200 active SKUs each year.

The data were compiled by ACNielsen from scanner data contributed by a nationally representative panel of grocery, drug and mass retailers.[3] Brand managers at P&G, the largest CPG manufacturer, considered this database to be the census of available products in the US and used it as their preferred source of data on competitors' levels of distribution and market share.

Measures

Distribution is measured using the standard industry metric, Percent All Commodities Volume or %ACV. The %ACV of SKU k in period t is calculated as a weighted average,

$$\%ACV_{kt} = 100 \times \frac{\sum_{n=1}^{S} 1_{knt} r_{nt}}{\sum_{n=1}^{S} r_{nt}}, \tag{1}$$

where $n = 1, \ldots, S$ indexes stores, 1_{knt} is an indicator that equals one if store n sold at least one unit of SKU k in period t and r_{nt} is the total dollar sales of all commodities in store n in period t. The constant 100 is included because %ACV is usually expressed in basis points. Market shares are defined as shares of category revenue, expressed in basis points. The primary qualitative conclusions presented below are robust to definition in terms of units or volume. %ACV and market share are averaged over quarters within a year to reduce seasonal fluctuations.

Descriptive statistics

Table 1 describes the 37 categories in the data. They include diverse nonperishable and semi-perishable categories like Salted Snacks, Laundry Detergent, Paper Towels, Dental Floss and Men's Fragrances. Most categories are defined broadly. For example, the coffee category includes all types of coffee (ground, whole bean, instant, etc.) as well as several types of coffee substitute. In sum, the dataset contains sales revenue of $164 Billion from 9,035 brands and 79,414 SKUs.

The data show that, to a greater degree than is commonly realized, distributions of SKU-level market share and %ACV cluster near zero and are highly dispersed at the top ends of their ranges. In the average category, the maximum SKU market share is about 32 times larger than the average, while the average SKU market share is 15 times larger than the median. The distribution data are only slightly less dispersed, as the maximum %ACV is about 15 times larger than the average, and the average %ACV is about 10 times larger than the median.

Further underscoring the rarity of a hit SKU, category leaders tend to offer large numbers of low-performing SKUs. The median SKU offered by a category-leading brand earned just 0.2 percent of category dollars and was offered in stores representing just 6.5 percent of ACV.

Even though the category-leading SKU has a share that is nearly 500 times larger than the median SKU, small-share SKUs still account for the large majority of category revenues. For the average category-leading brand, the most widely distributed SKU brings in about 14 percent of brand revenues, even though it achieves about 85 percent of the brand's overall retail distribution.

Empirical generalizations

This section begins with data showing the convexity of the typical relationship between distribution and market share, then presents descriptive models and parameter estimates.

Model-free evidence

Fig. 2 plots the distribution levels and market shares of SKUs in the four largest categories in the data. They clearly show an increasing, convex relationship between market share and %ACV.

Individual SKU movements over time are common, as new SKUs are frequently introduced into the category. However, while such movements are common, they also tend to be small, so the overall relationship changes slowly in mature categories. Fig. 3 shows graphically that the salty snacks category's curve remained roughly constant over quarters in 2004. This stability is typical of categories in the sample.

Models

Four models were estimated to describe the relationship between distribution and market share. Eq. (2) specifies a Common Parameters Model in which the relationship is a second-order polynomial and pools data across categories to make the most general statement possible:

$$s_{kt} = \beta_0 + (\%ACV_{kt})\beta_1 + (\%ACV_{kt})^2\beta_2 + \varepsilon_{kt} \tag{2}$$

where s_{kt} is the market share of sku k in period t, the β terms are parameters to be estimated, and ε_{kt} is an error term representing the effects of all non-distribution factors on market share.

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and advertising) that may depend on past levels of market share. Therefore, past distribution is likely to be correlated with current values of these variables, violating the exogeneity requirement for instrumental variables.

[3] The sample of stores included K-Mart and Target but excluded Wal-Mart, which did not share its scanner data with syndicated data vendors. It also excluded convenience stores, club stores and vending machines. The excluded retailers offer more limited assortments than most food and drug stores, so we would likely estimate higher degrees of convexity if the data included these additional channels. The sample also excluded private labels, as these brands control their distribution perfectly within their own chains and normally are not sold by competing retailers.

Table 1
Summary statistics.

Category	Ann. rev. ($MM)	Num. brands	Num. SKUs	SKU market shares (basis points)			SKU %ACV (basis points)		
				Avg.	Med.	Max.	Avg.	Med.	Max.
Air Care	1,299	391	3,413	.030	.000	1.2	4.0	0.0	83
Baby/Kid Wipes	452	69	779	.130	.020	4.6	4.1	0.5	83
Bath Tissue	3,661	94	813	.120	.005	5.5	5.5	0.5	87
Bleach	714	154	594	.170	.006	15.3	7.1	0.8	89
Car Care	46	71	290	.340	.020	7.7	2.4	0.0	52
Cat Food, Treats	2,054	139	2,208	.050	.003	1.2	8.2	1.0	89
Coffee	3,019	491	5,874	.020	.001	4.9	2.3	0.0	89
Dental Floss	236	103	531	.190	.010	3.5	6.2	0.5	87
Dentifrice	1,443	130	1,552	.060	.003	3.5	8.8	1.0	88
Denture Adhesives	165	28	102	.980	.090	13.7	13.8	2.0	88
Deoderants	1,275	158	2,018	.050	.002	1.0	10.7	1.0	84
Diapers & Bibs	2,397	164	2,510	.040	.001	1.2	3.6	0.3	81
Dish Care	1,098	113	1,046	.100	.005	2.4	6.5	0.8	88
Dog Food, Treats	3,025	347	3,759	.030	.002	1.3	5.4	0.8	84
Fabric Conditioners	899	67	775	.130	.010	3.2	6.4	1.0	86
Facial Skin Care	1,621	580	3,106	.030	.001	1.1	5.4	0.3	79
Facial Tissue	1,058	66	738	.140	.001	4.0	4.1	0.0	89
Feminine Care	1,448	43	1,313	.080	.003	1.7	10.3	1.0	91
Hand/Body Lotion	870	1,276	5,018	.019	.000	2.4	2.2	0.0	79
Laundry Detergent	3,483	137	1,682	.060	.003	2.0	5.8	0.8	87
Laxatives	607	114	1,032	.100	.010	2.0	4.8	1.0	81
Men's Fragrances	255	283	3,634	.030	.003	2.7	0.7	0.0	73
Men's Hair Color	118	18	117	.840	.060	9.2	8.9	0.8	74
Nasal Remedies	228	79	287	.350	.050	5.5	6.7	1.0	82
Oral Antiseptics	609	75	765	.130	.005	4.8	6.2	0.5	90
Pain Management	2,786	477	4,433	.020	.001	.9	4.9	0.0	93
Paper Napkins	411	62	687	.150	.004	6.5	2.7	0.5	62
Paper Towels	2,289	76	761	.130	.010	8.1	3.7	0.5	78
Personal Cleansing	1,741	815	8,610	.010	.000	1.4	2.3	0.0	93
Respiratory Care	2,983	403	3,292	.030	.002	2.2	6.1	0.8	93
Salted Snacks	7,647	804	9,613	.010	.000	3.5	3.1	0.0	95
Sore Throat	395	80	724	.140	.009	2.8	7.4	0.8	88
Stomach Remedies	1,355	122	1,419	.070	.004	8.7	8.4	1.0	91
Surface Care	2,166	793	3,675	.030	.001	1.3	4.4	0.0	91
Toothbrushes	787	192	1,957	.050	.001	3.4	4.7	0.0	75
Walter Filtration	146	21	287	.350	.007	22.3	2.5	0.0	66
Avg. across Cats	1,522	251	2,206	.145	.010	4.6	5.6	0.5	84

The purpose of this regression is to describe the relationship observed in the data between s_{kt} and $\%ACV_{kt}$. There are many reasons to believe that $\%ACV_{kt}$ is correlated with ε_{kt}; therefore, the β parameters are not interpreted as the causal effect of %ACV on share. The qualitative findings of this model can be reproduced by estimation in differences. However, differences in %ACV tend to be very small so this approach could not identify category-specific quadratic effects.

The Category-Specific Model in Eq. (3) allows the shape of the relationship to differ across categories in the data. Every sku k belongs to exactly one category c, denoted c_k.

$$s_{kt} = \beta_0 + (\%ACV_{kt})\beta_{1c_k} + (\%ACV_{kt})^2\beta_{2c_k} + \varepsilon_{kt}. \quad (3)$$

The Category Characteristics Model in Eq. (4) replaces the category-specific parameters with category characteristics to help explain when the distribution/share relationship is more or less convex in the data. Each category c has a set of $l = 1, \ldots, L$ category characteristics x_{cl}, including an intercept, share dispersion (as measured by the Herfindahl–Hirschman Index calculated using SKU-level market shares) and dummies for category size, value density (the typical SKU price:volume ratio) and type (Babies/Kids, Food, Healthcare, Beauty, Household/Cleaning, Personal Care and Pets).

$$s_{kt} = \sum_{l=1}^{L} x_{c_k l}[\beta_{0l} + \%ACV_{kt}\beta_{1l} + (\%ACV_{kt})^2\beta_{2l}] + \varepsilon_{kt}. \quad (4)$$

Another important question is whether distribution/share relationships are similar for different brands within the same category. The Brand-Specific Model in Eq. (5) answers this by estimating brand-specific relationships between market share and retail distribution. Each SKU k in category c_k belongs to a unique brand b_k. We denote the rank of the market share of brand b_k within category c_k as r_{kc}; for example, $r_{kc} = 1$ indicates that SKU k belongs to the leading brand in category c_k.

$$s_{kt} = \beta_0 + (\%ACV_{kt})\beta_{1r_{kc}} + (\%ACV_{kt})^2\beta_{2r_{kc}} + \varepsilon_{kt} \quad (5)$$

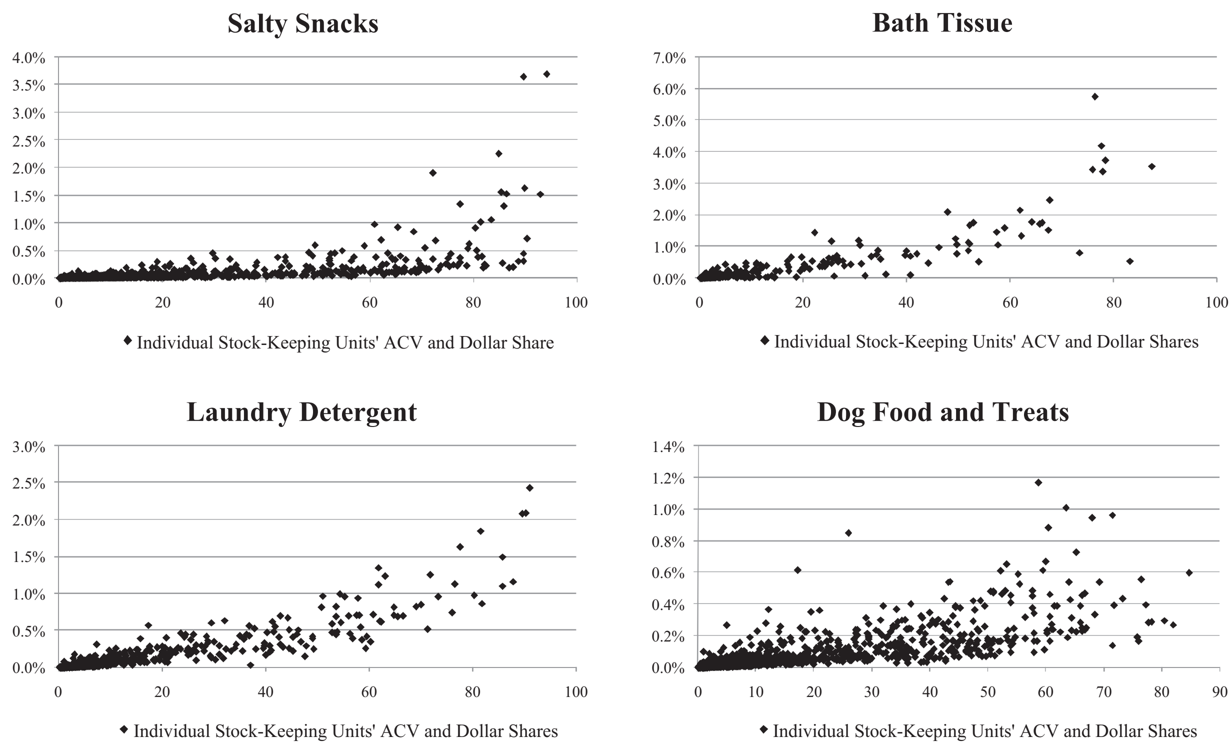

Fig. 2. SKUs in distribution-share space, 2004.

Many small brands typically offer SKUs with market shares and distribution levels that are very close to zero, and do not offer a large enough number of SKUs to estimate brand-specific parameters. Therefore, we cap the number of brand ranks included in the Brand-Specific Model at 9 and assign all SKUs offered by lower-ranked brands to a tenth "catch-all brand."

Model validation

Table 2 reports regression diagnostics for the four models. In the Common Parameters Model, retail distribution accounts for 30 percent of the variation in market shares. Allowing the relationship to vary across categories, as in the

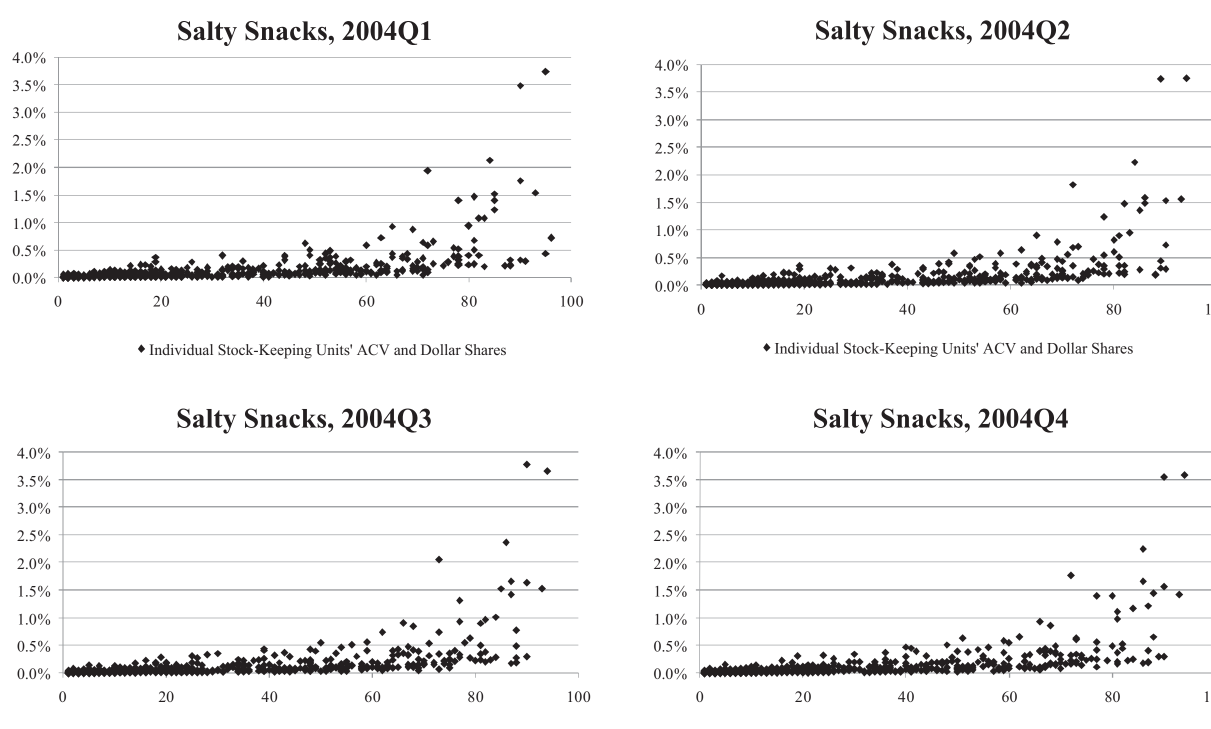

Fig. 3. SKUs in distribution-share space over time.

Table 2
Regression diagnostics.

	N. obs.	D.F.	*R*-Sq.	RMSE	*F*-Stat.	2003–04 Est. subsample[a]		2005 holdout subsample[a]	
						RMSE	*R*-Sq.	RMSPE	*R*-Sq.
Common Parameters Model	184,623	2	.305	.238	40,460	.244	.302	.333	.279
Category-Specific Model	184,623	74	.804	.126	10,232	.130	.802	.177	.797
Category Characteristics Model	184,623	32	.698	.157	13,302	.163	.692	.216	.697
Brand-Specific Model	184,623	735	.875	.101	1,749	.101	.881	.159	.837

[a] The model was re-estimated using data from 2003 and 2004; these columns report the root mean square prediction error and coefficient of determination in the 2005 subsample.

Category-Specific Model, increases this figure to 80 percent. The Category Characteristics Model retains most of this increase in fit, explaining 68 percent of the variation in the dependent variable, so the set of category characteristics appears to be fairly comprehensive. The Brand-Specific Model includes the largest number of parameters and consequently accounts for 88 percent of the variation in market shares.

Holdout validation was used to determine whether the relationship is stable over time and to check for overfitting. Each model was estimated using data from 2003 to 2004, 65 percent of the sample. These estimates were then used to predict market shares for all active SKUs in 2005 given observed levels of retail distribution. Table 2 shows that the root mean square prediction errors and R-square statistics were not very different between the estimation and validation subsamples, indicating that these relationships were fairly stable over time.

Parameter estimates

Table 3 establishes the overall shape of the relationship between distribution and market share using the Common Parameters Model. The effect of distribution is positive and convex, indicating that SKUs with higher levels of retail availability sell more per point of distribution as well as more overall. The parameter estimates are statistically significant at confidence levels well above 99.9 percent with T-statistics over 40. Consequently, this shows that the "double jeopardy" pattern that has been often observed using brand-level data is also found in SKU-level data.

Table 3 also shows how the relationship varies across categories, as estimated by the Category-Specific Model. In sum, 33 of 37 product categories (86 percent) exhibit a statistically significant pattern of increasing returns to distribution. This shows that the evidence found by the Common Parameters Model was provided by a general phenomenon across most of the categories in the data.

Looking further at the estimates, three categories (Coffee, Salted Snacks and Bleach) have negative parameter estimates on the first-order %ACV term. However, in two of these three cases (Coffee and Salted Snacks), the effect of $(\%\text{ACV})^2$ is sufficiently strong that the marginal effect of ACV on market share is everywhere positive and increasing. In the third case (Bleach), the relationship between distribution and market share is increasing and convex for all %ACV levels above 12. The estimated relationship between distribution and market share is approximately linear in three product categories (Diapers, Men's Fragrances, Toothbrushes) and concave in one (Laxatives).

To help understand these patterns, the Category Characteristics Model was estimated to identify how product category characteristics govern the convexity of the relationship. In the interest of completeness, Table 4 provides all parameter estimates. However, interpreting the interactions can be quite challenging, so we focus on the final column of the table, which reports the shape of the average marginal effect of each variable.

The Category Characteristics Model supports three conclusions. First, the relationship between distribution and market share exhibits greater convexity in higher-revenue product categories. The most likely explanation for this finding is the speed with which high-dollar product categories turn over. When product turnover is more frequent, retailers fill a higher proportion of category facings with the most popular SKUs to avoid stockouts.

Second, more concentrated categories (as measured by SKU-level HHI) exhibit more convex relationships between market share and retail distribution. Power is distributed more unevenly across brands in more concentrated categories, so leading SKUs' manufacturers wield greater influence with consumers and retailers. They are therefore able to achieve relatively greater levels of retail distribution for their product lines.

Third, the distribution/share relationship varies across types of product category. The Beauty industry exhibits the most convexity, followed by (in order) Personal Care, Pets, Healthcare, Household/Cleaning, Food and Babies/Kids.

The Brand-Specific Model extended the relationship from the category level to the brand level. Table 5 shows the estimated distribution/share relationships for each of the three leading brands in each product category. For comparison, it also shows the parameter estimates for the ninth-ranked brand in each category. Relationships vary significantly across brand ranks within a category as well as across product categories. While nearly all leading brands show convex relationships, only 9 of the 37 9th-ranked brands are estimated to have convex relationships.

Table 6 summarizes the estimated relationships for each of the nine leading brands in each product category. The degree of convexity of market share in retail distribution tends to be larger for higher-share brands, with 34 of 37 (90 percent) leading brands displaying this pattern. It continues to hold for 76 percent of second-ranked brands, as well as 76 percent, 61 percent, 72 percent and 61 percent of third-, fourth-, fifth- and sixth-ranked brands, respectively. The proportion of convex brand-specific

Table 3
Common and category parameter estimates.

	%ACV		$(\%ACV)^2$	
	Param. Est.	(*T*-Stat.)	Param. Est.	(*T*-Stat.)
Common Parameters Model				
Main Effect	.00496***	(41.6)	.00011***	(58.0)
Category-Specific Model				
Interaction with...				
Air Care	.00353***	(10.9)	.00010***	(16.4)
Baby/Kid Wipes	.01738***	(21.8)	.00026***	(20.0)
Bath Tissue	.00552***	(9.9)	.00039***	(41.5)
Bleach	−.02049***	(−36.2)	.00084***	(91.0)
Car Care	.12154***	(81.9)	.00086***	(19.4)
Cat Food & Treats	.00324***	(12.0)	.00005***	(10.2)
Coffee	−.00295***	(−9.6)	.00027***	(49.3)
Dental Floss	.02625***	(43.7)	.00014***	(12.5)
Dentifrice	.00302***	(10.2)	.00009***	(18.7)
Denture Adhesives	.00675***	(6.9)	.00118***	(80.0)
Deodorants	.00150***	(6.1)	.00006***	(14.8)
Diapers & Disposable Bibs	.01178***	(27.5)	.00001	(1.0)
Dish Care	.00656***	(15.9)	.00018***	(26.0)
Dog Food & Treats	.00390***	(14.4)	.00002***	(4.4)
Fabric Conditioners	.01312***	(28.1)	.00023***	(27.2)
Facial Skin Care	.00463***	(15.9)	.00004***	(6.8)
Facial Tissue	.02461***	(37.3)	.00022***	(23.3)
Feminine Care	.00242***	(7.2)	.00010***	(19.9)
Hair Coloring Mens	.06091***	(58.2)	.00069***	(38.3)
Hand & Body Lotion	.00521***	(15.3)	.00010***	(13.1)
Laundry Detergent	.00489***	(14.7)	.00013***	(23.5)
Laxatives	.02142***	(39.1)	−.00003***	(−3.4)
Men's Fragrances	.02458***	(33.5)	.00003	(1.7)
Nasal Remedies	.04014***	(42.5)	.00024***	(13.9)
Oral Antiseptics	.00154**	(2.6)	.00041***	(48.8)
Pain Management	.00213***	(8.3)	.00004***	(11.5)
Paper Napkins	.02000***	(21.0)	.00093***	(45.3)
Paper Towels	.00858***	(12.0)	.00073***	(50.3)
Personal Cleansing	.00188***	(8.2)	.00009***	(21.4)
Respiratory Care	.00094***	(3.4)	.00007***	(17.0)
Salted Snacks	−.00158***	(−7.3)	.00012***	(33.1)
Sore Throat	.00822***	(17.5)	.00021***	(29.0)
Stomach Remedies	.00109**	(3.1)	.00014***	(25.2)
Surface Care	.00224***	(8.1)	.00008***	(18.2)
Toothbrushes	.01065***	(26.1)	−.00001	(−0.7)
Water Filtration	.05951***	(46.8)	.00281***	(109.4)
Women's Hair Color	.00499***	(14.6)	.00009***	(10.9)
Common Param. Int.	.00487***	(7.9)		
Cat.-Specific Int.	.00442***	(13.4)		

*Statistically significant at the 95% confidence level.
** 99%.
*** 99.9%.

relationships falls below 50 percent for brands ranked below 6th in their category.

To summarize, we find the following empirical generalizations:

1. Market share is typically convex in retail distribution at the SKU level.
2. The degree of convexity increases with category revenues and concentration in category market shares.
3. The convex relationship is usually also found within leading brands' portfolios of SKUs.

One might ask how a manufacturer could profit by knowing the location and shape of its brands' distribution/share relationships. The next section considers this question.

Existing distribution/share relationships as a check of new SKU distribution assumptions

This section shows that the distribution/share relationship among a brand's existing SKUs tends to describe its new SKUs' locations as well. Therefore, the brand's distribution/share

Table 4
Category characteristics model parameter estimates.

Category Characteristics Model	Main Effect		ACV		ACV^2		Shape of Avg. Marginal Effect for 0 < % ACV < 100
	Param. Est.	(*T*-Stat.)	Param. Est.	(*T*-Stat.)	Param. Est.	(*T*-Stat.)	
Intercept	.00014	(0.0)	.03238***	(44.1)	−.00020***	(−17.0)	Convex
Interaction with...							
Cat. Size: Large ($500MM+)	−.00407	(−1.8)	−.02361***	(−47.5)	.00017***	(21.1)	Convex
Cat. Size: Medium ($100–500MM)	−.00561**	(−3.3)	−.02376***	(−56.3)	.00014***	(19.6)	Convex
Cat. Competition: SKU-level HHI	.00009***	(11.7)	.00006***	(37.5)	.00000***	(66.7)	Convex
Cat. Value Density: High	−.00149	(−1.1)	.00297***	(9.7)	−.00001	(−1.4)	Linear
Cat. type: Food	.00261	(1.0)	−.01520***	(−26.7)	.00008***	(9.1)	Convex
Cat. type: Healthcare	.00578	(1.9)	−.01339***	(−21.9)	.00006***	(6.3)	Convex
Cat. type: Beauty	.00575	(1.8)	−.00849***	(−13.3)	.00011***	(10.0)	Convex
Cat. type: Household/Cleaning	.00258	(0.9)	−.00718***	(−12.5)	.00005***	(5.1)	Convex
Cat. type: Personal Care	.00595	(1.9)	−.01131***	(−18.7)	.00007***	(6.8)	Convex
Cat. type: Pets	.00333	(1.1)	−.00668***	(−11.7)	.00002	(1.8)	Convex

*Statistically significant at the 95% confidence level.
** 99%.
*** 99.9%.

relationship may be a useful input into the new SKU go-to-market decision.

Problem description

The successful introduction of new SKUs is critical for consumer package goods manufacturers. New SKUs help to satisfy evolving consumer tastes, deter entry and fully leverage brand equity. However, new product development is expensive and bringing a new product to market is even more expensive. Urban and Hauser (1993) gave the example of Gillette's Ultra-Max shampoo: it cost $1.9 million to develop and $19 million to launch. FTC (2001) noted there is a dearth of systematic data on product launch costs, but asserted that about $4.2 million in slotting allowances alone was required to secure national distribution in grocery stores for a new SKU, representing about 30–50 percent of the total cost of bringing a typical SKU to market.

The importance of new SKU introductions is proven by their frequency: manufacturers launched 11,128 new SKUs in the 37 categories listed in Table 1 in 2004. Despite these efforts, 29.3 percent of those new SKUs had failed *completely* by the end of the calendar year. Category-leading brands' failure rate was slightly higher than the overall rate at 32 percent, showing that new SKU failure is a broad-based phenomenon. These figures are similar to Urban and Hauser's (1993) report that 35 percent of new products fail after launch.

The go-to-market decision for a new SKU, as described by managers at a major consumer packaged goods manufacturer, consists of three steps. First, a *break-even* market share is calculated based on the fixed and variable costs associated with the new SKU. Second, a *predicted* market share is calculated based on the new SKU's market potential. Third, if the predicted market share exceeds the break-even share, the new SKU is taken to market.

The predicted market share has four inputs: (1) consumer awareness, (2) trial rates (influenced by the attractiveness of the product concept, advertising, promotions and sampling), (3) repurchase rates and quantities (influenced by relative price and product quality), and (4) retail distribution. All four inputs must be determined prior to introducing the new SKU. Consumer awareness is predicted as a function of the advertising and consumer promotion budget. Trial and repurchase are validated by a variety of means including simulated store environments, post-purchase surveys, and pretest markets.

There is little comparable guidance available as to how distribution parameters should be chosen. As Lilien, Kotler, and Moorthy (1995, p. 496) noted, "the selection of a distribution index is somewhat arbitrary and may serve more as a tuning factor than a control variable." Clancy, Shulman, and Wolf (1994, p. 282) agreed that assumptions about distribution are a major issue in improving new products' market share forecasts.

The idea that pre-launch distribution assumptions may be a key factor in new SKU failure was proposed to us by a manager at P&G who, based on his personal experience of evaluating new SKU launches across many lines of business, hypothesized this to be the primary cause of new SKU failure. Brand managers' personal involvement in new SKU development initiatives sometimes led them to act as "product champions," more interested in taking a new SKU to market than in accurately assessing whether the new SKU will be profitable for the manufacturer. The easiest way to ensure a new SKU will be introduced is to overestimate the number of stores that will sell it.

This hypothesis seemed credible for three reasons. First, prior research has shown that managerial overconfidence often leads to unprofitable entry (Camerer and Lavallo, 1999; Lowe and Ziedonis, 2006). Second, managers rotate through business units rapidly, so they are unlikely to be held accountable for overly optimistic distribution forecasts. This potential principal/agent problem is consistent with the idea in Lilien et al. (1995) that the distribution assumption may be used as a tuning factor. Third, post-launch assessments of failed SKUs are rare. In fact, pre-launch decision inputs are seldom recorded completely, frustrating systematic evaluations of causes of new SKU

Table 5
Brand-specific parameter estimates.

	Leading brand				2nd brand				3rd brand				9th brand			
	%ACV		*%ACV*^{2}		*%ACV*		*%ACV*^{2}		*%ACV*		*%ACV*^{2}		*%ACV*		*%ACV*^{2}	
	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)	Param. Est.	(*T*-Stat)
Interaction with...																
Air Care	.00539***	(12.3)	.00005***	(5.8)	.00344***	(4.8)	.00008***	(5.8)	.00911***	(8.9)	.00008***	(5.3)	.00395	(1.6)	.00006	(1.2)
Baby/Kid Wipes	.01445***	(15.1)	.00034***	(23.1)	.03493***	(24.0)	−.00003	(−1.1)	.04050***	(12.0)	−.00024***	(−3.5)	.01403	(1.4)	−.00004	(0.0)
Bath Tissue	.00196*	(2.5)	.00050***	(34.7)	.00958***	(9.5)	.00018***	(11.4)	.00360**	(3.2)	.00047***	(23.3)	.00661	(0.2)	.00313	(0.5)
Bleach	−.14289***	(−108.4)	.00280***	(149.3)	.00866***	(5.9)	.00028***	(10.8)	.00668***	(3.8)	.00024***	(8.5)	.03160	(1.1)	−.00014	(−0.3)
Car Care	.08409***	(35.7)	.00121***	(21.2)	.00934	(1.3)	.01096***	(45.1)	.12405***	(32.6)	−.00130***	(−7.7)	.05403	(1.6)	.00405	(1.3)
Cat Food & Treats	.00439***	(13.6)	.00003***	(5.9)	.00059	(0.7)	.00018***	(9.7)	.00148*	(2.2)	.00005***	(4.1)	.01015**	(3.0)	.00001	(0.1)
Coffee	−.01086***	(−20.2)	.00045***	(52.9)	−.00175**	(−2.7)	.00029***	(25.9)	−.00714***	(−5.1)	.00034***	(13.1)	.00004	(0.0)	.00042**	(2.9)
Dental Floss	.01919***	(22.8)	.00017***	(12.7)	.02471***	(17.1)	.00038***	(15.1)	.01977***	(14.5)	.00023***	(8.0)	.01606*	(2.0)	.00037	(1.6)
Dentifrice	.00523***	(11.1)	.00009***	(11.7)	.00260***	(5.8)	.00009***	(12.9)	.00367***	(4.5)	.00005**	(3.1)	.00232	(0.9)	.00011	(1.1)
Denture Adhesives	−.00387**	(−3.1)	.00147***	(85.7)	.03294***	(20.9)	.00067***	(25.2)	.04825***	(19.8)	−.00003	(−0.7)	.06965	(0.7)	.00156	(0.1)
Deodorants	.00250***	(4.2)	.00004***	(4.3)	.00138*	(2.3)	.00005***	(5.1)	.00122*	(2.0)	.00007***	(6.8)	.00279**	(3.0)	.00004*	(2.0)
Diapers/Bibs	.01410***	(21.0)	−.00001	(−1.4)	.01621***	(24.3)	−.00005***	(−4.6)	.00796***	(6.4)	.00005**	(2.6)	.00879**	(2.8)	−.00006	(−0.7)
Dish Care	.01051***	(15.1)	.00020***	(16.9)	.00467***	(6.5)	.00019***	(17.6)	.00834***	(10.5)	.00012***	(7.9)	−.00251	(−1.1)	.00036***	(10.6)
Dog Food & Treats	.00412***	(11.8)	.00002***	(3.7)	.00618***	(12.5)	−.00004***	(−4.3)	−.00073	(−0.9)	.00018***	(10.9)	−.00134	(−0.2)	.00193	(1.7)
Fabric Conditioners	.01581***	(25.2)	.00020***	(19.0)	.01519***	(15.1)	.00019***	(12.2)	.00899***	(6.4)	.00025***	(6.1)	.01046**	(2.6)	.00009	(0.6)
Facial Skin Care	.00651***	(7.4)	.00003	(1.6)	.00572***	(6.1)	.00002	(1.2)	.01063***	(3.4)	.00010	(1.3)	.00072	(0.6)	.00008***	(4.4)
Facial Tissue	.01718***	(24.9)	.00031***	(32.6)	.03140***	(30.1)	.00013***	(8.8)	.03797***	(13.4)	.00015	(1.9)	.04963	(0.9)	.00019	(0.1)
Feminine Care	.00161**	(2.8)	.00014***	(17.4)	.00312***	(5.1)	.00006***	(7.7)	.00271***	(3.9)	.00011***	(12.0)	.00288	(0.2)	.00028	(0.2)
Hair Coloring Mens	.07513***	(56.5)	.00051***	(24.1)	.07011***	(37.3)	−.00030***	(−6.1)	.09227***	(10.3)	.00006	(0.1)	.06903	(0.1)	−.00788	(0.0)
Hand & Body Lotion	.00325*	(2.3)	.00017***	(6.2)	.00599***	(4.3)	.00013***	(5.0)	.00547***	(3.6)	.00014***	(4.2)	.01213***	(6.2)	−.00003	(−0.9)
Laundry Detergent	.00477***	(9.6)	.00017***	(22.1)	.00281***	(3.4)	.00013***	(11.0)	.00827***	(8.7)	.00006**	(3.2)	.00851***	(4.1)	.00014**	(3.3)
Laxatives	.01706***	(12.4)	.00011***	(3.9)	.01277***	(10.3)	.00003	(1.4)	.01169***	(6.6)	.00022***	(5.7)	.01424***	(5.3)	.00020***	(3.8)
Men's Fragrances	.02314***	(15.8)	.00016***	(6.1)	.04539***	(9.3)	−.00078	(−1.5)	.04348***	(14.3)	−.00101***	(−6.6)	.01436***	(6.4)	.00013**	(2.7)
Nasal Remedies	.04689***	(29.1)	.00011***	(3.8)	.04035***	(21.4)	.00033***	(11.6)	.02970***	(11.3)	.00033***	(6.8)	.07666	(1.4)	−.00056	(−0.3)
Oral Antiseptics	.01077***	(11.8)	.00034***	(28.7)	.00262*	(2.5)	.00027***	(17.4)	−.00101	(−0.4)	.00035***	(8.6)	.00832	(1.7)	.00017	(0.9)
Pain Management	.00306***	(6.1)	.00004***	(5.1)	.00223***	(3.6)	.00007***	(7.6)	.00116	(1.2)	.00005***	(3.8)	.00448	(1.6)	.00008	(0.4)
Paper Napkins	.00355	(1.4)	.00198***	(35.9)	.04737***	(16.7)	.00035***	(7.5)	−.00097	(−0.2)	.00194***	(17.9)	.00213	(0.6)	.00033	(1.5)
Paper Towels	.01513***	(17.7)	.00078***	(46.9)	.00125	(0.9)	.00073***	(26.8)	−.00957***	(−4.6)	.00090***	(23.2)	.36645	(0.7)	−.27144	(−0.5)
Personal Cleansing	.00622***	(10.5)	.00010***	(11.1)	.00324***	(6.4)	.00005***	(6.1)	.00481***	(8.0)	.00000	(0.4)	.00219*	(2.5)	.00003	(1.6)
Respiratory Care	.00259**	(3.2)	.00004**	(3.1)	.00150	(1.1)	.00007***	(4.2)	.00864***	(4.9)	.00007**	(2.9)	.00437*	(2.2)	.00003	(0.9)
Salted Snacks	−.00191***	(−3.5)	.00019***	(23.1)	−.00990***	(−14.4)	.00028***	(28.0)	−.00484***	(−4.6)	.00024***	(16.4)	.00656***	(5.0)	−.00001	(−0.3)
Sore Throat	.00729***	(12.0)	.00022***	(25.5)	.00741***	(6.3)	.00024***	(12.1)	.00905***	(6.8)	.00023***	(12.1)	.01892***	(3.6)	−.00029	(−1.0)
Stomach Remedies	.09444***	(35.6)	−.00022***	(−6.6)	.00926***	(9.3)	.00001	(0.8)	.00219***	(3.4)	.00005***	(5.5)	.00486***	(4.5)	.00002	(1.1)
Surface Care	.00879***	(8.7)	.00005**	(3.2)	.00062	(0.8)	.00011***	(10.0)	.00167*	(2.1)	.00007***	(5.1)	.00047	(0.1)	.00020*	(2.1)
Toothbrushes	.00912***	(13.3)	.00002*	(2.1)	.00635***	(8.2)	.00003*	(2.4)	.00721***	(4.7)	.00066***	(18.0)	.00544*	(2.4)	.00004	(0.7)
Water Filtration	.03423***	(25.9)	.00324***	(129.7)	.13342***	(41.6)	−.00042*	(−2.0)	.02285	(1.1)	.00761	(1.3)	.01432	(0.0)	.00841	(0.0)
Women's HC	.00401***	(4.2)	.00013***	(6.6)	.00422***	(5.0)	.00008***	(4.5)	.00426***	(4.0)	.00012***	(4.8)	.00464**	(3.0)	.00013*	(2.2)

Table 6
Counts of convex brand-specific relationships.

	Convex relationship estimated* for. . .									
	1st brand	2nd brand	3rd brand	4th brand	5th brand	6th brand	7th brand	8th brand	9th brand	Count convex
Air Care	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	7
Baby/Kid Wipes	Yes	No	No	No	No	No	Yes	No	No	2
Bath Tissue	Yes	Yes	Yes	Yes	Yes	No	No	No	No	5
Bleach	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	7
Car Care	Yes	Yes	No	No	No	Yes	No	No	No	3
Cat Food & Treats	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	6
Coffee	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	7
Dental Floss	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	7
Dentifrice	Yes	Yes	Yes	Yes	Yes	No	No	No	No	5
Denture Adhesives	Yes	Yes	No	No	No	Yes	No	Yes	No	4
Deodorants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	9
Diapers/Bibs	No	No	Yes	No	No	No	No	No	No	1
Dish Care	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	8
Dog Food & Treats	Yes	No	Yes	Yes	Yes	No	No	No	No	4
Fabric Conditioners	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	6
Facial Skin Care	No	No	No	Yes	Yes	No	Yes	Yes	Yes	5
Facial Tissue	Yes	Yes	No	Yes	No	No	No	No	No	3
Feminine Care	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	6
Hair Coloring Mens	Yes	No	No	No	No	No	No	No	No	1
Hand & Body Lotion	Yes	Yes	Yes	No	Yes	No	No	Yes	No	5
Laundry Detergent	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	7
Laxatives	Yes	No	Yes	No	Yes	No	Yes	No	Yes	5
Men’s Fragrances	Yes	No	No	Yes	Yes	Yes	No	No	Yes	5
Nasal Remedies	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	6
Oral Antiseptics	Yes	Yes	Yes	Yes	No	Yes	No	No	No	5
Pain Management	Yes	Yes	Yes	No	Yes	Yes	No	Yes	No	6
Paper Napkins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	8
Paper Towels	Yes	Yes	Yes	No	Yes	No	No	No	No	4
Personal Cleansing	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	6
Respiratory Care	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	6
Salted Snacks	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	7
Sore Throat	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	6
Stomach Remedies	No	No	Yes	Yes	Yes	No	No	No	No	3
Surface Care	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	9
Toothbrushes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	5
Water Filtration	Yes	No	No	No	No	No	No	No	No	1
Women’s HC	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	7
Count convex	34	28	28	22	26	22	14	14	9	

* “yes” indicates that the category-brandrank-specific effect of ACV^2 is positive and statistically at the 95% confidence level.

failure. We investigated tens of thousands of new SKU launches recorded by a major CPG manufacturer over two decades. We found that pre-launch distribution assumptions were recorded for only 15 percent of new SKU launches and that these 15 percent of launches were typically missing other important pre-launch data like awareness, trial, and repurchase. Less than 1 percent of all new SKU records contained complete pre-launch assumptions about all four inputs.

A brand’s existing distribution/share relationship is insufficient to predict a new SKU’s distribution level, as it does not contain information about the new SKU’s attributes or target market. However, it can provide a means to assess whether the new SKU’s predicted market share and the retail distribution assumption used to calculate it are consistent with the patterns observed within the brand’s portfolio of existing SKUs.

As important as this problem seems to be, we have not been able to find any previously published techniques to address it. Even an imperfect means to assess the realism of a new SKU’s pre-launch distribution assumption should be helpful.

Evidence from holdout samples

The goal is to gauge the usefulness of the distribution/share relationship in assessing new SKU distribution/share relationships. To do this, brand-specific distribution/share relationships were estimated using SKU data from 2004 only, excluding all 2005 data.[4] Then, a standard fit statistic was calculated to determine how well the relationship estimated using 2004 data

[4] Given the outliers in Table 1, we used Weighted Least Squares to control for localized heterogeneity. The weights were given by the inverse of each SKU’s %ACV. These results were qualitatively similar but slightly better than OLS. A more comprehensive approach to controlling for local heteroskedasticity is Local Polynomial Regression.

predicted the locations in distribution/share space for the brand's new SKUs introduced in 2005.

More formally, let K_j be the number of new SKUs introduced by brand j in 2005. Let *%ACV* be a K_j-vector of those SKUs' average quarterly %ACV levels,[5] let s_j be a K_j-vector of their market shares, and let $\hat{s}_{04}(\%ACV)$ be the market share predicted at distribution level *%ACV* by the brand-specific relationship estimated from the brand's existing SKUs in 2004. The degree to which the 2004 curve explains the new SKUs' location s in 2005 is $R^2 = 1 - \frac{[s_j - \hat{s}_{04}(\%ACV)]^T [s_j - \hat{s}_{04}(\%ACV)]}{(s_j - \bar{s})^T (s_j - \bar{s})}$, where $\bar{s}$ is the mean of s_j and T is the vector transpose operator.

This Pseudo R^2 statistic shows the degree to which the 2004 relationship predicted the 2005 new SKUs' locations better than a constant. If it lies between 0 and 1, it can be interpreted as the proportion of 2005 new SKUs' variance explained by the distribution/share relationship estimated from the existing SKUs in 2004. However, when the statistic is below zero, then a constant (more specifically, $\bar{s}$) is a better predictor. The farther below zero this statistic is, the worse the predictive ability of the existing SKUs' relationship relative to the new SKUs' mean share. When the mean share is a very good predictor, then $(s_j - \bar{s})^T (s_j - \bar{s})$ goes to zero, and the Pseudo R^2 statistic will go to negative infinity; therefore the Pseudo R^2 statistic may range from negative infinity to one. Because a small number of points may be predicted quite well by a constant, regardless of their consistency or inconsistency with the brand's existing distribution/share relationship, the analysis focuses on the 57 brands that introduced 8 or more new SKUs in 2005, and that were ranked among the top 3 in their product category.

Table 7 shows that the 2004 brand-specific existing distribution/share curves generally explain the variation in new SKUs' market shares quite well. Among leading brands, the median Pseudo R^2 is 0.61; for second-ranked brands, the median Pseudo R^2 is 0.67; and within third brands, the median Pseudo R^2 is 0.59. The Pseudo R^2 exceeded 0.5 for 25 out of 32 (78 percent) eligible leading brands, 18 of 28 (64 percent) second brands, and 14 of 22 (64 percent) third brands.

Fig. 4 illustrates how these relationships may be useful in a particular product category, Dog Food. The market leader, Purina, introduced 53 new SKUs in 2005. The relationship estimated using its 2004 SKUs' data explained 78 percent of the variation observed in those new SKUs' market shares. Similarly, 59 percent of the variation in Pedigree's 17 new SKU market shares can be explained by the relationship estimated using 2004 data.

However, unlike Purina and Pedigree, the 2004 relationship for the third brand (Iams) predicted its 21 new SKUs' locations very poorly, with a Pseudo R^2 of -14.18. This is because all of Iams' 21 new SKUs produced much lower levels of market share per point of retail distribution than the brand's existing SKUs did the previous year. Generally, points to the right of the curve have acquired too much distribution relative to their share, or have produced too little share per point of distribution. Absent marketer intervention to increase consumer demand, we would expect these items to lose both distribution and share as retailers drop them. Regardless of whether this poor performance came from consumer demand or retailers' expectations, SKUs that debut in this area of the distribution-share space are overwhelmingly likely to be withdrawn from the market.

In addition to the Pseudo R^2 statistic, Table 7 reports the mean relative prediction error for each brand's new SKUs. This is degree to which the average new SKU performed relative to the brand's portfolio of existing SKUs in 2004.

The Pseudo R^2 statistic was negative for eleven brands, as shown in bold in Table 7. In *all* of those cases, the cause of the low fit statistic was that the brand's new SKUs *underperformed* its existing product line. This can be seen in the mean relative prediction errors; they are always negative when the Pseudo R^2 statistic is negative.

In other words, there is a perfect correspondence at the brand level between the lack of a predictive relationship and new SKU underperformance. There were no brands whose new SKUs systematically gained more market share per point of retail distribution than the brand's existing SKU portfolio. This is consistent with the discussion above that the distribution assumption may be used as a tuning factor in go-to-market decisions for new SKUs.

Managerial implications

Existing distribution/share relationships normally predict new SKU performance well, *except* in cases that new SKUs underperform the existing product line. In fact, there was a perfect correspondence between poor predictions and poor new SKU performance.

Therefore, the relationship between distribution and market share for *existing* SKUs can be useful in the go-to-market decision for *new* SKUs. If the distribution assumption and predicted market share of a new SKU are inconsistent with the existing distribution/share relationship among the brand's existing SKUs, then the manufacturer should probably reconsider whether it will be profitable to take this SKU to market. At a minimum, an independent assessment of the assumptions used to calculate the new SKU's predicted market share should be undertaken.

As an example, consider the Iams panel in Fig. 4. Suppose that at the end of 2004, Iams considers whether to introduce a particular new SKU in 2005. It calculates the break-even share required for profitability to be 0.1 percent (in basis points). The data from Iams' existing product line suggests that a distribution level of about 21, plus or minus 5, is consistent with this break-even share. If the distribution assumption for the new SKU is a %ACV of about 24, then no concern needs to be raised about the process used to take the new SKU to market. On the other hand, if the distribution assumption were a %ACV of 45 and the new SKU's predicted share were 0.11, then one might suspect that a product champion had used the distribution assumption as a tuning factor to achieve the goal of taking the new SKU to market. This is the case in which an independent assessment of the rationale for the distribution assumption would be

[5] This average was calculated using quarters in which the new SKU achieved positive %ACV. For example, if a new SKU had quarterly %ACV figures of 0, 10, 4 and 0 in 2005, its average %ACV is computed as 7.

Table 7
2005 new SKU outcomes and predictions by 2004 distribution/share relationship.

	Leading brand					Second brand					Third brand				
	# new SKUs in 2005	Avg. new SKU %ACV	Avg. new Sku share (basis pts.)	Pseudo *R*-sq stat. for 2005 new SKUs	Mean Rel. Pred. Err.	# new SKUs in 2005	Avg. new SKU %ACV	Avg. new Sku share (basis pts.)	Pseudo *R*-sq Stat. for 2005 new SKUs	Mean Rel. Pred. Err.	# new SKUs in 2005	Avg. new SKU %ACV	Avg. new Sku share (basis pts.)	Pseudo *R*-sq Stat. for 2005 new SKUs	Mean Rel. Pred. Err.
Salted Snacks	43	19	0.23	0.58	37%	7	3	0.01	4	5	0.02				
Bath Tissue	40	17	0.41	0.85	10%	7	11	0.15	16	18	0.45	0.59	47%		
Laundry Detergent	44	12	0.11	0.22	−21%	14	9	0.05	0.93	−1%	15	12	0.08	0.47	−49%
Dog Food and Treats	53	9	0.05	0.78	3%	17	12	0.09	0.59	32%	21	13	0.02	**−14.18**	**−191%**
Coffee	9	3	0.04	**−0.42**	**−32%**	7	3	0.04			12	1	0.01	**−1.69**	**−33%**
Pain Management	34	15	0.10	0.79	27%	8	3	0.02			3	4	0.01		
Diapers & Disp. Bibs	22	4	0.10	0.58	32%	15	13	0.27	0.55	18%	32	10	0.07	**−0.78**	**−95%**
Paper Towels	19	5	0.10	**−3.90**	**−39%**	1	2	0.03	5	3	0.07				
Surface Care	9	8	0.06	0.58	−33%	11	14	0.11	0.62	19%	7	12	0.05		
Cat Food and Treats	37	16	0.09	0.72	1%	17	18	0.04	**−9.04**	**−149%**	2	6	0.02		
Personal Cleansing	39	7	0.07	0.91	6%	40	7	0.03	0.79	−6%	39	6	0.03	0.88	5%
Facial Skin Care	22	3	0.02	0.63	−12%	9	8	0.04	0.91	−13%	16	6	0.08	0.93	10%
Feminine Care	15	16	0.12	0.49	31%	33	5	0.02	0.20	−16%	9	18	0.09	**−0.19**	**−7%**
Stomach Remedies	5	3	0.11			7	2	0.02			18	4	0.01	0.74	−16%
Air Care	33	20	0.20	0.22	35%	26	20	0.14	0.41	4%	11	10	0.11	0.71	−15%
Deoderants	17	15	0.06	0.80	−6%	12	23	0.09	0.88	18%	18	11	0.05	0.79	7%
Dish Care	7	7	0.10			17	12	0.15	0.92	17%	11	6	0.08	0.52	19%
Facial Tissue	35	21	0.72	0.78	20%	2	2	0.03			0				
Fabric Conditioners	20	8	0.12	**−0.89**	**−32%**	10	8	0.15	0.71	−8%	9	3	0.04	0.80	15%
Women’s Hair Color	24	3	0.02	0.95	12%	22	20	0.13	0.91	9%	2	16	0.12		
Toothbrushes	19	14	0.23	0.70	40%	18	14	0.14	0.72	21%	6	2	0.10		
Oral Antiseptics	13	8	0.45	0.65	57%	13	14	0.12	**−0.19**	**−52%**	3	3	0.02		
Baby/Kid Wipes	10	1	0.02	**−1.48**	**−130%**	7	6	0.10			1	1	0.02		
Men’s Fragrances	7	3	0.14	25	2	0.12	0.54	24%	16	2	0.15	0.12	54%		
Dental Floss	60	9	0.09	0.30	22%	43	8	0.04	0.49	−8%	11	8	0.04	0.79	17%
Denture Adhesives	10	3	0.13	**−0.89**	**−58%**	1	49	3.69	0						
Walter Filtration	9	3	0.27	0.76	−8%	28	4	0.57	0.84	−1%	1	0	0.01		
Median	14	8	0.11	0.61	5%	9	8	0.09	0.67	2%	5	6	0.07	0.59	5%

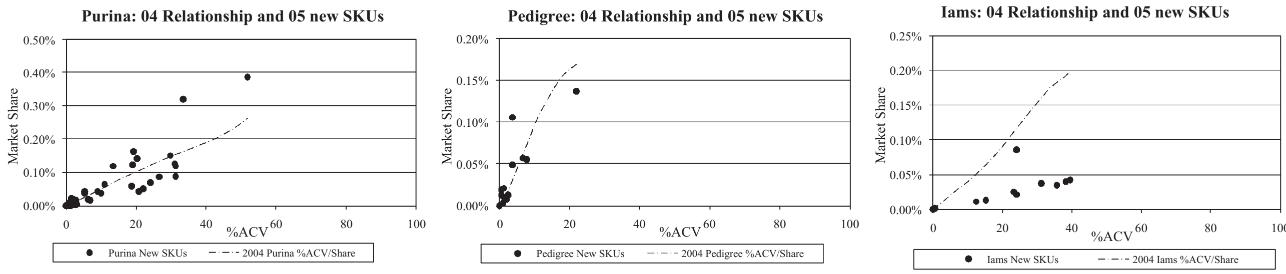

Fig. 4. 2004 brand-specific market-share/distribution relationships and 2005 new products.

advisable prior to launching the new SKU. If the SKU is still launched, it would also be smart to conduct an *ex post* review of how the pre-launch distribution assumption was validated by the marketplace.

It is important to note that implementing this suggestion may require some shifts in the way some manufacturers operate. Perhaps the most important would be some centralization of operations, to ensure that there is a quasi-independent check of managers' pre-launch distribution assumptions. However, if implemented poorly, the possible downside to such a check would be to reduce the speed with which a new SKU could be taken to market.

Discussion

This paper has analyzed data from a census of stock-keeping units in 37 product categories to uncover new empirical generalizations about the cross-sectional relationship between distribution and market share. Market share is usually increasing and convex in retail distribution, both across brands in a category as well as across SKUs within a leading brand. These findings show that the "double jeopardy" phenomenon faced by small brands is also faced by low-share SKUs within category leaders' product lines. Distribution/share relationships show greater degrees of convexity in larger product categories and more concentrated categories.

Further, holdout validation showed that a brand's existing distribution/share relationship is normally a good predictor of the future relationship between distribution and market share for the brand's new SKUs. Therefore, knowledge of this relationship may help manufacturers avoid unprofitable go-to-market decisions for new SKUs.

This article did not seek to estimate a causal relationship between distribution and market share. This has been a frequent topic of past research and remains a promising direction for further research at the SKU level. Two approaches are available. One is to find good instrumental variables that influence current distribution but not market share. A candidate instrument would be something that influences retailer adoption without directly influencing consumer purchases, such as slotting allowances or other trade promotions. The other possible approach would be to implement a dynamic panel estimator (e.g., Arellano and Bond, 1991), although this would require a longer time series than the one available in this paper.

Another fruitful direction for future research would be to do a retrospective study on the causes and consequences of unprofitable new SKU launches. Numerous approaches could be taken to study this important topic. We hope that the generalizations provided by this article can both reduce the number of unprofitable new SKU launches and stimulate more research in this important area.

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