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Brand-level Effects of SKU Reductions

Jie Zhang and Aradhna Krishna

When retailers reduce product assortment, how do shoppers re-allocate their purchases? This brand-level analysis examines the effects of SKU reductions on store brands and how market share may shift between brands of different profitability. Overall, the researchers find, SKU reductions have a negative impact on category purchase incidence, sales quantities, and revenue.

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Report Summary

When retailers make product assortment changes by eliminating certain stock keeping units (SKUs), how does this affect sales of individual brands? That is the main question Jie Zhang and Aradhna Krishna address in this study. Previous research on product assortment changes has primarily focused on their impact at the store and product category levels. While a category- or store-level analysis is very useful for retailers, a brand-level analysis has direct relevance not only for retailers but also for manufacturers.

Utilizing data from an online retailer who implemented a permanent systemwide SKU reduction program, the authors investigate how consumers reallocate purchases among the remaining brands. They use a joint model of purchase incidence, brand choice, and quantity and then conduct a "would-be" analysis that controls for changes in the marketing mix before and after the SKU reductions.

The results reveal substantial differences in how brands are affected by the SKU reductions. In

exploring possible factors driving those differences, the authors find that reduction in the number of brand sizes offered has more influence over a brand's purchase share after an SKU reduction than the reduction in the number of SKUs. They also find that brands with higher market share and those with frequent promotions tend to gain share and that an increase in a brand's share of SKUs in the category increases its share of purchases.

These findings suggest that the practice of deleting SKUs based on their share of brand sales should be used with caution, because eliminated SKUs' share of brand sales does not appear to be a good predictor of the change in a brand's sales after the SKU reduction. Finally, the results indicate that the SKU reduction effects on category purchase incidence, sales quantities, and revenue are generally negative, although the extent varies by category. Retailers seeking to make product assortment changes and manufacturers affected by those changes will both find the study's results of interest. ■

Introduction

In the last two decades, supermarkets have experienced a stock keeping unit (SKU) explosion (Kurt Salmon Associates 1993; Drèze, Hoch, and Purk 1994), with manufacturers seeing SKU proliferation as a way to increase their presence and market shares and retailers fearing that eliminating items could lower consumer assortment perceptions and decrease store visits. More recently, however, the higher costs of maintaining a large number of SKUs and competition from lower-cost alternative-format retailers such as Wal-Mart and Costco have driven many retailers to experiment with SKU reduction programs. Many grocery retailers have adopted efficient assortment policies, eliminating low-selling stock keeping units (Kurt Salmon Associates 1993). Marketing academics too have cast doubt on the value of SKU proliferation.

Some studies have shown that retailers can eliminate a substantial number of SKUs without negatively affecting consumers' assortment perceptions, store visits, or category sales (Arnold, Oum, and Tigert 1983; Broniarczyk, Hoyer, and McAlister 1998). Other studies, however, have shown that SKU reduction can decrease store-level shopping frequency and purchase quantity (Boatwright et al. 2004). An important unanswered question is how elimination of certain SKUs in the product assortment affects sales of individual brands. That is the main question we address in this research. Using data from a permanent SKU reduction program implemented by an online retailer, we examine how consumers reallocate their purchases among the remaining brands after certain SKUs are eliminated. To lead up to this analysis, we also take an in-depth look at the effects of SKU reduction on category purchase incidence, brand choice, and purchase quantity.[1]

Prior research on SKU reduction (henceforth called SR) has focused on the impact of SR on the category or on the store, but not on individual brands. While a category- or store-level analysis is very useful for retailers, a brand-level analysis is useful not only for retailers but also for manufacturers. To a manufacturer, the most relevant issue related to SR is what happens to the manufacturer's brand(s) after the SR program is implemented. A related question is what the manufacturer can do to emphasize the brands' strengths and minimize negative consequences from the SR. For retailers, a brand-level analysis provides information about what may happen to store brands as a result of SR. It also reveals how market share may shift between different brands (which could yield different profits for retailers). This perspective is not possible with a store- or category-level analysis.

Our findings control for changes in the marketing mix before and after SR. As we show, such an analysis prevents the drawing of spurious conclusions. We explore plausible drivers of differences in SR effects among brands. We examine two groups of brand-specific factors: brand characteristics (e.g., market share, price level, promotion frequency, store versus national brand), and the nature of the SR (e.g., number of SKUs eliminated, change in the share of SKUs, number of sizes eliminated, share of brand sales eliminated). Both manufacturers and retailers benefit from understanding the effects of these factors. Our research should help answer the following questions:

- Are certain types of brands more likely to gain market share and others more likely to lose market share after an SR? For instance, do larger-share brands become even larger, or are they more likely to lose share to smaller-share brands?
- Do brands with frequent promotions get a greater share of purchases in the post-SR market share reallocation period?
- What are the significant drivers of SR effects on brand choice?
- Is it a good practice to eliminate SKUs based on their share of their brand's sales?
- Which is the more significant determinant of brand share change after SR—the number of sizes deleted or the number of SKUs eliminated?

Table 1
Some Research Findings on SKU Reduction (SR)

Study	Consumer Assortment Perceptions	Category Purchase Probability and Category Sales	Store Choice, Store Shopping Frequency,and Store Sales
Broniarczyk, Hoyer, and McAlister (1998)	Moderate SR (as much as 25%) did not affect consumers' assortment perception as long as their favorite items were available and category space was held constant.	Two stores that eliminated their lowest-selling SKUs in five top categories (candy, beer, soft drinks, salty snacks, and cigarettes) experienced a sales increase (2% and 8%) in the five categories over the control stores.	Moderate SR did not affect consumers' store choice as long as their favorite items were available and category space was held constant.
Dreze, Hoch, and Purk (1994)		Category sales increased by approximately 4% when low-selling SKUs were removed and the space made available was allocated to high-selling items.	
Boatwright and Nunes (2001)		After SR, sales increased an average of 11% across the 42 categories examined. Sales rose in more than two-thirds of the categories. Category purchase probability dropped slightly, but it was compensated by increase in average sales per purchase occasion.	
Boatwright, Borle, Kadane, and Nunes (2004)		For a majority of categories, reduction in favorite items caused no changes in the category purchase incidence nor the category's share of the basket.	Store-level expected inter-purchase time increased by 23.4% on average and purchase spending during each store visit decreased by an average of 4.2% after SR.

■ Is it valid to look at change in market share as a proxy for the effect of SR on the probability of a brand's being chosen, or are changes in marketing-mix variables likely to be confounded with SR changes, thereby resulting in spurious conclusions?

We also explore systematic differences in reaction to SR across consumer segments. The online store environment we use for our analyses provides a unique opportunity to study the impact of assortment changes without confounding it with the effects of product display, shelf space allocation, or location on the shelf (Boatwright and Nunes 2001).

Literature Review

Prior research on product assortment changes has mainly looked at its impact on consumers' assortment perceptions, category-level purchase probability and sales, store choice, store shopping frequency, and store-level sales. Table 1 organizes key findings from prior research along these dimensions. These are based on four major studies, which we describe briefly below.

Broniarczyk, Hoyer, and McAlister (1998) examined how changes in product assortment affected consumers' perceptions of the assort-

ment size, which in turn were shown to influence their store choice. In their field study, two stores eliminated 54% of low-selling SKUs in five top categories (candy, beer, soft drinks, salty snacks, and cigarettes). The two stores experienced sales increases (2% and 8%, respectively) in the five categories over the control stores. In addition, shoppers reported finding it easier to shop in the test stores than in the control stores. SKU count, availability of favorites, and category space were found to affect store choice through assortment perception, and availability of favorites also had a direct link to store choice.

Drèze, Hoch, and Purk (1994) conducted a series of field experiments to measure the effectiveness of two shelf management techniques: space-to-movement, in which shelf sets are customized based on store-specific movement patterns, and product reorganization, in which product placement is manipulated to facilitate cross-category merchandising or ease of shopping. They also looked at the impact that shelf positioning and facing allocations had on sales of individual items. In their experiments, they found that category sales increased by nearly 4% when low-selling SKUs were deleted and the resultant available shelf facing was given to high-selling items. While Drèze, Hoch, and Purk (1994) studied the effects of shelf positioning and facing allocation on sales of individual brands, we focus on the effects of eliminating certain SKUs for each brand, controlling for the influence of shelf positioning and facing allocation.

More recently, Boatwright et al. (2004) examined purchase data from an SR experiment in which data were collected before and after SR for a large number of categories. They looked at the effects of SR on store and category purchase frequency and dollar sales and found negative results: both shopping frequency and purchase spending on each shopping trip declined as a result of SR. At the store level, they found that SR led to an average increase of 23.4% in expected interpurchase time and an average decrease of 4.2% in expected purchase spending per shopping trip. At the category level, for a

majority of categories, reduction in favorite items caused no change in category purchase incidence probability or in the category's share of the basket. The assortment reduction had a greater effect on store visit frequency than on purchase spending per visit.

The divergent findings in these studies suggest that more research is needed on the impact of SR. Moreover, none of these papers focused on brand-level effects of SR. It is also worth noting another way in which our study differs from the one by Boatwright et al. (2004): while purchase quantities in their study are measured in dollar amount, which could confound changes in purchase volume (in units) with changes in price, we model changes in purchase volume (in units) directly. We then examine the impact of SR on sales revenue based on volume and price. This provides a clearer picture of the impact of SR on each element of the purchase decision.

Model Formulation

We investigate the impact of SR on three components of individual household purchase behavior: category purchase incidence, brand choice, and purchase quantity. Previous research has shown that it is important to take into account interdependence in these components (e.g., Chiang 1991; Chintagunta 1993). We model these three purchase components jointly, using an approach similar to Hanemann (1984), Chiang (1991), Chintagunta (1993), Bell, Chiang, and Padmanabhan (1999), and Zhang and Krishnamurthi (2004).

To assess the impact of SR, one needs to control for the effects of other marketing-mix variables because they may change over the time period used for examining the impact of the SR. Our model controls for the effects of these variables, in particular the two most important ones, price and promotion.[2] A closer look at the data reveals that price and promotion did experience non-trivial changes during the time period under investigation, and there was an increase in the

overall category price and promotion levels in general (discussed in greater detail later).[3] Since we are particularly interested in brand-level effects of SR, such as to what type of brands consumers tend to switch after others are eliminated, we estimate the model using only brands that remained in the store after the SR. In such a model, the change in the conditional brand choice probability gives a direct indication of whether the brand has gained or lost market share as a result of the SR, controlling for a potential share increase for each remaining brand merely due to the elimination of other brands.

We describe each element of the model formulation as follows:

I_{it} = 1 if household i makes a category purchase in week t, 0 otherwise; B_{ikt} = 1 if household i purchases brand k in week t, 0 otherwise; Q_{ikt} = household i's purchase quantity of brand k in week t; SR_t = 0 if the time was before the SR, 1 if the time was after the SR.

The utility of brand k at time t for household i is given by:

$$U_{ikt} = \delta_{ki}^B SR_t + V_{ikt} + \varepsilon_{ikt}$$
$$= \delta_{ki}^B SR_t + \alpha_{ki} + X_{kt}\beta_i + \gamma_i LB_{ikt} + \varepsilon_{ikt}, k = 1, ..., K, \quad (1)$$

where α_{ki}, $k = 1, …, K−1$ are brand-specific constants, X_{kt} is a vector of marketing-mix variables including regular price and price cut, and LB_{ikt} = 1 if brand k was chosen by household i on the previous purchase occasion. β_i are coefficients of marketing-mix variables. The parameter γ_i measures a household's state dependence and is usually interpreted as an indicator of inertia ($\gamma_i > 0$) or variety seeking ($\gamma_i < 0$) by marketing researchers (e.g., Gupta, Chintagunta, and Wittink 1997; Seetharaman, Ainslie, and Chintagunta 1999). δ_{ki}^B, $k = 1, …, K−1$, captures the effect of the SR on each brand's utility for household i. α_{Ki} and δ_{Ki}^B are fixed to 0 for identification purposes.

Purchase incidence is modeled by assuming that household i makes a category purchase at t

if and only if at least one brand's utility in the category exceeds a threshold. We specify the category threshold as:

$$U_{i0t} = \delta_i^I SR_t + V_{i0t} + \varepsilon_{i0t} = \delta_i^I SR_t + \theta_{0i} + Y_{it}\theta_i + \varepsilon_{i0t} \quad (2)$$

where θ_{0i} is a constant, Y_{it} is a vector of covariates including a household's average purchase frequency in the initialization period ($FREQ_i$) and its mean-centered last-purchase quantity (LQ_{it}) (measured in ounces), and θ_i are coefficients of the covariates. The last-purchase quantity variable captures the effect of inventory in spirit (Jain and Vilcassim 1991; Chintagunta and Haldar 1998).[4] δ_i^I measures the effect of the SR on the threshold.

To model purchase quantities, let Q_{ikt}^* be a latent variable of household i's purchase quantity of brand k in week t. The observed purchase quantity $Q_{ikt} = Q_{ikt}^*$ if I_{it} = 1 and B_{ikt} = 1; Q_{ikt} = 0 otherwise. Q_{ikt}^* is specified as:

$$Q_{ikt}^* = \delta_i^Q SR_t + W_{ikt} + \xi_{ikt}$$
$$= \delta_i^Q SR_t + \phi_{0ki} + Z_{ikt}\phi_i + \xi_{ikt}, k = 1, ..., K, \quad (3)$$

where ϕ_{0kt} is a constant for brand k, Z_{ikt} is a vector of covariates including marketing-mix variables of brand k at time t (regular price and price cut) and household i's average purchase quantity in the initialization period (AQ_i). AQ_i is included as a control variable (measured in ounces). The effect of the SR on purchase quantity is measured by δ_i^Q.[5]

We adopt a formulation developed by Zhang and Krishnamurthi (2004) to accommodate the interdependence of the three purchase components. It is assumed that ε_{ikt}, $k = 0, 1, …, K$, follow i.i.d. Type I extreme value distribution with location parameter 0 and scale parameter 1. Let $\varepsilon_{ikt}^* = \max_{\substack{j = 0,1,...K \\ \text{and } j \neq k}} \{V_{ijt} + \varepsilon_{ijt}\} - \varepsilon_{ikt}$, and assume

that the joint distribution of ε_{ikt}^* and the quantity error term ξ_{ikt} follows the flexible bivariate logistic distribution proposed by Gumbel (1961), which involves a parameter reflecting the correlation of the two terms.[6] These

assumptions regarding the error terms lead to a closed-form expression of joint probability and enable estimation of the model by a standard maximum-likelihood model.

In this framework, the category purchase incidence probability is:

$$\Pr\{I_{it} = 1\} = \frac{\sum_{k=1}^{K}\exp(\delta_{ki}^{B}SR_t + V_{ikt})}{\exp(\delta_{i}^{I}SR_t + V_{i0t}) + \sum_{k=1}^{K}\exp(\delta_{ki}^{B}SR_t + V_{ikt})} \quad (4)$$

and the conditional brand choice probability given a purchase incidence is:

$$\Pr\{B_{ikt} = 1 \mid I_{it} = 1\} = \frac{\exp(\delta_{ik}^{B}SR_t + V_{ikt})}{\sum_{m=1}^{K}\exp(\delta_{im}^{B}SR_t + V_{imt})}, k = 1, \ldots, K. \quad (5)$$

If one reparameterizes Equation 4 to the following:

$$\Pr\{I_{it} = 1\} = \frac{\sum_{k=1}^{K}\exp(V_{ikt})}{\exp(\delta_{i}^{I^*}SR_t + V_{i0t}) + \sum_{k=1}^{K}\exp(V_{ikt})} \quad (6)$$

then the new parameter $\delta_{i}^{I^*}$ will directly reflect the effect of SR on the purchase incidence probability $\Pr\{I_{it} = 1\}$, with $\delta_{i}^{I^*} > 0$ indicating a decrease in $\Pr\{I_{it} = 1\}$, and $\delta_{i}^{I^*} < 0$ indicating an increase in $\Pr\{I_{it} = 1\}$. It can be shown that

$$\delta_{i}^{I^*} = \delta_{i}^{I} + \log\left(\frac{\sum_{k=1}^{K}\exp(V_{ikt})}{\sum_{k=1}^{K}\exp(\delta_{k}^{B} + V_{ikt})}\right) \quad (7)$$

We estimate $\delta_{i}^{I^*}$ for its ease of interpretation.

The model has been constructed at the individual household level so far. To capture unobserved consumer heterogeneity, we employ a latent-class formulation (see Kamakura and Russell 1989), in which parameters are segment specific, denoted by subscript $g = 1, \ldots, G$. The discrete latent-class specification has been shown to be empirically equivalent to contin-

uous methods of representing heterogeneity, such as the hierarchical Bayesian formulations (Andrews, Ainslie, and Currim 2002). The log likelihood function is given by:

$$LL = \sum_{i=1}^{N}\log\left(\sum_{g=1}^{G}q_g\prod_{t=1}^{T_i}\{\Pr_g(I_{it} = 0)^{1-I_{it}}\right.$$
$$\left.\prod_{k=1}^{K}\Pr_g(I_{it} = 1, B_{ikt} = 1, Q_{ikt} = q_{ikt})^{I_{it} \cdot B_{ikt}}\}\right), \quad (8)$$

where q_g is the probability of belonging to segment g, T_i is the number of observations for household i, and other terms are as shown previously. The number of latent segments G is determined empirically by comparing the Bayesian Information Criterion (BIC) of models with different G. The one the lowest BIC is selected.

To summarize, the parameters that we are particularly interested in are: $\delta_{g}^{I^*}$, the effect of the SR on category purchase incidence; δ_{kg}^{B}, the effect of the SR on brand k's utility, $k = 1, \ldots, K$; and δ_{g}^{Q}, the effect of the SR on purchase quantity.

Data Analyses

Our data were provided by an online grocery retailer which operates in several metropolitan markets nationwide. The retailer implemented a systemwide SR on virtually all product categories in January 1999. Our data set includes detailed household purchase information on three product categories (liquid laundry detergent, margarine, and spaghetti sauce) collected from a Midwestern market from January 1, 1997 to August 15, 1999. As part of the SR program, most brands had some of their SKUs eliminated and a few brands were eliminated altogether. Tables 2a and 2b provide a description of the category-level assortment changes and the brands eliminated by the SR program.

As Table 2a shows, the number of brands dropped from 14 to 11 for liquid detergent, from 12 to 10 for margarine, and from 17 to 11 for spaghetti sauce. At the category level, the number of SKUs decreased by 32.4% for liquid detergent,

Table 2a
Overall Category-level Assortment Changes

Category	Number of Brands		Number of SKUs		Number of Sizes		Market Share Eliminated
	Before	After	Before	After	Before	After	
Liquid detergent	14	11	74	50	7	6	1.067%
Margarine	12	10	55	45	5	5	.099%
Spaghetti sauce	17	11	127	89	17	12	.770%

Table 2b
Description of the Eliminated Brands

Category	Brand	Number of SKUs	Market Share
Liquid detergent	Ivory	1	.026%
	Ultra Yes	1	.833%
	Value Wise	1	.208%
Margarine	Move Over Butter	1	.020%
	Nucoa	1	.079%
Spaghetti sauce	Alessi	1	.146%
	Buitoni	1	.125%
	Del Monte	2	.166%
	Giannotti	1	.021%
	Value Wise	1	.250%
	Weight Watchers	1	.062%

18.2% for margarine, and 29.9% for spaghetti sauce. The number of sizes dropped from 7 to 6 for liquid laundry detergent, did not drop for margarine, and dropped from 17 to 12 for spaghetti sauce. The brands that were completely eliminated had few SKUs and accounted for a very small market share. Most of the SR occurred in brands that remained after the reduction.

As explained previously, we focused on the brands remaining after the SR to investigate how consumers' purchase decisions may change due to the assortment reduction. In our empirical analysis, we also had to delete a few very small brands that were not purchased enough to allow for reliable model estimation. Thus, the final data set for analysis includes 9 of the remaining

11 brands for liquid detergent (which accounted for 99.4% of total purchases for the 11 brands), 9 of the remaining 10 brands for margarine (which accounted for 98.7% of total purchases for the 10 brands), and 9 of the remaining 11 brands for spaghetti sauce (which accounted for 98.2% of total purchases for the 11 brands). For ease of exposition, hereafter we refer to the 9 brands under investigation for each product as "the category." Table 2c gives a detailed description of the brands we examined.

There was a great variation in the number and percentage of SKUs eliminated for each brand under investigation. Some did not have any SKUs eliminated (e.g., Surf detergent), while others had up to two-thirds of their SKUs removed (e.g., Healthy Choice spaghetti sauce). The SR also resulted in a substantial change in each brand's share of SKUs in the category, although the ranking of market shares across brands was not altered much. Table 2c also shows the number of sizes offered before and after the SR. There was little change in the number of sizes offered for most brands. For the six brands that did experience a drop in the number of sizes, the cut was moderate in absolute magnitude (one or two), although it could be considered substantial in terms of percentage (ranging from 17% to 67%).

We also look at the eliminated SKUs' share of brand sales; that is, the proportion of a brand's sales in the pre-SR period contributed by the SKUs that the SR eliminated. For example, if Tide had 100,000 units of sales, and the SKUs eliminated together accounted for 2,000 units

Table 2c
Description of SKU Reductions for Brands Studied

Category	Number of SKUs		Share of SKUs		Number of Sizes		Eliminated SKUs' Share of Brand Sales
	Before SR	After SR	Before SR	After SR	Before SR	After SR	
Liquid Detergent							
Wisk	10	7	15.9%	14.9%	3	3	16.7%
All	13	9	20.6%	19.1%	5	5	48.4%
Tide	18	13	28.6%	27.7%	6	5	4.6%
Cheer	5	4	7.9%	8.5%	2	1	3.3%
Arm & Hammer	3	3	4.8%	6.4%	1	1	0
Era	4	2	6.3%	4.3%	3	1	9.0%
Dreft	1	1	1.6%	2.1%	1	1	0
Surf	3	3	4.8%	6.4%	2	2	0
Store brand	6	5	9.5%	10.6%	4	4	2.6%
Overall	63	47	100%	100%	7	6	8.0%
Margarine							
Brummel & Brown	2	2	3.8%	4.5%	2	2	0
Fleischmann's	7	5	13.2%	11.4%	3	3	8.1%
I Can't Believe…	6	6	11.3%	13.6%	2	2	0
Imperial	4	3	7.5%	6.8%	2	2	1.0%
Land O' Lakes	7	7	13.2%	15.9%	2	2	0
Parkay	8	6	15.1%	13.6%	3	3	.4%
Promise	7	5	13.2%	11.4%	2	2	17.4%
Shedds Country	8	8	15.1%	18.2%	3	3	0
Store brand	4	2	7.5%	4.5%	2	1	8.5%
Overall	53	44	100%	100%	5	5	2.9%
Spaghetti Sauce							
Barilla	5	5	4.4%	5.9%	1	1	0
Classico	13	11	11.4%	12.9%	2	2	.9%
Five Brothers	11	6	9.6%	7.1%	2	2	25.6%
Healthy Choice	9	3	7.9%	3.5%	3	2	29.1%
Hunt's	2	2	1.8%	2.4%	2	2	0
Newman's Own	5	5	4.4%	5.9%	1	1	0
Prego	28	23	24.6%	27.1%	5	5	5.5%
Ragu	32	22	28.1%	25.9%	10	8	5.1%
Store brand	9	8	7.9%	9.4%	2	2	17.1%
Overall	114	85	100%	100%	13	12	5.5%

of sales, then the eliminated SKUs' share of brand sales for Tide would be 2%. At the category level, the eliminated SKUs only contributed a small proportion of sales in the pre-SR period (8.0% for liquid detergent, 2.9% for margarine, and 5.5% for spaghetti sauce). However, the eliminated SKUs' share of brand sales was substantially higher for a few brands. For example, it was 25.6% and 29.1%, respectively, for the spaghetti sauce brands Five Brothers and Healthy Choice, and it was 48.4% for the liquid detergent brand All. We will examine how

these brand-level SR-related changes affect the impact of the SR on each individual brand.

For each product category, the period from January 1 to August 15, 1997 (33 weeks), was the initialization period used to determine household average purchase frequency and quantity variables. The estimation data for the pre-SR period were gathered from January 1 to August 15, 1998, and the data for the post-SR period were gathered from January 1 to August 15, 1999. All the time periods are matched in terms of months in order to minimize the impact of seasonality effects. We did not use pre-SR data from August 16 to December 31, 1998, because we did not have data beyond August 15, 1999, for the post-SR period. For each product category, we chose those households that had made at least two purchases of any brand in the initialization period and at least one purchase of the brands retained for study (nine in each category) in the pre-SR period. This resulted in 191 households and 12,606 observations for liquid detergent, 244 households and 16,104 observations for margarine, and 234 households and 15,444 observations for spaghetti sauce in the estimation data. Although the households did not need to make a purchase in the post-SR period to be selected, they did in fact all make at least one category purchase after the SR. This is consistent with the finding of Boatwright et al. (2004) that there was very little attrition from the store after an assortment reduction experiment.

We present in Table 3 each brand's average regular price, price discount, shelf price, and market share (out of a total comprising the nine brands) before and after the SR. As the numbers indicate, in all three categories there were nontrivial changes in prices and price discounts. For most brands, regular prices were higher and discounts were deeper in the post-SR period. As a result of the higher regular prices, the average shelf price was 5.6% higher for liquid detergent, 17.1% higher for margarine, and 7.7% higher for spaghetti sauce in the post-SR period. It is worth noting, though, that a few brands experienced a decrease in shelf price, for example, the store brands for the liquid detergent and spaghetti sauce categories. These variations highlight the importance of adopting a model that can take into account changes in the key marketing-mix variables. For instance, the model must be able to determine whether the drop in the market share of Tide detergent after the SR is due to the SR or because of the rise in Tide's price. The same is true for Shedds Country margarine, Ragu spaghetti sauce, and many other brands whose price increased but market share decreased after the SR, as well as store brand liquid detergent, whose price decreased while its market share increased after the SR.

Using this data set, we estimated the model described in the previous section and then conducted a series of follow-up analyses based on the estimation results to investigate various aspects of the SR effects. Below we present four sets of results: (1) model estimation results, (2) assessment of the SR effects at the category and segment levels based on a would-be analysis, (3) assessment of the SR effects at the brand level based on a would-be analysis, and (4) an analysis that seeks to identify drivers of the differences in the SR effects among brands.

Model Estimation Results

A three-segment model appears to fit the data best for all three categories, based on Bayesian information criteria.[7] Parameter estimates for the three categories are reported in Tables 4-6, respectively. We summarize the effects of the marketing-mix variables and household-specific control variables first. After that, we report results for parameters that capture the effects of the SR.

In all three product categories, the effects of the marketing-mix variables and the household-specific control variables have the expected directions for all the significant parameter estimates. Specifically, the higher the regular price

Table 3
Average Prices, Discount Prices, and Market Share for Brands Studied (prices in cents/oz.)

Category	Regular Price		PriceCut		Shelf Price		Market Share	
	Before SR	After SR	Before SR	After SR	Before SR	After SR	Before SR	After SR
Liquid Detergent								
Wisk	7.06	8.01	.94	1.26	6.12	6.75	10.9%	12.9%
All	4.50	5.20	.38	.55	4.11	4.65	6.3%	10.9%
Tide	6.98	7.84	.57	.59	6.42	7.25	51.9%	48.7%
Cheer	6.64	7.07	.16	0	6.48	7.07	8.4%	6.5%
Arm & Hammer	4.93	5.01	.45	.60	4.48	4.41	5.7%	4.9%
Era	5.90	6.01	.01	.14	5.89	5.87	4.6%	3.9%
Dreft	9.73	10.08	0	0	9.73	10.08	6.6%	4.4%
Surf	6.00	6.65	.09	.63	5.91	6.02	3.3%	3.1%
Store brand	4.43	3.91	.10	.11	4.32	3.79	2.5%	4.7%
Overall	6.74	7.19	.47	.57	6.27	6.62	100%	100%
Margarine								
Brummel & Brown	14.75	15.66	.33	.71	14.43	14.95	6.2%	6.4%
Fleischmann's	13.56	17.82	.02	1.77	13.55	16.05	9.5%	9.7%
I Can't Believe…	14.83	16.12	.76	.79	14.07	15.33	26.5%	27.1%
Imperial	10.26	11.23	.11	.18	10.15	11.04	13.0%	9.5%
Land O' Lakes	13.56	16.33	.24	.40	13.32	15.93	8.3%	10.5%
Parkay	11.38	13.08	.48	.19	10.90	12.89	7.2%	7.4%
Promise	13.81	17.49	.23	.71	13.58	16.77	8.9%	12.6%
Shedds Country	6.98	7.96	.09	.52	6.88	7.44	15.7%	13.0%
Store brand	5.81	5.60	.90	.30	4.91	5.3	4.7%	3.9%
Overall	12.01	14.31	.37	.67	11.64	13.63	100%	100%
Spaghetti Sauce								
Barilla	9.78	10.85	.19	.45	9.58	10.40	5.4%	8.1%
Classico	10.97	11.98	.22	.25	10.75	11.74	15.3%	13.2%
Five Brothers	11.19	11.97	.37	.35	10.81	11.62	4.0%	4.8%
Healthy Choice	8.50	9.40	.41	.49	8.09	8.91	1.9%	3.8%
Hunt's	4.59	5.00	.30	.29	4.29	4.7	1.9%	1.8%
Newman's Own	8.95	9.47	.14	.22	8.82	9.24	5.9%	5.5%
Prego	7.87	8.18	.17	.48	7.70	7.70	34.9%	39.8%
Ragu	7.38	8.60	.43	.32	6.95	8.28	28.0%	20.7%
Store brand	7.61	6.81	.86	.81	6.75	5.99	2.7%	2.3%
Overall	8.45	9.20	.28	.40	8.17	8.80	100%	100%

the lower a brand's choice probability and the purchase incidence probability of the category, while the effects of price discount are the opposite. A higher household purchase frequency in the initialization period is associated with a lower category incidence threshold and thus a higher purchase incidence probability; the greater the quantity bought on the previous purchase occasion, the higher the category purchase incidence threshold and therefore the lower the purchase incidence probability. In addition, purchase quantity decreases with a

Table 4
Parameter Estimates: Liquid Detergent

Variables/Parameters		Segment 1	Segment 2	Segment 3
Brand Utility (baseline: store brand)				
α_k:	Wisk	1.654**	2.009**	1.471*
	All	.294	1.414*	.863
	Tide	2.530***	1.700**	1.876**
	Cheer	1.930***	1.289*	1.411*
	Arm & Hammer	−20.029***	−11.159***	.938
	Era	1.982**	1.884**	−1.192
	Dreft	4.744***	2.673***	1.786**
	Surf	1.560*	1.070	−.086
β:	Regular price	−.819***	−.047	−.247*
	Price cut	.364**	.226*	.326***
	State dependence (γ)	3.958***	3.344***	2.552***
δ_k^B (SR):	Wisk	.284	.389	.247
	All	.469	.016	.421
	Tide	1.562**	.924	.491
	Cheer	.558	−.671	.004
	Arm & Hammer	9.323***	−9.200***	.037
	Era	−.721	−.362	.958*
	Dreft	−.280	−.621	−.093
	Surf	.340	−.893	.596
Category Threshold				
	Constant	2.917***	8.085***	6.176***
	Purchase frequency	−4.161***	−6.154***	−9.755***
	Last purchase volume	.006	.022	.047*
	δ^{I^*} (SR)	−.156*	.056	.163**
Purchase Quantity				
ϕ_0:	Wisk	11.006***	8.763***	4.604***
	All	7.948***	18.623***	7.723***
	Tide	11.011***	18.503***	7.718***
	Cheer	9.078***	8.926***	8.027***
	Arm & Hammer	5.879***	12.291***	7.834***
	Era	9.452***	9.057***	7.992***
	Dreft	7.807***	17.666***	3.004**
	Surf	9.261***	8.911***	7.506***
	Store brand	8.426***	50.771***	5.234***
ϕ:	Regular price	−6.424***	.265	.121
	Price cut	5.528***	.303	2.673***
	Average purchase volume	.473***	.051	.151*
δ^Q (SR)		.471**	−.059	−.038
Segment Size		22.7%	26.2%	51.1%
Correlation			−.195	
−Log-likelihood			10,495.9	
Number of parameters			111	

*** p-value < .01; ** p-value < .05; * p-value < .10.

Table 5
Parameter Estimates: Margarine

Variables/Parameters		Segment 1	Segment 2	Segment 3
Brand Utility (baseline: Shedds Country)				
α_k:	Brummel & Brown	.601**	−.763**	−1.572***
	Fleischmann's	.402	.013	−1.628***
	I Can't Believe It's Not Butter!	.065	−.187	−1.502***
	Imperial	.176	−.096	−.354
	Land O' Lakes	.070	−1.644***	−.719*
	Parkay	−.383	.221	−.600**
	Promise	−1.135***	.628**	−1.515***
	Store brand	−.383*	.526**	−.282
β:	Regular price	.010	.100	.110
	Price cut	.019	−.013	−.046
	State dependence (γ)	3.834***	3.668***	3.446***
δ_k^B (SR):	Brummel & Brown	−.598	.138	−.124
	Fleischmann's	−.294	−.610	−.650
	I Can't Believe It's Not Butter!	.314	.456	.155
	Imperial	−.365	.032	−.490
	Land O' Lakes	.073	.988**	−.609*
	Parkay	−1.218	.032	−.691**
	Promise	.613	−.493	.177
	Store brand	−.201	−.890	−.468
Category Threshold				
	Constant	7.357***	7.232***	6.721***
	Purchase frequency	−10.018***	−3.993***	−5.513***
	Last purchase volume	.011***	.000	.010**
	δ^{I^*} (SR)	.258***	.340***	.486***
Purchase Quantity				
ϕ_0:	Brummel & Brown	18.443***	3.650***	9.488***
	Fleischmann's	10.801***	.772	17.016***
	I Can't Believe It's Not Butter!	17.819***	1.921**	9.490***
	Imperial	17.463***	−1.134	9.437***
	Land O' Lakes	17.909***	.856	9.885***
	Parkay	32.623***	2.242***	17.451***
	Promise	17.780***	1.947**	9.678***
	Shedds Country	48.286***	.160	16.477***
	Store brand	17.068***	3.230***	16.481***
ϕ:	Regular price	−.138**	−.018	−.105
	Price cut	.008	.049	.059
	Average purchase volume	.020***	.876***	.022***
δ^Q (SR)		.101	−.769***	.127
Segment Size		41.0%	26.5%	32.5%
Correlation			.034	
−Log-likelihood			18005.4	
Number of parameters			111	

*** *p*-value < .01; ** *p*-value < .05; * *p*-value < .10.

Table 6
Parameter Estimates: Spaghetti Sauce

Variables/Parameters		Segment 1	Segment 2	Segment 3
Brand Utility (baseline: Ragu)				
α_k:	Barilla	.694*	.366	−.981**
	Classico	.832*	.296	−.204
	Five Brothers	.939	−.328	−.846
	Healthy Choice	−.675*	−1.722***	−.719**
	Hunt's	−4.139***	−3.244***	.094
	Newman's Own	.831	−.035	−2.008***
	Prego	−.383**	−.481**	.571***
	Store brand	−.391	−1.693***	−.887***
β:	Regular price	−.411***	−.291*	.118
	Price cut	.103	.130	.124*
	State dependence (γ)	6.362***	2.961***	2.504***
δ_k^B (SR):	Barilla	1.807*	.053	.307
	Classico	1.549	.143	−.169
	Five Brothers	.603	.305	−.037
	Healthy Choice	.853	.310	.325
	Hunt's	−12.790***	.478	−.487
	Newman's Own	.140	−.548	.126
	Prego	2.159**	.723*	.241
	Store brand	−2.469**	−16.960***	.494
Category Threshold				
	Constant	5.300***	3.720**	5.939***
	Purchase frequency	−6.984***	−4.861***	−1.883***
	Last purchase volume	.074	.015	−.023
	δ^{I^*} (SR)	−.270**	.267*	.399**
Purchase Quantity				
ϕ_0:	Barilla	3.336***	6.202***	2.228
	Classico	2.704***	6.555***	2.233
	Five Brothers	2.148**	6.279***	1.612
	Healthy Choice	−.582	7.176***	1.909
	Hunt's	1.120	4.173***	1.687**
	Newman's Own	1.635*	5.442***	2.104
	Prego	1.182*	5.400***	1.967
	Ragu	.852	4.648***	1.840
	Store brand	−1.069	3.860***	1.806*
ϕ:	Regular price	−.313***	−.593***	−.081
	Price cut	.161	.287**	.189
	Average purchase volume	1.222***	.730***	.273***
δ^Q (SR)		.414***	.238*	.065
Segment Size		14.6%	53.1%	32.3%
Correlation			−.304	
−Log-likelihood			9362.0	
Number of parameters			111	

*** p-value < .01; ** p-value < .05; * p-value < .10.

brand's regular price and increases with its price discount, and a household's average purchase quantity in the initialization period is positively associated with its purchase quantity on any given occasion. The parameter estimates also reveal strong consumer heterogeneity. In general, the three segments for each category have different levels of brand constants and marketing-mix effects. In addition, the segments exhibit different degrees of state dependence.

We now look at the parameters that capture the impact of the SR on purchase incidence, brand utilities, and purchase quantity, denoted by δ^{I^*}, δ_k^{B}'s, and δ^{Q} in the tables. As explained previously, the signs of δ^{I^*} and δ^{Q} indicate the direction of the effect on purchase incidence and quantity, respectively, per purchase occasion. The parameter δ_k^{B} reflects how a brand's utility is affected by the SR, but it does not directly indicate how the brand's conditional choice probability is affected, because the choice probability also depends on the magnitude of changes in other brands' utilities. We focus on δ^{I^*} and δ^{Q} first and will examine the effects on brand choice probabilities later. In each product category, the pattern of these effects is distinctive across segments, and the differences seem to be associated with the segments' levels of state dependence.

For liquid detergent, the SR appears to have increased both purchase incidence probability (δ^{I^*} <0) and quantity per purchase occasion for the most state-dependent segment (Segment 1), not to have changed either significantly for the medium state-dependent segment (Segment 2), and to have decreased purchase incidence probability (δ^{I^*} >0) but not quantity per purchase occasion for the least state-dependent segment (segment three). For margarine, the SR seems to have decreased purchase incidence probability for all three segments and had a significant effect (a negative one) on quantity per purchase occasion only for Segment 2. The patterns for spaghetti sauce are fairly similar to those for liquid detergent: the SR appears to have increased both purchase incidence probability and quantity per purchase occasion for the

most state-dependent segment (Segment 1), decreased purchase incidence probability but increased quantity per purchase occasion for the medium state-dependent segment (Segment 2), and decreased purchase incidence probability but not quantity per purchase occasion for the least state-dependent segment (Segment 3).

SR effects at the category and segment levels

We assessed the magnitude of the SR impact on purchase incidence probability, quantity per purchase occasion, total purchase quantity, and total sales revenue based on the model estimation results (conditional brand choice probability is covered in the section on SR effects at the brand level). To control for changes in the market environment, we conducted a would-be analysis using data in the post-SR period. Specifically, we estimated two sets of the above measures using the same data, one set using all the parameters in the model and the other set using all the parameters except the ones capturing the SR effects. The second set represents the values of the above measures had there been no changes in the product assortment while keeping everything else the same as in the post-SR period data. Thus the difference between the values of a measure in the two sets gives the effect of the SR on that measure. Since there are 9 brands and 3 segments for each of the 3 categories, we have 81 segment- and brand-specific values for each measure. (Purchase incidence probability is segment specific but not brand specific.) We present summaries of the results at the category and segment levels in tables 7-9.

As indicated by tables 7-9, at the overall category level, the SR decreased the purchase incidence probability for all three categories. The impact on quantity per purchase occasion is more moderate and of a mixed pattern, with liquid detergent and spaghetti sauce experiencing a slight increase and margarine a slight decrease. Thus, the impact of the SR at the category level appears to be much stronger on purchase incidence than on quantity per purchase occasion. A similar pattern at the store level is

Table 7

Category- and Segment-level Effects of SKU Reductions: Liquid Detergent

	Incidence Probability	Average Quantity/Purchase Occasion (oz.)	Total Purchase Quantity/Household in 33 Weeks (oz.)	Total Sales Revenue/Household in 33 Weeks ($)
Segment 1				
(size: 22.7%, γ = 3.958)				
Without SR	.120	110.7	475.3	30.83
With SR	.137	115.4	566.4	37.40
Difference	.017	4.7	91.1	6.57
% Difference	+13.9%	+4.2%	+19.2%	+21.3%
Segment 2				
(size: 26.2%, γ = 3.344)				
Without SR	.095	184.9	536.9	38.02
With SR	.091	184.3	522.5	36.70
Difference	−.004	−.6	−14.4	−1.31
% Difference	−4.6%	−.3%	−2.7%	−3.5%
Segment 3				
(size: 51.1%, γ = 2.552)				
Without SR	.118	92.5	380.7	24.65
With SR	.104	92.1	338.8	22.06
Difference	−.014	−.4	−42.0	−2.58
% Difference	−11.6%	−.4%	−11.0%	−10.5%
Overall Average				
Without SR	.112	120.8	443.1	29.55
With SR	.108	121.5	438.6	29.38
Difference	−.004	.7	−4.6	−.17
% Difference	−3.9%	+.6%	−1.0%	−.6%

found by Boatwright et al. (2004). Total category purchase quantity and sale revenue in the entire post-SR period are also negatively affected by the SR, but the extent varies substantially across the three categories. While liquid detergent's total quantity and revenue decrease by only 1.0% and .6%, the drops for spaghetti sauce are 7.7% and 7.4%, and the drops for margarine are a much higher 24.2% and 23.9%. The SR's impact on the total category quantity and revenue seems to be mainly driven by the purchase incidence component.

Looking at the segment-specific results, there is great variation across consumer segments, and the pattern is consistent among the three categories: the higher the state dependence level of a segment, the more favorable (or less unfavorable) the impact of the SR is for the retailer. For liquid detergent and spaghetti sauce, there is an increase in total sales quantity and revenue due to the SR in the most state-dependent segment, while for margarine the least reduction in sales among the three segments occurs in the most state-dependent segment. In each category, there are drops in sales for the two less state-dependent segments, and the percentage reduction is higher with the level of state dependence. If we follow the interpretation in the literature and take the state dependence parameter

Table 8
Category- and Segment-level Effects of SKU Reductions: Margarine

	Incidence Probability	Average Quantity/Purchase Occasion (oz.)	Total Purchase Quantity/Household in 33 Weeks (oz.)	Total Sales Revenue/Household in 33 Weeks ($)
Segment 1				
(size: 41.0%, γ = 3.834)				
Without SR	.163	20.5	135.3	16.41
With SR	.135	20.6	111.3	13.58
Difference	−.028	.10	−24.0	−2.83
% Difference	−17.3%	+.5%	−17.7%	−17.2%
Segment 2				
(size: 26.5%, γ = 3.668)				
Without SR	.183	18.6	137.7	18.68
With SR	.140	17.9	99.9	13.68
Difference	−.044	−.8	−37.8	−5.01
% Difference	−23.8%	−4.1%	−27.5%	−26.8%
Segment 3				
(size: 32.5%, γ = 3.446)				
Without SR	.161	11.8	77.8	9.41
With SR	.107	11.9	51.6	6.21
Difference	−.054	.1	−26.3	−3.20
% Difference	−33.5%	+1.1%	−33.8%	−34.0%
Overall Average				
Without SR	.168	17.1	117.2	14.73
With SR	.127	17.0	88.8	11.21
Difference	−.041	−.1	−28.4	−3.53
% Difference	−24.3%	−.7%	−24.2%	−23.9%

as an indicator of the level of inertia/variety seeking, these results imply that variety-seeking/less inertial customers disliked the SR, while consumers with higher level of inertia either welcomed it or resented it less.

SR effects at the brand level

We now look at the impact of the SR on individual brands in each category, based on the would-be analysis described above. We present in Table 10 the results for two key measures: the conditional brand choice probability given a category purchase incidence, and the total purchase quantity of a brand by all households in the sample during post SR-period. The pattern of results for sales revenue is similar to the one

for quantity and is not discussed separately. Since our study focuses on the impact of the SR on individual brands and not on consumer response to the SR, both the key measures (choice and purchase quantity) are aggregated across segments. Note that these two measures do not always move in the same direction, because purchase quantity is affected not only by changes in the choice probability and purchase quantity on each occasion (which are brand specific) but also by changes in the purchase incidence probability (which are category specific and therefore the same for all the brands in the category).

Table 10 shows a high degree of variation among brands on the two measures. It appears that SR

Table 9
Category- and Segment-level Effects of SKU Reductions: Spaghetti Sauce

	Incidence Probability	Average Quantity/Purchase Occasion (oz.)	Total Purchase Quantity/Household in 33 Weeks (oz.)	Total Sales Revenue/Household in 33 Weeks ($)
Segment 1				
(size: 14.6%, γ = 6.362)				
Without SR	.162	45.3	235.8	20.79
With SR	.198	49.3	315.3	28.04
Difference	.036	4.0	79.5	7.25
% Difference	+22.2%	+8.8%	+33.7%	+34.9%
Segment 2				
(size: 53.1%, γ = 2.961)				
Without SR	.065	42.4	84.7	7.30
With SR	.051	44.8	71.1	6.16
Difference	−.014	2.4	−13.6	−1.14
% Difference	−21.6%	+5.6%	−16.0%	−15.6%
Segment 3				
(size: 32.3%, γ = 2.504)				
Without SR	.155	33.9	170.7	14.96
With SR	.110	34.6	124.9	10.88
Difference	−.045	.7	−45.8	−4.08
% Difference	−28.9%	+2.0%	−26.8%	−27.3%
Overall Average				
Without SR	.108	40.1	134.6	11.75
With SR	.092	42.1	124.2	10.88
Difference	−.017	2.1	−10.4	−.87
% Difference	−15.4%	+5.1%	−7.7%	−7.4%

not only changed the category purchase incidence but also altered consumers' choice among the remaining brands, so that some brands gained market share and some lost market share due to the assortment changes. As a result, although the SR has an overall negative effect on total category purchase incidence and purchase quantity, some brands' total quantity is hardly changed (and may even increase), whereas others are hit hard. As Table 10 shows, Dreft liquid detergent's total purchase quantity decreases from 5,462 to 3,592 ounces, whereas Tide's increases from 44,277 to 49,592 ounces. Barilla spaghetti sauce remains more or less at 2,400 ounces and so does Prego spaghetti sauce at 10,950 ounces. Interestingly, in all three categories, the SR appears to have caused a substantial drop in choice probability and total purchase quantity for the store brand, which may be alarming to the retailer.

The results for choice probabilities demonstrate the importance of a would-be analysis that controls for the effects of marketing-mix variables. We find that merely comparing a brand's market share before and after the SR does not provide an accurate assessment of the effects of the SR on brand choice, because it does not take into account other changes in the marketing-mix variables. For example, in the liquid detergent category, a simple comparison of market share before and after the SR—as presented in Table 3—would lead to the conclusion that the

Table 10
Brand-level Effects of SKU Reductions (aggregated across segments)

	Conditional Brand Choice Probability				Expected Total Purchase Quantity (oz.)			
	Without SR	**With SR**	**Difference**	**% Difference**	**Without SR**	**With SR**	**Difference**	**% Difference**
Liquid Detergent								
Wisk	.124	.125	.002	+1.3%	7,272.3	6,892.8	−379.5	−5.2%
All	.113	.117	.004	+3.2%	8,611.8	8,380.9	−230.9	−2.7%
Tide	.427	.494	.066	+15.5%	44,277.0	49,592.0	5,315.0	+12.0%
Cheer	.092	.076	−.016	−17.3%	5,952.5	4,801.2	−1,151.3	−19.3%
Arm & Hammer	.049	.040	−.009	−18.5%	3,712.7	2,661.8	−1,050.9	−28.3%
Era	.044	.033	−.011	−24.3%	3,372.9	2,615.0	−757.9	−22.5%
Dreft	.069	.046	−.023	−33.8%	5,461.5	3,592.3	−1,869.1	−34.2%
Surf	.035	.032	−.003	−8.3%	2,129.5	1,980.7	−148.8	−7.0%
Store brand	.047	.037	−.010	−20.6%	3,844.8	3,247.0	−597.8	−15.5%
Margarine								
Brummel & Brown	.065	.061	−.004	−6.9%	1,985.9	1,484.3	−501.7	−25.3%
Fleischmann's	.112	.097	−.014	−12.9%	2,564.9	1,666.8	−898.2	−35.0%
I Can't Believe…	.229	.258	.029	+12.7%	6,264.7	5,436.1	−828.6	−13.2%
Imperial	.112	.105	−.006	−5.7%	2,578.6	1,867.6	−711.0	−27.6%
Land O' Lakes	.105	.111	.007	+6.4%	2,133.8	1,746.6	−387.2	−18.1%
Parkay	.081	.065	−.016	−19.6%	2,754.8	1,627.5	−1,127.3	−40.9%
Promise	.083	.087	.004	+5.3%	2,263.6	1,659.2	−604.4	−26.7%
Shedds Country	.166	.174	.009	+5.3%	6,744.6	5,392.9	−1,351.8	−20.0%
Store brand	.048	.041	−.008	−15.7%	1,312.2	791.5	−520.7	−39.7%
Spaghetti Sauce								
Barilla	.088	.092	.004	+4.5%	2,431.3	2,448.8	17.4	+.7%
Classico	.169	.164	−.006	−3.3%	4,639.2	3,995.6	−643.6	−13.9%
Five Brothers	.060	.062	.002	+3.7%	1,314.0	1,226.2	−87.9	−6.7%
Healthy Choice	.033	.039	.006	+18.0%	804.7	770.8	−33.9	4.2%
Hunt's	.029	.022	−.007	−24.6%	793.8	423.1	−370.8	−46.7%
Newman's Own	.072	.055	−.017	−24.2%	1,727.8	1,492.6	−235.2	−13.6%
Prego	.287	.336	.049	+17.3%	10,951.0	10,930.0	−21.0	−.2%
Ragu	.217	.208	−.008	−3.9%	7,666.8	6,995.9	−670.9	−8.8%
Store brand	.045	.022	−.023	−51.6%	1,163.8	777.1	−386.7	−33.2%

SR had caused Tide to lose market share (the table shows a decrease from 51.9% to 48.7%) and caused the store brand to gain market share (the table shows an increase from 2.5% to 4.7%), while our analysis in Table 10 indicates the exact opposite: the choice probability increased for Tide (from .427 to .494) and decreased for the store brand (from .047 to .037). Similarly, Table 3 shows market share for Parkay mar-

garine increasing slightly (from 7.2% to 7.4%), whereas Table 10 shows that its choice probability decreases (from .081 to .065); for Shedds Country margarine the market share decreases from 15.7% to 13.0%, but its choice probability increases from .166 to .174.

From the would-be analysis, we also find that changes in choice probability and purchase

quantity for a brand do not correlate with its eliminated SKUs' share of brand sales. For some brands, the SR cut SKUs that represented a large share of the brands' total sales, yet the brands did not suffer much loss in total purchase quantity and even gained market share in the post-SR period. On the other hand, for some brands the SR eliminated only small-share SKUs, but the brands nevertheless experienced a large loss in both market share and purchase quantity in the post-SR period. For example, in the liquid detergent category, the brand All had the largest reduction in terms of share of brand sales eliminated at the time of the SR (48.4%), but in the post-SR period it gained market share by 3.2% and had the smallest percentage decrease in total purchase quantity among the eight detergent brands that experienced reduction in sales quantity. Contrarily, although for the store brand the SR eliminated SKUs that represented only 2.6% of the store brand's total sales, its market share dropped by 20.6% and its sales quantity decreased by 15.5% during the post-SR period. The brand Dreft represents a more extreme case. None of its SKUs were eliminated by the SR program; however, it suffered the largest decrease in market share and purchase quantity in both absolute and percentage terms. Such "surprisingly good" and "surprisingly bad" examples are also present in the margarine and spaghetti sauce categories. These findings suggest that eliminated SKUs' share of brand sales may not be a good predictor of a brand's performance after an assortment reduction. Retailers should therefore be cautious about deleting SKUs based on their share of brand sales, which seems to be a common heuristic used by many retailers and manufacturers.

To gain a better understanding of what may be responsible for the differences in how brands are affected by an SR, we conducted a second-stage analysis on brand-level effects, which we discuss below.

Identifying drivers of the differences in SR effects among brands

We conducted regression analyses on the 81 ob-

servations of brand- and segment-specific outcomes for the conditional choice probabilities and total purchase quantities from the first-stage analysis. This secondary analysis was exploratory in nature. For the first measure, we used the absolute difference in choice probability (with and without the SR) as the dependent variable rather than the percentage difference because the percentage difference is directly related to a brand's market share and therefore may not offer a good basis for comparison. For the second measure, we used the percentage difference in the total purchase quantities as the dependent variable, because the absolute quantities are not comparable across categories due to volume differences. We examined two groups of variables that may contribute to the differences in conditional choice probabilities among brands: brand characteristics and brand-level SR factors.

Brand characteristics:
- Market share before the SR
- Price level. Since prices are not directly comparable across categories, we created a price index variable for each category, defined

  as: $PI_k = \dfrac{average\ shelf\ price_k}{\max_j\{average\ shelf\ price_j\}}$, where k

  and j denote brands in a given category. The brand with the highest average price in the category has its price index equal to 1.
- Promotion frequency, which is defined as the percentage of weeks in which a brand was sold at a discounted price.
- Store brand, which is represented as a dummy variable taking the value of 1 for the store brands and 0 for the national brands.

Since the retailer or manufacturers could potentially change the prices and promotions as a response to the SR, which would create an endogeneity problem, we use price level and promotion frequency *before* the SR as explanatory variables.

Brand-level SR variables:
- Number of SKUs eliminated for the brand

Table 11

Pearson Correlation Coefficients of Variables in the Second-stage Analysis

	%ΔQUANT	MS	PI	LPROM	SBRAND	DSKU	ΔSKUSHR	DSIZE	DSHR	SDI
ΔPROB	.5462	.6800	.0444	.2388	−.1660	.2350	.1617	.0181	.0148	−.0000
%ΔQUANT		.2333	.0934	.0818	−.1784	.2806	−.0377	.1621	.2006	.1957
MS			.0839	.1985	−.2429	.4364	.1808	.2351	−.1768	.0001
PI				−.3500	−.4249	−.0801	.0931	−.2491	−.1425	−.0030
LPROM					.2780	.5451	.2063	.0847	.3477	−.2103
SBRAND						−.0547	−.1409	.0219	.0581	.0000
DSKU							−.5881	.5618	.4735	−.2318
ΔSKUSHR								−.4931	−.5308	.0000
DSIZE									.0733	.0752
DSHR										−.1040

ΔPROB = change in conditional brand choice probability; %ΔQUANT = percentage change in purchase quantity; MS = market share before the SR; PI = price index before the SR; LPROM = logarithm of promotion frequency before the SR; SBRAND = 1 if the brand is a store brand, 0 otherwise; DSKU = number of SKUs eliminated; ΔSKUSHR = change in the share of SKUs; DSIZE = number of sizes eliminated; DSHR = eliminated SKUs' share of sales; SDI = state dependence index.

- Change in the share of SKUs (ΔSKUSHR). A brand's share of SKUs (SKUSHR) is defined as its number of SKUs divided by the total number of SKUs in the category, and ΔSKUSHR = $SKUSHR_{after}$ − $SKUSHR_{before}$
- Number of sizes eliminated (DSIZE).
- Eliminated SKUs' share of brand sales, which is the proportion of a brand's sales in the pre-SR period contributed by the eliminated SKUs.

For the SR's effects on total purchase quantities, in addition to the above two groups of variables, we also looked at the state dependence level of each segment, because the first-stage analysis revealed that changes in the total purchase quantities are affected by changes in the purchase incidence, and the latter is clearly associated with a segment's degree of state dependence. To make the state dependence measure comparable across categories, we created a state dependence index (SDI), defined as

$$SDI_g = \frac{state\ dependence\ parameter_g}{\max_h\{state\ dependence\ parameter_h\}},$$

where g and h denote consumer segments in the sample for each category. This variable measures a segment's degree of state dependence relative to other segments in the data for each category. The most state-dependent segment has its SDI equal to 1.

Given the small number of observations relative to the number of explanatory variables of interest (81 observations, 8 explanatory variables for the brand share change, and 9 explanatory variables for percentage change in purchase quantity), we conducted a series of stepwise regressions, testing models with various subsets of the independent variables. Table 11 reports the correlation matrices of the two dependent variables and eight explanatory variables. Table 12 reports the final models, which contain only the significant explanatory variables (at α = .10 level). For the SR effects on brand choice, we identified four significant drivers: (1) market share, (2) logarithm of the promotion frequency, (3) number of sizes eliminated (DSIZE), and (4) change in the share of SKUs (ΔSKUSHR). Interestingly, number of SKUs eliminated and eliminated SKUs' share of brand sales were not significant. Note that DSIZE and ΔSKUSHR are significant when either is included in the model with the first two variables, but neither is significant when both are included in the same model. The reason is that they are negatively correlated (with a correla-

Table 12
Significant Drivers of Brand-level Effects of SKU Reductions

Dependent Variable	Independent Variable	Parameter Estimate	p-value
	Model 1:		
Change in conditional choice probability	Intercept	−.0175	< .0001
	Market share	.0987	< .0001
	log (Promotion frequency)	.0202	.0220
	Number of sizes eliminated	−.0077	.0128
	Model 2:		
	Intercept	−.0193	< .0001
	Market share	.0779	.0003
	log (Promotion frequency)	.0248	.0080
	Change in SKU share	.2174	.0314
Percentage change in purchase quantity	Intercept	−.4351	.0002
	Market share	.7568	.0038
	State dependence index	.2206	.0909

tion of −.493). Therefore, we present two separate models in Table 12.

The effects of market share, logarithm of the promotion frequency, and change in the share of SKUs are positive, while the effect of number of sizes eliminated is negative. It appears that after the SR, everything else being the same, market shares tend to shift toward larger brands and brands with more frequent promotions. The effects of market share and promotion frequency suggest that when consumers are faced with a reduced assortment from which to choose, they are likely to turn to brands that are more salient in their minds. Larger-share brands tend to have higher market exposure, and more frequent promotions also help bring a brand to consumers' attention, which may explain why higher-share brands and more frequently promoted brands tend to gain share after the SR. In addition, the logarithm of promotion frequency suggests a saturation effect after a certain point, which seems consistent with the salience speculation.

Further, we find that the nature of the assortment change also affects how consumers reallo-cate their purchases. Brands with a reduction in the number of sizes are likely to lose share to those that maintained the same number of sizes offered in the store. An interesting result is that the number of sizes deleted is a more significant determinant of brand share change after the SR than the number of SKUs eliminated, which is not significant. We also find that an increase in a brand's share of SKUs in the category tends to increase its share of purchases: if share of SKUs increases by one percentage point, market share increases by .22 percentage points on average.

For the SR effects on purchase quantities, two significant drivers emerge from the regression analysis: market share and the state dependence index. Both variables have a positive effect, indicating that larger-share brands are likely to gain a higher-percentage increase (or suffer a smaller-percentage decrease) in total sales than smaller-share brands when an SR occurs; similarly, purchase quantities for a brand will be higher (or decrease in purchase quantity will be smaller) when consumers are more state dependent than when they are less state dependent.

Discussion

As stated earlier, previous research on SRs has mainly focused on their impact at the store and category levels, which is important for retailers. By focusing on brand-level effects, our study provides insights not only for retailers but also for manufactures. The most relevant issue for a manufacturer is what impact the SR will have on the manufacturer's brand(s). The manufacturer wants to know how to emphasize the brands' strengths and minimize negative repercussions from the SR. For retailers, our brand-level analysis offers new insights into the effects of SRs on store brands and into how market share may shift between brands of different profitability—insights that are not possible with a store- or a category-level approach.

To summarize the key findings of our analyses: at the category level, after the retailer eliminates certain SKUs in the category, the general reac-

tion is negative despite the fact that some consumers welcome the change. In all three categories studied here, the overall weekly category purchase incidence probability in the store dropped, as did total category purchase quantities and sales revenue. This indicates that the store has lost certain category sales to competing channels or stores due to the SR, although the extent varies substantially across categories. At the brand level, consumers appear to have reallocated their purchases disproportionately among the remaining brands. Both brand characteristics and the nature of the SR influenced how they chose among these brands. As a result of the effects at the category and brand levels, total sales quantity and revenue for some brands are not affected much by the SR, while other brands are hit hard by the assortment reduction due to a "double whammy": decrease in category purchase incidence and decrease in brand choice.

We found that the SR had a negative impact on the retailer's category sales volume and revenue for all three categories we examined. The drop in overall sales appears to be driven mainly by a decrease in category purchase incidence, while the effect on quantity per purchase occasion is quite moderate and of mixed patterns. By and large, our results on category purchase incidence and overall category quantity and revenue lend support to Boatwright and colleagues' (2004) findings on store-level shopping frequency and purchase spending.

Although our study did not set out to investigate how and why categories differ in their sales as a result of SRs (see Boatwright and Nunes 2001 and Boatwright et al. 2004 for in-depth analyses on this topic), we did observe that the effects vary substantially across the three categories we examined. Liquid detergent showed very little drop in total sales volume (−1.0%) or revenue (−0.6%); spaghetti sauce experienced a moderate decrease in total sales volume (−7.7%) and revenue (−7.4%), but margarine suffered a substantial decrease in both measures (−24.2% and −23.9%). The pattern does not appear to be related to the number or percentage of SKUs

eliminated in each category. One plausible explanation is that the number of SKUs in the margarine category was already on the low side and reducing it further may have crossed a threshold and elicited strong negative assortment perceptions among consumers (Broniarczyk, Hoyer, and McAlister 1998). It implies that retailers should be cautious when selecting categories for implementing SRs, as Boatwright and colleagues (2004) have also pointed out.

At the brand level, our results indicate that brands differ substantially in terms of how they are affected by a retailer's SR initiative. We identified four significant drivers for the differential effects on brand choice probabilities: market share, promotion frequency, number of sizes eliminated, and change in the share of SKUs. Specifically, brands with higher market shares and more frequent promotions tended to gain share, brands that did not experience a cut in the number of sizes offered gained share from those that did, and an increase in a brand's share of SKUs in the category was likely to translate into higher purchase share. The significant effect of the number of sizes is consistent with the finding of Guadagni and Little (1983), who first showed that consumers exhibit high size loyalty.

We also identified two significant drivers for the percentage change in a brand's total purchase quantity—market share and state dependence index. Larger-share brands are likely to gain a higher percentage increase or suffer a smaller percentage decrease in total sales than smaller-share brands, and purchase quantity for a brand will increase by a greater percentage (or decrease by a smaller percentage) if consumers are more state dependent.

We find that attributing differences in market share to the effect of SKU change may be misleading because there can be confounding changes in other marketing-mix variables. For instance, in the liquid detergent category, a simple comparison of market share before and

after the SR would suggest that the SR had decreased the choice for Tide and increased the choice for the store brand, while our analysis indicates the exact opposite. Our results also indicate that the eliminated SKUs' share of brand sales does not predict changes in a brand's choice probability and purchase quantity after the SR, which cautions against the practice of deleting SKUs based on their share of brand sales. Instead, marketers should focus attention on other factors that may play a more important role in creating differences in SR effects among brands, such as those identified by this study.

For manufacturers of large-share brands, our results suggest that even though SRs may decrease the overall category sales in a store, they need not worry as much as manufacturers of small-share brands. We also found that a brand is likely to gain market share (up to a certain point, after which the effect appears to taper off) if it has frequent promotions, which we interpret to mean that a brand gains in market share (up to a point) when it is made more prominent in consumers' minds. Our results imply that although manufacturers may not have control over retailers' SR initiatives, they can mitigate the potential negative consequences for their brands. One good tactic would be for the manufacturer to negotiate with the retailer to minimize reduction in the number of sizes of the manufacturer's brands offered.

In addition, our study shows that an increase in a brand's share of category SKUs is likely to translate into higher purchase share, which means that brands with a large number of SKUs before an SR have an advantage over those with a smaller number of SKUs. For instance, in the spaghetti sauce category, Prego had 28 SKUs and Five Brothers had 11 SKUs in the store before the SR, and they each had 5 SKUs eliminated by the retailer. Prego's share of category SKUs increased and Five Brothers' share decreased after the SR, which seems a likely explanation for the much greater increase in the choice probability for Prego than for Five

Brothers in both absolute and percentage terms. This finding suggests that the SKU proliferation strategy undertaken by many manufacturers is not without merit. Having a large number of SKUs in a store may help a manufacturer counter potential negative consequences for its brand(s) in the event that the retailer undertakes an assortment reduction.

Our findings also have some interesting implications for retailers. The fact that large-share brands tend to gain shares after an SR may be good news for retailers from the perspective of trade relations. In addition, since the number of sizes eliminated and change in the share of SKUs both affect how a brand's choice probability will be affected by an assortment reduction, retailers should use discretion in determining what SKUs to eliminate and give favorable treatment to those brands that are more important to their businesses. Although our data may not have enough statistical power to permit drawing a definitive conclusion on the effect of SRs on store brands, findings from the first-stage analysis suggest that store brands are likely to suffer more unfavorable consequences from an SR than national brands. To minimize the negative effects of an SR on the store brand in any given category, a retailer can take steps such as maintaining the number of store-brand SKUs and thereby increasing the store brand's share of SKUs in the category and making it more prominent in consumers' minds. If a reduction of store brand SKUs is inevitable, the retailer should try to minimize the reduction in the number of sizes offered.

Our research has focused on the brand-level effects of SRs. Future research could extend our analysis by looking at issues such as how the nature of the product category influences the SR's brand-level effects, how SRs to brands in one category affect sales of the same brand in another category, and how profitable SR programs are for both retailers and manufacturers, based on cost savings information, among many other topics. ■

Acknowledgements

Notes

1. The data are not the same as those analyzed by Boatwright and Nunes (2001) and Boatwright et al. (2004). Although like their data, ours were provided by an online retailer, our data were collected from different markets and time periods. More details are provided in the Data Analyses section.

2. Displays and feature ads are not included because our data were collected in an online store.

3. We also controlled for the seasonality effect by matching the months of the year for the data before and after the SR. The details are given in next section.

4. Note that it would not be appropriate to include an inventory variable in our model because its computation requires the use of interpurchase duration, which is endogenous to the purchase incidence decision (Chintagunta and Haldar 1998).

5. One can make δ_i^Q brand specific. In our empirical analyses, the model with brand-specific δ_i^Q's did not provide significant improvement over the one with a common parameter for all brands, for all categories we have analyzed. Therefore, we present the current version in the model formulation.

6. By the definition of ε^*, a negative correlation coefficient means that the unobserved factors in the choice and quantity functions are *positively* correlated, and vice versa.

7. The Bayesian information criteria for models with one, two, three, and four segments is 11,707.8, 11,274.8, 11,019.9, and 11,041.9 for liquid detergent, 22,293.8, 19,763.3, 18,543.1, and 18,584.7 for margarine, and 9,998.4, 9,919.2, 9,897.3, and 9,950.1 for spaghetti sauce, respectively.

References

Andrews, Rick L., Andrew Ainslie, and Imran S. Currim (2002), "An Empirical Comparison of Logit Choice Models with Discrete versus Continuous Representations of Heterogeneity." *Journal of Marketing Research* 39 (November), 479–87.

Arnold, Stephen J., Te H. Oum, and Douglas J. Tigert (1983), "Determinant Attributes in Retail Patronage: Seasonal, Temporal, Regional, and International Comparisons." *Journal of Marketing Research* 20 (May), 149–57.

Bell, David R., Jeongwen Chiang, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization." *Marketing Science* 18 (4), 504–26.

Boatwright, Peter, Sharad Borle, Joseph B. Kadane, and Joseph C. Nunes (2004), "Effect of Product Assortment Changes on Customer Retention." Pittsburgh, Penn.: Carnegie Mellon University. Working Paper.

_____, and Joseph C. Nunes (2001), "Reducing Assortment: An Attribute-Based Approach." *Journal of Marketing* 65 (July), 50–63.

Boatwright, Peter, Sharad Borle, Joseph B. Kadane, and Joseph C. Nunes (2004), "Effect of Product Assortment Changes on Customer Retention." Pittsburgh, Penn.: Carnegie Mellon University. Working Paper.

Broniarczyk, Susan M., Wayne D. Hoyer, and Leigh McAlister (1998), "Consumers' Perceptions of the Assortment Offered in a Grocery Category: The Impact of Item Reduction." *Journal of Marketing Research* 35 (May), 166–76.

Chiang, Jeongwen (1991), "A Simultaneous Approach to the Whether, What, and How Much to Buy Questions." *Marketing Science* 10 (4), 297–315.

Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households." *Marketing Science* 12 (2), 184–208.

Chintagunta, Pradeep K. and Sudeep Haldar (1998), "Investigating Purchase Timing Behavior in Two Related Product Categories." *Journal of Marketing Research* 35 (February), 43–53.

Drèze, Xavier, Stephen J. Hoch, and Mary E. Purk (1994), "Shelf Management and Space Elasticity." *Journal of Retailing* 70 (4), 301–26.

Guadagni, Peter M., and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data." *Marketing Science* 2 (3), 203–38.

Gumbel, E. J. (1961), "Bivariate Logistic Distributions."

Journal of the American Statistical Association 56 (294), 335–49.

Gupta, Sachin, Pradeep K. Chintagunta, and Dick R. Wittink (1997), "Household Heterogeneity and State Dependence in a Model of Purchase Strings: Empirical Results and Managerial Implications." *International Journal of Research in Marketing* 14 (4), 341–57.

Hanemann, W. Michael (1984), "Discrete Continuous Models of Consumer Demand." *Econometrica* 52 (3), 541–61.

Jain, Dipak C., and Naufel J. Vilcassim (1991), "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach." *Marketing Science* 10 (1), 1–23.

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

Kurt Salmon Associates (1993), *Efficient Consumer Response: Enhancing Consumer Value in the Grocery Industry*. Food Marketing Institute Report No. 9-526, Washington, D.C.: Food Marketing Institute.

Seetharaman, P. B., Andrew Ainslie, and Pradeep Chintagunta (1999), "Investigating Household State Dependence Effects across Categories." *Journal of Marketing Research* 36 (November), 488–500.

Zhang, Jie, and Lakshman Krishnamurthi (2004), "Customizing Promotions in Online Stores." *Marketing Science* 23 (4), 561–78.