JIE ZHANG and ARADHNA KRISHNA*

When retailers make product assortment changes by eliminating certain stockkeeping units (SKUs), how does this affect sales of individual brands? This is the main question the authors address in this article. Using data from an online retailer that implemented a permanent systemwide SKU reduction (SR) program, the authors investigate how the program affected various components of purchase behavior for individual brands. They find substantial variations in the SR effects across brands, categories, and consumers. They explore possible drivers for these differences and find that higher-market-share, higher-priced, and more frequently promoted brands tend to gain share and that reduction in the number of sizes, reduction in the number of SKUs, and change in SKU share in the category are important in affecting change in a brand's purchase share after the SR. They also find that SRs lead to an increase in category purchase incidence and quantity for highly state-dependent consumers and frequent buyers but a decrease in category purchase and quantity for mildly state-dependent consumers and infrequent buyers. In addition, SRs tend to cause more changes in brand choice probabilities among consumers of lower state dependence and higher price and promotion sensitivity. These findings are of importance both to retailers wanting to make product assortment changes and to manufacturers affected by them.

Brand-Level Effects of Stockkeeping Unit Reductions

In the past two decades, supermarkets have experienced a stockkeeping unit (SKU) explosion (Drèze, Hoch, and Purk 1994; Kurt Salmon Associates 1993); manufacturers view SKU proliferation as a way to increase their presence and market share, and retailers fear 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 pressure from lower-cost competitors, such as Wal-Mart and Costco, have driven many retailers to experiment with SKU reduction (hereinafter, SR) programs. Another reason for reducing the number of SKUs is the recognition by manufacturers and retailers that carrying too many items could cause clutter in the store and increase consumers' confusion (Broniarczyk, Hoyer, and McAlister 1998). As a result, some retailers and manufacturers (e.g., Pier 1 Imports, Sunbeam) have adopted efficient assortment policies by eliminating low-selling items (*Business Wire* 1998; *Home Textile Today* 2005). Marketing academics also 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; Boatwright and Nunes 2001, 2004; Iyenger and Lepper 2000), and other studies have shown that SR can decrease store-level shopping frequency and purchase quantity (Borle et al. 2005). An important unanswered question is how elimination of certain SKUs in the product assortment affects sales of individual brands. This is the main question we address in this research. Using data from an online retailer that implemented a permanent systemwide SR program, we examine how consumers reallo-

*Jie Zhang is Assistant Professor of Marketing, Robert H. Smith School of Business, University of Maryland (e-mail: jiejie@rhsmith.umd.edu). Aradhna Krishna is Isadore and Leon Winkelman Professor of Marketing, Stephen M. Ross School of Business, University of Michigan (e-mail: aradhna@umich.edu). The authors thank an anonymous online retailer for providing the data used in this study. They are grateful to Michel Wedel and the three anonymous *JMR* reviewers for their many valuable comments and suggestions. They also thank seminar participants at the Marketing Science Conference, Dartmouth College, University of Delaware, University of Iowa, University of Maryland, University of Michigan, University of Wisconsin, Indiana University, and University of Southern California for their input.

To read and contribute to reader and author dialogue on JMR*, visit http://www.marketingpower.com/jmrblog.*

ISSN: 0022-2437 (print), 1547-7193 (electronic)

cate their purchases among the remaining brands after certain SKUs are eliminated in the category and store. To lead up to this analysis, we conduct an in-depth examination of the effects of SR on category purchase incidence, brand choice, and purchase quantity.

Prior research on SR has focused on its impact on the category or store but not on individual brands. Although a category- or store-level analysis is useful for retailers, a brand-level analysis provides unique insights valuable not only for retailers but also for manufacturers. For a manufacturer, the most relevant issue related to SR is what happens to its brands after an SR program is implemented by a retailer. A related question is what the manufacturer can do to emphasize its brands' strengths and minimize negative consequences from the SR. For retailers, the brand-level analysis provides information about what may happen to their 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 analyses control for changes in the marketing mix before and after SR and consumers' responses to these changes. As we show, such an analysis prevents drawing spurious conclusions. We explore plausible drivers of differences in SR effects among brands and consumers. Specifically, 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 for a brand (e.g., number of SKUs eliminated, number of sizes eliminated, share of brand sales eliminated). We further examine the moderating effects of consumer characteristics (e.g., the degree of state dependence, purchase frequency, the nature of the SR for a consumer) on the impact of SR. The effects of each of these factors are important to understand for both manufacturers and retailers. This research helps answer the following questions:

- Are certain types of brands more likely to gain market share after an SR? For example, do larger-share brands become even larger, or are they more likely to lose share to smaller-share brands? Are high-priced brands likely to gain or lose share? Do brands with frequent promotions obtain a greater share of purchases in the post-SR market share reallocation period?
- How does the nature of SR for a brand (e.g., reduction in number of sizes, reduction in number of SKUs) change the brand's purchase share?
- How does SR affect the purchase share and quantity of private label brands?
- Is it valid to view change in market share as a proxy for the effect of SR on a brand's choice probability, or are changes in marketing-mix variables likely to be confounded with SR changes, thus resulting in spurious conclusions?
- Are there any systematic differences in the reaction to SR across consumers?

The online store environment we use for the 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 (see Boatwright and Nunes 2001). We organize the rest of the article as follows: In the next section, we discuss prior research findings on SR. Then, we describe our model. Following that, we present the data analysis results and conclude with managerial implications and suggestions for further research.

LITERATURE REVIEW

Prior research on product assortment changes has mainly considered their impact on consumers' assortment perceptions, category-level purchase probability and sales, store choice, and store-level shopping frequency and sales. We describe five major studies on these topics here.

Broniarczyk, Hoyer, and McAlister (1998) focus on how changes in product assortment affect consumers' perceptions of the assortment size, which in turn is shown to influence store choice. In their field study, two treatment stores had 54% of low-selling SKUs eliminated in the top five categories (candy, beer, soft drinks, salty snacks, and cigarettes). These stores experienced sales increases (2% and 8%) in the five categories compared with the control stores. In addition, shoppers reported finding it easier to shop in the test stores than in the control stores. The SKU count, availability of favorites, and category space affected store choice through assortment perception, and availability of favorites also had a direct link to store choice.

Iyenger and Lepper (2000) compare consumer reaction to small (6 SKUs) versus large (30 SKUs) assortments for jams and chocolates. They find that shoppers were initially attracted to retail shelves that offered large assortments. However, when the shoppers were at the shelves, they were more likely to make a purchase from a small than a large assortment.

In a series of field experiments, Drèze, Hoch, and Purk (1994) measure the effectiveness of two shelf management techniques: "space-to-movement," in which shelf sets were customized on the basis of store-specific movement patterns, and "product reorganization," in which product placement was manipulated to facilitate cross-category merchandising or ease of shopping. They also examine the impact of shelf positioning and facing allocations on sales of individual items. In their experiments, they find that category sales increased by approximately 4% when there was an increase in shelf facings of the high-selling items as a result of the deletion of low-selling SKUs. In contrast to Drèze, Hoch, and Purk's study, we focus on the effects of eliminating certain SKUs for each brand and control for the influence of shelf positioning and facing allocation.

Boatwright and Nunes (2001, 2004) examine purchase data collected from an SR field experiment for a large number of categories and conclude that there were no significant changes in the overall category sales due to the SR. Borle and colleagues (2005) examine the effects of SR on store and category purchase frequency and dollar sales but find negative results; both shopping frequency and purchase spending on each shopping trip declined as a result of SR. At the store level, they find that SR led to an average increase of 23% in expected interpurchase time and an average decrease of 4% 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 basket. The assortment reduction had a greater effect on store visit frequency than on purchase spending per visit. When Borle and colleagues compare the results of their study with those of Boatwright and Nunes, they find that the differences were mainly caused by the different set of categories examined in each study.

The divergent findings in these studies suggest that more research is needed on the impact of SR. Moreover, none of these studies focused on brand-level effects of SR. It is also worth noting another distinction between our study and that of Borle and colleagues (2005). Whereas they measure purchase quantities in dollar amounts, which could confound changes in purchase volume (in units) with changes in price, we model changes in purchase volume (in units) directly and then examine the impact of SR on sales revenue in terms of 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 purchase behavior for individual households: category purchase incidence, brand choice, and purchase quantity. Previous research has shown that it is important to account for the interdependence in these decisions (e.g., Chiang 1991). We model these three purchase components jointly using an approach similar to that of Hanemann (1984), Chiang (1991), Bell, Chiang, and Padmanabhan (1999), and Zhang and Krishnamurthi (2004).

To assess the impact of SR, it is necessary to control for the effects of other marketing-mix variables because they may change over the period used for examining the impact of the SR. In addition, the model should accommodate possible changes in consumers' responses to the other marketing-mix variables in the post-SR period. Our model controls for the effects of these variables, in particular the two most important ones, price and promotion. A closer examination of the data reveals that price and promotion experienced nontrivial changes during the period under investigation, and there was an increase in the overall category price and promotion levels in general. Further investigation indicates that these changes were exogenous to the SR program but coincided with its timing (for details, see the "Data Analysis" section). We assume that changes in consumers' responses to price and promotion, if any, were due to changes in price and promotion but not to the SR program. Our data do not allow us to separate out the possible effects of the SR program on price and promotion coefficients, because the two types of changes occurred at the same time. Nonetheless, our empirical analysis indicates that there were only minor differences in the price and promotion coefficients in the two periods, and thus, even if the SR program may contribute to the changes in the coefficients, these effects are negligible in magnitude and thus unlikely to alter the findings of the study.[1] We also control for the seasonality effect by matching the months of the year of the data with and without the SR. We provide the details in the next section.

Because we are particularly interested in brand-level effects of SR, such as what type of brands consumers tend to switch to 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, which is not confounded by the potential share increase for each remaining brand merely due to the elimination of other brands.

[1]We thank an anonymous reviewer for pointing out this issue.

We define $SR_t = 0$ if the time is before the SR, and $SR_t = 1$ if it is after the SR. The utility of brand k at time t for household i is given by

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

where α_{ki}, $k = 1, \ldots, K - 1$, are brand-specific constants; X_{kt} is a vector of marketing-mix variables, including regular price and price cut; $LB_{ikt} = 1$ if brand k was chosen by household i on the previous purchase occasion; β_i^B are coefficients of marketing-mix variables in the brand utility functions (they are allowed to be different in the pre- and post-SR periods to capture the notion that price and promotion changes may cause shifts in consumers' price and promotion sensitivities); γ_i measures a household's state dependence and is usually interpreted as an indicator of inertia ($\gamma_i > 0$) or variety seeking ($\gamma_i < 0$) (e.g., Gupta, Chintagunta, and Wittink 1997; Seetharaman, Ainslie, and Chintagunta 1999); δ_{ki}^B, $k = 1, \ldots, K - 1$, capture the effect of the SR on each brand's utility for household i; and α_{Ki} and δ_{Ki}^B are fixed to be 0 for identification purposes.

We model purchase incidence 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

$$(2)\quad \begin{aligned} U_{i0t} &= \delta_i^{I} SR_t + V_{i0t} + \varepsilon_{i0t} \\ &= \delta_i^{I} SR_t + \alpha_{0i} + Y_{it}\beta_i^{I} \\ & w + \psi_i^{I}\log(t) + \varepsilon_{i0t}, \end{aligned}$$

where α_{0i} is the 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 previous purchase quantity (LQ_{it}); and β_i^I are coefficients of the covariates. The previous purchase quantity variable refers to the quantity at the previous category purchase occasion and, in spirit, captures the effect of inventory (Chintagunta and Haldar 1998; Jain and Vilcassim 1991). 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 (see Chintagunta and Haldar 1998). In addition, an inventory variable might not have captured the entire inventory, because we have only household purchase data from the online store. The variable t indicates week, and the parameter ψ_i^I captures the possible trend of category purchase frequency over time at the store.[2] Finally, δ_i^I measures the effect of the SR on the threshold. Note that a positive ψ_i^I or δ_i^I indicates a negative effect on the purchase incidence probability, and vice versa.

To model purchase quantities, let Q_{ikt}^* be a latent variable of household i's purchase quantity of brand k in week t, and let Q_{ikt} be household i's actual purchase quantity of brand k in week t; in addition, we define $I_{it} = 1$ if household i makes a category purchase in week t and 0 if otherwise, and we define $B_{ikt} = 1$ if household i purchases brand k in week t

[2]The log-transformation of t provides better fit to the data than the linear form in our empirical analyses.

and 0 if otherwise. The observed purchase quantity $Q_{ikt} = Q^*_{ikt}$ if $I_{it} = 1$ and $B_{ikt} = 1$, and $Q_{ikt} = 0$ otherwise. We specify Q^*_{ikt} as follows:

$$(3)\qquad \begin{aligned} Q^*_{ikt} &= \delta^Q_i SR_t + W_{ikt} + \xi_{ikt} \\ &= \delta^Q_i SR_t + \alpha^Q_{ki} + Z_{ikt}\beta^Q_i + \psi^Q_i \log(t) + \xi_{ikt}, \\ &\quad k = 1, \ldots, K, \end{aligned}$$

where α^Q_{ki} is a constant for brand k and 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) as a control variable. We allow β^Q_i, the coefficient vector for Z_{ikt}, to be different for the pre- and post-SR period. The parameter ψ^Q_i captures possible trend of purchase quantity over time. The effect of the SR on purchase quantity is measured by δ^Q_i.[3]

To accommodate the interdependence of the three purchase components, we extended a formulation that Zhang and Krishnamurthi (2004) developed. Our model allows for a more flexible distribution of the error terms than what was assumed in their model, which leads to a nested logit formulation of the purchase incidence and choice components. By assuming a flexible bivariate distribution of the error term in the quantity equation (ξ_{ikt}) and a transformation of the error terms in the brand utility and category threshold equations (ε_{ikt}, k = 0, 1, …, K), we were able to derive a closed-form expression of the joint probability of purchase incidence, choice, and quantity and thus use standard maximum likelihood estimation procedure to estimate the model.[4]

In our model, the category purchase incidence probability is

$$(4)\qquad \Pr\{I_{it} = 1\} = \frac{\left[\sum_{j=1}^{K} \exp(\delta^B_{ki} SR_t + V_{ijt})\right]^{1-\phi}}{\exp(\delta^I_i SR_t + V_{i0t}) + \left[\sum_{j=1}^{K} \exp(\delta^B_{ki} SR_t + V_{ijt})\right]^{1-\phi}},$$

and the joint probability of purchase incidence and brand choice is

$$(5)\qquad \Pr\{I_{it} = 1, B_{ikt} = 1\} = \frac{\exp(\delta^B_{ki} SR_t + V_{ikt})\left[\sum_{j=1}^{K} \exp(\delta^B_{ji} SR_t + V_{ijt})\right]^{-\phi}}{\exp(\delta^I_i SR_t + V_{i0t}) + \left[\sum_{j=1}^{K} \exp(\delta^B_{ji} SR_t + V_{ijt})\right]^{1-\phi}},$$

$$k = 1, \ldots, K,$$

where $\phi \in (0, 1)$ is a parameter measuring the similarity among the brands. If Equation 4 is reparameterized into

$$(6)\qquad \Pr\{I_{it} = 1\} = \frac{\left[\sum_{j=1}^{K} \exp(V_{ijt})\right]^{1-\phi}}{\exp(\delta^{I*}_i SR_t + V_{i0t}) + \left[\sum_{j=1}^{K} \exp(V_{ijt})\right]^{1-\phi}},$$

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

$$(7)\qquad \delta^{I*}_i = \delta^I_i + (1-\phi)\log\left[\sum_{j=1}^{K} \exp(V_{ijt}) \Big/ \sum_{j=1}^{K} \exp(\delta^B_{ji} + V_{ijt})\right].$$

We estimate δ^{I*}_i for its ease of interpretation. Note that Equation 5 is modified accordingly.

Thus far, the model has been constructed at the individual household level. We employ a latent-class formulation to capture unobserved consumer heterogeneity (see Kamakura and Russell 1989), in which parameters are segment specific, denoted by subscript g = 1, …, G. The discrete latent-class specification has been shown to be empirically equivalent to continuous approaches for representing heterogeneity, such as the hierarchical Bayesian formulations (Andrews, Ainslie, and Currim 2002). The log-likelihood function is given by

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

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, and the one that yields the lowest BIC is selected. To summarize, the parameters that we are particularly interested in are δ^{I*}_g, the effect of the SR on category purchase incidence; δ^B_{kg}, the effect of the SR on brand k's utility, k = 1, …, K; and δ^Q_g, the effect of the SR on purchase quantity.

DATA ANALYSIS

Data Description

Our data are provided by an online grocery retailer that operates in several metropolitan markets in the United States. The retailer implemented a systemwide SR program 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 during the January 1, 1997–August 15, 1999, period. As part of the SR program, most brands had some of their SKUs eliminated, and a few brands were eliminated altogether. Panels A and B in Table 1 provide a description

[3]It is possible to make δ^Q_i brand specific. In our empirical analyses, the model with brand-specific δ^Q_i does not provide significant improvement over the one with a common parameter for all brands, for all categories we analyzed. Therefore, we present the current version in the model formulation.

[4]Details of the model, the likelihood function, and its derivation appear in the Web Appendix at http://www.marketingpower.com/content84060.php.

Table 1
DESCRIPTIVE STATISTICS OF THE SR PROGRAM

A: Overall Category-Level Assortment Changes

	Number of Brands		*Number of SKUs*		*Number of Sizes*		
Category	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Market Share Eliminated (%)*
Liquid detergent	14	11	74	50	7	6	9.0
Margarine	12	10	55	45	5	5	3.0
Spaghetti sauce	17	11	127	89	17	12	6.2

B: Description of the Eliminated Brands

Category	*Brand*	*Number of SKUs*	*Market Share (%)*
Liquid detergent	Ivory	1	.03
	Ultra Yes	1	.83
	Value Wise	1	.21
Margarine	Move Over Butter	1	.02
	Nucoa	1	.08
Spaghetti sauce	Alessi	1	.15
	Buitoni	1	.13
	Del Monte	2	.17
	Giannotti	1	.02
	Value Wise	1	.25
	Weight Watchers	1	.06

of the category-level assortment changes and the brands eliminated by the SR program.

The two panels in Table 1 show that 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% for liquid detergent, 18% for margarine, and 30% for spaghetti sauce, and the cumulative market shares for the eliminated SKUs were much smaller (9%, 3%, and 6%, respectively). The number of sizes dropped from 7 to 6 for liquid laundry detergent, remained at 5 for margarine, and dropped from 17 to 12 for spaghetti sauce. The brands that were completely eliminated had few SKUs and accounted for a small market share. Most of the SRs occurred in the brands that remained after the reduction.

As we explained previously, we focus on the brands remaining after the SR to investigate how consumers' purchase decisions in the store may have changed because of the assortment reduction, including how they may have reallocated purchases among the remaining brands. We also needed to delete a few small brands with too few purchases 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% of total purchases for the 11 brands), 9 of the remaining 10 brands for margarine (99% of total purchases for the 10 brands), and 9 of the remaining 11 brands for spaghetti sauce (98% of total purchases for the 11 brands). For ease of exposition, hereinafter, we refer to the 9 brands under investigation for each product as the "category."

For each product category, we use January 1–August 15, 1997 (33 weeks), as the initialization period for the household average purchase frequency and quantity variables. The estimation data cover January 1–August 15, 1998 (33 weeks), as the period before the SR, and January 1–August 15, 1999 (33 weeks), as the period after the SR. The two periods are matched in terms of months to minimize the impact of seasonality effects. For concerns of seasonality, we do not use data from August 16 to December 31, 1998, because we do not have data beyond August 15, 1999, in the post-SR period. For each category, we choose households that made at least two purchases of any brand in the initialization period (for computing the household average purchase frequency and quantity) and at least one purchase of the brands retained for the study (nine in each category) in the pre-SR period. This results 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 these households did not need to make a purchase in the post-SR period to be selected, all made at least one category purchase after the SR. This is consistent with Borle and colleagues' (2005) finding that there was little attrition from the store after an assortment reduction experiment.

Our data show that for most brands, both regular prices and price discounts were higher in the post-SR period. As a result, the average shelf price was 6% higher for liquid detergent, 17% higher for margarine, and 8% higher for spaghetti sauce in the post-SR period. However, note that a few brands experienced a decrease in shelf price (e.g., the private label brands for the liquid detergent and spaghetti sauce categories).[5] These variations highlight the importance of adopting a model-based approach to adjust for changes in the key marketing-mix variables and responses

[5]In the Web Appendix (see Additional Table 1; http://www.marketingpower.com/content84060.php), we present the average regular price, price discount, shelf price, and market share of each brand before and after the SR. Note that the market shares represent each brand's share of sales among the brands studied (i.e., not including those eliminated by the SR or taken out because of insufficient purchase observations).

to them. For example, if we were to compare the market share of Tide detergent in the two periods, it would not be clear whether the drop in market share was due to the SR or to a rise in its price level. Similarly, the market share increase for the private label liquid detergent can be explained both by the SR and by the post-SR shelf price decrease.

Using this data set, we first estimate the model described in the previous section and then conduct a series of follow-up analyses based on the model estimation results to investigate various aspects of the SR effects. We present three sets of results: (1) model estimation results; (2) SR effects at the brand level, after we control for changes in other marketing-mix variables and responses to them; and (3) an analysis that attempts to identify drivers of the differences in the SR effects among consumers and brands.

Results

Model estimation results. A three-segment model appears to fit the data best for all three categories based on BIC. The BIC for models with one, two, three, and four segments is 11,690.8, 11,193.8, 11,026.5, and 11,187.0, respectively, for liquid detergent; 22,318.6, 19,780.9, 18,627.5, and 18,645.2, respectively, for margarine; and 10,442.4, 9,991.9, 9,984.7, and 10,134.3, respectively, for spaghetti sauce. Parameter estimates for the three categories appear in Tables 2–4. The ρ^2 and adjusted-ρ^2 terms indicate that our model performs well for all three categories. Nonetheless, the model could have been further improved if we had data on other variables that affected purchase behavior. We summarize the effects of the marketing-mix variables and household-specific control variables first, and then 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 direction for all the significant parameter estimates. Specifically, regular price negatively affects a brand's choice probability and the category purchase incidence probability, whereas 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 quantity bought on the previous purchase occasion increases the category purchase incidence threshold and therefore reduces the purchase incidence probability. In addition, purchase quantity decreases with a 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 the quantity purchased on a given occasion.

The parameter estimates also reveal strong consumer heterogeneity. The three segments for each category exhibit different brand preferences, marketing-mix effects, and degree of state dependence. We also find a significant decreasing trend in the category incidence probability over time for most segments in all three categories (the parameter estimate for log[t] is positive and significant or marginally significant for seven of the nine category segments). It is critical to control for these overall trends in consumers' purchase behaviors in the online store to obtain an accurate assessment of the impact of SR. That is precisely what we do when we examine segment-level SR effects subsequently.

We now examine parameters that capture the impact of SR on purchase incidence, brand utility, and purchase quantity, denoted by δ^{I*}, δ_k^B, and δ^Q, respectively. As we explained previously, the signs of δ^{I*} and δ^Q indicate the direction of the effect on purchase incidence and quantity per purchase occasion, respectively. 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 on δ_k^B subsequently. In each product category, these effects seem to be associated with the level of state dependence of the segments.

We expect that the higher the level of state dependence, the more positive the effects of SR would be, that is, if the consumer's favorite SKU has not been eliminated. By definition, highly state-dependent (i.e., inertia-prone) consumers are more likely to purchase brands that they like repeatedly and thus should favor a shopping environment with narrower choice and less clutter. With a less cluttered online store environment, we expect that they will make more product category purchases and also purchase larger quantities. (An increase in both category purchase frequency and quantity is possible because of store switching and consumption expansion.) Our results are consistent with this expectation in all three product categories.

SR effects at the brand level. In this section, we assess the magnitude of the SR impact on purchase incidence probability, conditional brand choice probabilities, quantity per purchase occasion, total purchase quantity, and total sales revenue. The basis for this analysis is the posterior values of these measures for each household, which we obtained by using the model estimation results and purchase history data of each household. The posterior value of a particular measure for a household is the weighted average of the segment-specific values, weighted by a household's posterior segment membership probabilities.

To control for changes in the marketing-mix variables and responses to them, we conduct a "would-be" analysis using data in the pre-SR period. Specifically, we estimate two sets of posterior values for the outcome measures using the same data: one set with all pre-SR period parameters in the model (no SR effect parameters) and the other set with the same pre-SR period parameters plus the SR effects parameters. Note that the pre-SR period values of the independent variables are used in the computation of both sets. The first set represents the expected values of the outcome measures in the actual pre-SR period. The second set represents the expected values of the outcome measures had there been the SR, all else being equal to the pre-SR period data. Therefore, the differences between the two sets give the effects of the SR on the outcome measures. This approach is based on the assumption that the price and promotion changes in the data were due to exogenous reasons other than the SR program. Our information about the online retailer's operations and a check of external marketplace price and promotion data indicate that the changes were indeed exogenous. Alternatively, we could compute

Table 2
PARAMETER ESTIMATES FOR LIQUID DETERGENT

Variables/Parameters	*Segment 1*	*Segment 2*	*Segment 3*
Brand Utility (baseline: private label)			
α_k: Wisk	2.867**	–.472	1.078*
All	.519	.984	.802
Tide	2.568**	1.236**	1.842***
Cheer	1.788*	.472	1.574**
Arm & Hammer	–18.469***	–11.018***	.988
Era	2.441**	.447	.661
Dreft	4.979***	–2.103**	2.981***
Surf	1.588*	.573	.340
β^B: Regular price (before SR)	–.833**	.211	–.470**
Price cut (before SR)	.427*	.424	.519**
Regular price (after SR)	–.960**	–.523*	–.243
Price cut (after SR)	.609*	.423	.456
State dependence (γ)	5.098***	3.262***	2.510***
δ_k^B (SR): Wisk	.482	2.515***	.321
All	–.126	.250	.399
Tide	2.121**	1.736**	.402
Cheer	.591	.630	–.635
Arm & Hammer	10.247***	–9.200***	–.201
Era	–.694	1.038*	–.369
Dreft	–.088	4.053***	–1.186*
Surf	–.008	–.007	.329
Category Threshold			
Constant	2.495**	2.404***	2.702***
Purchase frequency	–5.721***	–5.754***	–7.057***
Previous purchase volume	–.003	.025**	.032***
log(t)	.249***	.176**	.144*
δ^{I^*} (SR)	–.362*	–.123	.180
Purchase Quantity			
α_k^Q: Wisk	4.367***	9.860***	8.574***
All	3.446***	19.546***	8.960***
Tide	4.915***	19.567***	8.886***
Cheer	3.264***	9.959***	8.927***
Arm & Hammer	6.727***	12.091***	8.943***
Era	3.368***	10.065***	9.042***
Dreft	2.447***	18.896***	3.856**
Surf	9.915***	9.813***	8.678***
Private label	4.581***	51.466***	6.119***
β^Q: Regular price (before SR)	.291	–1.046***	.372
Price cut (before SR)	3.630***	.811**	1.520*
Regular price (after SR)	–.151	–.942**	.367
Price cut (after SR)	3.698***	.753**	1.514**
Average purchase volume	.485***	.055	.048
log(t)	–.111	–.105	–.051
δ^Q (SR)	2.792***	–.541	.164
ϕ (brand similarity)	.109	.902	.989
θ (interdependence of incidence, choice, quantity)		–.692	
Segment size	18.5%	27.0%	54.5%

–Log-likelihood [$-L(\beta)$]	10,403.3	ρ^2	.787
Number of parameters (M)	132	Adjusted ρ^2	.784

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: $\rho^2 = 1 - L(\beta)/L(0)$, and adjusted $\rho^2 = 1 - [L(\beta) - M]/L(0)$, where L(0) = log-likelihood when all parameters are zero.

the SR effects using the post-SR period values of the independent variables and the post-SR period price and promotion coefficients, which is also consistent with the observation that changes in prices and promotions were exogenous. We compared the two methods and found the results to be similar. Note that our approach can be easily modified for the situation in which price and promotion changes are endogenous to an SR program, in which case the pre-SR period price and promotion data and coefficients should be used in the first set and the post-SR period price and promotion data and coefficients should be used in the second set of outcome measures.

We begin by summarizing the overall impact of SR at the category level in terms of purchase incidence probability,

Table 3

PARAMETER ESTIMATES FOR MARGARINE

Variables/Parameters	*Segment 1*	*Segment 2*	*Segment 3*
Brand Utility (baseline: Shedd's Country Crock)			
α_k: Brummel & Brown	.903*	.626	–2.626***
Fleischmann's	–.609	.572	–2.462***
I Can't Believe It's Not Butter	–.487	.272	–2.358***
Imperial	–.305	.225	–.792**
Land O' Lakes	–1.562***	.267	–1.793***
Parkay	–.166	.762	–1.288***
Promise	.626*	–.265	–3.129***
Private label	.559	–.096	–.405
β^B: Regular price (before SR)	.088	–.055	.132
Price cut (before SR)	.019	.020	–.043
Regular price (after SR)	.073	–.014	.118
Price cut (after SR)	–.048	.107	.004
State dependence (γ)	4.292***	3.929***	3.048***
δ_k^B (SR): Brummel & Brown	.686	–1.204*	–.127
Fleischmann's	–.003	–1.170*	–.699
I Can't Believe It's Not Butter	.912	–.326	.096
Imperial	.266	–.934	–.294
Land O' Lakes	1.233*	–.747	–.493
Parkay	.477	–1.701**	–.495
Promise	–.425	–.601	.438
Private label	–1.074	–.423	–.010
Category Threshold			
Constant	7.584***	7.181***	6.704***
Purchase frequency	–6.097***	–9.177***	–5.302***
Previous purchase volume	.004	.004	–.000
log(t)	.214**	.186**	.071
δ^{I^*} (SR)	–.234*	.487*	.635**
Purchase Quantity			
α_k^Q: Brummel & Brown	5.089***	17.806***	8.485***
Fleischmann's	1.342	10.130***	10.062***
I Can't Believe It's Not Butter	2.201**	17.194***	8.561***
Imperial	.649	17.065***	8.498***
Land O' Lakes	2.836**	17.141***	8.896***
Parkay	1.376	33.675***	16.271***
Promise	2.574**	9.357***	9.121***
Shedd's Country Crock	2.309**	47.942***	15.424***
Private label	4.649***	16.644***	15.355***
β^Q: Regular price (before SR)	.375	–1.025**	–.519
Price cut (before SR)	2.663***	1.268**	.492
Regular price (after SR)	.334	–1.025**	–.594
Price cut (after SR)	2.637***	1.253**	.593
Average purchase volume	.854***	.017	.046*
log(t)	–.502***	.036	.017
δ^Q (SR)	.533	.140	.899
ϕ (brand similarity)	.042	.053	.035
θ (interdependence of incidence, choice, quantity)		.082	
Segment size	36.0%	33.6%	30.4%

–Log-likelihood [$-L(\beta)$]	17,988.2	ρ^2	.766
Number of parameters (M)	132	Adjusted ρ^2	.768

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: $\rho^2 = 1 - L(\beta)/L(0)$, and adjusted $\rho^2 = 1 - [L(\beta) - M]/L(0)$, where L(0) = log-likelihood when all parameters are zero.

average quantity per purchase occasion, total purchase quantity, and revenue. The three categories exhibit vast differences. The spaghetti sauce category enjoyed the greatest increase in total purchase quantity and revenue (12.4% and 15.4%, respectively) due to the SR. The liquid detergent category also experienced an increase in purchase quantity and revenue (7.1% and 10.2%, respectively). In contrast, the overall reaction to the SR in the margarine category was negative, with a sharp decline in both total purchase quantity and revenue (dropped by 17.8% and 15.7%, respectively).[6] It appears that the average purchase incidence probability across households decreased substantially for margarine (21.2%) and a little for detergent (1.4%) but

[6]Note that our category-level findings may be due to the SR program being storewide. These results are likely to be modified if an SR is implemented in a single category. We thank an anonymous reviewer for this insight.

Table 4
PARAMETER ESTIMATES FOR SPAGHETTI SAUCE

Variables/Parameters	*Segment 1*	*Segment 2*	*Segment 3*
Brand Utility (baseline: Ragu)			
α_k: Barilla	.670	.788**	–3.540***
Classico	.871	.829**	–3.382**
Five Brothers	.855	.566	–4.654***
Healthy Choice	–.865	–1.757**	–2.442***
Hunt's	–4.535***	–3.772***	–1.039
Newman's Own	1.030	.299	–3.881***
Prego	–.171	–.027	–.147
Private label	–.875	–1.554**	–2.114***
β^B: Regular price (before SR)	–.451***	–.472**	–.003
Price cut (before SR)	.138	.438***	.126
Regular price (after SR)	–.356*	–.401*	–.760***
Price cut (after SR)	.130	.386	.607*
State dependence (γ)	6.277***	3.033***	2.458***
δ_k^B (SR): Barilla	1.298	.112	2.436**
Classico	.222	.004	2.735**
Five Brothers	.139	–.049	3.407**
Healthy Choice	1.982**	.674	1.758**
Hunt's	–10.732***	.576	–.296
Newman's Own	–.405	–.643	1.781*
Prego	2.578***	1.275	.723
Private label	–1.422*	–17.332	1.236*
Category Threshold			
Constant	5.059***	2.357***	1.808***
Purchase frequency	–6.797***	–7.084***	–2.533***
Previous purchase volume	.079***	–.007	.028*
log(t)	.039	.252**	.341*
δ^{I*} (SR)	–.397	–.042	.278
Purchase Quantity			
α_k^Q: Barilla	2.351***	8.515***	3.001***
Classico	1.300**	9.247***	2.940***
Five Brothers	.880	8.401***	2.413***
Healthy Choice	–1.430**	9.540***	2.503***
Hunt's	.643	5.925***	2.082***
Newman's Own	.530	7.646***	2.602***
Prego	.122	7.894***	2.404***
Ragu	–.114	6.656***	2.458***
Private label	–1.110*	6.746***	2.349***
β^Q: Regular price (before SR)	–1.819**	–6.634***	–1.690***
Price cut (before SR)	4.176***	.125	5.639***
Regular price (after SR)	–1.914**	–6.720***	–1.613**
Price cut (after SR)	3.828***	.518	5.236***
Average purchase volume	1.173***	.475***	.263***
log(t)	.031	–.322**	.049
δ^Q (SR)	1.141***	.454	–.660
ϕ (brand similarity)	.182	.290	.951
θ (interdependence of incidence, choice, quantity)		–.899	
Segment size	15.9%	53.2%	30.9%

–Log-likelihood [$-L(\beta)$]	9348.1	ρ^2	.781
Number of parameters (M)	132	Adjusted ρ^2	.778

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: $\rho^2 = 1 - L(\beta)/L(0)$, and adjusted $\rho^2 = 1 - [L(\beta) - M]/L(0)$, where L(0) = log-likelihood when all parameters are zero.

increased slightly for spaghetti sauce (.9%), whereas the average quantity per purchase occasion increased moderately for all three categories (3.5%–5.9%). Regardless of whether category-level effects were positive or negative, effects of SR at the brand level were mixed in every category. We examine this next.

Two key measures at the brand level appear in Table 5: the average conditional brand choice probability given a category purchase incidence and the average household purchase quantity in the 33 weeks of the pre-SR period. The pattern of results for sales revenue is similar to the one for quantity, and therefore we do not discuss it separately. Because our study focuses on the impact of SR on individual brands, we average both measures (choice and purchase quantity) across households. Note that these two measures do not always move in the same direction, because total purchase quantity is affected not only by changes in the choice probability and purchase quantity on each occasion,

Table 5
BRAND-LEVEL EFFECTS OF SR

	Average Conditional Brand Choice Probability				*Average Household Purchase Quantity in 33 Weeks (Ounces)*			
	Without SR	*With SR*	*Difference*[a]	*% Difference*	*Without SR*	*With SR*	*Difference*[a]	*% Difference*
Liquid Detergent								
Wisk	.097	.116	.019**	+20	44.6	54.5	9.9**	+22
All	.078	.085	.007*	+9	34.0	31.9	–2.1	–6
Tide	.502	.548	.046**	+9	331.9	372.7	40.8**	+12
Cheer	.085	.055	–.030**	–35	32.1	23.3	–8.8**	–27
Arm & Hammer	.058	.044	–.014**	–24	26.1	17.3	–8.8**	–34
Era	.044	.029	–.015**	–34	22.7	18.4	–4.3*	–19
Dreft	.067	.068	.001	+1	21.5	40.8	19.3**	+90
Surf	.033	.024	–.009**	–27	15.9	11.9	–4.0**	–12
Private label	.037	.031	–.006**	–16	14.2	11.1	–3.1**	–22
Margarine								
Brummel & Brown	.057	.055	–.002	–4	4.9	4.2	–.7*	–14
Fleischmann's	.097	.084	–.013**	–13	5.1	4.1	–1.0**	–20
I Can't Believe It's Not Butter	.231	.255	.024**	+10	18.7	18.1	–.6	–3
Imperial	.127	.121	–.006	–5	9.5	7.4	–2.1**	–22
Land O' Lakes	.097	.101	.004	+4	5.6	4.4	–1.2**	–21
Parkay	.077	.065	–.012**	–16	8.4	4.8	–3.6**	–43
Promise	.081	.078	–.003	–4	6.7	6.9	.2	+3
Shedd's Country Crock	.177	.190	.013**	+7	20.0	15.2	–4.8**	–24
Private label	.055	.050	–.005*	–9	5.0	3.7	–1.3**	–26
Spaghetti Sauce								
Barilla	.081	.096	.015**	+19	9.6	12.6	3.0**	+31
Classico	.163	.234	.071**	+44	19.5	26.4	6.9**	+35
Five Brothers	.057	.070	.013**	+23	4.9	6.2	1.3**	+27
Healthy Choice	.028	.035	.007**	+25	3.1	3.7	.6**	+19
Hunt's	.022	.009	–.013**	–59	2.7	.8	–1.9**	–70
Newman's Own	.080	.058	–.022**	–28	8.7	9.6	.9	+10
Prego	.293	.311	.018**	+6	47.8	58.8	11.0**	+23
Ragu	.243	.176	–.067**	–28	40.3	37.5	–2.8	–7
Private label	.033	.012	–.021**	–64	3.2	1.5	–1.7**	–53

*$p < .05$.
**$p < .01$.
[a]Based on t-test of the difference.

which are brand specific, but also by changes in the purchase incidence probability, which are category specific and, therefore, the same for all brands in the category.

Table 5 shows a high degree of variation among brands on the two measures. It appears that SR not only changed the category purchase incidence but also altered consumers' choice among the remaining brands, so that some brands gained market share and others lost market share. As a result, in every category, some brands gained in total sales quantity, and others suffered substantial sales loss due to the SR, regardless of the direction of the category-level effect. For example, although the total category purchase quantity for spaghetti sauce increased by 12.4% with the SR, the Hunt's brand and private label both suffered a severe loss in sales (by 70% and 53%, respectively). Conversely, despite a loss in total category sales quantity of 17.8% for margarine, there was no significant change in sales for the I Can't Believe It's Not Butter brand and even a slight increase in sales for the Promise brand. Note that in all three categories, SR seems to have caused a substantial drop in choice probability and total purchase quantity for the private label brand, which should be alarming to the retailer. We discuss the possible reasons for this subsequently.

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 account for 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 (see Additional Table 1 in the Web Appendix at http://www.marketingpower.com/content84060.php) would lead to the conclusion that the SR caused Tide to lose market share by 3.2% and caused the private label brand to gain market share by 2.2%, whereas our analysis in Table 5 indicates the exact opposite; the purchase share increased by 4.6 percentage points for Tide and decreased by .6 percentage points for the private label, both of which are statistically significant.

Drivers of the differences in SR effects among consumers and brands. To obtain a comprehensive picture of how the SR affected purchase behavior across consumers and brands differently, we conduct regression analyses based on data pooled across categories on each of the three purchase decision components: category purchase incidence, conditional brand choice probability, and quantity given a purchase occasion. We analyze the first and third components at the household level because the effects do not vary across brands (with 669 observations in each analysis), and we analyze the second component at the household × brand level (6021 observations resulted from having nine brands in each category and 669 households in the data of three categories combined).

We first describe the regression analyses on the SR effects on households' average purchase incidence probability and purchase quantity, given a category purchase occasion. Both dependent variables are standardized within each category because the categories differ in the magnitude of purchase incidence probabilities and purchase quantities. We use the following five household-specific factors as explanatory variables:

1. Level of state dependence,
2. Purchase frequency,
3. Whether a household's favorite brand was eliminated by the SR,
4. Whether a household's favorite SKU was eliminated by the SR, and
5. Eliminated SKUs' share of purchase quantity for a household.

We standardize the level of state dependence and purchase frequency within each category to control for the magnitude differences across categories. A favorite brand/SKU is defined as the most frequently purchased brand/SKU by a household in the pre-SR period. We did not include a variable for whether a household's favorite size was eliminated, because no household in our data experienced it. The results appear in Table 6 (Models 1 and 2). As the table shows, state dependence and purchase frequency have positive, significant effects on the change in purchase incidence probability, and the former also has a positive, significant effect on the change in quantity given a purchase occasion, which indicates that the higher a household's state dependence and purchase frequency, the more positive its reaction was to the SR. A closer examination of the data reveals that even for the margarine category, which experienced substantial sales reduction due to the SR, the highly state-dependent and frequent buyers of this category still increased their purchase incidence probability and/or average quantity for purchase occasion. This is particularly encouraging news for retailers because consumers of high state dependence and purchase frequency are arguably their most valuable customers. We did not find significant effects of the other three factors, possibly because of low variations in these variables across households and strong collinearity among them in the data.

We now describe the regression analysis for the SR effects on the conditional brand choice probabilities. The dependent variable is the difference in a conditional choice probability (with and without SR) obtained from the would-be analysis. We examine two groups of brand-specific factors: brand characteristics and brand-level SR variables.

The brand characteristics are as follows:

- *Market share*: This refers to the market share before the SR.
- *Price level*: Because prices are not directly comparable across categories, we use the standardized average shelf price for a brand within each category.

Table 6

DRIVERS OF THE DIFFERENCES IN THE SR EFFECTS ACROSS CONSUMERS AND BRANDS

Dependent Variable	*Explanatory Variable*	*Parameter Estimate*	*p-Value*
Model 1:	Intercept	–.0147	.5686
Standardized change in category purchase incidence	Standardized state dependence	.8042	<.0001
	Standardized purchase frequency	.0469	.0112
	Favorite brand being eliminated	–.2059	.6320
	Favorite SKU being eliminated	.1730	.2578
	Eliminated SKUs' share of household purchase	.0954	.6587
Model 2:	Intercept	.0090	.8221
Standardized change in quantity given a purchase occasion	Standardized state dependence	.3563	<.0001
	Standardized purchase frequency	.0516	.1623
	Favorite brand being eliminated	–.9686	.1475
	Favorite SKU being eliminated	.1972	.4065
	Eliminated SKUs' share of household purchase	–.2339	.4861
Model 3:	Intercept	–.0278	<.0001
Change in conditional choice probability	Market share	.1259	<.0001
	Standardized price level	.0095	<.0001
	log(promotion frequency)	.0355	<.0001
	Number of sizes eliminated (DSIZE)	.0028	.1238
	DSIZE × share of purchase	–.0557	<.0001
	Number of SKUs eliminated (DSKU)	.0064	<.0001
	$DSKU^2$	–.0013	<.0001
	Change in SKU share	.1119	<.0001
	Eliminated SKUs' share of brand sales	.0210	.0978
Model 4:	Intercept	.0260	<.0001
Sum of squares of changes in brand choice probabilities	Standardized state dependence	–.0211	<.0001
	Standardized purchase frequency	.0006	.7826
	Favorite brand being eliminated	–.0253	.5160
	Favorite SKU being eliminated	.0059	.6680
	Eliminated SKUs' share of household purchase	.0333	.0887
	Standardized regular price sensitivity	–.0232	<.0001
	Standardized price promotion sensitivity	.0364	<.0001

- *Promotion frequency*: This is defined as the percentage of weeks in which a brand was on price promotion.

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

The brand-level SR variables are as follows:

- *Number of SKUs eliminated for the brand (DSKU)*: We include the quadratic terms of DSKU to capture possible nonlinear effect of this variable. Boatwright and Nunes (2001) find that the number of SKUs eliminated for a category has a nonlinear effect on the category sales; a moderate cut increases sales, and a deep cut decreases sales. We investigate whether such an effect also exists at the brand level.
- *Number of sizes eliminated (DSIZE)*: We include both a main effect of DSIZE and its interaction with a brand's share of purchase for a household. As in many previous studies (e.g., Bucklin, Gupta, and Siddarth 1998; Tellis and Zufryden 1995), we use the share-of-purchase variable as a measure for a household's loyalty to a given brand. The interaction term is intended to capture the possible moderating effect of a household's loyalty to a brand on the impact of size reduction for the brand.
- *Change in the share of SKUs* (ΔSKUSH): We define a brand's share of SKUs (SKUSHR) as its number of SKUs divided by the total number of SKUs in the category, and $\Delta\text{SKUSHR} = \text{SKUSHR}_{\text{after}} - \text{SKUSHR}_{\text{before}}$.
- *Eliminated SKUs' share of brand sales*: This is the proportion of a brand's sales in the pre-SR period contributed by the eliminated SKUs.

Parameter estimates from the regression appear in Table 6 (Model 3).[7] For the SR effects on brand choice, we identified six significant drivers: (1) market share, (2) price level, (3) logarithm of the promotion frequency,[8] (4) number of sizes eliminated and its interaction with a brand's share of purchase for a household, (5) the quadratic terms of number of SKUs eliminated, and (6) change in the share of SKUs. Notably, we did not find a significant effect of the eliminated SKUs' share of brand sales.

The effects of market share, price level, logarithm of the promotion frequency, and change in the share of SKUs are positive. It appears that after the SR, all else being equal, market shares tend to shift toward larger brands, higher-priced brands, and brands with more frequent promotions. These effects imply that when consumers are faced with a reduced product assortment and reallocate their purchases among the remaining brands and product options, they are likely to switch to familiar brands or premium brands; higher-priced brands tend to be premium brands, larger share brands have higher market exposure, and more frequent promotions also help bring consumers' attention to a brand. A possible reason behind the switch is that the SR program may have reinforced consumers' need for ease of shopping, and familiar or premium brands tend to come to their minds more easily. The effects of market share, price level, and promotion frequency may also explain why the private label brand suffered sales loss in each category; specifically, private labels tend to have small market share, low price levels, and less frequent promotions (as is the case in our data).

Furthermore, we find that the nature of the assortment change also affects how consumers reallocate their purchases. Brands with a larger reduction in the number of sizes tend to lose share. Notably, this effect appears to increase with a household's share of purchase of a brand. In other words, the more loyal a household is to a brand, the more severe the negative effect is for the household when the brand had a size reduction. Another notable finding is that the nonlinear effect of the number of SKUs eliminated, as first documented by Boatwright and Nunes (2001) for category-level sales, exists at the brand level. All else being equal, a brand's choice probability first increases with the number of SKUs eliminated and then decreases after a certain point. This implies that a brand could benefit from the elimination of certain SKUs to reduce clutter and thus ease consumers' purchase decisions, but a deep reduction in its number of SKUs would decrease its appeal to consumers. Finally, we find that an increase in a brand's share of SKUs in the category tends to increase its share of purchases; all else being equal, if share of SKUs increases by 1 percentage point, on average, the market share would increase by .11 percentage points.

To examine how households differed in the SR effects on their brand choice probabilities, we first computed the sum of squares of changes in the conditional brand choice probabilities for each household and then ran a regression analysis of this variable on household characteristics.[9] This sum-of-squares measure captures a household's total amount of changes in brand choice probabilities due to SR. In addition to the five household characteristics listed previously, we also included standardized household-specific posterior regular price and price cut coefficients for the pre-SR period as explanatory variables in the regression model. (We tested the regular price and price cut coefficients in both the choice and the quantity parts and found the choice coefficients to be nonsignificant. Therefore, we kept only the quantity price and promotion sensitivity in the final model.) The results appear in Table 6 (Model 4). Model 4 indicates that the SR program caused more changes in brand choice probabilities among consumers of lower state dependence and higher price and promotion sensitivity. When we combine findings from Models 1, 2, and 4, it appears that the SR program affected consumers of high state dependence and purchase frequency mainly through its effects on purchase incidence and quantity decisions, whereas its impact on brand choice behavior is most profound for consumers of low state dependence and high price and promotion sensitivity.

The significant drivers identified in Models 1–3 all contribute to the differences across brands and households in the SR effects on a household's total brand purchase quantity because this purchase quantity results from the three individual purchase components. This is confirmed by our regression analysis for the SR effects on total brand purchase quantity during the 33 weeks in the pre-SR period.

[7]We report the correlation coefficients of the variables in Additional Table 2 (see the Web Appendix at http://www.marketingpower.com/content84060.php).

[8]Our empirical analysis shows that the logarithm of promotion frequency provides better fit to the data than the linear form of promotion frequency.

[9]We thank an anonymous reviewer for suggesting this analysis.

DISCUSSION

As we stated previously, prior research on product assortment reductions 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 additional insights for both manufactures and retailers. The most relevant issue for a manufacturer regarding SR is the impact on its brands. The manufacturer wants to know what it can do to emphasize its brands' strengths and minimize negative repercussions. Retailers benefit from a brand-level analysis by obtaining a better understanding of how market share may shift between brands with different profitability and what may happen to their private label brands; this type of insights is not possible with a store- or category-level approach.

To summarize the key findings of our analyses, we found a large variation in the impact of SR across consumers and individual brands and categories. Consumers with higher state dependence and more frequent purchases welcomed the change by increasing category purchase frequency and purchase quantity, whereas consumers with lower state dependence and less frequent purchases reduced their purchases as a result of SR. In addition, the SR program caused more changes in brand choice probabilities among consumers of lower state dependence and higher price and promotion sensitivity.

At the brand level, consumers appeared to reallocate their purchases among brands substantially after the SR. 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 were not affected much by the SR, whereas other brands experienced drastic reductions (or increases) in brand choice and purchase quantity. We identified six significant drivers for the differential effects on brand choice probabilities: market share, price level, promotion frequency, number of sizes eliminated, number of SKUs eliminated, and change in the share of SKUs in the category. Brands with higher market shares, higher price levels, and more frequent promotions tended to gain share. A moderate reduction in the number of SKUs increased a brand's choice probability, whereas a deep cut hurt its chances of being chosen. In addition, an increase in a brand's share of SKUs was likely to translate into higher purchase share. Finally, brands that experienced a smaller cut in the number of sizes gained share from those that had greater size reduction; this effect was accentuated by a household's share of purchase of the brand. The significant effect of the number of sizes is consistent with the findings of Guadagni and Little (1983), who show that consumers exhibit high loyalty to size. In summary, our findings demonstrate that how a brand is affected by SR is not only driven by the assortment change but also influenced by the characteristics of the brand and its consumers.

Although our study did not set out to investigate how and why categories differ in their SR effect on sales (for in-depth analyses of this topic, see Boatwright and Nunes 2001; Borle et al. 2005), we observe that the effects varied substantially across the three categories examined here. Spaghetti sauce experienced the largest increase in total sales volume (12.8%) and revenue (14.8%), and liquid detergent also had an increase in its total sales volume (7.1%) and revenue (10.2%). In contrast, margarine suffered a substantial decrease in both measures (–17.8% and –15.7%, respectively). The pattern seems related to the total number of SKUs in each category. It appears that reducing assortment in a category with a large number of SKUs helps cut down its clutter and thus has a beneficial effect, whereas eliminating SKUs in a category with an already low number of SKUs can elicit strong negative assortment perceptions among consumers (Broniarczyk, Hoyer, and McAlister 1998). This finding implies that retailers should take caution in selecting categories for implementing SR, a point of view we share with Borle and colleagues (2005).

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 example, in the liquid detergent category, a simple comparison of market share before and after the SR suggests that the SR decreased the choice for Tide and increased the choice for the private label brand; however, our analysis indicates that the opposite occurred. Our results also indicate that eliminated SKUs' share of brand sales does not predict changes in a brand's choice probability and purchase quantity after the SR. Retailers have mainly focused on sales measures in efficient assortment decisions. However, our findings imply that they should instead focus attention on other factors that may play a more important role in contributing to the differences in SR effects among brands, such as those we identified herein.

For manufacturers of large-share brands or premium brands, our results suggest that even if an SR program decreases the overall category sales in a store, they need not worry as much as manufacturers of small-share brands or lower-priced brands. In addition, it would help a brand gain market share if the brand were made more prominent in consumers' minds, such as by increasing its promotion frequency. Moreover, our results imply that though a manufacturer may not have control over retailers' SR initiatives, it can mitigate the potential negative consequence on its brands. For example, if a manufacturer must eliminate a certain number of SKUs, it should negotiate with the retailer to minimize reduction in the number of sizes of its brands.

Our study also offers valuable implications for retailers. The finding that consumers with high state dependence and purchase frequency reacted favorably to the SR is encouraging news to retailers that are faced with the dilemma of whether to implement "efficient assortment" policies. The finding that large-share brands tend to gain shares after an SR is also good news for retailers from the perspective of trade relations. In addition, because the number of sizes eliminated, the number of SKUs eliminated, and the change in the share of SKUs all play a role in how a brand's choice probability is affected by an assortment reduction, a retailer should use discretion in determining which SKUs to eliminate. The results from our first-stage analysis suggest that private label brands are likely to suffer more unfavorable consequences of SR than national brands. This cautions the retailer to minimize the negative effects of SR on its private label brands; a retailer can take some preventive measures, such as maintaining the number of private label SKUs (and thus increasing its share of SKUs in the category) and increasing the promotion frequency of the private label brands. If a reduction of private label SKUs is inevitable, the retailer should try to minimize the reduction in the number of sizes offered.

Our analysis is based on data provided by an online retailer. As we mentioned previously, the online store environment 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. Nonetheless, we expect the effects to be somewhat different in online and bricks-and-mortar stores because of differences in consumer purchase behavior between the two channels. Previous research has shown that online consumers are more convenience conscious, more state dependent, and less promotion sensitive than their offline counterparts (e.g., Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2007). Combining this with the findings from the current study, we expect that, all else being equal, the SR effects on purchase incidence, quantity given a purchase occasion, and total sales and revenue will be more negative in bricks-and-mortar stores than the results of this study suggest. In addition, we expect that there will be stronger brand-switching effects (i.e., those in Model 4) among bricks-and-mortar consumers than among online consumers.

This research attempts to direct academic focus on brand-level effects of SR. Many worthwhile topics remain to be explored in this area. In terms of methodology, a limitation of our model is that it does not incorporate serial correlation across observations for the same household. Our model accounts for state dependence, consumer heterogeneity, and interdependence in the three purchase components, which helps mitigate the impact of serial correlation. Nonetheless, further research could extend our model by incorporating serial correlation. The model could also be constructed at the SKU level and then aggregated to the brand level. It would be worthwhile to compare the results from SKU-level models with our results from brand-level models. In terms of substantive topics, an important issue for further research would be to incorporate product attributes/features in the assessment of the impact of assortment changes. Another important issue would be to conduct direct profitability analyses of SR programs, which would require cost-saving information from both retailers and manufacturers. In addition, issues such as the nature of product category on brand-level effects of SR and the impact of a brand's SR in one category on the same brand sales in another category, among many other topics, could be examined. Finally, the finding that brands with larger market shares and higher prices tend to gain shares from those with smaller market shares and lower prices, such as private labels, has important implications for both manufacturers and retailers. This study is the first to demonstrate such a pattern. Although these effects are consistent with our conjecture, we believe that more empirical studies are needed to test their generalizability. This would be another worthy direction for further research.[10]

[10]We thank an anonymous reviewer for suggesting several of the ideas discussed here.

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), 504–526.

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

——— and ——— (2004), "Correction Note for 'Reducing Assortment: An Attribute-Based Approach,'" *Journal of Marketing*, 68 (July), iv.

Borle, Sharad, Peter Boatwright, Joseph B. Kadane, Joseph C. Nunes, and Galit Shmueli (2005), "The Effect of Product Assortment Changes on Customer Retention," *Marketing Science*, 24 (4), 616–22.

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.

Bucklin, Randolph E., Sunil Gupta, and S. Siddarth (1998), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors," *Journal of Marketing Research*, 35 (May), 189–97.

Business Wire (1998), "Sunbeam Completes Record Year for Sales, Earnings & Global Expansion," (January 28), 1.

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

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

Degeratu, Alexandru, Arvind Rangaswamy, and Jianan Wu (2000), "Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price, and Other Search Attributes," *International Journal of Research in Marketing*, 17 (1), 55–78.

Drèze, Xavier, Stephen J. Hoch, and Mary E. Purk (1994), "Shelf Management and Space Elasticity," *Journal of Retailing*, 70 (4), 301–326.

Guadagni, Peter M. and John D.C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (3), 203–238.

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.

Home Textile Today (2005), "Pier 1 Reduces SKUs to Up Sales," (March 14), 4.

Iyengar, S. and M. Lepper (2000), "When Choice Is Demotivating: Can One Desire Too Much of a Good Thing?" *Journal of Personality and Social Psychology*, 79 (6), 995–1006.

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, DC.

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

Tellis, Gerard J. and Fred S. Zufryden (1995), "Tackling the Retailer Decision Maze: Which Brands to Discount, How Much, When, and Why?" *Marketing Science*, 14 (3), 271–99.

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

——— and Michel Wedel (2007), "The Effectiveness of Customized Promotions in Online and Offline Stores," working paper, Robert H. Smith School of Business, University of Maryland.