Decomposition of the Sales Impact of Promotion-Induced Stockpiling

by

Kusum L. Ailawadi*
Karen Gedenk**
Christian Lutzky***
Scott A. Neslin****

July 25, 2006

*Kusum L. Ailawadi is Charles Jordan 1911 TU’12 Professor of Marketing at the Tuck School of Business at Dartmouth, 100 Tuck Hall, Hanover, NH 03755, U. S. A. (Phone: +1 603 646 2845, Fax: +1 603 646 1308, e-mail: kusum.ailawadi@dartmouth.edu).

**Karen Gedenk is Professor of Marketing at the University of Cologne, Department of Marketing, Albertus-Magnus-Platz, 50923 Cologne, Germany (Phone: +49 221 470 2639, Fax: +49 221 470 5157, e-mail: gedenk@wiso.uni-koeln.de).

***Christian Lutzky is a doctoral student at the University of Cologne, Department of Marketing, Albertus-Magnus-Platz, 50923 Cologne, Germany (Phone: +49 221 470 3995, Fax: +49 221 470 5157, e-mail: lutzky@wiso.uni-koeln.de).

****Scott A. Neslin is Albert Wesley Frey Professor of Marketing at the Tuck School of Business at Dartmouth, 100 Tuck Hall, Hanover, NH 03755, U. S. A. (Phone: +1 603 646 2841, Fax: +1 603 646 1308, e-mail: scott.neslin@dartmouth.edu).

Acknowledgments: We thank session attendees at the 2004 INFORMS Marketing Science Conference and the 2005 AMA Doctoral Consortium for their helpful comments. This research was supported by the German National Science Foundation (Deutsche Forschungsgemeinschaft) and the Tuck Associates Program.
Decomposition of the Sales Impact of Promotion-Induced Stockpiling

ABSTRACT

Promotion-induced consumer stockpiling has a negative impact for manufacturers because it moves forward in time brand sales that would have occurred later at full margin. But the resulting increase in consumer inventory also has two potential benefits, i.e., increased category consumption and pre-emptive brand switches (where the additional inventory of the promoted brand pre-empts the consumer’s purchase of a competing brand in the future). Further, there is a potential impact on repeat purchases of the stockpiled brand after the promotion. In this paper, the authors present a model and simulation based method to measure the benefits and costs of stockpiling and assess their relative magnitude. They find that the benefits are substantial but consumption appears to be the most important, followed by pre-emptive switching and then an increase in repeat purchases. These benefits easily offset the negative aspect of consumer stockpiling, namely, purchase acceleration by loyal customers who would have bought the brand at regular price later.

Keywords: Promotion bump, stockpiling, brand choice, repeat rates.
Decomposition of the Sales Impact of Promotion-Induced Stockpiling

Consumer stockpiling is a fundamental consequence of sales promotion (Neslin 2002). It occurs because the promotion induces consumers to buy sooner or buy more than they would have otherwise (Blattberg, Eppen, and Lieberman 1981; Neslin, Henderson, and Quelch 1985). Either way, consumers end up with more quantity than they would have had in the absence of promotion. Blattberg, Eppen, and Lieberman (1981) show that promotion-induced stockpiling allows retailers to transfer inventory holding costs to consumers. Evidence of consumer stockpiling is found directly in panel data analyses of purchase incidence and quantity (Bucklin and Gupta 1992; Bucklin, Gupta, and Siddarth 1998; Chintagunta and Haldar 1998; Gupta 1988), and indirectly in the detection of post-promotion dips in weekly sales data (Macê and Neslin 2004; van Heerde, Leeftlang, and Wittink 2000 and 2004).

Whether consumer stockpiling hurts or benefits the manufacturer of the promoted brand depends upon what consumers do after the promotion. If the resultant extra household inventory leads consumers to consume more of the category, this is a benefit to the manufacturer. We call this the “consumption effect”. If the extra inventory pre-empts future purchases of the promoted brand, this is a cost to the manufacturer because the manufacturer’s profit margin is typically lower during promotion periods compared to non-promotion periods (e.g., see Neslin, Powell, and Schneider Stone 1995). We call pre-emption of the promoted brand’s future purchases “loyal acceleration.” If the extra inventory pre-empts future purchases of competing brands, this is a benefit to the manufacturer because it takes consumers out of the market for competing brands (Lodish 1986, p. 41). We call this “pre-emptive switching.” If the extra inventory affects future brand choice after the promotion, this can either benefit or hurt the manufacturer,
depending on whether the brand’s future purchase probability increases or decreases. We call this the “repeat purchase effect”.

Figure 1 summarizes these phenomena. The promotion sales bump consists of current brand switching and stockpiling. The stockpiling portion of the bump is the sum of consumption, pre-emptive switching, and loyal acceleration. The repeat purchase effect reflects how stockpiling affects future brand choice, although this is not a direct component of the bump.

[Figure 1 Goes About Here]

Researchers recognize and have attempted to measure the consumption, loyal acceleration, and pre-emptive switching effects. Consumption effects in particular have recently attracted significant attention. Additional category consumption arises through new users, fewer stock-outs, and faster use-up. Ailawadi and Neslin (1998) explicitly model faster use-up, or flexible consumption, and find it to be a significant factor in the yogurt market and even to some extent in the ketchup market. Subsequent research confirms that increased consumption can account for a substantial portion of the promotion-induced sales bump (e.g., Bell, Chiang, and Padmanabhan 1999; Foubert 2004; van Heerde, Leeflang, and Wittink 2004).

Previous research supports the existence of loyal acceleration and pre-emptive switching, although the phenomena are difficult to disentangle from post-promotion effects like the repeat purchase effect. For example, loyal acceleration measured as a post-promotion dip in aggregate data (e.g., Macé and Neslin 2004) may be under-estimated due to positive repeat purchase effects or it may be exaggerated by negative repeat purchase effects. Van Heerde, Leeflang, and Wittink (2004) combine pre-emptive switching and loyal acceleration in their analysis and note that separating them is an important avenue for research. A recent working paper by van Heerde and Gupta (2005) measures several important components of the bump, including pre-emptive
switching and loyal acceleration, but does not separate these from post-promotion repeat purchase effects. Chan, Narasimhan, and Zhang (2004) decompose the promotional bump into increased consumption of the brand, brand switching within the promotion week, brand switching within subsequent weeks, and stockpiling of the brand. Their work provides especially strong evidence of consumption effects, but they do not explicitly measure pre-emptive switching or distinguish between loyal acceleration and the repeat purchase effect.

To the extent that loyal acceleration and pre-emptive switching exist, it appears that the former is substantial. Chan, Narasimhan, and Zhang (2004) and Neslin, Henderson, and Quelch (1985) find that loyal customers are more likely to accelerate than non-loyal customers. Krishna (1994) and Sun, Neslin, and Srinivasan (2003) draw on a dynamic structural model to provide a rationale for why loyal customers would be more likely to accelerate than non-loyal customers: Only for loyal customers does the consumption utility for the additional product offset the additional household inventory cost incurred by stockpiling.

Although several researchers have studied the effect of promotion on repeat rates, the differential effect of promotion-induced stockpiling on repeat purchases has not previously been investigated. The effect could emerge as follows. Stockpiling means that the consumer uses more of the brand before the next purchase. From a behavioral learning standpoint, this provides more reinforcement before the next purchase, so the behavior of buying the brand is more likely to persist (see Rothschild and Gaidis 1981). Thus, stockpiling should have a positive effect on repeat purchases under behavioral learning. From a cognitive learning viewpoint, stockpiling provides a longer post-purchase evaluation period (Engel, Blackwell, and Miniard 1995). There are then two possibilities: If involvement is high, the consumer has more time to uncover the strengths or weaknesses of the brand (Engel, Blackwell, and Miniard 1995, pp. 263, 273-276). If
involvement is low, stockpiling provides more time to establish inertia or induce boredom (Engel, Blackwell, and Miniard 1995, pp. 158-160). Thus, under cognitive learning, stockpiling could yield more repeat purchases (through inertia or higher brand knowledge) or fewer repeat purchases (through boredom or variety seeking).

In summary, promotion-induced stockpiling by consumers has the potential to produce consumption, pre-emptive switching, loyal acceleration, and repeat purchase effects. Previous research suggests these effects exist but has not disentangled them and assessed their individual contribution. The purpose of this paper is to provide a unified analysis of the sales impact of promotion-induced stockpiling for the manufacturer. We develop a method for measuring promotion-induced stockpiling, consumption, pre-emptive switching, loyal acceleration, and repeat purchases, and quantify their magnitudes in two product categories. We proceed as follows. First we describe our model and estimation method. Second, we discuss the data used for our empirical investigation. Next, we present the estimated model results. We then quantify the consumption, pre-emptive switching, loyal acceleration, and repeat purchase effects of stockpiling using a Monte Carlo simulation. We also quantify their relative magnitude in financial terms. Finally, we discuss the implications of our work for managers and researchers.

**MODEL**

*Overview*

We formulate an integrated brand choice, purchase incidence and purchase quantity model to investigate the potential impact of promotion-induced stockpiling. As in previous incarnations of choice/incidence/quantity models, we model these decisions conditional on shopping trip and store choice (e.g., Bucklin and Lattin 1992, Tellis and Zufryden 1995):

\[
P_{\text{inc}}(j \& q) = P_{\text{inc}}(\text{inc}) \times P_{\text{inc}}(j \mid \text{inc}) \times P_{\text{inc}}(q \mid \text{inc} \& j)
\]
where:

\[ P_{ht}(j & q) = \text{Probability household } h \text{ buys } q \text{ units of brand } j \text{ on shopping trip } t. \]

\[ P_{ht}(\text{inc}) = \text{Probability household } h \text{ purchases the category on trip } t. \]

\[ P_{ht}(j|\text{inc}) = \text{Probability household } h \text{ purchases brand } j \text{ on trip } t, \text{ given household } h \text{ makes a category purchase.} \]

\[ P_{ht}(q|\text{inc } & \text{ } j) = \text{Probability household } h \text{ buys } q \text{ units of brand } j \text{ on trip } t, \text{ given household } h \text{ makes a category purchase and buys brand } j. \]

The incidence and choice components of the model are handled in the nested logit framework (Ben-Akiva and Lerman 1985), the quantity model is a truncated Poisson (Mullahy 1986), and we allow for flexible consumption (Ailawadi and Neslin 1998). We use a continuous mixture model to account for cross-sectional heterogeneity in model parameters. Assuming that the parameters are normally distributed, we estimate their mean and standard deviation (Erdem, Mayhew, and Sun 2001; Gönül and Srinivasan 1993). We do not impose a covariance structure on the random effects within and across the incidence, choice, and quantity equations to keep the computational burden manageable. Empirically, of course, correlations can and do occur between pairs of random effects. The three equations are jointly estimated using simulated maximum likelihood (Erdem 1996; Seetharaman 2004; Sun, Neslin, and Srinivasan 2003; Train 2003).

**Choice Model**

Given the nested logit framework, the choice model takes the form of a multinomial logit. We add a term to the standard utility equation that allows us to investigate the repeat purchase impact of stockpiling. This term augments the usual state dependence parameter according to whether the brand purchased on the previous purchase occasion was purchased in a larger than usual quantity on that occasion. We therefore have:
(2) \( P_{ht}(j|\text{inc}) = \frac{e^{V_{ht}}}{\sum_k e^{V_{kt}}} \)

(3) \( V_{ht} = \beta_{0h} + \beta_{1h} \text{PRICE}_{ht} + \beta_{2h} \text{PROMO}_{ht} + \beta_{3h} \text{LAST}_{ht} + \beta_{4h} \text{LPROMO}_{ht} + \beta_{5h} \frac{Q_{ht}}{Q_h} \)

where:

\( \text{PRICE}_{ht} = \) Regular price of brand \( j \) available to household \( h \) on shopping trip \( t \).

\( \text{PROMO}_{ht} = \) Promotion indicator, equal to 1 if brand \( j \) available to household \( h \) on shopping trip \( t \) is on promotion; 0 otherwise.

\( \text{LAST}_{ht} = \) Last brand purchased indicator for state dependence, equal to 1 if household \( h \) bought brand \( j \) on the previous purchase occasion before shopping trip \( t \); 0 otherwise.

\( \text{LPROMO}_{ht} = \) Last purchase on promotion indicator, equal to 1 if household \( h \) bought \( j \) on promotion on the previous purchase occasion before shopping trip \( t \); 0 otherwise.

\( Q_{ht} = \) Quantity (ounces) bought of brand \( j \) if household \( h \) bought brand \( j \) on the previous purchase occasion before shopping trip \( t \); 0 otherwise.

\( \bar{Q}_h = \) Average quantity (ounces) of the category purchased per purchase occasion by household \( h \) during an initialization period.

The new part of the model is the \( \frac{Q_{ht}}{\bar{Q}_h} \) term. As a result, if household \( h \) bought brand \( j \) on the previous purchase occasion before shopping trip \( t \), we get the following contribution to utility:

(4) Contribution \( = \beta_{3h} + \beta_{4h} \text{LPROMO}_{ht} + \beta_{5h} \frac{Q_{ht}}{\bar{Q}_h} \)

We expect the state dependence term \( \beta_{3h} \) to be positive per previous literature -- all else equal, previous purchase of the brand reinforces preference and the household is more likely to purchase it on the current purchase occasion (e.g., Ailawadi, Gedenk, and Neslin 1999; Seetharaman 2004; Seetharaman, Ainslie, and Chintagunta 1999). We expect \( \beta_{4h} \) to be negative, consistent with previous research showing that promotion purchases are less reinforcing than
non-promotion purchases (Gedenk and Neslin 1999; Guadagni and Little 1983). This may be
due to a diminishing of brand attitude because the consumer attributes his or her purchase to the
promotion, not the brand (Dodson, Tybout, and Sternthal 1978).

Finally, a positive $\beta_{5h}$ would mean that higher than usual purchase quantity on the
previous purchase occasion (i.e., stockpiling) result in greater purchase reinforcement, and the
likelihood is higher that the household will purchase brand $j$ on the current purchase occasion.
Therefore, $\beta_{5h}$ represents the potential repeat purchase benefit of stockpiling. As noted earlier,
stockpiling may breed boredom or variety seeking, in which case $\beta_{5h}$ would be negative. All
parameters are assumed to follow a normal distribution across consumers.

*Incidence Model*

In the nested logit formulation, the purchase incidence model takes the form:

$$p_{ht}(\text{inc}) = \frac{e^{W_{ht}}}{1 + e^{W_{ht}}} \tag{5}$$

$$W_{ht} = \kappa_{0h} + \kappa_{1h} \left( I_{NV_{ht}} - I_{NV_h} \right) + \kappa_{2} \bar{C}_h + \kappa_{3h} INCVAL_{ht} \tag{6}$$

$$INCVAL_{ht} = \ln \left( \sum_k e^{V_{stu}} \right) \tag{7}$$

where:

$INV_{ht}$ = Inventory (ounces) of household $h$ on shopping trip $t$.

$\overline{INV}_h$ = Average inventory (ounces) of household $h$ during the initialization period.

$\bar{C}_h$ = Average daily consumption (ounces) of household $h$ during the initialization period.

$INCVAL_{ht}$ = “Inclusive Value” for household $h$ on shopping trip $t$. 
The variables in this binomial logit incidence model are standard (e.g., Ailawadi and Neslin 1998; Bucklin, Gupta, and Siddartha 1998). We allow for heterogeneity in all coefficients except for $\kappa_2$, the coefficient of $\bar{C}_h$, because $\bar{C}_h$ only takes one value per household and therefore cannot have a unique coefficient per household.

### Purchase Quantity

The purchase quantity model is a truncated Poisson (Mullahy 1986). It is written as:

$$ P_{ht}(q \mid \text{inc} \& j) = \frac{(\lambda_{hjt})^q}{(e^{\lambda_{hjt}} - 1)q!} \quad (q = 1, 2, \ldots, \infty) $$

(8)

$$ \lambda_{hjt} = e^{\gamma_0 + \gamma_1 (\text{INV}_{ht} - \bar{\text{INV}}_h) + \gamma_2 \bar{C}_h + \gamma_3 \text{BRANDPREF}_{hj} + \gamma_4 \text{PRICE}_{ht} + \gamma_5 \text{PROMO}_{ht}} $$

(9)

where:

$\bar{U}_h$ = Average number of units purchased per purchase occasion by household $h$ during the initialization period.

BRANDPREF$_{hj}$ = Percentage of category purchases by household $h$ that are of brand $j$ during the initialization period.

All the terms in the model are standard (e.g., Ailawadi and Neslin 1998; Bucklin, Gupta, and Siddartha 1998; Krishnamurthi and Raj 1991). We account for heterogeneity in all model parameters except for the coefficients of $\bar{U}_h$ and BRANDPREF$_{hj}$ since those variables only take one value each per household.

### Inventory and Consumption

Our inventory and consumption model allows for flexible consumption as in Ailawadi and Neslin (1998). Both variables are updated daily:

$$ \text{INV}_{hd} = \text{INV}_{h,d-1} + Q_{h,d-1} - \text{CONS}_{h,d-1} $$

(10)

$$ \text{CONS}_{hd} = \text{INV}_{hd} \left[ \frac{\bar{C}_h}{\bar{C}_h + (\text{INV}_{hd})^\epsilon} \right] $$

(11)
where:

\[ \text{CONS}_{hd} = \text{Consumption (ounces) of household h on day d.} \]

\[ \text{Q}_{hd} = \text{Quantity (ounces) purchased by household h on day d.} \]

As Equation 10 makes clear, previous purchases, inventory levels, and consumption all determine the household’s current inventory level. In Equation 11, the parameter \( f \) reflects consumption flexibility. It governs the extent to which consumption increases with higher levels of inventory. High values of \( f \) imply less flexible consumption because consumption initially increases with inventory and then levels off. Low values of \( f \) imply flexible consumption, where consumption continually increases with inventory.

**Estimation**

The model is estimated jointly using simulated maximum likelihood (Train 2003). The likelihood function is:

\[
L = \prod_h \prod_t \prod_j \left[ \left( \frac{e^{W_{ht}}}{1 + e^{W_{ht}}} \right)^{Y_{ht}} \left( \frac{1}{1 + e^{W_{ht}}} \right)^{1 - Y_{ht}} \left( \frac{\sum_k e^{V_{htk}}}{\lambda_{hjt} q} \right) \right]^{Z_{hjt}}
\]

where:

\[ Z_{hjt} = \text{Brand purchase indicator, equals 1 if household h purchased brand j on shopping trip t; 0 otherwise.} \]

\[ Y_{ht} = \text{Category purchase indicator, equals 1 if household h purchased the category on shopping trip t; 0 otherwise.} \]

**DATA**

We use Nielsen scanner panel data for the ketchup and yogurt categories. The first 26 weeks of the data are used for initialization and the remaining 112 weeks for estimation. In the

---

1 Simulated maximum likelihood estimates of model parameters and their standard errors can be sensitive to starting values and the scaling of variables. We ensured the robustness of our estimates by testing various starting values and by scaling the variables in our model so that all parameter estimates lay between -1 and +1. The latter proved to be particularly important and we thank Kenneth Train for highlighting to us the importance of scaling. Of course, for ease of exposition, we report results after converting the estimates back to the original scales of the variables.
ketchup category, we analyze the 28 and 32 ounce sizes of four brands. The selected brands and sizes account for 81.1% of all ketchup sales. In the yogurt category, we analyze all 6 and 8 ounce sizes which account for 90.9% of all yogurt sales. Six of the yogurt brands have shares of 5% or more and account for 84.4% of sales of the selected sizes. We aggregate the remaining seven brands into an “all-others” brand.

We select households that (a) make at least one shopping trip over each four-week period in the data; (b) purchase only the selected brands and sizes; and (c) make at least three purchases during the initialization period and at least one purchase during the estimation period. The first filter ensures that we exclude transient households. The second filter ensures that we account for all category purchases and consumption of the included households, while avoiding the need to model size choice (e.g., Chintagunta 1993; Jedidi, Mela, and Gupta 1999). We combine the 6 and 8 ounce sizes of yogurt and the 28 and 32 ounce sizes of ketchup because consumers are not likely to make choice and quantity decisions based on a distinction between such similar sizes. The third filter ensures that we obtain reliable values of $U_h$, $C_h$, and $INV_h$ from the initialization period, although it creates a somewhat heavier user group, especially for ketchup.

These selection criteria result in 163 households for the ketchup category and 263 households for the yogurt category. We retained a random half of the 263 yogurt households to make computing time more manageable, resulting in 131 households. As shown in Table 1, the 131 yogurt households generated 30,003 shopping trips and 2,309 purchase occasions in the calibration period. This amounts to an average interpurchase time of 6.4 weeks. The 163 ketchup households generated 36,337 shopping trips and 1,899 purchase occasions in the calibration period. This amounts to an average interpurchase time of 9.6 weeks.
Table 2 provides market shares, prices, promotion activity, and the average value of \( \frac{Q_{hj}}{\bar{Q}_h} \) for the brands in our sample. The average \( \frac{Q_{hj}}{\bar{Q}_h} \) is very close to 1 for ketchup brands and varies more in the yogurt category. However, the variation is not connected with brand share, so we can be confident that the \( \frac{Q_{hj}}{\bar{Q}_h} \) variable is not merely a surrogate for brand preference. The brand price and promotion variables are weighted averages of UPC level price per ounce and a promotion indicator respectively, where the weights are UPC market shares. Note that the price variable is the regular shelf price per ounce while the promotion indicator is one if the UPC has a temporary price reduction (TPR) and/or a display or feature (e.g., Gedenk and Neslin 1999; Jedidi, Mela, and Gupta 1999). TPRs are identified using the algorithm described by Gedenk and Neslin (1999). Thus, we clearly separate regular price changes from promotions and can focus on the PROMO variable in our interpretation of the results and in our simulations. Table 3 provides sample means and standard deviations of all variables.

MODEL ESTIMATES

The first step is to test the incremental contribution of the \( \frac{Q_{hj}}{\bar{Q}_h} \) term in the choice model, since it captures the impact of stockpiling on repeat purchases. The mean and standard deviation of the term’s coefficient, \( \beta_{sh} \), are estimated. Table 4 shows that this improves fit since the \( \chi^2 \) statistic for the likelihood ratio test is statistically significant for both categories.

\[ \chi^2 \]

A JMR reviewer suggested that, like the LAST effect, the \( \frac{Q_{hj}}{\bar{Q}_h} \) effect may also be smaller for promotional purchases. We tested this hypothesis by including an interaction between LPROMO and \( \frac{Q_{hj}}{\bar{Q}_h} \). The coefficient was negative, as hypothesized, but it was not statistically significant and it did not improve fit.
We now turn our attention to the parameter estimates. Table 5 shows the estimated means and standard deviations for all the model parameters. All but two of the mean estimates are significant and have the expected sign and most of the standard deviations are substantial, showing that there is considerable heterogeneity across households. The incidence model shows negative estimated inventory coefficients and the inclusive value estimates are significantly positive and less than one, as they should be (Ben-Akiva and Lerman 1985; Train 2003). In the quantity model, price and promotion are significant and have the correct signs. BRANDPREF is significant for ketchup, i.e., households buy larger quantities if they have a higher preference for the ketchup brand being bought. Inventory is not significant – its role seems to be primarily in determining when to purchase the category.

[Table 5 Goes About Here]

Our main interest, however, is in the brand choice model and the estimates for LAST, LPROMO, and \( \frac{Q_{hjt}}{\bar{Q}_h} \). In both categories, the mean for the LAST coefficient is positive, and the mean for the LPROMO coefficient is negative but smaller than the LAST coefficient. Thus, we confirm Gedenk and Neslin’s (1999) finding that previous purchases reinforce brand loyalty but promotion purchases are less reinforcing than non-promotion purchases.

Importantly, the estimated mean for \( \frac{Q_{hjt}}{\bar{Q}_h} \) is significantly positive for both yogurt and ketchup. Whether it is through behavioral or cognitive learning, stockpiling yields higher brand preference on the next purchase occasion for the average household. The insignificant standard deviation for yogurt suggests that the stockpiling effect is positive for virtually all households. However, for ketchup, the large standard deviation (.30 relative to a mean of .40) implies that several households have negative parameter values. Presumably, some customers get bored with a ketchup brand when they have it in the household for a long time. Indeed, there is a positive
correlation between our household level estimates of the LAST and \( Q_{hj} / \bar{Q}_h \) coefficients, which is consistent with the hypothesis that a positive \( Q_{hj} / \bar{Q}_h \) effect is driven by inertia while a negative effect is driven by variety-seeking or boredom.

Table 6 shows the contribution of the three state dependence related parameters to future utility and repeat purchase probabilities. For example, if the average household makes a non-promotion purchase of yogurt and buys its usual quantity, the contribution to utility at the next purchase occasion is 1.33+.36*1=1.69. If the usual quantity is bought but the purchase is on promotion, the average contribution is 1.33-.92+.36*1=.77. If the purchase is on promotion but the household buys twice its usual quantity, the contribution is 1.33-.92+.36*2=1.13.

[Table 6 Goes About Here]

To illustrate how this translates into purchase behavior, the table also shows repeat purchase probabilities of a yogurt (Dannon) and ketchup (Heinz) brand for these 3 scenarios. The probabilities are computed using the mean parameter estimates from the brand choice model, average prices, and assuming that no brands are on promotion at the next purchase occasion. Thus, if the average household makes a non-promotion purchase of Dannon and buys its usual quantity, the probability that it will purchase Dannon at the next purchase occasion is 41%. This repeat probability is only 22% if the original purchase is made on promotion, and it is 29% if the household buys double the normal quantity on promotion. Thus, stockpiling at least partially makes up for the lower purchase reinforcement of a typical promotion purchase.

In summary, the model estimates suggest a positive impact of promotion-induced stockpiling on repeat purchases. We undertake a simulation study in the next section to quantify the impact of this effect, along with promotion-induced consumption, pre-emptive switching, and loyal acceleration in terms of net unit sales.
QUANTIFICATION OF STOCKPILING EFFECTS: METHOD

Decomposition Approaches

In order to assess the sales impact of promotion-induced stockpiling, we need to decompose a brand’s promotional bump into its switching and stockpiling components, further decompose the stockpiling component into loyal acceleration, pre-emptive switching, and consumption, and finally quantify the repeat purchase effect of stockpiling. The decomposition of the promotion bump has received a lot of attention from researchers, beginning with the work of Gupta (1988). Three main approaches have been used.

The first is a mathematical decomposition. Many researchers have decomposed total promotional sales elasticity estimated from scanner panel data into choice, incidence, and quantity elasticities (Bell, Chiang, and Padmanabhan 1999; Bucklin, Gupta, and Siddarth 1998; Chiang 1991; Gupta 1988). However, van Heerde, Gupta, and Wittink (2003) show that the results of this elasticity decomposition have sometimes been incorrectly interpreted. They suggest that a decomposition approach based on unit sales is more meaningful, and show how this can be derived mathematically. Both of these mathematical approaches are difficult to apply in our case because we are investigating dynamic phenomena (repeat purchases, consumption, pre-emptive switches) for which there are no dependent variables in our model. In addition, these phenomena depend on the interplay among several parameters in the model, not just one. So the notion of taking derivatives of a dependent variable or a parameter with respect to promotion, which underlies the mathematical approaches, does not seem feasible in our case.

The second is a regression-based approach using weekly store sales data (van Heerde, Leeflang, and Wittink 2004). This approach has the benefit of assessing net unit sales effects, which are ultimately of interest to managers. However, it is not designed to separate phenomena
such as loyal acceleration and pre-emptive switching from repeat purchase effects, all of which affect sales of the promoted and competitive brands in subsequent periods after a promotion.

The third approach utilizes Monte Carlo simulation. Purchase histories of a panel of households are simulated using estimated model parameters and a simulated “base” case is compared with a simulated “promotion” case where a new promotion is added for one brand (Ailawadi and Neslin 1998; Seetharaman 2004; Silva-Risso, Bucklin, and Morrison 1999; van Heerde and Gupta 2005). We use this approach because it allows us to distinguish among the various stockpiling effects and repeat purchases at the individual household level, and still obtain aggregate unit sales effects. We extend previous work by separating pre-emptive switching from loyal acceleration and quantifying the effect of stockpiling on repeat purchases.

**Decomposition Method**

Following existing research, we simulate a base case purchase history for each household in our sample and then simulate a promotion case where we add a promotion for one brand. We compare the promotion and base cases to quantify the consumption, pre-emptive switching, loyal acceleration, and repeat purchase effects.

We use actual household purchase histories and our estimated parameters to compute household-level parameters (Train 2003, Chapter 11). In order to avoid having to combine data from the different stores, we select one large store in the dataset, and, for the purpose of the simulation, assume that all households shop at that store. We use the prices and promotions in that store during the 112-week calibration period as the store environment data for the simulation. We then simulate each household’s purchase probabilities given that household’s parameters and initialization constants ($\bar{U}_h$, $\bar{C}_h$, $\bar{INV}_h$), and given the store environment. Using one store for the simulation is not a problem because we compare simulated base case choices
with simulated promotion case choices to quantify and decompose the bump. As long as the
store environment is the same for the base and promotion cases, and that store environment is
within the range of the estimation data, it is not important which particular store is used.

We translate simulated purchase probabilities into simulated behavior by drawing
uniform random numbers. For instance, if the probability of a household making a purchase in
the category is .7, we draw a random number between 0 and 1. If the number lies between 0 and
.7, we infer that the household makes a purchase. We believe this is a better way to translate
probabilities into choices than simply choosing the option with the highest probability.

We employ 1,000 replications. Within each replication, we use the same set of random
numbers for the base and the promotion case to ensure a clean comparison. The only factor that
differs between the simulated base case and the simulated promotion case is the insertion of an
additional promotion in one week in the promotion case. Each household that goes shopping in
this week is exposed to the promotion during its first shopping trip that week. We repeat the
simulation four times by inserting the promotion in different weeks so that our results are not
driven by the idiosyncrasies of any one week.

Before providing details of our decomposition method, we present stylized examples of
three households to illustrate its basic principles. For simplicity, we assume two brands and a
time horizon of four shopping trips. The only difference between the base and promotion cases
is that, in the latter, a promotion is added for Brand A in trip 1. The first example is as follows:

<table>
<thead>
<tr>
<th>Trip</th>
<th>Base</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (promo)</td>
<td>B</td>
<td>4A</td>
</tr>
<tr>
<td>2</td>
<td>2A</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>B</td>
<td>B</td>
</tr>
</tbody>
</table>
In the base case, the household purchases Brand B in trip 1, two units of Brand A in trip 2, and Brand B in trips 3 and 4. In the promotion case, the household purchases four units of Brand A during the promotion trip, then doesn’t purchase the category again until trip 4, when he or she purchases Brand B. The promotion bump for A is 4 units. It is apparent that one unit of this bump is explained by a current period switch from B to A. This accounts for the unit of B in trip 1 in the base case. Now, consider the next category purchase in the promotion case. Any purchase in the base case between the promotion trip and that purchase is a candidate for a loyal acceleration or a pre-emptive switch. The base case purchase of two units of A in trip 2 represents loyal acceleration – two extra units of A during the promotion in trip 1 pre-empted the purchase of two units of A in trip 2. This leaves one unexplained unit of the bump. The base case purchase of B in trip 3 represents a pre-emptive switch – an extra unit of A during the promotion in trip 1 pre-empted the purchase of B in trip 3. With this pre-emptive switch the bump of A is fully explained – one unit is a current brand switch, two units are loyal acceleration, and one unit is a pre-emptive switch. There is no consumption effect as the total category units purchased in the base and promotion case are equal. All units purchased in the base case through trip 3 have been accounted for in explaining the bump. The only unaccounted units left are those purchased in trip 4. One unit of B is purchased in both the base and promotion case, so there is no repeat purchase effect in this example.

Now, consider a second example:

<table>
<thead>
<tr>
<th>Trip</th>
<th>Base</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (promo)</td>
<td>B</td>
<td>4A</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>4</td>
<td>B</td>
<td>B</td>
</tr>
</tbody>
</table>
Again, there is a bump of four units for A of which one unit is a current period brand switch. That leaves three units of the bump unexplained. We go to the next purchase in the promotion case but there are no base case purchases between that purchase and trip 1 that were pre-empted by the promotion. Next, we calculate the total consumption effect by subtracting three total category units in the base case from six total category units in the promotion case. These three units of additional consumption can be allocated to the bump. The bump is now fully explained and the purchase of one unit of B in the first trip has been accounted for. The remaining category purchases are equal in the base case and promotion case. We subtract the number of A purchases in the base case (i.e., 0) from the number of A purchases in the promotion case (i.e., 1) to get a repeat purchase effect of one unit. Thus, the promotion induced one current period brand switch, three units of extra consumption, and one unit of additional repeat purchase for this household.

Finally, consider a third example:

<table>
<thead>
<tr>
<th>Trip</th>
<th>Base</th>
<th>Promotion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (promo)</td>
<td>2B</td>
<td>4A</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>B</td>
<td>B</td>
</tr>
</tbody>
</table>

Again, the bump for A is four units but two units are current period switches from B. This accounts for the two units of B in trip 1 in the base case and leaves two units of the bump unexplained. We go to the next purchase in the promotion case and find that one unit of A in trip 2 in the base case was pre-empted by the promotion. Thus, there is one loyal acceleration and one unit of the bump is left unexplained. Next, we calculate the total consumption effect, which is two units. Since there is only one unexplained unit of the bump, only one unit of increased category consumption can be allocated to it. The other unit of increased consumption is
allocated to the next post-promotion purchase in the promotion case, i.e., on trip 3 when the household reverted back to its preferred brand B. Now, the bump is fully explained (two current switches, one loyal acceleration, and one increased consumption) and there is also a post-promotion increase in category consumption. The only unaccounted purchases left are those made in trip 4. One unit of B is purchased in both the base and promotion case, so there is no repeat purchase effect in this example.

We formalize this decomposition method in an algorithm that considers all the contingencies that can occur. The detailed algorithm is provided in the Appendix and the corresponding GAUSS code is available from the authors, but we describe the key steps here. For each household, we first calculate the bump for the promoted brand A during the promotion trip by subtracting the units of A bought in the base case from the units of A bought in the promotion case. If this promotion bump is positive, we decompose it as follows. At each step, we keep track of the base and promotion case purchases that have been accounted for.

1. Calculate the reduction in purchases of B (a composite of all other brands) during the promotion trip; allocate these as current period brand switches.

2. Go to the next purchase in the promotion case. All purchases in the base case that occur between the promotion trip and this purchase are potential loyal accelerations or pre-emptive switches. Allocate them until either the base case purchases or the bump run out.

3. If a portion of the bump remains, it has to be explained by consumption or by additional pre-emptive switching and loyal acceleration. First, calculate the total change in category consumption by subtracting total category purchases in the base case from those in the promotion case.

4. If there is an increase in consumption, allocate it to the remaining bump until either the increased consumption units or the bump run out. Any increased consumption left over comes from extra purchases in post-promotion trips and is allocated in Step 5. To explain

---

3 A promotion for A may result in a positive bump for B instead of A. Our interest is in the “normal” case of a bump for the promoted brand, but we do analyze households with a positive bump for B separately.

4 It is also possible for category consumption to decrease. We show how decreased consumption is allocated in the Appendix.
any left over bump, go beyond the next category purchase identified in Step 2 to allocate additional loyal acceleration or pre-emptive switches until the bump runs out.

5. The promotion bump has now been fully explained and all purchases in the base case that were used to explain the bump have been tracked. However, post-promotion changes in consumption must be allocated before we can isolate the repeat purchase effect. Allocate consumption increases to previously unaccounted purchases in the promotion case because these are extra category units bought and consumed after the promotion.

6. After Step 5, there are an equal number of unaccounted category purchases remaining in the promotion and base cases. Subtract the remaining A units in the base case from the remaining A units in the promotion case to obtain the change in repeat purchases.

Note that we give precedence to certain phenomena over others in allocating the promotion bump. It is unambiguous that current period brand switching is the first phenomenon to which the bump should be allocated – units switched from purchases of other brands that would have occurred during the current trip must logically precede behavior that occurs later, i.e., increased consumption or fewer units purchased on subsequent trips. It is also unambiguous that the repeat purchase effect is not part of the bump, so it should be computed after the bump has been fully allocated. However, some prioritization is necessary to resolve potential ambiguities between loyal acceleration and pre-emptive switching versus consumption. We allocate the bump first to loyal acceleration and pre-emptive switching until the next purchase occasion (step 2) and then to consumption (step 4). However, we test the sensitivity of our results to reversing this precedence and find that they are very similar.

Finally, if there is still any portion of the bump left over, we allocate it to additional loyal acceleration and pre-emptive switching beyond the next purchase occasion. This makes sense because a household is more likely to “pre-empt” its next purchase of the category or consume more than it is to pre-empt a subsequent purchase farther out in the future.

Note, also, that any increase in consumption that cannot be allocated to the promotion bump is taken from unaccounted promotion case purchases of Brand A or B in the order in
which the purchases are made. Analogously, since any decrease in consumption cannot be allocated to the promotion bump, it is taken from unaccounted base case purchases of A or B in the order in which the purchases are made. It makes sense that any consumption effects beyond the promotion bump should occur sooner rather than later. Indeed, we find that the households return to “equilibrium”, i.e., they have identical purchases in the base and promotion cases, much before the end of the simulation period.

**QUANTIFICATION OF STOCKPILING EFFECTS: RESULTS**

We decompose the promotion bump for each household that has a positive bump for the promoted brand A and aggregate the bump and components across those households. The households who have a positive bump for a competing brand even though brand A is promoted are analyzed separately in Section 6.4. We repeat the simulation four times by inserting a promotion in different weeks during the 112-week period. Since the results are very similar across the four simulations, we report averages.

*Yogurt Results*

Table 7 displays the detailed results of the decomposition of the promotion bump for four yogurt brands, while Figure 2 highlights the main results graphically. The numbers in the first row of Table 7 show that there was a significant promotion bump for all brands. For example, the promotion for Dannon induced a 318% increase in sales (a bump of 12.4 units on a baseline of 3.9 units), which is in the range of what promotions typically achieve (Narasimhan, Neslin, and Sen 1996).

[Table 7 and Figure 2 Go About Here]

The first set of rows under “Promotion Bump” shows the decomposition of the bump. Across all the yogurt brands, increased consumption is the largest component of the bump,
followed by current brand switching. On average, these components account for over 90% of the bump, pre-emptive switching accounts for 5%, and loyal acceleration for 4%. The limited shelf life of yogurt undoubtedly accounts for the large consumption effect and limits the magnitude of the latter two effects. The patterns are stable across brands, but one difference deserves mention. The total bump for the store brand is substantial and almost 65% of it is explained by increased consumption. Perhaps store brand promotions bring marginal customers into the market.

The second set of rows under “Post-Promotion Effects” shows the repeat purchase and consumption effects of the promotion beyond the immediate bump. The difference in repeat units of the promoted brand between the promotion and base case simulations is the total repeat purchase effect. But, we want to isolate only the part of the repeat purchase effect that is due to stockpiling. In order to do that, we re-do the promotion case simulation but this time, we cap the promotional purchases at $Q_h$. In other words, we determine what the repeat purchases would be if households did not stockpile. Subtracting these repeat purchases from the repeat purchases in the original promotion case simulation gives us the repeat effect that is due to stockpiling. Across the board, we find that this effect is positive. Although the repeat purchase effect is not a component of the bump, converting it to a percentage of the bump is helpful in assessing its magnitude relative to the other stockpiling effects. This percentage varies from 1.6% for Dannon to 3.3% for Weight Watchers. It appears small, but, as we show subsequently, this magnitude of repeat rate effect is not insignificant for a manufacturer in financial terms.

The last row of the table shows that the longer term effect of the promotion on consumption is negative on average. This could happen if the promotion induces the household to switch to a less preferred brand. Subsequent preference increases for the promoted brand but is lower for other previously preferred brands. In terms of the model, the result is a decrease in
the post-promotion inclusive value, which in turn lowers future purchase incidence.

Behaviorally, the decline in consumption is due to post-purchase evaluation (Engel, Blackwell, and Miniard 1995, pp. 263, 273-276). The usage experience for the less preferred brand is not as positive as for preferred brands. In addition the positive experience from preferred brands is now less recent, hence less memorable and less accessible in memory. This could result in less positive attitude toward the category as a whole and hence lower purchase rates in future periods. Essentially, the less positive usage experience from consuming a less preferred brand has at least temporarily turned off the consumer to the category. However, eventually the consumer does buy the category again, most probably his or her preferred brand, and the positive usage experience stimulates positive post-purchase evaluation and future purchasing.

Note, however, that the total effect of the promotion on consumption (direct plus subsequent effects) is highly positive. It ranges from 49.2% of the bump for Yoplait to 64.6% for the store brand.

Ketchup Results

Table 8 displays decomposition results for the four brands of ketchup; the highlights are in Figure 3. This category is much more concentrated than yogurt. Heinz is the market leader by far, with a share of approximately 57% in our data. Hunt and the store brand follow with shares of about 18% and 17% respectively, and Del Monte lags with a share of about 12%. As in yogurt, all brands show a large promotion bump relative to their baseline sales.

[Table 8 and Figure 3 Go About Here]

However, the decomposition of the bump is quite different from yogurt. Current brand switching is the largest component for all brands except Heinz, the highest being 58.6% for Del Monte. As would be expected (e.g., Ailawadi and Neslin 1998), the consumption component is
smaller than in yogurt. Importantly, loyal acceleration and pre-emptive switching are much larger here than in yogurt. Indeed, pre-emptive switching accounts for 10.1% and 13.9% of the promotion bumps for Hunt and the store brand respectively.

The repeat rate effect of stockpiling is positive across the board but it is smaller for ketchup than for yogurt. Finally, the average effect of promotion on subsequent consumption is small but there is a lot of variation across brands, with a large positive effect for Heinz and a large negative effect for Hunt. The total effect on consumption (direct plus second order effects) is smaller than in yogurt, as we expected. The numbers are 16.2% for Hunt, 32% for the store brand, and 30.6% for Del Monte. Heinz is the exception with 74.3%.

There are some interesting differences between Heinz and the other brands. Heinz has the smallest current switching component, and the largest loyal acceleration and consumption components. It makes sense that the brand switching effect is small, since Heinz already has a market share of 57%. The large magnitude of loyal acceleration is consistent with Macé and Neslin’s (2004) finding that high share brands experience the largest post-promotion dips. It also makes sense that the longer term consumption effect is not negative for Heinz. As noted earlier, a negative effect can occur if the household switches to a less preferred brand on promotion, which may lower the inclusive value, which, in turn lowers future purchase incidence. Heinz enjoys much higher preference in the market than other brands, so this is less likely to happen.

In summary, we have found that, across brands in both categories, increased consumption dominates, followed by pre-emptive switching and loyal acceleration, and finally repeat purchases. Recall that our decomposition procedure gives priority to loyal acceleration and pre-emptive switching over consumption in explaining the bump. We wanted to make sure that our results are not driven by this prioritization. For instance, would giving precedence to
consumption wipe out the pre-emptive switching and/or loyal acceleration components? We therefore repeated our simulation-based decomposition with this prioritization reversed. Although there were some small differences in numbers, the relative magnitudes of the pre-emptive switching, loyal acceleration, and consumption components remained substantially unchanged. Detailed results are available from the authors upon request.

*Financial Impact*

Table 9 presents calculations to assess the relative magnitude of these stockpiling effects in financial terms for a typical one-week promotion offered nation-wide by the manufacturer. The steps are as follows:

(i) The unit sales effects in Tables 7 and 8 are based on a promotion offered during a single shopping trip, whereas a typical promotion runs for a week. We redid our simulation by introducing a promotion for the full week and found that the promotional bump in that case was approximately 2.3 times the units shown in Table 7 for yogurt, and 2.1 times the units shown in Table 8 for ketchup. We use these multipliers to compute consumption, pre-emptive switching, loyal acceleration, and repeat purchase effects in units of a one-week promotion in Table 9.

(ii) We extrapolate these effects to a national basis by taking into account the size of our sample relative to the population, national penetration rates, and realistic trade deal pass-through percentages. Specifically, we multiply our effects per household by the number of households in the U.S., category penetration (from IRI’s Marketing Fact Book), the percentage of category buyers who buy more than three times in a year (to correspond to our sample selection), and the trade deal pass-through rate (from Abraham and Lodish 1993, p. 265, Figure 6; Besanko, Dubé, and Gupta 2005).

(iii) We assume realistic numbers for profit margins and trade deal discounts. Specifically, we use a manufacturer price of $0.50 per unit for yogurt and $1.00 per unit for ketchup, a regular manufacturer margin of 50%, and a trade deal discount of 10% of the manufacturer’s selling price. Note that the promotional margin applies to consumption and pre-emptive switching benefits, the difference between regular and promotional margin applies to the loyal acceleration cost, and regular margin applies to the repeat purchase benefit.

[Table 9 Goes About Here]
Table 9 indicates that the net financial impact of stockpiling is positive and can be in the high $100,000’s. As Abraham and Lodish (1987, pp. 119-120, Figures 9 and 10) show, the profitability of national trade deal campaigns can swing roughly between +$3,000,000 and -$3,000,000, so $100,000’s can make the difference between a profitable and an unprofitable trade deal. The biggest contributor is consumption of course, followed by pre-emptive switching (especially in the ketchup category). Repeat purchase effects from stockpiling do not contribute as much in dollar terms, but they are still in the $10,000’s at least for yogurt. Further, in five of the eight cases we analyze, their magnitude is large enough to more than offset the cost of loyal acceleration.

The table also highlights some interesting differences in net benefit across brands. Market leaders like Heinz experience substantial acceleration of their own future sales but the financial benefit of stockpiling is still high for these brands because the absolute size of their promotion bumps is large and so is the consumption component. The store brand has large consumption and repeat rate effects, so it gets a substantial financial benefit from stockpiling. In fact, it gets the strongest benefit in yogurt and the second strongest benefit in ketchup.

The conclusion from this analysis is that consumption, pre-emptive switching, and repeat purchases are important benefits of promotion-induced stockpiling, both as a percentage of the promotion bump, and in financial terms. All three phenomena contribute, although consumption is clearly most important, followed by pre-emptive switching and repeat purchases. Loyal acceleration is an important cost of stockpiling, but can be offset by any of the benefits alone.

*Competitive Brand Promotion Bump*

The focus of our study is the impact of stockpiling the promoted product. However, as van Heerde, Gupta, and Wittink (2003) make clear, a promotion for Brand A can induce a bump
for competing brands. For example, the Brand A promotion could remind some customers to buy the category who would not otherwise have bought, but these customers buy their preferred brand, Brand B. In our simulations, we found this happened for 4% to 17% of households, depending on the brand for which a promotion is added. We wanted to examine the magnitude of this bump and its components.

To do this, we analyzed the households with a positive bump for a competing brand when we inserted a promotion for brand A, aggregating across all competing brands to create a Brand B. The results are shown in Table 10. Comparing the bumps of the promoted brand A and the aggregate brand B, the latter is of course much smaller – on average, it is about 13% the size of the promoted brand’s bump. The table shows that, for both categories, increased consumption accounts for almost the entire competitive bump, with some loyal acceleration. There is little current or pre-emptive switching, which makes sense. There is no reason why a promotion on brand A would induce a household to switch from Brand A to a non-promoted competing brand. On the other hand, the Brand A promotion may remind the household about the category and induce them to buy their preferred brand sooner than they would have otherwise (loyal acceleration) or when they would not have otherwise (consumption).

[Table 10 Goes About Here]

In summary, the competitive brand bump is much smaller than the promoted brand bump and most of it can be explained by consumption and loyal acceleration, which do not directly take away sales from the promoted brand. However, the consumption benefit is one that could have been enjoyed by the promoted brand and any potential repeat purchases of the promoted brand are also lost. Hence bumps for the non-promoted brand can hurt the promoted brand, and it makes sense to monitor this possibility in practice. Our simulation provides the tool to do so.
DISCUSSION AND CONCLUSION

We have presented a unified analysis of the four sales effects of promotion-induced stockpiling: consumption, pre-emptive switching, loyal acceleration, and repeat purchases. We have developed a model and simulation method for measuring these effects, and quantified their magnitude in two product categories.

From a modeling standpoint, our contribution is to demonstrate the importance of adjusting state dependence in choice models by the relative size of the previous purchase. This is the $Q_{h,t}/Q_h$ term in Equation 3. It is easily added to choice models and we have found that it is statistically and managerially important. Its coefficient is positive, and hence stockpiling increases the positive state dependence effects typically observed in choice models.

Substantively, we have shown that all four effects of stockpiling are important, whether expressed as a percentage of the current period promotion-induced bump in sales, or in financial terms. On both measures, consumption appears to be the most important, and this represents an important benefit to manufacturers. The financial impact of pre-emptive switching, loyal acceleration, and repeat purchases is similar in magnitude. Pre-emptive switching is somewhat more important than the others, and along with the positive repeat purchase effect, it represents additional benefits for manufacturers. Either of these benefits can offset the negative financial impact of loyal acceleration.

Our paper also contributes to the body of research that has been developing in recent years on methods to decompose the promotional bump. After carefully investigating various decomposition approaches, we concluded that a simulation-based method with panel data is best suited to the phenomena we examine. It allows us to measure complex promotional effects such as repeat purchases and to separate loyal acceleration from pre-emptive switching, while still
having the managerial relevance of unit sales effects. We also want to note our contribution to an issue recently highlighted by van Heerde, Gupta, and Wittink (2003) that a promotion on one brand can lead to a bump for other brands in the category. Although it is not the main focus of our work, we do provide a deeper understanding of this effect by quantifying the magnitude of the bump for competing brands and examining its components.

Our work has several implications for researchers. First is to include $Q_{ht}/\bar{Q}_h$ in choice models because the magnitude of state dependence depends on whether consumers have stockpiled or not on their previous purchase occasion. Second is that further research is needed to understand the behavioral mechanism that drives the $Q_{ht}/\bar{Q}_h$ effect. We hypothesized this could be due to behavioral or cognitive learning, but cannot discern which mechanism was at work in our scanner panel data. Understanding the applicable mechanism would provide insights on how the $Q_{ht}/\bar{Q}_h$ effect could be enhanced through design of promotions.

Third, while we have demonstrated simulation to be a useful tool for measuring the components and subsequent impact of the promotion bump, we had to make some assumptions, albeit justifiable ones, about prioritizing components of the promotion bump. We would encourage future researchers to improve our simulation approach or even develop closed form mathematical approaches for measuring these effects if possible. In this vein, we note that our results show a somewhat higher consumption component than Ailawadi and Neslin (1998). This may be due to model specification (e.g., we include unobserved heterogeneity whereas they do not), idiosyncratic factors in the competitive environment and brands selected (see Ailawadi and Neslin 1998, p. 396), and the fact that we model and simulate specific brand-sizes whereas they model all brand-sizes and when they simulate the effect of an additional promotion of a brand,
they promote all sizes of that brand. This simply points out the need for future research to help
generalize the exact levels of the effects we measure.

Fourth, our research reinforces the emerging recognition of the importance of
consumption effects due to promotion (Ailawadi and Neslin 1998; Bell, Iyer, and Padmanabhan
2002; Chan, Narasimhan, and Zhang 2004; Sun 2005). Our results illustrate that consumption
can be important even in a category like ketchup, where flexible consumption is not a major
factor. At first the importance of consumption in the ketchup category might seem counter-
intuitive. However, note that it is much less important than in yogurt. For ketchup the “fewer
stock-outs” mechanism may be important even though faster usage is not.

Fifth, our research distinguishes the direct consumption effects of promotion-induced
stockpiling from longer-term consumption effects that can be negative. As explained earlier,
technically, this is due to a lower inclusive value in the incidence equation; behaviorally it is due
to less satisfactory post-purchase evaluation coupled with more distant, less accessible positive
category experiences. The fact that we find these negative longer-term consumption effects
suggests the need for further research to flesh out the conditions under which the long-term
consumption effect will be negative.

Sixth, one might think that it is “easier” for consumers to buy their preferred brand earlier
(loyal acceleration) than to switch both the timing of their purchase and the brand chosen.
However, we found somewhat more pre-emptive switching than loyal acceleration in both
categories, except in the case of a very strong market share leader like Heinz. This suggests we
need to understand better the drivers of loyal acceleration versus pre-emptive switching, and how
they vary across brands.
Lastly, our results have implications for the calculation of promotion profitability. The most important benefits of stockpiling are contained in the current period promotion bump. After subtracting out the brand’s post-promotion dip (presumably the loyal acceleration), the resulting net promotion bump includes pre-emptive switches and short-term consumption. It does not include increases in repeat purchases. Since the latter is smaller in magnitude than short-term consumption and pre-emptive switching, a “bump analysis” may suffice in some instances. However, if results are close to breakeven, analysis of the repeat effects may be required to determine whether in fact the promotion was profitable.

Managerially, our results show that stockpiling has a more complicated impact than simply mortgaging future sales. Accelerating loyal purchases is certainly a consequence of stockpiling. But stockpiling also produces higher category consumption, pre-empt purchases of competitive brands, and increases repeat purchases. These effects more than make up for the negative impact of loyal acceleration. Also, repeat purchase effects are not as large as the consumption and pre-emptive switching effects, but they can have a substantial impact. Managers should factor this into their promotional strategies and tactics. For example, they should include strong product messages on their packages, since these packages will be in the household for a long period of time when customers stockpile.

Our findings generally cast promotion-induced stockpiling in a positive light because it increases consumption, pre-empts competitive sales, and has a positive repeat purchase. At first blush, this would suggest that manufacturers should increase promotion in an effort to induce more stockpiling. However, other long-term considerations that are beyond the scope of the present paper but have been noted in previous literature might offset such a recommendation. First, competitors might respond to increased promotion with their own promotions. The
evidence on competitor response to promotion is somewhat mixed. Ailawadi, Kopalle, and Neslin (2005) find that competitors do react especially to major changes in promotion policy, while Steenkamp et al. (2005) find that many times competitors do not react to marginal increases in promotion. However, it is plausible that an increase in promotion meant to stimulate stockpiling could increase pre-emptive as well as current period switching to a degree that competitors do take notice and respond. Second, consumers adapt to promotion increases in ways that make it less effective. For example, Foekens, Leeflang, and Wittink (1999) and Kopalle, Mela, and Marsh (1999) find that increased promotion frequency makes subsequent promotions less effective. This could be due to a reference price effect or simply to promotion wearout. In summary, our results do suggest that stockpiling is a more positive phenomenon for manufacturers than previously thought, but one must also take into account long-term competitor and consumer response before recklessly turning up the intensity of promotional efforts.

There are some important avenues for extending our work. First, researchers can examine how the benefits of promotion-induced stockpiling vary according to brand and category characteristics. This would require the application of the analysis described in this paper to several product categories and brands. Second, van Heerde, Leeflang, and Wittink (2004) have shown that the relative magnitudes of the switching and stockpiling components differ for features, displays, and pure price cuts. Although our work focuses less on the size of these components and more on the subsequent impact of stockpiling, it may be worthwhile to examine whether those subsequent elements, too, are affected by the type and depth of promotion. Third, the competitive implications of the impact of stockpiling on repeat rates are intriguing. Future analytical research should investigate the equilibria implied by these effects and future empirical research should investigate competitive response to these effects. They
should also be considered in evaluating the long-term effectiveness and desirability of promotions. Fourth, we have aggregated “close” sizes such as six and eight ounces in the yogurt category to create the brand choice alternatives. We appropriately keep track of actual ounces in our inventory and consumption calculations, and define our key stockpiling measure, $Q_{ht}/\bar{Q}_h$, in ounces, but future researchers may wish to examine various sizes more specifically. Fader and Hardie (1996) provide a parsimonious way for handling this. Fifth, we assume that consumption rate is independent of brand preference. This may be reasonable because for our particular categories, yogurt is perishable no matter what the brand, and ketchup is a secondary product whose consumption is undoubtedly based on household consumption of products such as hamburgers and hot dogs. However, in general, a more complete model would explicitly consider consumption to be a function of brand preference.

Finally, researchers should examine the impact of stockpiling from the perspective of the retailer. For example, the distinction between pre-emptive switches and loyal acceleration is not as relevant to the retailer unless brands differ in their regular retail margins. However, timing effects of either form may be very relevant because retailer margins during promotion periods are typically different from margins during regular periods. Our analysis also shows differences between store and national brands in the promotion bump, its components, and stockpiling impact that have implications for retailers’ promotion decisions. In addition, retailers would want to expand our model to take into account store switching and potential pre-emptive store switching as well (see Bucklin and Lattin 1992).
### TABLE 1
CHARACTERISTICS OF THE DATASET

<table>
<thead>
<tr>
<th></th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of households</td>
<td>131</td>
<td>163</td>
</tr>
<tr>
<td>Number of shopping trips (calibration)</td>
<td>30,003</td>
<td>36,337</td>
</tr>
<tr>
<td>Number of purchase occasions (calibration)</td>
<td>2,309</td>
<td>1,899</td>
</tr>
<tr>
<td>Average interpurchase time (calibration)</td>
<td>6.4 weeks</td>
<td>9.6 weeks</td>
</tr>
<tr>
<td>Number of brands</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Sizes</td>
<td>6 &amp; 8 oz.</td>
<td>28 &amp; 32 oz.</td>
</tr>
<tr>
<td>% of market accounted for</td>
<td>90.9%</td>
<td>81.1%</td>
</tr>
</tbody>
</table>
### TABLE 2
DESCRIPTIVE STATISTICS OF BRANDS

<table>
<thead>
<tr>
<th>Brand</th>
<th>Unit Market Share (%)</th>
<th>Average Price Per Ounce</th>
<th>% of Trips When Brand is on Promotion</th>
<th>Average Ratio of Purchase Quantity to Household Average (Mean $Q_{wi}/\bar{Q}_h$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yogurt</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dannon (6 and 8 oz.)</td>
<td>25.1</td>
<td>.08</td>
<td>8.7</td>
<td>.97</td>
</tr>
<tr>
<td>Weight Watchers (8 oz.)</td>
<td>7.9</td>
<td>.08</td>
<td>5.4</td>
<td>1.05</td>
</tr>
<tr>
<td>Yoplait (6 oz.)</td>
<td>14.2</td>
<td>.11</td>
<td>6.8</td>
<td>.83</td>
</tr>
<tr>
<td>Store Brand (6 oz.)</td>
<td>27.8</td>
<td>.07</td>
<td>27.0</td>
<td>1.06</td>
</tr>
<tr>
<td>QCH (8 oz.)</td>
<td>4.5</td>
<td>.05</td>
<td>15.1</td>
<td>.97</td>
</tr>
<tr>
<td>WBB (8 oz.)</td>
<td>11.1</td>
<td>.06</td>
<td>21.8</td>
<td>1.33</td>
</tr>
<tr>
<td>Other (6 and 8 oz.)</td>
<td>9.4</td>
<td>.06</td>
<td>9.5</td>
<td>1.03</td>
</tr>
<tr>
<td>Ketchup</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heinz (28 and 32 oz.)</td>
<td>53.8</td>
<td>.04</td>
<td>16.2</td>
<td>.99</td>
</tr>
<tr>
<td>Del Monte (28 and 32 oz.)</td>
<td>12.0</td>
<td>.04</td>
<td>13.6</td>
<td>.97</td>
</tr>
<tr>
<td>Hunt (32 oz.)</td>
<td>17.6</td>
<td>.03</td>
<td>14.4</td>
<td>1.08</td>
</tr>
<tr>
<td>Store Brand (28 and 32 oz.)</td>
<td>16.6</td>
<td>.03</td>
<td>6.3</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Note: All values in the table are based on calibration sample.
### TABLE 3
DESCRIPTIVE STATISTICS OF VARIABLES

<table>
<thead>
<tr>
<th>Variable</th>
<th>Yogurt Mean</th>
<th>Yogurt Std. Deviation</th>
<th>Ketchup Mean</th>
<th>Ketchup Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular price of chosen brand in $ per ounce (PRICE)</td>
<td>.08</td>
<td>.02</td>
<td>.04</td>
<td>.01</td>
</tr>
<tr>
<td>Promotion dummy variable for chosen brand (PROMO)</td>
<td>.32</td>
<td>.44</td>
<td>.32</td>
<td>.37</td>
</tr>
<tr>
<td>Dummy variable for whether chosen brand was bought last time (LAST)</td>
<td>.65</td>
<td>.48</td>
<td>.68</td>
<td>.47</td>
</tr>
<tr>
<td>Dummy variable for whether chosen brand was bought on promotion last time (LPROMO)</td>
<td>.17</td>
<td>.36</td>
<td>.20</td>
<td>.32</td>
</tr>
<tr>
<td>Average category quantity in ounces purchased per purchase occasion during initialization period ($Q_h$)</td>
<td>22.14</td>
<td>10.52</td>
<td>33.29</td>
<td>6.68</td>
</tr>
<tr>
<td>Average daily category consumption in ounces during initialization period ($\bar{C}_h$)</td>
<td>.83</td>
<td>.91</td>
<td>.74</td>
<td>.37</td>
</tr>
<tr>
<td>Average number of units purchased per purchase occasion during initialization period ($\bar{U}_h$)</td>
<td>2.96</td>
<td>1.37</td>
<td>1.06</td>
<td>.20</td>
</tr>
<tr>
<td>Average category inventory in ounces during initialization period ($\bar{INV}_h$)</td>
<td>.69</td>
<td>.89</td>
<td>11.76</td>
<td>3.68</td>
</tr>
</tbody>
</table>

Note: PRICE, PROMO, LAST, and LPROMO are based on calibration sample
<table>
<thead>
<tr>
<th></th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base Model without (Q_{hjt}/Q_h) &amp; Full Model with (Q_{hjt}/Q_h)</td>
<td>Base Model without (Q_{hjt}/Q_h) &amp; Full Model with (Q_{hjt}/Q_h)</td>
</tr>
<tr>
<td>LL</td>
<td>-13.131.58</td>
<td>-13,120.98</td>
</tr>
<tr>
<td># Parameters</td>
<td>38</td>
<td>40</td>
</tr>
<tr>
<td>(\chi^2) statistic</td>
<td>21.20**</td>
<td>6.62*</td>
</tr>
</tbody>
</table>

** p<.01;  * p< .05
### TABLE 5
PARAMETER ESTIMATES

<table>
<thead>
<tr>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td><strong>Standard Deviation</strong></td>
</tr>
<tr>
<td>PRICE</td>
<td>-23.07** (3.31)</td>
</tr>
<tr>
<td>PROMO</td>
<td>1.84** (.12)</td>
</tr>
<tr>
<td>LAST</td>
<td>1.33** (.13)</td>
</tr>
<tr>
<td>LPROMO</td>
<td>-.92** (.11)</td>
</tr>
<tr>
<td>Q_{ij}/\bar{Q}_h</td>
<td>.36** (.09)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Choice Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>INV - \bar{INV}_h</td>
</tr>
<tr>
<td>\bar{C}_h</td>
</tr>
<tr>
<td>INCVAL</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Incidence Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>INV - \bar{INV}_h</td>
</tr>
<tr>
<td>\bar{U}_h</td>
</tr>
<tr>
<td>PRICE</td>
</tr>
<tr>
<td>PROMO</td>
</tr>
<tr>
<td>BRANDPREF</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Quantity Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>INV - \bar{INV}_h</td>
</tr>
<tr>
<td>\bar{U}_h</td>
</tr>
<tr>
<td>PRICE</td>
</tr>
<tr>
<td>PROMO</td>
</tr>
<tr>
<td>BRANDPREF</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>\hat{f}</td>
</tr>
</tbody>
</table>

Note: Standard errors are in parentheses

** p < .01; * p < .05
<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAST</td>
<td>1.33</td>
<td>.73</td>
</tr>
<tr>
<td>LPROMO</td>
<td>-.92</td>
<td>-.53</td>
</tr>
<tr>
<td>$Q_{hjt} / \bar{Q}_h$</td>
<td>.36</td>
<td>.40</td>
</tr>
</tbody>
</table>

**Contribution to utility depending on previous purchase:**

- Previous purchase is non-promotion purchase of normal quantity: 1.69, 1.13
- Previous purchase is promotion purchase of normal quantity: .77, .60
- Previous purchase is promotion purchase of double the normal quantity: 1.13, 1.00

**Repeat purchase probability of given brand depending on previous purchase**

<table>
<thead>
<tr>
<th>Dannon</th>
<th>Heinz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous purchase is non-promotion purchase of normal quantity: .41, .83</td>
<td></td>
</tr>
<tr>
<td>Previous purchase is promotion purchase of normal quantity: .22, .74</td>
<td></td>
</tr>
<tr>
<td>Previous purchase is promotion purchase of double the normal quantity: .29, .81</td>
<td></td>
</tr>
</tbody>
</table>
TABLE 7  
DECOMPOSITION OF THE PROMOTION BUMP: YOGURT

<table>
<thead>
<tr>
<th>Promotion Bump</th>
<th>Dannon</th>
<th>Weight Watchers</th>
<th>Yoplait</th>
<th>Store Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Units</td>
<td>% of Bump</td>
<td>Units</td>
<td>% of Bump</td>
</tr>
<tr>
<td>Baseline Units</td>
<td>3.88</td>
<td>--</td>
<td>2.44</td>
<td>--</td>
</tr>
<tr>
<td>Unit Bump</td>
<td>12.45</td>
<td>100%</td>
<td>7.87</td>
<td>100%</td>
</tr>
<tr>
<td>Current Switches</td>
<td>4.78</td>
<td>38.4%</td>
<td>2.71</td>
<td>34.4%</td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>.41</td>
<td>3.3%</td>
<td>.34</td>
<td>4.3%</td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>.76</td>
<td>6.1%</td>
<td>.35</td>
<td>4.5%</td>
</tr>
<tr>
<td>Consumption</td>
<td>6.50</td>
<td>52.2%</td>
<td>4.47</td>
<td>56.8%</td>
</tr>
<tr>
<td>Repeat Effect of Stockpiling</td>
<td>.20</td>
<td>1.6%</td>
<td>.26</td>
<td>3.3%</td>
</tr>
<tr>
<td>Consumption</td>
<td>-1.61</td>
<td>-12.9%</td>
<td>-.45</td>
<td>-5.8%</td>
</tr>
</tbody>
</table>

Note: Reported units are averages across simulations where a promotion was inserted in four different weeks.
## TABLE 8
DECOMPOSITION OF THE PROMOTION BUMP: KETCHUP

<table>
<thead>
<tr>
<th>Promotion Bump</th>
<th>Heinz</th>
<th></th>
<th>Del Monte</th>
<th></th>
<th>Hunt</th>
<th></th>
<th>Store Brand</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Units</td>
<td>% of Bump</td>
<td>Units</td>
<td>% of Bump</td>
<td>Units</td>
<td>% of Bump</td>
<td>Units</td>
<td>% of Bump</td>
</tr>
<tr>
<td>Baseline Units</td>
<td>3.78</td>
<td>--</td>
<td>.80</td>
<td>--</td>
<td>.88</td>
<td>--</td>
<td>1.14</td>
<td>--</td>
</tr>
<tr>
<td>Unit Bump</td>
<td>9.41</td>
<td>100%</td>
<td>3.86</td>
<td>100%</td>
<td>4.36</td>
<td>100%</td>
<td>3.94</td>
<td>100%</td>
</tr>
<tr>
<td>Current Switches</td>
<td>1.77</td>
<td>18.8%</td>
<td>2.26</td>
<td>58.6%</td>
<td>2.47</td>
<td>56.6%</td>
<td>1.55</td>
<td>39.4%</td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>1.54</td>
<td>16.4%</td>
<td>.21</td>
<td>5.4%</td>
<td>.12</td>
<td>2.8%</td>
<td>.33</td>
<td>8.3%</td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>.68</td>
<td>7.2%</td>
<td>.25</td>
<td>6.5%</td>
<td>.44</td>
<td>10.1%</td>
<td>.55</td>
<td>13.9%</td>
</tr>
<tr>
<td>Consumption</td>
<td>5.42</td>
<td>57.6%</td>
<td>1.14</td>
<td>29.5%</td>
<td>1.33</td>
<td>30.5%</td>
<td>1.51</td>
<td>38.4%</td>
</tr>
<tr>
<td>Repeat Effect of Stockpiling</td>
<td>.10</td>
<td>1.1%</td>
<td>.03</td>
<td>.8%</td>
<td>.04</td>
<td>.9%</td>
<td>.06</td>
<td>1.4%</td>
</tr>
<tr>
<td>Consumption</td>
<td>1.57</td>
<td>16.7%</td>
<td>.04</td>
<td>1.1%</td>
<td>-.63</td>
<td>-14.3%</td>
<td>-.25</td>
<td>-6.4%</td>
</tr>
</tbody>
</table>

Note: Reported units are averages across simulations where a promotion was inserted in four different weeks.
## TABLE 9
FINANCIAL IMPACT OF STOCKPILING

<table>
<thead>
<tr>
<th>Effect</th>
<th>Period</th>
<th>Level of Analysis</th>
<th>Measure</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Dannon</td>
<td>Weight Watch</td>
</tr>
<tr>
<td>Consumption</td>
<td>Promotion Week</td>
<td>Sample</td>
<td>Units</td>
<td>14.945</td>
<td>10.283</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>.1141</td>
<td>.0785</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Units</td>
<td>1,801,388</td>
<td>1,239,459</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$ Profit</td>
<td>360,278</td>
<td>247,892</td>
</tr>
<tr>
<td>Pre-Emptive Switching</td>
<td>Promotion Week</td>
<td>Sample</td>
<td>Units</td>
<td>1.755</td>
<td>.814</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>.0134</td>
<td>.0062</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Units</td>
<td>211,520</td>
<td>98,137</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$ Profit</td>
<td>42,304</td>
<td>19,627</td>
</tr>
<tr>
<td>Loyal Acceleration</td>
<td>Promotion Week</td>
<td>Sample</td>
<td>Units</td>
<td>.945</td>
<td>.773</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>.0072</td>
<td>.0059</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Units</td>
<td>113,938</td>
<td>93,147</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$ Loss</td>
<td>(5,697)</td>
<td>(4,657)</td>
</tr>
<tr>
<td>Repeat Purchases</td>
<td>Post-Promotion</td>
<td>Sample</td>
<td>Units</td>
<td>.460</td>
<td>.600</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>.0035</td>
<td>.0046</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Units</td>
<td>55,444</td>
<td>72,355</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$ Profit</td>
<td>13,861</td>
<td>18,089</td>
</tr>
<tr>
<td><strong>Total Benefits</strong></td>
<td>National</td>
<td></td>
<td>$ Profit</td>
<td>410,746</td>
<td>280,951</td>
</tr>
</tbody>
</table>

### Key Parameters
- **# HH’s in Sample**: 131, 163
- **# HH’s in US**: 90,000,000, 90,000,000
- **Penetration (IRI Marketing Fact Book)**: 68%, 73%
- **% That Buy ≥ 3 Times/Yr. (Sample Data)**: 43%, 29%
- **Trade Deal Passthrough**: 60%, 60%
- **Regular margin**: $0.25, $0.50
- **Promotional margin**: $0.20, $0.40

*Note: The sample unit numbers are obtained by multiplying numbers in Tables 7 and 8 by 2.3 and 2.1 respectively, to translate from the trip to the weekly level.*
## TABLE 9
### DECOMPOSITION OF COMPETING BRANDS’ PROMOTION BUMP

<table>
<thead>
<tr>
<th>Promotion Bump</th>
<th>Yogurt (units)</th>
<th>Dannon</th>
<th>Weight Watchers</th>
<th>Yoplait</th>
<th>Store Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promoted Brand Bump</td>
<td>12.45</td>
<td>7.87</td>
<td>14.08</td>
<td>25.52</td>
<td></td>
</tr>
<tr>
<td>Aggregate Competitor Bump</td>
<td>2.03</td>
<td>1.03</td>
<td>2.30</td>
<td>2.38</td>
<td></td>
</tr>
<tr>
<td>Current Switches</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
<td></td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>.15</td>
<td>.06</td>
<td>.15</td>
<td>.10</td>
<td></td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>.02</td>
<td>.01</td>
<td>.02</td>
<td>.13</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>1.87</td>
<td>.96</td>
<td>2.13</td>
<td>2.15</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Post-Promotion Effects</th>
<th>Ketchup (units)</th>
<th>Heinz</th>
<th>Del Monte</th>
<th>Hunt</th>
<th>Store Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Repeat Effect of Stockpiling</td>
<td>.02</td>
<td>.01</td>
<td>.01</td>
<td>.03</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>.33</td>
<td>.13</td>
<td>.44</td>
<td>.15</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Promotion Bump</th>
<th>Ketchup (units)</th>
<th>Heinz</th>
<th>Del Monte</th>
<th>Hunt</th>
<th>Store Brand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Promoted Brand Bump</td>
<td>9.42</td>
<td>3.85</td>
<td>4.36</td>
<td>3.94</td>
<td></td>
</tr>
<tr>
<td>Aggregate Competitor Bump</td>
<td>.38</td>
<td>.68</td>
<td>.69</td>
<td>.46</td>
<td></td>
</tr>
<tr>
<td>Current Switches</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
<td>.00</td>
<td></td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>.06</td>
<td>.11</td>
<td>.15</td>
<td>.10</td>
<td></td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>.04</td>
<td>.05</td>
<td>.01</td>
<td>.01</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>.27</td>
<td>.52</td>
<td>.53</td>
<td>.35</td>
<td></td>
</tr>
</tbody>
</table>

| Post-Promotion Effects | Repeat Effect of Stockpiling | .00 | .00 | .00 | .00 |
| Consumption | .01 | .23 | .23 | .59 |
FIGURE 1
A FRAMEWORK FOR QUANTIFYING THE IMPACT OF PROMOTION-INDUCED STOCKPILING

Sales Impact of Promotion-Induced Stockpiling =

Stockpiling

Promotion Bump

Current Period Brand Switching

Pre-Emptive Switches

Loyal Acceleration

Consumption

Repeat Purchases

FIGURE 2
DECOMPOSING THE SALES IMPACT OF PROMOTION-INDUCED STOCKPILING: YOGURT

Promotion Bump

% of short-term bump

Dannon  Weight Watchers  Yoplait  Store Brand

Pre-emptive Switches
Accelerated Loyals
Consumption
Current Switches

Post-Promotion Effects

% of short-term bump

Repeat Effect of Stockpiling
Consumption
FIGURE 3
DECOMPOSING THE SALES IMPACT OF PROMOTION-INDUCED STOCKPILING: KETCHUP

Heinz Delmonte Hunt Store Brand

Promotion Bump

% of short-term bump

50 60 70 80 90 100

Pre-emptive Switches
Accelerated Loyals
Consumption
Current Switches

Repeat Effect of Stockpiling
Consumption

% of short-term bump

-20 -10 0 10 20

Promotion Bump

% of short-term bump

50 60 70 80 90 100

Pre-emptive Switches
Accelerated Loyals
Consumption
Current Switches

Repeat Effect of Stockpiling
Consumption

48
APPENDIX

Decomposition Algorithm

Calculation of Bump:
Calculate the household’s bump for the promoted brand A as the number of units of A purchased in promotion case minus number of units of A purchased in base case, during the promotion trip. Call this \( \Delta A \). If \( \Delta A \) is positive, proceed to decompose the bump, otherwise, go to the next household.

Decomposition of Bump:

1. Calculate the number of units of Brand B purchased in the base case minus number of units of B purchased in the promotion case. Call this \( \Delta B \). If \( \Delta B \) is positive, some units of B were switched to A in the promotion trip. Allocate this current switching to the bump of A until either \( \Delta B \) runs out or the bump runs out. Call this current switching \( S \) and keep track of the base case purchases of B that have been accounted as current switches.

2. The remaining portion of the bump to be explained by loyal acceleration, pre-emptive switches, or increased consumption is \( \Delta A-S \). If \( \Delta A-S=0 \) the bump is fully explained by current switching.

3. Go to the next purchase in the promotion case. See if there are any purchase occasions before this trip in the base case and/or more purchased units on this trip in the base case than in the promotion case. Call them \( L \) and allocate them in order as pre-emptive switches (PS) or loyal acceleration (LA). Do this until either the bump runs out or the \( L \) purchases run out. Keep track of the base case purchases that have been accounted as loyal acceleration or pre-emptive switches. Note that the remaining units in the bump equal \( \Delta A-S-PS-LA \). If \( \Delta A-S-PS-LA = 0 \) the bump is fully explained by brand switching, pre-emptive switching, and loyal acceleration. If not, consumption and possibly additional pre-emptive switching and loyal acceleration explain the remainder of the bump.

4. Calculate CONS, the total change in consumption between promotion and base cases. This is simply the difference between total category purchases in the promotion case and total category purchases in the base case. CONS is made up of two components – CONSA1 and CONS2. CONSA1 is the portion of the promotion bump of A that represents increased consumption of the category. CONS2 is the change in consumption of the category beyond the promotion bump of A. We will quantify these two components below.

If CONS > 0 and \( \Delta A-S-PS-LA \leq CONS \), go to step 5, Case 1. If CONS > 0 and \( \Delta A-S-PS-LA > CONS \), go to step 5, Case 2. If CONS \( \leq 0 \), go to step 5, Case 3.

5. Case 1: \( \Delta A-S-PS-LA \leq CONS \), CONS > 0
   a. Set CONSA1 = \( \Delta A-S-PS-LA \). The bump is fully explained.
   b. Compute CONS2 as CONS – CONSA1.
   c. If CONS2 is zero, proceed to step 6. If CONS2 > 0, there are extra purchases of the category in the promotion case compared to the base case, after the promotion bump is
explained. Allocate CONS2 to unaccounted purchases in the promotion case in order. Then, proceed to step 6.

5. Case 2: $\Delta A-S-PS-LA > CONS$, $CONS > 0$
   a. Set $CONSA1 = CONS$. The remaining unexplained bump is $\Delta A-S-PS-LA-CONSA1 > 0$.
   b. Proceed further in the base case, explaining the remaining bump with pre-emptive switching or loyal acceleration. Keep track of the base case purchases that have been accounted.
   c. Set $CONS2 = 0$ because there is no increase in category consumption beyond the promotion bump. Proceed to step 6.

5. Case 3: $CONS \leq 0$. Additional consumption cannot explain the remaining bump $= \Delta A-S-PS-LA$.
   a. Therefore, proceed further in the base case, explaining the remaining bump with pre-emptive switching or loyal acceleration. But, we still need to account for the negative CONS.
   b. Set $CONS2 = CONS$.
   c. If $CONS2$ is zero, proceed to step 6. If $CONS2 < 0$, there are extra purchases of the category in the base case compared to the promotion case, after the promotion bump is explained. Allocate $CONS2$ to unaccounted purchases in the base case in order. Then, proceed to step 6.

6. Now, the number of category purchases left unaccounted in the promotion case equals the number of category purchases left unaccounted in the base case. Subtract the number of units of A in the base case from the number of units of A in the promotion case to get the repeat purchase effect.
REFERENCES


