The Benefits of Promotion-Induced Stockpiling

by

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Promotion-induced consumer stockpiling is often viewed negatively because it moves forward in time sales that would have occurred later at full margin. This paper examines three potential benefits of promotion-induced consumer stockpiling for manufacturers: increased category consumption, pre-emptive brand switches, and additional repeat purchases. We find that all three benefits are substantial but consumption appears to be the most important, followed by pre-emptive switching and then additional repeat purchases. These benefits easily offset the negative aspect of consumer stockpiling, namely, purchase acceleration by loyal customers who would have bought the brand later anyway.
The Benefits of Promotion-Induced Stockpiling

1. INTRODUCTION

Consumer stockpiling is a fundamental consequence of sales promotion (Neslin 2002). It takes two forms: accelerated purchase timing and additional purchase quantity (Blattberg, Eppen, and Lieberman 1981; Neslin, Henderson, and Quelch 1985). Accelerated purchase timing means that a category purchase that would have taken place later takes place now. Additional purchase quantity means that promotion is not moving a purchase occasion forward, but the consumer purchases additional quantity compared to what he or she would have bought without the promotion. Evidence of stockpiling is found directly in panel data analyses of purchase incidence and quantity (Blattberg, Eppen, and Lieberman 1981; Bucklin and Gupta 1992; Bucklin, Gupta, and Siddarth 1998; Chintagunta and Halder 1998; Gupta 1988; Neslin, Henderson, and Quelch 1985), and indirectly in the detection of post-promotion dips in weekly sales data (Macé and Neslin 2004; van Heerde, Leeflang, and Wittink 2000 and 2004).

Perhaps because of a focus on the post-promotion dip, manufacturers often view stockpiling negatively because it pulls forward sales that would have occurred later at full margin (Blattberg and Neslin 1993; Neslin, Powell, and Stone 1995; Silva-Risso, Bucklin, and Morrison 1999). This is an accurate assessment if stockpiling consists only of the brand’s own sales that would have occurred later (see Neslin and Shoemaker 1983). Neslin, Powell, and Stone (1995) show in this case that promotions are significantly less profitable and optimal promotion expenditures should decrease.

However, a more in-depth view reveals that stockpiling is composed of three phenomena: accelerated loyals, additional category consumption, and pre-emptive switches. Loyal
acceleration represents the brand’s own sales that are pulled forward from the future. These are customers who would have bought the brand in the future anyway but decide to make the purchase now instead. Chan, Narasimhan, and Zhang (2004) and Neslin, Henderson, and Quelch (1985) find that loyal customers are more likely to accelerate than non-loyal customers. This is reinforced by Macé and Neslin’s (2004) finding that high share brands have larger post-promotion dips. Krishna (1994) as well as Sun, Neslin, and Srinivasan (2003) draw on a dynamic structural model to provide a rationale for why loyals would be more likely to accelerate than non-loyals: Only for loyals does the consumption utility for the additional product offset the additional household inventory cost incurred by stockpiling.

Whereas accelerated loyals represent the non-incremental impact of promotion-induced stockpiling, additional category consumption and pre-emptive switches represent incremental sales for the brand. Additional category consumption arises through 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, Leefflang, and Wittink 2004).

Pre-emptive switching is the purchase of the promoted brand now instead of a competing brand later. The purchase of a competing brand has therefore been pre-empted. Pre-emptive switching is also called “accelerated switching” (van Heerde, Leefflang, and Wittink 2004) since it involves an accelerated category purchase coupled with a brand switch. Managers instinctively see the value of pre-emptive switching – they think of it as taking customers out of the market so that they don’t buy a competing brand (Lodish 1986, p. 41). But it has rarely been
investigated empirically. Van Heerde, Leeflang, and Wittink (2004) combine pre-emptive switching and accelerated loyals in their analysis but note that separating them is an important avenue for research. Chan, Narasimhan, and Zhang (2004) distinguish between brand switching in the promotion period and subsequent brand switching, and they find evidence of both. But, their brand switching in subsequent periods is conceptually very different from pre-emptive switching and is, in fact, not a part of stockpiling at all.

Loyal acceleration, additional consumption, and pre-emptive switching are a decomposition of stockpiling, in that they sum to the total stockpiling effect. An additional potential benefit of stockpiling is its impact on repeat purchasing of the brand. Stockpiling could be highly beneficial to the promoted brand if it makes the customer more loyal to that brand. Although several researchers have studied the effect of promotion on repeat rates, the differential effect that stockpiling the promoted brand can have on repeat purchasing has not been investigated previously.

The effect could emerge through the extra purchase quantity aspect of stockpiling, which means the consumer uses more of the brand before the next purchase. From a behavioral learning standpoint, this provides more reinforcement before the next purchase, and therefore the behavior of buying the brand is more likely to persist (see Rothschild and Gaidis 1981). From a cognitive learning viewpoint, this provides a longer post-purchase evaluation period (Engel, Blackwell, and Miniard 1995). There are then two possibilities: Under high involvement, the consumer has more time to uncover either the strengths or weaknesses of the brand (Engel, Blackwell, and Miniard 1995, pp. 263, 273-276). Under low involvement, stockpiling provides more time to establish inertia or induce boredom (Engel, Blackwell, and Miniard 1995, pp. 158-160). Thus, under behavioral learning, stockpiling should yield more repeat purchases. Under
cognitive learning, stockpiling could yield more repeat purchases (through inertia or higher brand knowledge) or fewer repeat purchases (through boredom or variety seeking).

Figure 1 summarizes these effects of stockpiling. The immediate promotion sales bump consists of current brand switching and stockpiling. Stockpiling in turn consists of consumption, preemptive switching, and loyal acceleration. The consumption and preemptive switching components of the promotion bump together with repeat purchasing effects comprise the benefits of stockpiling to manufacturers while loyal acceleration comprises its negative impact.

[Figure 1 Goes About Here]

The purpose of this paper is to develop a method for measuring the three potential benefits of stockpiling and demonstrate the magnitude of the benefits 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 discuss the estimated model results. We then calculate the consumption, preemptive switching, loyal acceleration, and repeat purchasing effects of stockpiling using a Monte Carlo simulation. Finally, we discuss the implications of our research for managers and researchers.

2. MODEL

2.1 Overview

We formulate an integrated brand choice, purchase incidence and purchase quantity model to investigate the three potential benefits 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):

\[
P_{ht}(j & q) = P_{ht}(inc) * P_{ht}(j | inc) * P_{ht}(q | inc & j)
\]
where:

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

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 several of the 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). The three equations are jointly estimated using simulated maximum likelihood (Erdem 1996; Seetharaman 2004; Sun, Neslin, and Srinivasan 2004; Train 2003).

2.2 Choice Model

Given the nested logit framework, the choice model takes the form of a multinomial logit. We add a term in 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:

\[
P_{ht}(j \mid \text{inc}) = \frac{e^{V_{htj}}}{\sum_k e^{V_{htk}}}
\]

\[
V_{htj} = \beta_{0hj} + \beta_{1h} PRICE_{htj} + \beta_{2h} PROMO_{htj} + \beta_{3h} LAST_{htj} + \beta_{4h} PROMO_{htj} + \beta_{5h} \frac{Q_{htj}}{Q_h}
\]
where:

\[ Price_{hjt} = \text{Regular price of brand } j \text{ available to household } h \text{ on shopping trip } t. \]

\[ Promotio_{hjt} = \text{Promotion indicator, equal to 1 if brand } j \text{ available to household } h \text{ on promotion on shopping trip } t; 0 \text{ otherwise.} \]

\[ Last_{hjt} = \text{Last brand purchased indicator for state dependence, equal to 1 if household } h \text{ bought brand } j \text{ on his or her previous purchase occasion before shopping trip } t; 0 \text{ otherwise.} \]

\[ LPromotio_{hjt} = \text{Last purchase on promotion indicator, equal to 1 if household } h \text{ bought } j \text{ on promotion on his or her previous purchase occasion before shopping trip } t; 0 \text{ otherwise.} \]

\[ Q_{hjt} = \text{Quantity bought of brand } j \text{ if household } h \text{ bought brand } j \text{ on his or her previous purchase occasion before shopping trip } t; 0 \text{ otherwise.} \]

\[ Qh = \text{Average quantity of the category purchased per purchase occasion by household } h \text{ during an initialization period.} \]

\[ beta_{0hj} \ldots, beta_{5h} = \text{Heterogeneous parameters.} \]

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

\[
(4) \quad \text{Contribution} = \beta_{3h} + \beta_{4h} Promotio_{hjt} + \beta_{5h} \frac{Q_{hjt}}{Q_h}
\]

We expect the state dependence term \( \beta_{3h} \) to be positive per previous literature (e.g., Ailawadi, Gedenk and Neslin 1999; Seetharaman 2004; Seetharaman, Ainslie, and Chintagunta 1999). This means that all else being equal, previous purchase of the brand reinforces brand preference and the household is more likely to purchase on the current shopping trip. We expect \( \beta_{4h} \) to be negative, consistent with previous research (Gedenk and Neslin 1999; Guadagni and Little 1983), to signify that promotion purchases are less reinforcing than non-promotion purchases.
Finally, a positive $\beta_{sh}$ would mean that higher purchase quantities than usual (i.e., stockpiling) result in greater purchase reinforcement, and the likelihood is higher that the household will purchase brand $j$ on the current shopping trip if he or she purchases the category. Therefore, $\beta_{sh}$ represents the potential repeat purchase benefit of stockpiling. As noted earlier, stockpiling may breed boredom or variety seeking, in which case $\beta_{sh}$ would be negative.

2.3 Incidence Model

Given the nested logit formulation, the purchase incidence model takes the form of a binomial logit:

\[
P_{ht}(inc) = \frac{e^{W_{ht}}}{1 + e^{W_{ht}}}
\]

\[
W_{ht} = \kappa_{0h} + \kappa_{1} \frac{INV_{ht}}{INV_{h}} + \kappa_{2} \overline{C}_{h} + \kappa_{3h} IncVal_{ht}
\]

\[
IncVal_{ht} = \ln \left( \sum_{k} e^{V_{htk}} \right)
\]

where:

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

$\overline{INV}_{h}$ = Average inventory of household $h$ during initialization period.

$\overline{C}_{h}$ = Average daily consumption of household $h$ during initialization period.

$IncVal_{ht}$ = “Inclusive Value” for household $h$ on shopping trip $t$.

$\kappa_{0h}$, $\kappa_{3h}$ = Heterogeneous parameters.

$\kappa_{1}$, $\kappa_{2}$ = Homogeneous parameters.

The variables in the incidence model are standard (e.g., Ailawadi and Neslin 1998; Bucklin, Gupta, and Siddartha 1998). We allow for heterogeneity in the baseline incidence and
inclusive value coefficients ($\kappa_{0h}$ and $\kappa_{3h}$). The latter is particularly important because it reflects the effect of promotion on purchase incidence and the focus of our study is on the impact of promotion. The inventory and consumption rate parameters ($\kappa_i$ and $\kappa_2$) are treated as homogeneous. These variables themselves reflect household heterogeneity in consumption and inventory, so it seems unnecessary to also make their coefficients heterogeneous.¹

### 2.4 Purchase Quantity

The purchase quantity model is a truncated Poisson (Ailawadi and Neslin 1998; Mullahy 1986). It is written as:

\[
P_h(q | inc \& j) = \frac{(\lambda_{hjt})^q}{(e^{\lambda_{hjt}} - 1)q!} \quad (q = 1, 2, \ldots, \infty)
\]

\[
\lambda_{hjt} = e^{\gamma_0 + \gamma_1 \text{INV}_{ht} + \gamma_2 \overline{U}_h + \gamma_3 \text{PRICE}_{ht} + \gamma_4 \text{PROMO}_{ht}}
\]

where:

- $\overline{U}_h$ = Average number of units purchased per purchase occasion by household $h$ during the initialization period.
- $\gamma_0, \gamma_1, \gamma_2$ = Homogeneous parameters.
- $\gamma_3, \gamma_4$ = Heterogeneous parameters.

All the terms in the model are standard. We account for heterogeneity in the PRICE and PROMO coefficients. Analogous to the incidence model, coefficients of the inventory and average purchase quantity variables are considered homogeneous because those variables themselves reflect heterogeneity in households.

¹ We had convergence problems when we did attempt to make these parameters heterogeneous.
2.5 Inventory and Consumption

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

\[
INV_{hd} = INV_{h,d-1} + Q_{h,d-1} - CONS_{h,d-1}
\]

\[
CONS_{hd} = INV_{hd} \left[ \frac{C_h}{C_h + (INV_{hd})^f} \right]
\]

where:

\[
CONS_{hd} = \text{Consumption of household } h \text{ on day } d.
\]

\[
Q_{hd} = \text{Quantity purchased by household } h \text{ on day } d.
\]

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.

2.6 Estimation

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

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

where:

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

\[
Y_{ht} = \text{Category purchase indicator, equals 1 if household } h \text{ purchased the category on shopping trip } t; 0 \text{ otherwise.}
\]
In order to reduce the computational burden, we use the values of $f$ estimated by Ailawadi and Neslin (1998) for the same categories using the same database instead of estimating them again. These values are $f = -0.65$ for yogurt and $f = +0.9$ for ketchup.

3. DATA

We use Nielsen scanner panel data for the ketchup and yogurt categories. We chose these two categories because they have been used in prior research on promotion effects, thus allowing us to build on existing work and make comparisons more easily. We use the first 26 weeks of the data for initialization and the remaining 112 weeks for estimation.

In the 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 aggregate “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 ensures that we account for all category purchases and consumption of the included households, while avoiding the need to model size choice; the third ensures that we obtain reliable values of $\overline{U}_h$, $\overline{C}_h$, and $\overline{INV}_h$ 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 randomly split the 263 yogurt households in half to make the database smaller and hence more tractable, resulting in 131 yogurt households. 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 once every 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 once every 9.6 weeks. Table 1 summarizes these statistics.

Table 1 Goes About Here

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 (e.g., Gedenk and Neslin 1999). 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. TPRs are identified using the algorithm described by Gedenk and Neslin (1999). Thus, we clearly separate regular price from price promotion effects and can focus on the PROMO variable in our interpretation of the results and in our simulations.

4. MODEL ESTIMATES

The first step is to test the incremental contribution of the $Q_{hjt}/\overline{Q}_h$ term in the choice model of equation (3), since it captures the potential impact of stockpiling on future brand preference. The mean and standard deviation of the term’s coefficient, $\beta_{sh}$, are estimated. The table below shows that the investment in these two parameters is worth it for both categories, since the $\chi^2$ statistic for the likelihood ratio test is significant at the 1% level.
We now turn our attention to the parameter estimates. Table 2 shows the estimated means and standard deviations for the choice, incidence, and quantity models. All mean estimates have the right sign in the choice and incidence models and almost all standard deviations are substantial, showing that there is considerable heterogeneity across households. The incidence model shows negative estimated inventory coefficients. Although it is difficult to compare coefficients across models, ketchup purchasing seems to be more inventory-driven than yogurt, which makes sense. The inclusive value estimates are significantly positive and less than one, as they should be (Ben-Akiva and Lerman 1985; Bucklin and Gupta 1992; Train 2003). In the quantity model, price and promotion have the correct signs but inventory does not have a significant effect in either category. It appears that inventory’s role is primarily in determining when to purchase the category; purchase quantity is determined mainly by price and promotion.

Our main interest, however, is in the brand choice model and the state dependence estimates for \( LAST \), \( LPROMO \), and \( \frac{Q_{bij}}{\bar{Q}_h} \) in particular. In both categories, the mean for the \( LAST \) coefficient is positive, and the mean for the \( LPROMO \) coefficient is negative but smaller in magnitude than the \( LAST \) coefficient. Thus, we confirm Gedenk and Neslin’s (1999) finding that

<table>
<thead>
<tr>
<th></th>
<th>Yogurt Base Model without Q/( \bar{Q} )</th>
<th>Yogurt Full Model with Q/( \bar{Q} )</th>
<th>Ketchup Base Model without Q/( \bar{Q} )</th>
<th>Ketchup Full Model with Q/( \bar{Q} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LL</td>
<td>-13.165.80</td>
<td>-13,157.52</td>
<td>-8,457.44</td>
<td>-8,442.65</td>
</tr>
<tr>
<td># Parameters</td>
<td>33</td>
<td>35</td>
<td>27</td>
<td>29</td>
</tr>
<tr>
<td>( \hat{\chi}^2 ) statistic</td>
<td>16.56(^*)</td>
<td></td>
<td>29.58(^*)</td>
<td></td>
</tr>
</tbody>
</table>

\(^*\) \( p < 0.01 \)
previous purchases reinforce brand loyalty, although promotion purchases are not as reinforcing as non-promotion purchases.

Importantly, the estimated mean for $Q_{hjt} / Q_{h}$ is significantly positive for both yogurt and ketchup. Whether it be 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 estimated standard deviation (0.38 relative to a mean of 0.51) implies that, while the vast majority of households have positive parameter values, some do have negative values. Presumably, in this category some customers get bored with the brand when they have it in the household for a long time.

Examining average effects in more detail, the table below shows the contribution to future utility of various purchases. For example, in the yogurt category, if the household makes a non-promotion purchase and buys its usual quantity, the contribution to utility is $1.20+0.26*1=1.46$. If the usual quantity is bought but the purchase is a promotion purchase, the contribution is $1.20-0.87+0.26=0.59$. If the purchase is a promotion purchase but the household buys twice its usual quantity (stockpiling), the contribution is $1.20-0.87+0.26*2=0.85$.

<table>
<thead>
<tr>
<th>Parameter Values</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LAST</strong></td>
<td>1.20</td>
<td>0.73</td>
</tr>
<tr>
<td><strong>LPROMO</strong></td>
<td>-0.87</td>
<td>-0.49</td>
</tr>
<tr>
<td>$Q_{hjt} / Q_h$</td>
<td>0.26</td>
<td>0.51</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Contribution to Utility</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Promotion Purchase of Normal Quantity</td>
<td>1.46</td>
<td>1.24</td>
</tr>
<tr>
<td>Promotion Purchase of Normal Quantity</td>
<td>0.59</td>
<td>0.75</td>
</tr>
<tr>
<td>Promotion Purchase of Double the Normal Quantity</td>
<td>0.85</td>
<td>1.26</td>
</tr>
</tbody>
</table>
These results suggest that stockpiling at least partially makes up for the lower purchase reinforcement of a typical promotion purchase. In the yogurt category, a non-promotion purchase is still more reinforcing, but in the ketchup category, a stockpiled promotion purchase with double the normal quantity is as reinforcing as a non-promotion purchase. The more positive results for ketchup are probably due to the fact that stockpiled product stays with the customer for a longer period of time. From a behavioral learning standpoint, this means more usage occasions and more reinforcements. From a cognitive learning standpoint, this means more time to develop inertia-driven loyalty or to better understand the product’s attributes.

In summary, the model estimates show that the positive impact of stockpiling on household preferences is substantively meaningful. We undertake a simulation study in the next section to quantify the impact in terms of net unit sales.

5. QUANTIFICATION OF STOCKPILING EFFECTS: METHOD

5.1 Decomposition Approaches

In order to assess the magnitude of the benefits of 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 purchasing 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 purchasing, 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, the approach is not designed to separate phenomena such as loyal acceleration and repeat purchase, both of which affect sales of the focal brand in the future.

The third approach utilizes Monte Carlo simulation. Purchase histories of a panel of households are simulated using estimated model parameters and the “base” case is compared with a “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, Gupta, and Venkataraman 2004). We use this approach because it allows us to distinguish among the various stockpiling effects and repeat purchasing, and measure them in unit sales. We extend previous simulations by separating pre-emptive switching from loyal acceleration, and by quantifying the effect of stockpiling on repeat purchases.
5.2 Decomposition Method

Following existing research, we use our estimated model parameters to 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 count the brand’s promotion bump, current period brand switches, accelerated loyals, pre-emptive brand switches, extra consumption, and extra repeat purchases.

We employ 1,000 replications. In each replication, we draw a set of parameters for each household using our estimates of the distributions of these parameters. We use the same initialization constants ($U_h$, $C_h$, and $INV_h$) as for the estimation. We then simulate each household’s purchases given the store environment. To avoid the need for accessing multiple store environments, all the households in our simulation shop at one large store that carries all the brands. The store environment file provides the values of price and promotion for each brand in each week of the 112-week simulation. The only factor that differs between the base case and promotion case is the insertion of one additional promotion during the simulation period. The promotion is inserted in week 23 for yogurt and week 41 for ketchup. Each household that goes shopping in this week is exposed to the promotion during its first shopping trip that week.\(^2\) We use the same set of random numbers for both the base and the promotion case to ensure a clean comparison between the two cases.

Before providing detail of our decomposition method, we present stylized examples of two households to illustrate its basic principles. For simplicity, we assume two brands and a

\(^2\) We also simulated a scenario in which the promotion was inserted for all shopping trips during the week. The possibility of more than one purchase occasion during the promotion made the decomposition of the promotion bump more complicated, but there was no substantive change in the results.
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 Brand A is 4 units. It is apparent that one of these units represents a current period switch from B to A. That leaves three units of the bump to be accounted for. 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 either an accelerated loyal or a pre-emptive switch. The base case purchase of two units of Brand A in trip 2 can be interpreted as loyal acceleration – these are purchases of Brand A that would have occurred in trip 2 had there not been a promotion in trip 1. Allocating these two purchases to the promotion bump as loyal acceleration leaves one unit of the bump unaccounted for. The base case purchase of Brand B in trip 3 can be allocated to the bump as a pre-emptive brand switch – an extra purchase of Brand A due to the promotion in trip 1 pre-empted the purchase of Brand B in trip 3. Once this pre-emptive switch is allocated, the bump of Brand A is fully accounted for. One unit is a current brand switch, two units are loyal acceleration, and one unit is a pre-emptive brand switch. There are no consumption and repeat purchase effects in this example.

Now, consider a second example:
Again, there is a bump of four units for Brand A and one of them is a current period brand switch. That leaves three units of the bump unaccounted for. We go to the next purchase in the promotion case but there are no base case purchases between that purchase and trip 1 that we could consider accelerated loyals or pre-emptive switches. We therefore calculate the total consumption effect by subtracting three total category units in the base case from six total category units in the promotion case, yielding three units of additional consumption. We allocate those three units to the bump. The bump is now fully accounted for. We then consider the remaining purchases. Total remaining category purchases are equal in the base case and promotion case. We subtract the number of Brand A purchases in the base case (i.e., 0) from the number of Brand 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.

We formalize this decomposition method in an algorithm that considers all the contingencies that can occur. The detailed algorithm is provided in the Appendix, but we describe the key aspects here. For each household:

1. Calculate the short-term promotion bump for Brand A (the promoted brand) by computing the difference in sales of Brand A between the promotion case and base case during the promotion trip.³

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

³ It is possible that a promotion for Brand A may result in a positive bump for Brand B. Although this happened rarely (12% of the time in yogurt and 10% in ketchup), we later analyze the cases of a positive bump for Brand B. Our focus however is on the usual case of a positive promotion bump for Brand A.
3. Go to the next category purchase in the promotion case. All purchases in the base case that occur between this purchase and the promotion purchase are potential loyal accelerations or pre-emptive switches. Allocate them until either the base case purchases or the bump run out.

4. Calculate the total consumption effect by subtracting total category purchases in the base case from total category purchases in the promotion case. This effect can be either positive or negative.

5. There are three cases. **Case 1:** There is a positive consumption effect and no remaining unexplained bump after Step 3. This means that increased category consumption occurred not through the promotion bump but from extra purchases in post-promotion trips. **Case 2:** There is a positive consumption effect and unexplained bump remaining after Step 3. We allocate as much as possible of this remaining bump to increased consumption. If it can be fully allocated and there is still increased consumption left over, this consumption occurred in subsequent weeks and is not part of the bump. If the bump is not fully explained even after allocating consumption, we go beyond the next category purchase identified in Step 3 to find additional accelerated loyals or pre-emptive switches until the bump is fully accounted for. **Case 3:** If there is a decrease in category consumption, it obviously can not explain the bump. It must represent fewer purchases in post-promotion trips. As in Case 2, we therefore go beyond the next category purchase identified in Step 3 to fully explain the bump.

6. The promotion bump has now been fully accounted for, and we have tracked all purchases in the base case that were used to account for the bump. However, we still need to quantify the post-promotion repeat purchase effect and separate it from any post-promotion changes in consumption. Therefore, we now track purchases in the base and promotion cases that account for the post-promotion consumption changes. Positive changes are allotted to previously unaccounted purchases in the promotion case because these are extra category units bought and consumed after the promotion. Negative changes are allotted to previously unaccounted purchases in the base case because these are category units that were bought and consumed in the base case but not in the promotion case.

7. After Step 6, there is an equal number of unaccounted category purchases left in the promotion and base cases. We subtract the remaining Brand A purchases in the base case from the remaining Brand A purchases in the promotion case to yield incremental (or “decremental”) repeat purchases.

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4 A decrease in category consumption could happen as follows: The promotion could induce the household to switch to a less preferred brand. This increases subsequent preference for the promoted brand but lowers it for other previously preferred brands, the net result being a decrease in the post-promotion inclusive value, which in turn lowers purchase incidence in the future.
Note we give precedence to certain phenomena over others in explaining the promotion bump, since some prioritization is necessary to resolve potential ambiguities. We allocate the bump to current period brand switching first, then to loyal acceleration and pre-emptive switching up to the next purchase occasion, then to consumption, and finally to loyal acceleration and pre-emptive switching beyond the next purchase occasion. This prioritization is defensible in that (i) a current period switch is the “easiest” thing for the household to do, since it requires a change in brand but not a change in timing, and (ii) 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 subtracted 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 subtracted from unaccounted base case purchases of Brand 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.

6. QUANTIFICATION OF STOCKPILING EFFECTS: RESULTS

6.1 Yogurt Results:

Table 3 displays the results of the simulation based decomposition of the promotion bump for four of the yogurt brands. Dannon and Yoplait are the two leading brands with market shares of approximately 24% each in our data, while Weight Watchers and the Store Brand have
shares of approximately 9% and 15% respectively. The promotion bump numbers in the first row show that there was a significant promotion impact for all brands, judged relative to their baseline. For example, the promotion for Dannon yogurt induced a bump of 24.97 units on a baseline of 7.88 units. This is a 317% increase in sales, which is within the range of what promotions typically achieve (Narasimhan, Neslin, and Sen 1996).

[Table 3 Goes About Here]

The first set of rows under “Promotion Bump” shows the decomposition of the bump into its components. Across all the brands of yogurt, increased consumption is the largest component of the bump, followed by current brand switching. Together, these two components account for over 90% of the bump, pre-emptive switching accounts for 4-5%, and loyal acceleration is the smallest component at 2-3%. 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 very stable across brands, but one difference deserves mention. The total bump for the store brand is substantial. Indeed, it is higher than for the other brands, and it is accounted for mostly by increased consumption. Perhaps store brand promotions serve to 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. We present repeat purchases separately for two groups of households – those who stockpile on promotion (\(Q_{hjt}/\bar{Q}_h > 1\)) and those who do not (\(Q_{hjt}/\bar{Q}_h = 1\)). Across the board, stockpilers show higher repeat purchases of the promoted brand than non-stockpilers, though the effect is strongest for the small share Weight Watchers and store brands. In order to quantify the repeat purchase benefit of stockpiling in unit sales, we subtract the repeat purchases per non-stockpiler from the repeat
purchases per stockpiler and multiply the difference by the number of stockpilers. This gives a repeat purchase benefit of 0.67 and 0.64 units respectively for Weight Watchers and the store brands, and 0.32 and 0.27 units respectively for Dannon and Yoplait. As a percentage of the promotional bump, this effect varies from 1.1% for Yoplait to 5.1% for Weight Watchers.\(^5\) These percentages appear small, but, as we show subsequently, the financial impact of this magnitude of repeat rate effect is not insignificant for a manufacturer.

The last row of the table shows that the longer term effect of the promotion on consumption is negative on average. This may appear counterintuitive at first. However, note that the consumption component of the promotion bump, which is due to faster usage rate and fewer stock-outs, is very high. What is left in the post-promotion effect is any second order mechanisms (through changes in the inclusive value in the incidence model; see Footnote 4). These second order effects have not been quantified before to the best of our knowledge, and, in our analysis, they are negative on average. But, the total effect of the promotion on consumption (direct plus second order effects) is highly positive, ranging from 42.8% for Yoplait to 56.7% for the store brand.

### 6.2 Ketchup Results:

Table 4 displays decomposition results for the four brands of ketchup. 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 14% respectively, and Del Monte lags with a share of about 10%. As in yogurt, all brands show a large promotion bump relative to their baseline sales.

\[\text{Table 4 Goes About Here}\]

\(^5\) Although the repeat purchase effect is not a component of the promotion bump, converting it to a percentage of the bump is helpful in assessing its magnitude relative to the other stockpiling benefits.
In this category, 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 55% for Del Monte. As would be expected (e.g., Ailawadi and Neslin 1998), the consumption component is smaller than in yogurt. Importantly, the loyal acceleration and pre-emptive switching components are much larger here than in yogurt. Indeed, pre-emptive switching accounts for 17% and 18.6% of the promotion bumps for Hunt and the store brand respectively.

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. 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.

Stockpilers show higher repeat purchases of the promoted brand than non-stockpilers, and the effect is stronger for small share brands than for Heinz, which hardly sees any repeat rate benefit. Finally, except for Heinz, the longer term effect of promotion on consumption is negative in this category too, but the total effect (direct plus second order effects) is positive: 20.9% for Hunt, 21.6% for Del Monte, 28.3% for the store brand, and 43.3% for Heinz.\(^6\)

### 6.3 Financial Impact:

Across brands in both categories, we have found that, among the potential benefits of stockpiling, consumption dominates, followed by pre-emptive switching, and then repeat purchasing. Table 5 presents calculations to assess the financial impact of these benefits for a typical one-week promotion offered nation-wide by the manufacturer. The steps are as follows:

(i) The unit sales effects in Tables 3 and 4 are based on a promotion offered during a single shopping trip, whereas a typical promotion runs for a week. We redid our

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\(^6\) It 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 as a result of the promotion, which may lower the inclusive value, which, in turn lowers future purchase incidence. Heinz enjoys much higher preference in the market than the other brands, so the likelihood of this happening is small.
simulation by introducing a promotion for the full week and found that the promotional bump in that case was approximately 2.3 times the bump shown in Table 3 for yogurt, and 2.1 times the bump shown in Table 4 for ketchup. We use these multipliers to compute consumption, pre-emptive switching, loyal acceleration, and repeat purchasing effects of a one-week promotion in Table 5.

(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 passthrough percentages. Specifically, we multiply our effects per household by the number of households in the U.S., the penetration of the category (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 passthrough rate.

(iii) We assume realistic numbers for profit margins and trade deal discounts. Specifically, we use a manufacturer price of $0.70 per unit for yogurt and $2.00 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 short-term 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. This accentuates the profit importance of repeat effects.

Table 5 indicates that the profit impact of the benefits of stockpiling 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 of course consumption, followed by pre-emptive switching (especially in the ketchup category). Repeat purchasing effects do not contribute as much in dollar terms, but they are still in the $10,000’s. Further, in all but two 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 financial impact across brands. Market leaders like Heinz experience substantial acceleration of their own future sales and

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7 In the simulation we implicitly assume passthrough is 100% since each household is exposed to the promotion. But passthrough percentages of 60% might be more realistic for a national campaign (e.g., see Abraham and Lodish 1993, p. 265, Figure 6).
garner lower repeat rate effects, but the financial benefit of stockpiling is still very high for these brands, because the absolute size of their promotion bumps is large. The store brand enjoys large consumption and repeat rate benefits, 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 the simulations is that the stockpiling benefits of promotion are significant both in terms of a percentage of the current period promotion bump, and financial impact. All three aspects – consumption, pre-emptive switching, and repeat purchasing – contribute, although consumption is clearly most important, followed by pre-emptive switching and repeat purchasing.

6.4 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 customers to buy the category who would not otherwise have bought, but these customers buy their preferred brand, Brand B. We wanted to examine the magnitude of this bump and its components.

To do this, we aggregated across all competitive brands to create a Brand B and analyzed the bump for Brand B. The results are shown in Table 6. Comparing the promoted brand and aggregate competitors’ bumps, the latter is of course much smaller – on average, it is about 10% the size of the promoted brand’s bump. The table shows that, for both categories, increased consumption accounts for almost all of the competitors’ bump, with some loyal acceleration. There is little current or pre-emptive switching, which makes sense. There is no reason why a

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8 We aggregate to create Brand B for two reasons. First, our decomposition algorithm becomes much more complex if we try to identify switching among more than two brands. This is fine for analysis of the promoted brand because all we care about is switches between that brand and all others, but not if we wish to examine competitive interactions among three or more brands. Second, the magnitude of the aggregate competitive bump is relatively small, as shown in Table 6, so splitting it for specific brands would result in a very small impact.
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).

The post-promotion consumption effect is small but positive, and there is a small increase in repeat purchases due to state dependence. Of course, there is no repeat purchase benefit for stockpilers, since that benefit comes from stockpiling of a promoted brand in our model.

[Table 6 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 accelerated loyals, 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 make sense to monitor this possibility in practice. Our simulation provides the tool to do so.

7. DISCUSSION AND CONCLUSION

We have identified three potential benefits of promotion-induced consumer stockpiling – additional consumption, pre-emptive brand switching, and additional repeat purchases, developed a model and simulation method for measuring them, and calculated their impact in two product categories.

From a modeling standpoint, our contribution is to demonstrate the importance of adjusting state dependence in choice models by the size of the previous purchase. This is the \( Q / Q_h \) term in Equation 3. This term is easily added to choice models and we have found it to
be statistically and managerially important. The term can be expected to increase the positive state dependence effects typically observed in choice models.

Substantively, we have shown that all three benefits of stockpiling are important, whether expressed as a percentage of the current period promotion-induced bump in sales, or in terms of financial impact. On both measures, consumption appears to be the most important benefit of stockpiling, followed by pre-emptive switching and repeat purchasing. The total profit impact of these effects can make the difference between a profitable and unprofitable trade deal promotion, and even the smallest of these three benefits can easily offset the cost 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 is best suited to the phenomena we examine. It allows us to measure complex promotional effects such as repeat purchasing 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 that has recently been 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 \( Q / \overline{Q}_h \) in choice models because the magnitude of state dependence depends on whether consumers have stockpiled or not on their previous purchase equation. Second is that further research is needed to understand the behavioral mechanism that drives the \( Q / \overline{Q}_h \) 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 $Q/Q^*$ 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.

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 2004). 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 significantly less important than in yogurt. Also, ketchup may be a declining category where promotions are keeping people in the category franchise, and the “fewer stock-outs” mechanism may be important even though faster usage is not.

Fifth, our research distinguishes between the direct consumption effects of promotion induced stockpiling and the longer term effects that can occur through changes in the attractiveness of the category (i.e., inclusive value) and subsequent purchase incidence. The fact that, in most cases, the longer term consumption effects were negative in our analysis, is important and worth examining further.

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 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 various influences of accelerated loyals versus pre-emptive switchers, 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. That means that after subtracting out the brand’s post-promotion dip (presumably the accelerated loyals), the resulting net promotion bump includes pre-emptive switches and short-term consumption. It does not include increases in repeat purchases. Since this effect 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 longer term effects may be required to determine whether in fact the promotion was profitable.

Managerially, our results suggest that stockpiling has a more complicated impact than simply mortgaging future sales. Yes, accelerating loyal purchases is certainly a consequence of stockpiling. But stockpiling also produces higher category consumption, pre-empts purchases of competitive brands, and increases repeat purchases. These effects can more than make up for the negative profitability impact of accelerated loyals. For example, in the ketchup category, 30.7% of the promotion bump represented accelerated sales that need to be subtracted from the bump to produce net incremental sales. But 36.6% of the bump was due to added consumption and 13.5% of the bump was pre-emptive switching. In addition, the equivalent of 4.8% of the bump represented increased repeat purchases by stockpilers. Managers may therefore want to encourage stockpiling rather than discourage it.

Also from a managerial perspective, the repeat purchasing effects are not as large as the consumption and pre-emptive switching effects, but they can have a substantial impact. In the
long term, multiplied by several promotions over several years, stockpiling may allow the brand to build its franchise rather than erode it. Managers should factor this into their promotional strategies as well as 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.

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 elements of the stockpiling component, it may be worthwhile to examine whether those subsequent elements too are affected by the type and depth of promotion.

Finally, researchers should also examine these issues more from the perspective of the retailer. For example, the distinction between pre-emptive switches and loyal acceleration may not be as relevant to the retailer as quantifying store switches from competition (see Bucklin and Lattin 1992), which would be very valuable to the retailer. Any “pulling forward” from his/her own future sales of the category may be beneficial or harmful depending whether retail margins are higher during the promotion or off it. Our analysis also shows differences between store brands and national brands in terms of the promotion bump, its components, and stockpiling benefits, that have implications for retailers’ promotion decisions.
Overall, we hope our work will contribute to a more sophisticated view of stockpiling as a potentially beneficial phenomenon rather than solely as a detriment. We look forward to additional research to amplify and further test this viewpoint.
### TABLE 1
**DESCRIPTIVE STATISTICS OF DATA**

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<th>Ketchup</th>
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<td>Number of purchase occasions (calibration)</td>
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<td>Average interpurchase time (calibration)</td>
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<td>Number of brands</td>
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<td>% of market accounted for</td>
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### TABLE 2
**PARAMETER ESTIMATES**

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<th>Choice Model</th>
<th>Yogurt</th>
<th>Ketchup</th>
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<td>Standard Deviation</td>
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<td>(0.03)</td>
<td>0.41**</td>
<td>(0.20)</td>
</tr>
</tbody>
</table>

Note: Standard errors are in parentheses
**  p < 0.01;  *  p < 0.05
### TABLE 3
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>7.88</td>
<td>--</td>
<td>3.82</td>
<td>--</td>
</tr>
<tr>
<td>Unit Bump</td>
<td>24.97</td>
<td>100%</td>
<td>13.25</td>
<td>100%</td>
</tr>
<tr>
<td>Current Switches</td>
<td>9.26</td>
<td>37.1%</td>
<td>5.32</td>
<td>40.2%</td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>0.73</td>
<td>2.9%</td>
<td>0.43</td>
<td>3.3%</td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>1.23</td>
<td>4.9%</td>
<td>0.65</td>
<td>4.9%</td>
</tr>
<tr>
<td>Consumption</td>
<td>13.75</td>
<td>55.1%</td>
<td>6.85</td>
<td>51.7%</td>
</tr>
<tr>
<td>Repeat Purch./Stockpiler</td>
<td>0.40</td>
<td>--</td>
<td>0.43</td>
<td>--</td>
</tr>
<tr>
<td>Repeat Purch./Non-stockpiler</td>
<td>0.30</td>
<td>--</td>
<td>0.01</td>
<td>--</td>
</tr>
<tr>
<td>Repeat Effect of Stockpiling</td>
<td>0.32</td>
<td>1.3%</td>
<td>0.67</td>
<td>5.1%</td>
</tr>
<tr>
<td>Consumption</td>
<td>-1.78</td>
<td>-7.1%</td>
<td>-0.91</td>
<td>-6.8%</td>
</tr>
</tbody>
</table>

* (Repeat Purch./Stockpiler – Repeat Purch./Non-stockpiler) x No. of Stockpilers
### TABLE 4
DECOMPOSITION OF THE PROMOTION BUMP: KETCHUP

<table>
<thead>
<tr>
<th>Promotion Bump</th>
<th>Heinz</th>
<th>Del Monte</th>
<th>Hunt</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>5.03</td>
<td>--</td>
<td>0.97</td>
<td>--</td>
</tr>
<tr>
<td>Unit Bump</td>
<td>10.94</td>
<td>100%</td>
<td>4.56</td>
<td>100%</td>
</tr>
<tr>
<td>Current Switches</td>
<td>2.07</td>
<td>18.9%</td>
<td>2.50</td>
<td>54.9%</td>
</tr>
<tr>
<td>Accelerated Loyals</td>
<td>3.21</td>
<td>29.4%</td>
<td>0.42</td>
<td>9.1%</td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>1.22</td>
<td>11.1%</td>
<td>0.44</td>
<td>9.6%</td>
</tr>
<tr>
<td>Consumption</td>
<td>4.44</td>
<td>40.6%</td>
<td>1.20</td>
<td>26.3%</td>
</tr>
<tr>
<td>Post-Promotion Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repeat Purch./Stockpiler</td>
<td>0.19</td>
<td>--</td>
<td>0.31</td>
<td>--</td>
</tr>
<tr>
<td>Repeat Purch./Non-stockpiler</td>
<td>0.19</td>
<td>--</td>
<td>0.27</td>
<td>--</td>
</tr>
<tr>
<td>Repeat Effect of Stockpiling</td>
<td>0.01</td>
<td>0.1%</td>
<td>0.05</td>
<td>1.2%</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.30</td>
<td>2.7%</td>
<td>-0.21</td>
<td>-4.7%</td>
</tr>
</tbody>
</table>

* (Repeat Purch./Stockpiler – Repeat Purch//Non-stockpiler) x No. of Stockpilers
### TABLE 5
FINANCIAL IMPACT OF STOCKPILING

<table>
<thead>
<tr>
<th>Effect</th>
<th>Period</th>
<th>Set</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 Promotion Week</td>
<td>Sample</td>
<td>Units</td>
<td>31.63</td>
<td>15.76</td>
<td>29.42</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.2414</td>
<td>0.1203</td>
<td>0.2246</td>
</tr>
<tr>
<td></td>
<td>National</td>
<td>Units</td>
<td>3811802</td>
<td>1898971</td>
<td>3545669</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$ Profit</td>
<td>1067305</td>
<td>531712</td>
<td>992787</td>
</tr>
<tr>
<td>Pre-Emptive Switching Week</td>
<td>Sample</td>
<td>Units</td>
<td>2.83</td>
<td>1.50</td>
<td>2.74</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.0216</td>
<td>0.0114</td>
<td>0.0209</td>
</tr>
<tr>
<td></td>
<td>National</td>
<td>Units</td>
<td>340983</td>
<td>180194</td>
<td>329894</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$ Profit</td>
<td>95475</td>
<td>50454</td>
<td>92370</td>
</tr>
<tr>
<td>Loyal Acceleration Promotion Week</td>
<td>Sample</td>
<td>Units</td>
<td>1.68</td>
<td>0.99</td>
<td>1.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.0128</td>
<td>0.0075</td>
<td>0.0091</td>
</tr>
<tr>
<td></td>
<td>National</td>
<td>Units</td>
<td>202372</td>
<td>119205</td>
<td>144155</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$ Loss</td>
<td>(14166)</td>
<td>(8344)</td>
<td>(10091)</td>
</tr>
<tr>
<td>Repeat Purchases Post-Promotion</td>
<td>Sample</td>
<td>Units</td>
<td>0.74</td>
<td>1.54</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.0056</td>
<td>0.0118</td>
<td>0.0047</td>
</tr>
<tr>
<td></td>
<td>National</td>
<td>Units</td>
<td>88711</td>
<td>185739</td>
<td>74850</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$ Profit</td>
<td>31049</td>
<td>65009</td>
<td>26198</td>
</tr>
<tr>
<td><strong>Total Benefits</strong></td>
<td>National</td>
<td>$ Profit</td>
<td>1179663</td>
<td>638830</td>
<td>1101264</td>
</tr>
</tbody>
</table>

**Key Parameters**

- Yogurt: 131
- Ketchup: 163
- # HH’s in Sample: 90,000,000
- % That Buy ≥ 3 Times/Yr. (Sample Data): 43%
- Trade Deal Passthrough: 68%
- Regular margin: $0.35

Note: The sample unit numbers are obtained by multiplying the numbers in Tables 3 and 4 by 2.3 for yogurt and 2.1 for ketchup, to translate from the trip to the weekly level.
### TABLE 6
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>24.97</td>
<td>13.25</td>
<td>25.04</td>
<td>32.92</td>
<td></td>
</tr>
<tr>
<td>Aggregate Competitor Bump</td>
<td>2.66</td>
<td>1.69</td>
<td>2.96</td>
<td>2.88</td>
<td></td>
</tr>
<tr>
<td>Current Switches</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Accelerated Loyal</td>
<td>0.13</td>
<td>0.07</td>
<td>0.12</td>
<td>0.13</td>
<td></td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>2.49</td>
<td>1.60</td>
<td>2.83</td>
<td>2.68</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 Purch./Stockpiler</td>
<td>0.15</td>
<td>0.20</td>
<td>0.28</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>Repeat Purch./Non-stockpiler</td>
<td>0.23</td>
<td>0.22</td>
<td>0.13</td>
<td>0.30</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>0.37</td>
<td>0.22</td>
<td>0.44</td>
<td>0.33</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>10.94</td>
<td>4.56</td>
<td>4.86</td>
<td>4.86</td>
<td></td>
</tr>
<tr>
<td>Aggregate Competitor Bump</td>
<td>0.47</td>
<td>0.68</td>
<td>0.64</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>Current Switches</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Accelerated Loyal</td>
<td>0.10</td>
<td>0.17</td>
<td>0.21</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>0.08</td>
<td>0.07</td>
<td>0.03</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>0.29</td>
<td>0.44</td>
<td>0.40</td>
<td>0.30</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 Purch./Stockpiler</td>
<td>0.08</td>
<td>0.15</td>
<td>0.05</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td>Repeat Purch./Non-stockpiler</td>
<td>0.19</td>
<td>0.06</td>
<td>0.02</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.03</td>
<td></td>
</tr>
</tbody>
</table>
FIGURE 1
FRAMEWORK

Consumption
Pre-Emptive Switches
Repeat Purchases
Benefits of Stockpiling

Stockpiling
Accelerated Loyals

Promotion Bump
Current Period Brand Switching

Benefits of Stockpiling = Consumption + Repeat Purchases

Pre-Emptive Switches + Consumption = Benefits of Stockpiling

Repeat Purchases + Pre-Emptive Switches + Consumption = Benefits of Stockpiling

+ Repeat Purchases

Benefits of Stockpiling = Benefits of Stockpiling + Repeat Purchases

Figure 1: Framework showing the relationship between consumption, pre-emptive switches, repeat purchases, and benefits of stockpiling.
APPENDIX

Decomposition Algorithm

Note:
Calculate the total bump for Brands A and B during the promotion for Brand A. We analyze the brand that has a positive bump – the “focal brand”. The following assumes Brand A is the focal brand. However, the same algorithm is applied to Brand B with the roles of A and B reversed in those few cases where the bump of B is positive, even though A is promoted.

Calculation and Decomposition of Bump:
1. Calculate the bump for Brand A (call this X) as the number of units of A purchased in promotion case minus number of units of A purchased in base case.
2. Calculate current switches from B to A. Call this S and keep track of the base case purchases of B that have been accounted as current switches.
3. Calculate X-S. X-S will be allocated as accelerated loyals, pre-emptive switches, or increased consumption.
4. Go to the next purchase in the promotion case. Call this trip P. If there are any purchase occasions in the base case before trip P and/or more purchases in the base case on trip P compared to the promotion case, allocate them in order as either pre-emptive switches or accelerated loyals. Do this until either you allocate all these purchases or you’ve accounted for all X-S purchases. Call the number allocated L and compute X-S-L. Note that X-S-L ≥ 0 and keep track of the base case purchases that have been accounted as accelerated loyals or pre-emptive switches.
5. Calculate the difference between total category purchases in the promotion case and total category purchases in the base case. Call this CONS. CONS is the total change in consumption between promotion and base cases. If CONS > 0 and X-S-L = 0, go to step 6, Case 1. If CONS > 0 and X-S-L ≤ CONS, go to step 6, Case 2. If CONS > 0 and X-S-L > CONS, go to step 6, Case 3. If CONS ≤ 0, go to step 6, Case 4.
6. Case 1: X-S-L = 0, CONS > 0
   a. Set CONSA1 = 0, where CONSA1 is the portion of the promotion bump of A that represents increased consumption of the category.
   b. Set CONSREM (i.e. the remaining portion of CONS) = CONS. Create CONSA2 and CONSB2 (where CONSA2 and CONSB2 are changes in consumption of the category beyond the promotion bump of A, that can be allocated to brands A and B respectively) by allocating CONSREM to unaccounted purchases in the promotion case, as follows:
      (i) Begin by setting CONSA2 = 0 and CONSB2 = 0.
      (ii) Now, go to the first unaccounted purchase in the promotion case. Let Q be the number of units of the category purchased (or remaining unaccounted). If brand A was purchased, set CONSA2 = CONSA2 + min(Q, CONSREM). If brand B was purchased, set CONSB2 = CONSB2 + min(Q, CONSREM).
      (iii) Now, update CONSREM = CONSREM – MIN(Q, CONSREM). If CONSREM =0, proceed to step 6c. If CONSREM > 0, continue to the next unaccounted purchase in the promotion case and repeat step (ii) above.
   c. Subtract CONSA2 and CONSB2 from Brand A and Brand B unaccounted purchases respectively.

41
6. Case 2: $X-S-L \leq CONS$, $CONS > 0$
   a. Set $CONSA1 = X-S-L$, where $CONSA1$ is the portion of the promotion bump of A that represents increased consumption of the category. Now, the bump is fully accounted for.
   b. Compute $CONSREM$ (i.e. the remaining portion of $CONS$) as $CONS - CONSA1$. If $CONSREM$ is zero, proceed to step 7. If $CONSREM > 0$, create $CONSA2$ and $CONSB2$ (where $CONSA2$ and $CONSB2$ are changes in consumption of the category beyond the promotion bump of A, that can be allocated to brands A and B respectively) by allocating $CONSREM$ to unaccounted purchases in the promotion case, as follows:
      (i) Begin by setting $CONSA2 = 0$ and $CONSB2 = 0$.
      (ii) Now, go to the first unaccounted purchase in the promotion case. Let $Q$ be the number of units of the category purchased (or remaining unaccounted). If brand A was purchased, set $CONSA2 = CONSA2 + \min(Q, CONSREM)$. If brand B was purchased, set $CONSB2 = CONSB2 + \min(Q, CONSREM)$.
      (iii) Now, update $CONSREM = CONSREM - \min(Q, CONSREM)$. If $CONSREM = 0$, proceed to step 6c. If $CONSREM > 0$, continue to the next unaccounted purchase in the promotion case and repeat step (ii) above.
   c. Subtract $CONSA2$ and $CONSB2$ from Brand A and Brand B unaccounted purchases respectively in the promotion case.

6. Case 3: $X-S-L > CONS$, $CONS > 0$
   a. Set $CONSA1 = CONS$. Then $X-S-L - CONSA1 = Z > 0$.
   b. Proceed further in the base case, allocating the next $Z$ unaccounted purchases either to pre-emptive switching or accelerated loyals. Keep track of the base case purchases that have been accounted.

6. Case 4: $CONS \leq 0$. Then, additional consumption cannot explain the bump.
   a. Therefore, proceed further in the base case, allocating the $X-S-L$ unaccounted purchases to either pre-emptive switching or accelerated loyals. But, we still need to account for the negative $CONS$.
   b. Set $CONSREM = |CONS|$. If $CONSREM$ is zero, proceed to step 7. If $CONSREM > 0$, create $CONSA2$ and $CONSB2$ by allocating $CONSREM$ to unaccounted purchases in the base case, as follows:
      (i) Begin by setting $CONSA2 = 0$ and $CONSB2 = 0$.
      (ii) Now, go to the first purchase (or part thereof) in the base case that has not already been accounted for. Let $Q$ be the number of units of the category purchased (that are not already accounted). If brand A was purchased, set $CONSA2 = CONSA2 - \min(Q, CONSREM)$. If brand B was purchased, set $CONSB2 = CONSB2 - \min(Q, CONSREM)$.
      (iii) Now, update $CONSREM = CONSREM - \min(Q, CONSREM)$. If $CONSREM = 0$, proceed to step 6c. If $CONSREM > 0$, continue to the next purchase occasion in the base case and repeat step (ii) above.
   c. Subtract $CONSA2$ and $CONSB2$ from unaccounted Brand A and Brand B purchases respectively in the base case.

7. Now, the total number of category purchases left in the promotion case equals the number of category purchases left in the base case. Then the increment in purchases of brand A is the repeat purchase effect.
REFERENCES


