Acknowledgments: We thank session attendees at the 2004 INFORMS Marketing Science Conference for their helpful comments. This research was supported by the Tuck Associates Program.
The Benefits of Promotion-Induced Stockpiling

ABSTRACT

Promotion-induced consumer stockpiling is often viewed as a negative 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 consumption, pre-emptive brand switches, and additional repeat purchases. We develop a model for measuring these phenomena. The model incorporates a stockpiling term in the brand choice equation to capture the impact of previous stockpiling on future brand preference. We then estimate the model for two product categories and use a simulation-based decomposition to quantify the benefits of stockpiling. We find that the benefits of stockpiling are substantial. All three benefits are significant, but consumption appears to be the most important, followed by pre-emptive switching and then additional repeat purchases. Together these factors easily offset the negative aspect of consumer stockpiling, namely, accelerated loyal customers who merely represent sales of the brand that would have occurred anyway. We also find that the dollar magnitudes of stockpiling benefits are large enough to make an otherwise unprofitable trade deal profitable. We discuss implications of these results for further research as well as for practice.
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; Neslin, Henderson, and Quelch 1985; Gupta 1988; Bucklin and Gupta 1992; Bucklin, Gupta, and Siddarth 1998; Chintagunta and Haldar 1998; Bell, Chiang, and Padmanabhan 1999; Pauwels, Hanssens, and Siddarth 2002), and indirectly in the detection of post-promotion dips in weekly sales data (van Heerde, Leeflang, and Wittink 2000; Macé and Neslin 2004).

Perhaps because of a focus on the post-promotion dip, manufacturers often view stockpiling as a negative because it moves forward in time 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 promotion expenditures therefore should decrease.
However, a more in-depth view reveals that stockpiling is composed of three phenomena: accelerated loyals, additional consumption or category expansion, and pre-emptive switches. Accelerated loyals represent sales the brand borrows from the future. These are customers who would have bought the brand in the future anyway but decide to make the purchase now instead. Neslin, Henderson, and Quelch (1985) and Chan, Narasimhan, and Zhang (2004) 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. Essentially, only for loyals does the consumption utility for the additional product offset the additional household inventory costs incurred by stockpiling.

Whereas accelerated loyals represent the non-incremental impact of promotion-induced stockpiling, additional consumption and pre-emptive switches represent incremental brand sales. Additional consumption arises through fewer stock-outs and faster use-up. Ailawadi and Neslin (1998) explicitly measure 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 2005; Chan, Narasimhan, and Zhang 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, Leeflang, and Wittink 2005) since it involves an accelerated category purchase coupled with a brand switch, but it has rarely been
Van Heerde, Leeflang, and Wittink (2005) lump together pre-emptive switching and accelerated loyals. In a recent working paper, Chan, Narasimhan, and Zhang (2004) find evidence of pre-emptive switching. It is noteworthy that 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).

Loyal acceleration, additional consumption, and pre-emptive switching are a decomposition of stockpiling, in that they sum to the total stockpiling effect. The 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. It could emerge through the extra purchase quantity aspect of stockpiling, which means the consumer has to use 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 Minniard 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 Minniard 1995; pp. 263; 273-276). Under low involvement, stockpiling provides more time to establish inertia or induce boredom (Engel, Blackwell, and Minniard 1995; pp. 158-160). Thus, under the behaviorist viewpoint, 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, pre-emptive switching, and loyal acceleration effects. The consumption and pre-emptive 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 model and 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 the model used to measure the benefits of stockpiling, and its estimation. Second, we discuss the data used for our empirical investigation. Next we discuss the estimated model results. We then calculate the consumption, pre-emptive switching, loyal acceleration, and repeat purchasing effects of stockpiling using a Monte Carlo simulation. Finally, we discuss the implications for managers and researchers.

2. MODEL

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):

\[ P_{ht}(j \& q) = P_{ht}(inc) \times P_{ht}(j|inc) \times P_{ht}(q|inc \& j) \]  

(1)

where:

- \( P_{ht}(j \& q) \) = Probability household \( h \) buys \( q \) units of brand \( j \) on shopping trip \( t \).
- \( P_{ht}(inc) \) = Probability household \( h \) purchases the category on trip \( t \).
- \( P_{ht}(j|inc) \) = Probability household \( h \) purchases brand \( j \) on trip \( t \), given household \( h \) makes a category purchase.
- \( P_{ht}(q|inc \& j) \) = Probability household \( h \) buys \( q \) units of brand \( j \) on trip \( t \), given household \( h \) 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-household heterogeneity in several of the model parameters, assuming that the parameters are normally distributed and estimating their mean and standard deviation (Gönül and Srinivasan 1993; Erdem, Mayhew, and Sun 2001). The three equations are jointly estimated using simulated maximum likelihood (Erdem 1996; Sun, Neslin, and Srinivasan 2004; Seetharaman 2004; Train 2003).

**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:
\[ P_{ht}(j \mid inc) = \frac{e^{V_{hjt}}}{\sum_k e^{V_{hkt}}} \]  

(2)

\[ V_{hjt} = \beta_{0h} + \beta_{1h} PRICE_{hjt} + \beta_{2h} PROMO_{hjt} + \beta_{3h} LAST_{hjt} + \beta_{4h} LPROMO_{hjt} + \beta_{5h} \frac{Q_{hjt}}{\bar{Q}_h} \]  

(3)

where:

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

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

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

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

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

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

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

The new part of the model is the \( \frac{Q_{hjt}}{\bar{Q}_h} \) 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:

\[ \text{Contribution} = \beta_{3h} + \beta_{4h} LPROMO_{hjt} + \beta_{5h} \frac{Q_{hjt}}{\bar{Q}_h} \]  

(4)

We expect the state dependence term \( \beta_{3h} \) to be positive per previous literature (e.g., Seetharaman, Ainslie, and Chintagunta 1999; Seetharaman 2004; Ailawadi, Gedenk and Neslin
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 (Guadagni and Little 1983; Gedenk and Neslin 1999), to signify that promotion purchases are less reinforcing than non-promotion purchases.

Finally, a positive $\beta_{5h}$ 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, $\beta_{5h}$ represents the potential repeat purchase benefit of stockpiling. As noted earlier, it is possible that stockpiling breeds boredom or variety seeking, in which case $\beta_{5h}$ would be negative. An important contribution of this paper is to estimate $\beta_{5h}$ and assess its importance.

**Incidence Model**

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

$$P_{ht}(inc) = \frac{1}{1 + e^{W_{ht}}} \quad (5)$$

$$W_{ht} = \kappa_{0h} + \kappa_{1} \frac{INV_{ht}}{INV_{h}} + \kappa_{2} \bar{C}_{h} + \kappa_{3h} INCVAL_{ht} \quad (6)$$

$$INCVAL_{ht} = \ln\left(\sum_{k} e^{V_{hkt}}\right) \quad (7)$$

where:

- $INV_{ht}$ = Inventory of household $h$ on shopping trip $t$.
- $\bar{INV}_{h}$ = Average weekly inventory of household $h$ during initialization period.
\( \bar{C}_h \) = 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 all standard (e.g., Ailawadi and Neslin 1998; Bucklin, Gupta, and Siddarth 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 (\( \kappa_1 \) 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.\(^1\)

**Purchase Quantity**

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

\[
P_{ht}(q | inc \& j) = \frac{(\lambda_{hjt})^q}{(e^{\lambda_{hjt}} - 1)q!} \quad (q = 1, 2, \ldots, \infty) \quad (8)
\]

\[
\lambda_{hjt} = e^{\gamma_0 + \gamma_1 \frac{INV_{ht}}{INV_h} + \gamma_2 \bar{U}_h + \gamma_3 PRICE_{hjt} + \gamma_4 PROMO_{hjt}} \quad (9)
\]

where:

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

\(^1\) We had convergence problems when we did attempt to make these parameters heterogeneous.
\[ \gamma_0, \gamma_1, \gamma_2 = \text{Homogeneous parameters.} \]

\[ \gamma_{3h}, \gamma_{4h} = \text{Heterogeneous parameters.} \]

All the terms in the model are standard (e.g., Ailawadi and Neslin 1998). 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.

**Inventory and Consumption**

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

\[ INV_{hd} = INV_{h,d-1} + Q_{h,d-1} - CONS_{h,d-1} \quad (10) \]

\[ CONS_{hd} = INV_{hd} \left[ \frac{\bar{C}_h}{\bar{C}_h + (INV_{hd})^f} \right] \quad (11) \]

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.

**Estimation**

The model is estimated jointly using simulated maximum likelihood (Train 2003). The likelihood function is:
\[ L = \prod_{h} \prod_{t} \prod_{j} \left[ \frac{e^{V_{ht}^{j}}}{\sum_{k} e^{V_{ht}^{k}}} \right] Z_{hjt} \left( \frac{e^{-W_{ht}^{j}}}{1 + e^{-W_{ht}^{j}}} \right)^{1-Y_{ht}^{j}} \left( \frac{1}{1 + e^{-W_{ht}^{j}}} \right)^{Y_{ht}^{j}} \left( \frac{\lambda_{hjt}^{q}}{(e^{\lambda_{hjt}^{q}} - 1)q!} \right)^{Z_{hjt}} \right] \]  

(12)

where:

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

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

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 differ in consumption flexibility and therefore we would expect more of a consumption benefit from stockpiling in yogurt than in ketchup. 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 which account for 81.8 % of all ketchup sales. We analyze 4 brands which account for 99.2 % of the sales of the selected sizes. In the yogurt category, we analyze all 6 and 8 ounce sizes which account for 91.4 % of all yogurt sales. Six of the yogurt brands have shares of 5% or more and account for 83.7% 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 in the initialization period (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 and 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 $Q_{ht}/\overline{Q}_h$ 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, $\beta_{5h}$, are estimated. Table 2 shows that the investment in these two parameters is worth it for both categories. The likelihood ratio test indicates that the improvement in LL is significant at the 1% level, and BIC is improved in both cases.

[Table 2 Goes About Here]

We now turn our attention to the parameter estimates. Table 3 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 the 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 less than one, as they should be (Ben-Akiva and Lerman 1985; Train 2003), and significantly positive, indicating that promotion increases the likelihood of purchase incidence. 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 in determining when to purchase the category; the number of units to buy is determined by price and promotion rather than inventory.
Our main interest, however, is in the brand choice model and the state dependence estimates for LAST, L PROMO, and $Q_{hjt} / Q_h$ in particular. The mean for the LAST coefficient is positive in both categories, and the mean for the L PROMO coefficient is negative in both categories, replicating the now well-known finding that previous purchases reinforce brand loyalty, although promotion purchases are not as reinforcing as non-promotion purchases.

The estimated mean for $Q_{hjt} / Q_h$ is significantly positive for both yogurt and ketchup, yielding the important finding that for the average household, stockpiling yields higher brand loyalty in the future. Whether it be through behavioral or cognitive learning, larger quantity purchased yields higher brand preference on the next purchase occasion. The estimated standard deviation for yogurt (0.14 relative to a mean of 0.32) suggests that the stockpiling effect is positive for virtually all households. However, for ketchup, the estimated standard deviation (0.57 relative to a mean of 0.57) implies that approximately 16% of households have negative parameter values. While the vast majority is still positive, this does suggest that in this category some customers get bored with the product when they have it for a long time.

Examining average effects in more detail, the following table shows the contribution to future utility of various purchases.

<table>
<thead>
<tr>
<th>Parameter Values</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAST</td>
<td>1.15</td>
<td>0.72</td>
</tr>
<tr>
<td>L PROMO</td>
<td>-0.98</td>
<td>-0.49</td>
</tr>
<tr>
<td>$Q_{hjt} / Q_h$</td>
<td>0.32</td>
<td>0.57</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>1.47</td>
<td>1.29</td>
</tr>
<tr>
<td>Promotion Purchase of Normal Quantity</td>
<td>0.49</td>
<td>0.80</td>
</tr>
<tr>
<td>Promotion purchase of Double the Normal Quantity</td>
<td>0.81</td>
<td>1.37</td>
</tr>
</tbody>
</table>
For example, in the yogurt category, if the household makes a non-promotion purchase and buys its usual quantity, the contribution to utility is $1.15 + 0.32 \times 1 = 1.47$. If the usual quantity is bought but the purchase is a promotion purchase, the contribution is $1.15 - 0.98 + 0.32 = 0.49$. If the purchase is a promotion purchase but the household buys twice its usual quantity (stockpiling), the contribution is $1.15 - 0.98 + 0.32 \times 2 = 0.81$.

These results suggest that stockpiling makes up for the lower purchase reinforcement of a typical promotion purchase. In the yogurt category, a non-promotion purchase is more reinforcing, but in the ketchup category, a stockpiled promotion purchase is at least 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 understand the product’s attributes in more detail.

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

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 into choice, incidence, and quantity elasticities (e.g., Gupta 1988; Chiang 1991; Bucklin, Gupta, and Siddarth 1998; Bell, Chiang, and Padmanabhan 1999). However, van Heerde, Gupta, and Wittink (2003) show that the results of this elasticity decomposition have often 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 would be 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 does not seem feasible in our case.

The second is a regression-based approach using weekly store sales data (van Heerde, Leeflang, and Wittink 2005). 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 (e.g., Ailawadi and Neslin 1998; Silva-Risso, Bucklin, and Morrison 1999; van Heerde, Gupta, and Venkataraman
We use this approach since it allows us to distinguish among the various stockpiling effects and repeat purchasing, and these effects are measured 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.

Following existing researchers, 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 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 household-level parameters using the means and standard deviations in Table 3. 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 the same store (a large store that carries all the brands). The store environment file provides the values of price and promotion for each brand in each week. The only factor that differs between the base case and promotion case is the insertion of an additional promotion during the 112 week simulation. The promotion is inserted in week 23 for yogurt and week 41 for ketchup. 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.

5.2 Our Decomposition Method

Our strategy is to calculate for each household the short-term promotion bump of the promoted brand, and utilize differences in purchases between the promotion and base cases to
explain that bump. First we allocate current period brand switching, then loyal acceleration and pre-emptive switching, and then consumption to explain the bump. After this allocation, there are an equal number of category purchases left in the promotion and base cases. We proceed to subtract the remaining sales of the promoted brand in the base case from its remaining sales in the promotion case to obtain the number of additional repeat purchases.

Before providing more detail, we present stylized examples of two households to illustrate the method. For simplicity, we assume two brands, a time horizon of four weeks, and one shopping trip per week. The only difference between the base and promotion cases is that, in the latter, a promotion is added for Brand A in week 1. The first example is as follows:

<table>
<thead>
<tr>
<th>Week</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 Week 1, two units of Brand A in Week 2, and Brand B in Weeks 3 and 4. In the promotion case, the household purchases four units of Brand A during the promotion week, then doesn’t purchase the category again until Week 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 week 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 Week 2 can be interpreted as loyal acceleration – these are purchases of Brand A that would have occurred in Week 2 had there not been a promotion in Week 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 Week 3 can be allocated to the
bump as a pre-emptive brand switch – an extra purchase of Brand A due to the promotion in
Week 1 pre-empted the purchase of Brand B in Week 3. Once this pre-emptive switch is
allocated, the four unit 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 no repeat purchase effects in this example.

Now, consider a second example:

<table>
<thead>
<tr>
<th>Week</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 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 Week 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 weeks. Total category purchases in the remaining weeks 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 the above ideas in an algorithm that considers all the contingencies that can occur. For example, a household may make multiple purchases during the promotion week, the total consumption effect may be greater than the promotional bump, a promotion on Brand A may result in a bump for Brand B etc. This detailed algorithm is provided in the Appendix, but we present an overview 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 week.

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

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 week are potential loyal accelerations or pre-emptive switches. Allocate them until either the base case purchases or the bump runs out.

4. Calculate the total consumption effect by subtracting total category purchases in the base case from total category purchases in the promotion case.

5. There are now three possible cases: In Case 1, there is still an unexplained bump after Step 3 and we can fully explain it by increased consumption. If there is any increased consumption left over, that extra consumption occurred not only through the bump in the promotion week but from extra purchases in subsequent weeks as well. We thus differentiate between short-term and long-term increases in consumption. In Case 2, there is still an unexplained bump after Step 3, and this bump is not fully explained even after allocating the extra consumption. In this case, we go beyond the next category purchase identified in Step 3 to find additional accelerated loyalys or pre-emptive switches until the bump is fully accounted for. In Case 3, there is no bump left to explain after Step 3, so we proceed to Step 6.

6. Subtract any unallocated (i.e, long-term) extra consumption units from post-promotion sales of Brand A in the promotion case.

7. After Step 6, there will be an equal number of category purchases left in the promotion and base cases. Subtract the remaining Brand A purchases in the base case from the remaining Brand A purchases in the promotion case to get incremental (or possibly “decremental”) repeat purchases.
Two underlying assumptions in our algorithm deserve mention. First, we give precedence to certain phenomena over others in explaining the promotion bump. Some prioritization is necessary to resolve potential ambiguities. We allocate the bump to current period brand switching first, then loyal acceleration and pre-emptive switching, and finally consumption. This prioritization is conservative from the viewpoint of quantifying stockpiling benefits, in that we give non-stockpiling phenomena (current brand switches) first crack at explaining the bump. It also seems defensible that 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.

Second, any increase in consumption not allocated to the promotion bump is subtracted from Brand A sales in the post-promotion period in Step 6. Thus, we assume long-term additional consumption due to the promotion of Brand A is manifested in extra units of Brand A. If some of that additional consumption came from extra units of Brand B (the composite of all other brands) purchased in the post-promotion period, our estimate of the consumption effect for Brand A would be inflated and our estimate of its repeat purchase effect would be deflated.2

5.3 Results

Table 4 displays the results of the simulations for three brands of yogurt and one brand of ketchup. The promotion bump numbers in the first line tell us 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 48.48 units on a baseline of 14.41 units. This is a 236% increase in sales, typical of what promotions achieve (Narasimhan, Neslin, and Sen 1996).

---
2 It is possible that the promotion may decrease consumption. This 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 brands, the net result being a decrease in the inclusive value, which, in turn lowers purchase incidence in the future. Just as we assume that additional consumption of the category is manifested in extra units of the promoted brand, we also assume that reduced consumption of the category is manifested in fewer units of the promoted brand.
The results show that in general, consumption is the most important benefit of stockpiling, followed by pre-emptive switching and then by additional repeat purchases. In the yogurt category, consumption accounts for 45.1%, 46.3%, and 51.4% of the promotion bump for the three brands. This is similar in magnitude to the percentage of the bump accounted for by current period brand switching. Together, brand switching and consumption are the primary effects of yogurt promotions. Undoubtedly the limited shelf life of yogurt hampers the number of loyal accelerations and pre-emptive switches. In the ketchup category, however, pre-emptive switching and repeat purchasing are more important.

The table also shows the repeat rate effect across all households and separately for two groups of households – those who stockpile on promotion ($Q_{hit}/\bar{Q}_h > 1$) and those who do not ($Q_{hit}/\bar{Q}_h \leq 1$). For the three yogurt brands the stockpiling effect on repeat rates turns negative promotion impacts for non-stockpilers into positives for stockpilers. For example, Dannon lost 0.123 sales per non-stockpiler during the post-promotion period, whereas it gained 0.151 sales per stockpiler in the post-promotion period. The difference is due to promotion-induced stockpiling. It amounts to 0.274 units * 5.403 stockpilers = 1.480 units. The result alerts us that overall positive repeat purchase effects of promotion (Gedenk and Neslin 1999; Seetharaman 2004) may be due to a positive effect among stockpilers offsetting a negative effect among non-stockpilers. Stockpiling turns gradual erosion of the brand franchise into a gradual building up.3

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3 One might ask how the repeat purchase effect for non-stockpilers could be negative while the calculations in Section 3 showed that a promotion purchase is more reinforcing than no purchase. The reason is that in the base case, many people buy the brand without the promotion and hence get a large reinforcement. In the promotion case, these people buy the brand on promotion and get less reinforcement, especially if they do not stockpile. The promotion does bring in new purchasers who gain reinforcement. But it is certainly possible for lower reinforced households to outweigh the higher reinforced new purchasers and the net result is fewer repeat purchases.
Table 5 presents calculations to assess the profit contribution of benefits of stockpiling. We extrapolate these 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\textsuperscript{4}. We assume realistic numbers for profit margins and trade deal discounts. Note that the trade deal margin applies to short-term consumption and pre-emptive switching benefits, whereas regular trade margin applies to additional repeat purchases and long-term consumption. This accentuates the profit importance of long-term 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, though they are still in the $10,000’s.

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 profits. 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.

Analyzing the Competitive Brand Promotion Bump: The focus of our study is the impact of stockpiling the promoted product. However, as van Heerde et al. (2003 and 2005) make clear,

\textsuperscript{4} 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).
a promotion for Brand A can induce a bump for competing brands. For example, the Brand A promotion could encourage customers to buy the category who would not otherwise have bought, but these customers buy their preferred brand, Brand B.

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 and competitive brand bumps, the competitive bump is of course much smaller. It is very small for ketchup (about 4% of the promoted brand’s bump), but a bit larger for yogurt (between 8% and 12%). Table 6 shows that for yogurt, much of the stockpiling benefit for competitive brands is due to increased consumption, but, for ketchup, it is due to both increased consumption and loyal acceleration.

In summary, the competitive brand bump is much smaller than the promoted brand bump. In addition, most of the competitive bump can be explained by consumption and accelerated loyals, which does not affect the promoted brand. However, pre-emptive switches and additional repeat purchases for Brand B would indicate a loss of sales for the promoted brand. Hence it does make sense from a managerial perspective to monitor this possibility in practice. Our simulation provides the tool to do so.

6. DISCUSSION AND CONCLUSION

We have identified three potential benefits of promotion-induced consumer stockpiling – additional consumption, pre-emptive brand switching, and additional repeat purchases,

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5 We aggregate to create Brand B for two reasons. First, our algorithm becomes much more complex when we try to identify switching among more than two brands. That is fine for analysis of the promoted brand because all we care about is switches between that brand and all others, but not fine if we wish to examine competitive interactions among three or more brands. Second, the magnitude of competitive bumps is relatively small, accounting for example only for 4.4% of simulated households for whom promotion has an impact in ketchup and 12.5% of such households in yogurt. So splitting these competitive efforts for specific brands would result in a very small impact.
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 $Q/Q$ 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 profit. 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 easily make the difference between a profitable and unprofitable trade deal promotion.

Our work has several implications for researchers. First is to include $Q/Q_h$ in choice models because the magnitude 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 $Q/Q_h$ 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 $Q/Q_h$ effect could be enhanced through design of promotions. Third is that we have demonstrated simulation to be a useful tool for measuring complex promotional impacts such as repeat purchasing and pre-emptive switching. However, we had to make assumptions (e.g., prioritizing potential explanations for the promotion bump as discussed earlier) in order to make
the analysis tractable. 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; Sun 2004; Chan, Narasimhan and Zhang 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, 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, we had expected that accelerated loyals would be more prevalent than pre-emptive switches. While accelerated loyals were indeed more prevalent in the ketchup category, pre-emptive switches were more prevalent in the yogurt category. This suggests we need to understand better the various influences of accelerated loyals versus pre-emptive switchers.

Lastly, our results have implications for the calculation of promotion profitability. The most important benefits of stockpiling contained in the current period promotion bump. That means that after subtracting out the 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 or long-term consumption effects. Fortunately, we find these effects are smaller in magnitude than short-term consumption and pre-emptive switching, so a “bump analysis” may suffice. However, if results are close, e.g., a trade deal is
within $100,000 or so of breaking even, 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 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 in fact 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. However, they can turn a negative repeat
purchase effect into a positive one. In the long term, multiplied by several promotions over
several years, stockpiling allows 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 two major avenues for expanding our work. First is to 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. A second avenue would be to examine these issues more from the
perspective of the retailer. For example, the retailer might think of pre-emptive switches as *store*
switches from competition (see Bucklin and Lattin 1991). Also, the retailer might wish to
encourage accelerated (store) loyal purchases because the retailer makes better margins on the
promoted brand during the promotion week (as opposed to lower margins for the manufacturer).

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 build upon this viewpoint.
References


Appendix

Simulation Algorithm

Household selection:
1. Calculate the total bump for Brands A and B during the promotion week. Only analyze cases where Brand A or B has a positive bump and the other brand has no change or a negative bump. We analyze the brand that has a positive bump – the "focal brand". The following assumes Brand A is the focal brand, but the same algorithm could be applied to Brand B with the roles of A and B reversed.

Initialization:
2. Define ACUM = the cumulative unallocated bump for Brand A. Let ACUM = 0.
3. Let BCUM = the cumulative unallocated bump for Brand B. Let BCUM = 0.
4. Let T be the total number of trips in the promotion week.
5. Let t = the current trip being considered.

Promotion week loop:
7. Calculate the bump for Brand A at trip t – call this X.
   a. Case 1: X>0
      i. Calculate switches from B to A in trip t. Call this S.
      ii. Calculate X-S. These represent accelerated switches + pre-emptive switches (including purchases of Brand B in the base case that have taken place earlier in the week for t = 1) plus CONSA1.
      iii. Go to the next purchase in the promotion case after the promotion week. Call this trip P.
      iv. If there are any purchase occasions before trip P in the base case, allocate them in order as either pre-emptive switches or accelerated loyals until either you allocate all these purchases or you’ve accounted for all X-S purchases. Call the number allocated C. Note that C≤X-S
      v. Let ACUM = ACUM + X-S-C.
   b. Case 2: X≤0
      i. Let ACUM = ACUM + X.
8. Calculate the bump for Brand B at trip t – call this Y.
   a. Let BCUM = BCUM + Y - any purchases from B allocated to A as either current period switches or pre-emptive switches.
9. Let t = t+1. Repeat steps 6, 7, and 8 until we’re at the end of the promotion week.

Calculation of consumption and repeat purchases:
10. Calculate difference in consumption directly by summing total consumption in the promotion case minus total consumption in the base case. Call this CONS. CONS is the change in consumption between promotion and base cases. Assume CONS ≥ 0. If CONS ≤ 0, proceed to Step 12.
11. Case 1: ACUM ≤ CONS: In this case, let CONSA1 = ACUM, where CONSA1 is the portion of the promotion bump that represents increased consumption of the category.
   a. If BCUM > 0, let CONSA2 = CONS − CONSA1 − BCUM (or 0 if CONS − CONSA1 − BCUM < 0), where CONSA2 represents the increase in consumption captured by increased category purchases in the post-promotion weeks.
   b. IF BCUM ≤ 0: CONSA2 = CONS − CONSA1.
c. Subtract CONSA2 from Brand A purchases in the post-promotion period. The total number of category purchases left in the promotion case must equal the number of category purchases left in the base case. Then the increment in purchases of brand A is the repeat purchase effect.

12. Case 2: ACUM > CONS: In this case, let CONSA1 = CONS. Then ACUM – CONSA1 = Z > 0. Proceed further in the base case, allocating the next Z unmatched purchases to either pre-emptive switching or accelerated loyals. The total number of purchases left in the base case must equal the number of purchases left in the promotion case. Then the increment in purchases of Brand A is the repeat purchase effect for Brand A.

13. If CONS ≤ 0 and ACUM > 0, additional consumption cannot explain the promotion bump. Therefore, proceed further in the base case, allocating the next ACUM unmatched purchases to either pre-emptive switching or accelerated loyals. Then subtract |CONS| Brand A purchases from the base case. The total number of purchases left in the base case must equal the number of purchases left in the promotion case. Then the increment in purchases of Brand A is the repeat purchase effect for Brand A.
Table 1

Descriptive Statistics of Data

<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>Number of purchases (calibration)*</td>
<td>2,402</td>
<td>1,904</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>91.4%</td>
<td>81.1%</td>
</tr>
</tbody>
</table>

* There are more purchases than purchase occasions because some purchase occasions contain purchases of several brands.
Table 2

Incremental Fit Due to Addition of $Q/\overline{Q}$ Term in Equation 3

<table>
<thead>
<tr>
<th></th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base Model</td>
<td>Full Model</td>
</tr>
<tr>
<td></td>
<td>without $Q/\overline{Q}$</td>
<td>with $Q/\overline{Q}$</td>
</tr>
<tr>
<td>LL</td>
<td>-13,165.80</td>
<td>-13,145.90</td>
</tr>
<tr>
<td>BIC</td>
<td>13,335.95</td>
<td>13,326.36</td>
</tr>
<tr>
<td># Parameters</td>
<td>33</td>
<td>35</td>
</tr>
</tbody>
</table>
### Table 3
Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>Yogurt</th>
<th></th>
<th>Ketchup</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td><strong>Choice Model</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE</td>
<td>-17.07 (2.95)</td>
<td>25.42 (2.02)</td>
<td>-120.08 (0.01)</td>
<td>4.16 (0.01)</td>
</tr>
<tr>
<td>PROMO</td>
<td>1.99 (0.10)</td>
<td>0.82 (0.11)</td>
<td>2.46 (.11)</td>
<td>0.66 (0.14)</td>
</tr>
<tr>
<td>LAST</td>
<td>1.15 (0.11)</td>
<td>0.47 (0.07)</td>
<td>0.72 (0.19)</td>
<td>1.19 (0.11)</td>
</tr>
<tr>
<td>LPROMO</td>
<td>-0.98 (0.12)</td>
<td>0.31 (0.13)</td>
<td>-0.49 (0.13)</td>
<td>0.42 (0.21)</td>
</tr>
<tr>
<td>Q/\bar{Q}</td>
<td>0.32 (0.08)</td>
<td>0.14 (0.06)</td>
<td>0.57 (0.17)</td>
<td>0.57 (0.09)</td>
</tr>
<tr>
<td><strong>Incidence Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INV/INV</td>
<td>-0.03 (0.01)</td>
<td>-0.31 (0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>\bar{C}</td>
<td>0.49 (0.03)</td>
<td>0.90 (0.06)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INCVAL</td>
<td>0.42 (0.04)</td>
<td>0.36 (0.04)</td>
<td>0.44 (0.03)</td>
<td>0.19 (0.03)</td>
</tr>
<tr>
<td><strong>Quantity Model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INV/\bar{INV}</td>
<td></td>
<td>n.s.</td>
<td></td>
<td>n.s.</td>
</tr>
<tr>
<td>\bar{U}</td>
<td>0.23 (0.01)</td>
<td>2.43 (0.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE</td>
<td>-3.09 (0.92)</td>
<td>3.49 (0.24)</td>
<td>-27.78 (0.67)</td>
<td>25.15 (2.27)</td>
</tr>
<tr>
<td>PROMO</td>
<td>0.35 (0.03)</td>
<td>0.11 (0.02)</td>
<td>0.77 (0.12)</td>
<td>0.56 (0.09)</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
## Table 4

**Simulation Results**

<table>
<thead>
<tr>
<th></th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dannon</td>
<td>Weight Watchers</td>
</tr>
<tr>
<td><strong>Sales “Bump”</strong></td>
<td>48.478</td>
<td>26.711</td>
</tr>
<tr>
<td><strong>Brand Switch</strong></td>
<td>20.186</td>
<td>13.206 (49.4%)</td>
</tr>
<tr>
<td><strong>Accelerated Loyal</strong></td>
<td>1.054</td>
<td>0.288 (1.1%)</td>
</tr>
<tr>
<td><strong>Pre-emptive Switch</strong></td>
<td>2.320</td>
<td>1.168 (4.4%)</td>
</tr>
<tr>
<td><strong>Consumption</strong></td>
<td>24.918</td>
<td>12.049 (45.1%)</td>
</tr>
<tr>
<td><strong>Repeat Purchases</strong></td>
<td>0.213</td>
<td>-0.167</td>
</tr>
<tr>
<td><strong>R. Stockpilers</strong></td>
<td>0.817</td>
<td>0.021</td>
</tr>
<tr>
<td><strong>R. Non-Stockpilers</strong></td>
<td>-0.604</td>
<td>-0.188</td>
</tr>
<tr>
<td><strong># Stockpilers</strong></td>
<td>5.403</td>
<td>3.051</td>
</tr>
<tr>
<td><strong># Non-Stockpilers</strong></td>
<td>4.915</td>
<td>2.814</td>
</tr>
<tr>
<td><strong>Rep./Stockpiler</strong></td>
<td>0.151</td>
<td>0.007</td>
</tr>
<tr>
<td><strong>Rep./Non-stockpiler</strong></td>
<td>-0.123</td>
<td>-0.067</td>
</tr>
<tr>
<td><strong>Repeat effect from stockpiling</strong></td>
<td>1.480 (3.0%)</td>
<td>0.226 (0.8%)</td>
</tr>
<tr>
<td><strong>Consumption</strong></td>
<td>1.741</td>
<td>1.030</td>
</tr>
<tr>
<td><strong>Baseline Sales</strong></td>
<td>14.405</td>
<td>5.521</td>
</tr>
</tbody>
</table>

* (Rep./Stockpiler - Rep./Non-stockpiler) * # Stockpilers

**Note:** Entries are average number of units per replication, across 1,000 replications.

Percentages are numbers expressed as a percentage of the promotion week bump.
### Table 5

**Profit Impact**

<table>
<thead>
<tr>
<th>Benefit (long-term)</th>
<th>Period</th>
<th>Population</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>National</td>
<td>Profit</td>
<td>$844,618</td>
<td>$398,711</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Benefit</th>
<th>Period</th>
<th>Population</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>Promotion Week</td>
<td>Sample</td>
<td>Total</td>
<td>24.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.1902</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Total</td>
<td>3,010,128</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Profits</td>
<td>$677,279</td>
</tr>
<tr>
<td>Pre-Emptive Switching</td>
<td>Promotion Week</td>
<td>Sample</td>
<td>Total</td>
<td>2.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.0177</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Total</td>
<td>280,237</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Profits</td>
<td>$70,059</td>
</tr>
<tr>
<td>Repeat Purchases</td>
<td>Post-Promotion</td>
<td>Sample</td>
<td>Total</td>
<td>1.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per HH</td>
<td>0.0113</td>
</tr>
<tr>
<td></td>
<td></td>
<td>National</td>
<td>Total</td>
<td>178,820</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Profit</td>
<td>$44,705</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Key Parameters</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td># HH’s in Sample</td>
<td>131</td>
<td>163</td>
</tr>
<tr>
<td># HH’s in US</td>
<td>90,000,000</td>
<td>90,000,000</td>
</tr>
<tr>
<td>Penetration*</td>
<td>68%</td>
<td>73%</td>
</tr>
<tr>
<td>% Cat Buyers That Buy ≥ 3 Times/Yr.**</td>
<td>43%</td>
<td>29%</td>
</tr>
<tr>
<td>Trade Deal Passthrough</td>
<td>60%</td>
<td>60%</td>
</tr>
<tr>
<td>Unpromoted profit margin</td>
<td>$0.25</td>
<td>$1.00</td>
</tr>
<tr>
<td>Promoted profit margin</td>
<td>$0.23</td>
<td>$0.90</td>
</tr>
</tbody>
</table>

** Source: Sample Data
### Table 6

**Competitive Impact of Promotion**

<table>
<thead>
<tr>
<th>Promotion Week</th>
<th>Yogurt</th>
<th>Ketchup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dannon</td>
<td>Weight Watchers</td>
</tr>
<tr>
<td>Promoted Brand Bump</td>
<td>48.478</td>
<td>26.711</td>
</tr>
<tr>
<td>Competitive Brand Bump</td>
<td>4.023</td>
<td>3.243</td>
</tr>
<tr>
<td>Brand Switch</td>
<td>0.027 (0.7%)</td>
<td>0.012 (0.4%)</td>
</tr>
<tr>
<td>Accelerated Loyal</td>
<td>0.194 (4.8%)</td>
<td>0.119 (3.7%)</td>
</tr>
<tr>
<td>Pre-emptive Switches</td>
<td>0.019 (0.5%)</td>
<td>0.013 (0.4%)</td>
</tr>
<tr>
<td>Consumption</td>
<td>3.783 (94.0%)</td>
<td>3.099 (95.6%)</td>
</tr>
<tr>
<td>Post-Promotion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repeat Purchase (Stockpilers)</td>
<td>0.027</td>
<td>0.005</td>
</tr>
<tr>
<td>Repeat Purchase (Non-Stockpilers)</td>
<td>0.020</td>
<td>-0.015</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.694</td>
<td>0.629</td>
</tr>
</tbody>
</table>

* Entries are average number of units per replication, across 1,000 replications. Percentages are numbers expressed as a percentage of the promotion week bump of the competitive brand.
Figure 1
Framework

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

Stockpiling

Promotion Bump

Current Period Brand Switching

Accelerated Loyals