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# Discussion Paper

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**IS  $\frac{3}{4}$  OF THE SALES PROMOTION BUMP DUE TO BRAND SWITCHING? NO IT IS  $\frac{1}{3}$ .**

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# Is 3/4 of the Sales Promotion Bump Due to Brand Switching?

No, it is 1/3.

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## **Is 3/4 of the Sales Promotion Bump Due to Brand Switching? No, it is 1/3.**

### Abstract

Several researchers have decomposed sales promotion elasticities based on household scanner panel data. A key result is that the majority of the sales promotion elasticity, about 74 percent on average, is attributed to secondary demand effects (brand switching) and the remainder to primary demand effects (timing acceleration and quantity increases). We demonstrate that this result does *not* imply that if a brand gains 100 units in sales during a promotion the other brands in the category lose 74 units (74 percent). We offer a complementary decomposition measure based on unit sales. This measure shows the ratio of the current cross-brand unit sales loss to the current own-brand unit sales gain during promotion, and we report empirical results for this measure. We also derive analytical expressions that transform the elasticity decomposition into a decomposition of unit sales effects. These expressions show the nature of the difference between the two decompositions. To gain insight into the magnitude of the difference, we apply these expressions to previously reported elasticity decomposition results. We find that on average about one third of the unit sales increase is attributable to losses incurred by other brands in the same category (i.e., they lose 33 units). Thus, secondary demand effects account for a far smaller percent of the unit sales promotion effect than has been inferred from elasticity decomposition results. We find that the difference is due to the manner in which the two decomposition measures deal with the category expansion that occurs during a promotion. One interpretation is that the elasticity decomposition yields a *gross* measure of brand switching, in the sense that category sales are held constant. The unit sales decomposition yields a *net* measure of brand switching: it accommodates the category expansion effect that applies to both promoted and nonpromoted brands in the models.

## *INTRODUCTION*

A seminal contribution to modeling sales promotion effects is the study by Gupta (1988). He distinguishes three components of household response: category purchase timing, brand choice, and purchase quantity. He finds in the coffee category that the percent of the own-brand sales elasticity with respect to a particular promotion due to the brand switching elasticity is 84 percent, due to purchase acceleration elasticity is 14 percent, and due to quantity elasticity is 2 percent. He notes that such a decomposition may be used to compare the effectiveness of alternative promotional offerings and to determine the most suitable promotion for a brand.

Gupta's approach was extended in the nineties by Chiang (1991), Chintagunta (1993) and Bucklin, Gupta, and Siddarth (1998), and generalized to many categories and brands by Bell, Chiang, and Padmanabhan (1999). Across these decomposition studies we find that secondary demand effects (brand switching) on average account for the vast majority (about 74 percent) of the total elasticity, leaving 26 percent for primary demand effects (purchase acceleration and quantity increases). We summarize the elasticity decomposition results in Table 1. In this table the fraction secondary demand effects is never less than 40 percent (yogurt) and is as high as 94 percent (margarine).

[Insert Table 1 about here]

A frequently used interpretation of this decomposition of a promotional elasticity is that if a brand gains 100 units during a promotion, and 74 percent of the sales elasticity is attributable to brand switching, the other brands in the category (are estimated to) lose 74 units. Several researchers, including ourselves (see Table 2 for a partial listing of such studies), seem to interpret Gupta's (1988) elasticity decomposition in this way. An important point of our paper is that this interpretation is incorrect, since the secondary demand component of the elasticity decomposition

cannot be interpreted as the ratio of the loss in sales of competing brands to the gain in sales of the promoted brand (i.e., 74 percent of the elasticity is not equal to 74 out of 100 units).

[Insert Table 2 about here]

Neslin (2002, pp. 62-63) notes: “Another methodological issue is to link the elasticity-derived decomposition to the managerial question, What percentage of the promotion bump represents stockpiled product, switching, etc.? The answer is crucial for understanding the profitability as well as the competitive impact.” Our purpose is to clarify this issue, and to propose a measure that shows how much of the contemporaneous change in unit sales for a promoted brand can be attributed to cross-brand sales changes as opposed to primary demand effects. To be consistent with the elasticity-based household-level approach, we only consider contemporaneous effects of promotions. Pauwels, Hanssens, and Siddarth (2002) assess the long-term effects of price promotions on incidence, choice, and quantity, based on elasticities.

We demonstrate how the elasticity and unit sales decomposition measures complement each other, and together allow for a more complete assessment of sales promotion effectiveness. Our transformation equation is instructive for researchers who use household models of purchase incidence, brand choice, and quantity. It shows there is a straightforward unit sales decomposition that is easily obtained from those models. Since the literature includes many elasticity decomposition results, a variant of our transformation can also be applied to infer a unit sales effect decomposition from extant household model results. When we do this, we find that the elasticity decomposition, in which the cross-brand component is about 3/4 of the total effect, translates to a unit sales decomposition in which the cross-brand effect is about 1/3. That is, if the promoted brand gains 100 units, other brands lose 33 units. Therefore, the transformation of an elasticity into a unit sales decomposition provides a very different assessment of the nature of sales promotion effects.

We proceed as follows. We first review and clarify the elasticity decomposition based on household data. We show mathematically how the elasticity decomposition may be transformed to a unit sales effect decomposition. This transformation gives insight into the nature of the difference between the two decompositions. Next, to gain insight into the magnitude of this difference we undertake two studies. In Study 1, we use the transformation equations to infer unit sales effects from elasticity results for three categories for which we estimate household-level decomposition models. We also present an equation that approximates the ratio of secondary demand effects to the own-brand sales effect if only aggregate elasticities are available. In Study 2, we apply the latter equation to the elasticity decomposition results in Bell, Chiang, and Padmanabhan (1999). Both approaches provide convincing evidence that on average about 1/3 of the unit sales increase due to promotions is attributable to cross-brand effects. We conclude with managerial implications, conclusions, and directions for future research.

*TRANSFORMING ELASTICITY DECOMPOSITION TO UNIT SALES DECOMPOSITION*

For the decomposition of contemporaneous sales promotion effects into secondary and primary demand effects based on *elasticities*, we start with the key equation underlying this decomposition<sup>1</sup>:

$$(1) \quad S_j = P(I)P(C_j | I)Q_j$$

where:

- $S_j$  = unit sales of brand  $j$
- $\{ I \}$  = household makes a category purchase (purchase incidence)
- $\{ C_j \}$  = household chooses brand  $j$
- $P(I)$  = probability of category purchase incidence

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<sup>1</sup> This equation is specified for a “purchase occasion,” i.e., an occasion when a household has an opportunity to purchase a brand in the category. This is usually operationalized as a shopping trip. The subscript for purchase occasion is suppressed throughout for convenience.

$P(C_j | I)$  = probability of choice of brand  $j$ , given purchase incidence

$Q_j$  = quantity bought given purchase of brand  $j$ .

Define  $D_j$  as the actual price relative to the regular price for brand  $j$  on the purchase occasion. Based on equation (1), the elasticity of brand sales with respect to  $D_j$  is given by the chain rule for the product of functions:

$$(2) \quad \eta_{s_j} = \frac{\partial S_j}{\partial D_j} \frac{D_j}{S_j} = \frac{\partial P(I)}{\partial D_j} \frac{D_j}{P(I)} + \frac{\partial P(C_j | I)}{\partial D_j} \frac{D_j}{P(C_j | I)} + \frac{\partial Q_j}{\partial D_j} \frac{D_j}{Q_j}$$

or

$$(3) \quad \eta_{s_j} = \eta_{I_j} + \eta_{C_j} + \eta_{Q_j}$$

where:

$\eta_{s_j}$  = sales elasticity of brand  $j$

$\eta_{I_j}$  = elasticity of category purchase incidence with respect to  $D_j$

$\eta_{C_j}$  = elasticity of choice probability of brand  $j$ , conditional on purchase incidence

$\eta_{Q_j}$  = elasticity of purchase quantity, conditional on purchase incidence and choice of brand  $j$ .

Equation (3) shows that the sales elasticity may be additively decomposed into the elasticities of three components. Using this property, several researchers have provided percentage decompositions of the sales elasticity (see Table 1). Across all categories, the average brand-switching component is by far the largest (74 percent), followed by purchase quantity (15 percent), and purchase timing (11 percent). However, the percentages differ substantially across categories, as also suggested by Blattberg, Briesch, and Fox (1995). For example, categories for which household inventories tend to be modest, such as Margarine and Ice cream, show relatively small purchase quantity percentages. For more detail on reasons for differences across categories and brands, see Bell, Chiang, and Padmanabhan (1999).



Bell, Chiang, and Padmanabhan (1999) use the concept of “primary demand effect” for the sum of the purchase incidence elasticity and the purchase quantity elasticity. Both elasticities reflect earlier or larger purchases in the category, and result in consumers having higher inventories and/or increased consumption. The distinction between these two types of primary demand effects is only modestly meaningful for managerial purposes since both may capture stockpiling as well as consumption. Therefore we combine them into one measure so that the primary demand fraction out of the total effect is (see also Bell, Chiang, and Padmanabhan 1999):

$$(4) \quad PD_{\text{elast},j} = \frac{\eta_{I_j} + \eta_{Q_j}}{\eta_{S_j}} .$$

The secondary demand effect is the brand choice elasticity, and it reflects switching behavior. The fraction of secondary demand effects based on the elasticities is:

$$(5) \quad SD_{\text{elast},j} = \frac{\eta_{C_j}}{\eta_{S_j}} .$$

Gupta (1988) provides the following example of a feature-and-display elasticity for Folgers 16 oz. coffee:  $\eta_s = 0.248$ ;  $\eta_c = 0.210$ ;  $\eta_I = 0.034$ ; and  $\eta_Q = 0.004$ . Hence,  $PD_{\text{elast}} = (0.034+0.004)/0.248 = 0.16$  and  $SD_{\text{elast}} = 0.210/0.248 = 0.84$ .

Gupta interpreted this fraction to mean that the vast majority of the sales effect is due to brand switching: “The results indicate that more than 84% of the sales increase due to promotions comes from brand switching...” (Gupta 1988, p. 342). This interpretation dominates the marketing literature, as we show in Table 2. We now demonstrate via an example that this interpretation is correct only if *category volume is held constant when the cross-brand effect is assessed*. The measure for cross-brand effects we propose accounts for a changing category volume. This is appropriate if the objective is to determine the part of a sales increase for the promoted brand that is attributable to changes in other brands’ sales.

Suppose<sup>2</sup> Folgers 16 oz. has an initial choice probability of 18% (i.e., its market share under non-promoted conditions is 18%). Also, suppose the initial purchase incidence probability in a given week is 20%, the number of purchase occasions is 1000, and the conditional purchase quantity for each brand is 1 unit. Then category sales in that week are 200 units, sales of Folgers 16 oz. are 36 units, and sales of the other brands are 164 units. If there is a feature-and-display activity in the next week, and  $\eta_s = 0.248$  (see above), sales of Folgers 16 oz. will be  $1.248 \times 36 = 45.2$  units. Where does the increase of 9.2 units come from? The choice probability for Folgers 16 oz. increases to  $1.210 \times 18\% = 21.8\%$ , so that the other brands together have 78.2% choice probability. If we hold the category constant at 200 units, then under this promotion the nonpromoted brands together sell  $0.782 \times 200 = 156.4$  units. This represents a gross decline of 7.6 units from the original sales of 164 units, which is approximately 84% of the 9.2 unit sales increase for Folgers 16 oz., corresponding to the elasticity decomposition result.

Actually, category incidence is not constant since the incidence probability is now  $1.034 \times 0.20 = 0.207$ . This leads to  $0.207 \times 1000 = 207$  purchase incidents. Of the 7 additional purchase incidents, 78.2% should result in purchases of nonpromoted brands, according to the model, leading to an increase of  $0.782 \times 7 = 5.4$  units. Hence the net change in sales for the nonpromoted brands equals  $-7.6 + 5.4 = -2.2$  units (net total sales for the nonpromoted brands is 161.8 units). The net decline is 24.3% of the 9.2 unit sales increase for Folgers 16 oz., and this represents our measure of cross-brand effects in the unit sales effect decomposition.

The key difference between the percentage attributable to brand switching according to the elasticity decomposition (84%) and the unit sales decomposition (24%) lies in the way the two approaches treat the category expansion induced by the increase in the purchase incidence

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<sup>2</sup> We thank a reviewer for motivating this example.

probability. Although both approaches allow the category to expand during a promotion, the elasticity decomposition keeps the category constant when the brand switching fraction is calculated (Bucklin, Gupta, and Siddarth 1998, p. 196). In contrast, the unit sales decomposition accounts for the fact that the model allows the nonpromoted brands to benefit partly from this category expansion. That is, the typically lower conditional purchase probabilities for nonpromoted brands apply to a larger category incidence probability. Put differently, the unconditional choice probability for the nonpromoted brands (the product of the incidence probability and the conditional choice probability) decreases much less than the conditional choice probability does.

To formally derive the relationship between the elasticity decomposition and the net unit sales effect decomposition, we start with expressions of unit sales and define the following identity equation<sup>3</sup>:

$$(6) \quad S_j = \sum_{k=1}^J S_k - \sum_{\substack{k=1 \\ k \neq j}}^J S_k .$$

This equation says that own-brand sales of brand  $j$  equals category sales (summation across all  $J$  brands) minus cross-brand sales on the same occasion (summation across all  $J$  brands except for brand  $j$ ). We now consider infinitesimal changes in a sales promotion variable, i.e. temporary price cuts, since point elasticities are also based on such changes.<sup>4</sup> An infinitesimal temporary price reduction for brand  $j$  is denoted by  $\partial D_j$ . The own-brand sales effect due to this promotion is

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<sup>3</sup> This equation is also specified for a household purchase occasion.

<sup>4</sup> We use the framework of derivatives and point elasticities, instead of arc elasticities, because we want to stay as close as possible to the household model nomenclature. From a managerial perspective arc elasticities are more appropriate since temporary price cuts are not infinitesimal but quite large (often more than 10 percent). However, in practice we expect the differences between arc and point elasticities to be small.

$\partial S_j / \partial D_j$ . Using (6), we can write this as the effect on category sales minus the effect on cross-brand sales:

$$(7) \quad \partial S_j / \partial D_j = \partial \sum_{k=1}^J S_k / \partial D_j - \partial \sum_{\substack{k=1 \\ k \neq j}}^J S_k / \partial D_j .$$

We now divide both sides of (7) by the own-brand sales effect ( $\partial S_j / \partial D_j$ ). The left-hand side then equals 1, and the right hand side consists of two terms. The first term is the ratio of the effect of the promotion on category sales to the own-brand sales effect, or the primary demand component:

$$(8) \quad \text{PD}_{\text{sales},j} = \text{Primary Demand Effects Ratio} = \frac{\partial \sum_{k=1}^J S_k / \partial D_j}{\partial S_j / \partial D_j} .$$

The second term is the ratio of minus the cross-brand sales effect (loss) over the own-brand sales effect, or the secondary demand component:

$$(9) \quad \text{SD}_{\text{sales},j} = \text{Secondary Demand Effects Ratio} = \frac{-\partial \sum_{\substack{k=1 \\ k \neq j}}^J S_k / \partial D_j}{\partial S_j / \partial D_j} .^5$$

The primary and secondary demand effects ratios sum to one by definition.

We now show the relationship between the elasticity decomposition (equations 4 and 5) and the unit sales decomposition (equations 8 and 9). Starting with the elasticity decomposition on a purchase occasion, we obtain (see the Appendix) the following expressions for  $\text{SD}_{\text{sales},j}$  and  $\text{PD}_{\text{sales},j}$  :

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<sup>5</sup> When defined in this manner,  $\text{SD}_{\text{Sales}}$  is appropriately not restricted to lie between 0 and 1. If a promotion for brand  $j$  increases the cumulative sales of other brands,  $\text{SD}_{\text{Sales}}$  will be negative (and  $\text{PD}_{\text{Sales}}$  will be larger than 1) Also, if the promotion reduces the cumulative sales of other brands by an amount greater than the sales gain of brand  $j$ ,  $\text{SD}_{\text{Sales}}$  will be larger than 1 (and  $\text{PD}_{\text{Sales}}$  will be smaller than 0). We do not force  $\text{SD}_{\text{Sales}}$  to lie in the interval  $[0,1]$  since values out of this range are theoretically possible and managerially relevant. Of course, with model-based estimates there is always a possibility that an out of range value is due to estimation inaccuracies.

$$(10) \quad SD_{\text{sales},j} = -\sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}} \right) \left( \frac{Q_k}{Q_j} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right)$$

and

$$(11) \quad PD_{\text{sales},j} = 1 - SD_{\text{sales},j}.$$

where  $\eta_{C_{kj}}$  is the elasticity of choice probability of brand  $k$  when  $j$  is promoted, conditional on purchase incidence, and the other symbols have been defined before.

Equations (10) and (11), which are central to this paper, enable us to demonstrate the difference in both the nature and the magnitude of the elasticity and unit sales decompositions. To illustrate the nature of the difference, we formulate a simplified version of (10) (equation (A2) in the Appendix) that obtains if we assume that the non-promotional purchase quantities are equal across brands<sup>6</sup> ( $Q_j = Q_k = Q \ \forall j, k$ ):

$$(12) \quad SD_{\text{sales},j} = \frac{\eta_{C_j}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1 - P(C_j | I))}{P(C_j | I)} = SD_{\text{elast},j} - A.$$

Equation (12) shows that to obtain the secondary demand effects ratio in net unit sales, we have to subtract from the gross elasticity-based fraction an amount,  $A$ , which is the fraction of the sales elasticity attributable to the incidence elasticity times the inverse of the odds of conditionally

choosing brand  $j$ :  $A = \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1 - P(C_j | I))}{P(C_j | I)}$ . Since  $A$  is ordinarily a positive quantity, equation (12)

shows that in the unit sales decomposition, the secondary demand effect ratio is smaller than it is in the elasticity decomposition. As we demonstrated in the Folgers example, the net change in sales of nonpromoted brands consists of two parts: a *negative* part due to decreased conditional choice

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<sup>6</sup> Note that we do not make the assumption that the quantity elasticity is zero. Further, it is straightforward to show that the quantity contribution to the primary demand effect in the elasticity decomposition ( $= \eta_{Q_j} / \eta_{S_j}$ ) is exactly equal to the quantity contribution to the primary demand effect in the unit sales decomposition.

probabilities and a *positive* part due to an increase in the category purchase incidence probability. That is, even though in aggregate their conditional choice probabilities tend to decrease, the model allows other brands to also experience a gain from the increased purchase incidence probability reflected in the quantity  $A$ .

A mathematical explanation for the quantity  $A$  is that due to the promotion for brand  $j$ , there is an increase in the overall purchase incidence probability of size  $\eta_{I_j} P(I)$ . Keeping the conditional choice probability and purchase quantity constant, this leads to a sales increase of the nonpromoted brands of size  $\eta_{I_j} P(I)(1 - P(C_j | I))Q$ . When we express this sales increase relative to the sales increase of brand  $j$ , we obtain  $A$ :

$$\frac{\eta_{I_j} P(I)(1 - P(C_j | I))Q}{\eta_{S_j} P(I)P(C_j | I)Q} = \frac{\eta_{I_j} (1 - P(C_j | I))}{\eta_{S_j} P(C_j | I)} \equiv A.^7$$

We note that equation (12) does not imply that the smaller the conditional choice probability  $P(C_j | I)$ , the smaller the secondary demand effects ratio in net unit sales ( $SD_{\text{sales},j}$ ). That is because the elasticities are also functions of  $P(C_j | I)$ . Therefore, the direction of the change in  $SD_{\text{sales},j}$  is difficult to predict when  $P(C_j | I)$  decreases.<sup>8</sup>

To illustrate our approach, we again consider the example in Gupta (1988, p. 352) that 84% of the sales elasticity is due to brand switching. We do not have the individual purchase occasion data, so we use an aggregate approximation (see equation (A3) in the Appendix):

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<sup>7</sup> As noted in footnote 5, it is possible that the decreased conditional choice probabilities of non-promoted brands may be exactly offset, or even exceeded, by the increased category purchase incidence probability, resulting in  $SD_{\text{sales},j}$  being zero or negative (and  $PD_{\text{sales},j}$  is equal to or larger than 1). A reviewer pointed out that this does not mean that the promotion does not have a competitive effect, since the conditional choice probability of the nonpromoted brands decreases. However this applies to a temporarily increased category incidence probability.

<sup>8</sup> We thank a reviewer for raising this issue.

$$(14) \quad SD_{\text{sales},j}^{\text{aggr}} = \frac{\eta_{C_j}^{\text{aggr}}}{\eta_{S_j}^{\text{aggr}}} - \frac{\eta_{I_j}^{\text{aggr}}}{\eta_{S_j}^{\text{aggr}}} \frac{(1 - ms_j)}{ms_j}.$$

Assuming again 18% market share for Folgers 16 oz., we estimate the secondary demand effects ratio in unit sales to be:  $SD_{\text{sales}} = 0.847 - 0.137 * ((1-0.18)/0.18) = 22.2$  percent. This percentage is close to the 24.3 percent we obtained above in the numerical example. The difference is due to the use of an arc elasticity in the example, whereas (14) is based on point elasticities. For example, if we use a 0.001 increase (instead of an increase of 1) in the feature variable in the numerical example, we find  $SD_{\text{sales}}$  to be 22.2%. Importantly, the contribution of secondary demand effects based on *unit sales* is much smaller than the 84 percent based on *elasticities*. To provide empirical results on the magnitude of the difference between the elasticity and unit sales decompositions, we undertake Studies 1 and 2.

#### *STUDY 1: BRAND SWITCHING BASED ON HOUSEHOLD DATA*

We use the transformations to obtain unit sales decompositions from three household panel data sets: yogurt, tuna, and sugar. The yogurt data consist of 28,720 store visits by 223 households in Springfield, MO. Of these visits, 2424 resulted in purchases of one of the following four brands: Yoplait, Dannon, Weight Watchers, and Hiland. We model purchase incidence, brand choice and purchase quantity. The model is essentially the one in Bucklin, Gupta, and Siddarth (1998) -- a latent class model with nested logit specification for incidence and brand choice, and a truncated-at-1 Poisson model for quantity. We find a three-segment model fits the yogurt data best.

The tuna data consist of 17,771 store visits by 270 households in Sioux Falls, SD. Of these trips, 1740 resulted in purchases of one of the following two brands: Chicken of the Sea and Star Kist. The product is a 6.5 oz. can of water- or oil-based chunky tuna. We use the same model as for yogurt, and find that a three-segment model fits these data best as well. The sugar data consist of 17,492 store visits by 266 households in Springfield, MO. Of these visits, 1824 resulted in purchases of one of the following two brands: Private Label and C&H. These are the two largest

brands of 5 lb. bags of sugar in the market. Using the same model as for yogurt and tuna, we also find here that a three-segment model fits the data best.

We summarize the results in Table 3. For yogurt, the secondary demand ratio based on elasticities (equation 5) is on average 0.58, whereas the secondary demand ratio based on unit sales effects (equation 10) is only 0.33 (the approximate formula (14) based on aggregate quantities yields 0.29). For tuna, the average elasticity-based secondary demand ratio is 0.49, whereas in unit sales it is 0.22 (0.23 based on the aggregate approximation). For sugar, the elasticity decomposition attributes 0.65 to secondary demand, whereas in unit sales it is 0.45 whether based on individual or aggregate data. We conclude that the unit sales effect decomposition shows that the net brand switching effect is much less than what one might believe based on the elasticity decomposition. On average across these three categories, the cross-brand effect is 33% of the own-brand effect, whereas it is 57% in the elasticity decomposition. Further, the aggregate approximation formula provides results close to the average results from the purchase occasion level transformation. This suggests that it is meaningful to apply the aggregate approximation formula to published results for which we do not have individual data.

[Insert Table 3 about here]

## *STUDY 2: BRAND SWITCHING BASED ON PUBLISHED HOUSEHOLD DECOMPOSITION RESULTS*

We now reconsider the decomposition results in Bell, Chiang, and Padmanabhan (1999)<sup>9</sup>. We reproduce in Table 4 for each product category the secondary demand elasticity ratio (Bell et al.'s Table 5). Next to those values we show the secondary demand ratios of unit sales based on equation

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<sup>9</sup> We thank David Bell for providing the average elasticity results and market shares for all 173 brands. Since he was unable to provide the individual-level data, we had to use the approximate formula (14) instead of the exact formula (10).



(14). The  $SD_{sales}$  ratios represent share-weighted averages, similar to Bell, Chiang, and Padmanabhan (1999). The differences between columns 2 and 3 are dramatic. On average, the secondary demand effects ratio based on the elasticity decomposition is 0.75, whereas it is only 0.13 based on a unit sales decomposition. However, the number 0.13 is strongly affected by the negative numbers for Ice Cream and Butter. For these categories, the application of (14) generates negative values for  $SD_{sales}$  (corresponding to values for  $PD_{sales}$  that are larger than 1) As discussed in footnote 5, this is a theoretically feasible result. For example, the promotion of one brand of butter or ice cream may stimulate households to also buy nonpromoted brands. The negative result occurs if the incidence effect is so large that the loss for the nonpromoted brands due to a decrease in conditional brand choice is smaller than the gain from the category expansion that also applies to the nonpromoted brands.

[Insert Table 4 About Here]

We note that instances of positive net cross-brand effects of price promotions (negative ratios in Table 4) are consistent with Sethuraman, Srinivasan, and Kim (1999, p. 30). Based on a meta-analysis of cross-price elasticities, they find that approximately 10 percent are negative. In Table 4 the number  $-1.64$  for  $SD_{sales}$  for ice cream (corresponding to  $PD_{sales} = 2.64$ ) means that if one brand promotes and gains 100 units, the other brands together gain 164 units. There are 11 ice cream brands, so on average the 10 other brands gain 16.4 units, not an implausible result. For example, the promotion of one brand may trigger consideration of the category with positive effects for nonpromoted brands if brand preferences are strong. For butter,  $SD_{sales} = -0.26$  ( $PD_{sales} = 1.26$ ) which means that if the promoted brand gains 100 units, the other brands together gain 26 units. There are 4 brands, so on average the 3 other brands gain 8.7 units. In general, categories with flexible purchase incidence and strong brand preferences may be susceptible to such cross-brand

effects. It seems plausible that category sales of ice cream and butter are quite sensitive to promotions of individual brands (butter may substitute for margarine). Nevertheless, the aggregate formula (14) is also an imperfect approximation of the actual ratio based on (10), and any errors may contribute to this result for ice cream and butter.

If we exclude these two categories, the secondary demand ratio is 0.33, which happens to be the same as the average across the three categories in Table 3. Importantly, no matter how we compute the average in Table 4, the ratio of brand switching over unit sales is not nearly as large as it is in elasticity. For example, the *lowest* elasticity fraction is 0.49 (butter in column one), whereas the *highest* unit sales ratio is 0.51 (margarine in column two). The implication is clear: secondary demand effects based on unit sales are far smaller than one might conclude from the elasticity decomposition.

#### *MANAGERIAL IMPLICATIONS*

The elasticity and unit sales decompositions can be viewed as complementary measures of sales promotion effectiveness. Both measures are of interest to retailers and to brand managers of the promoted and nonpromoted brands. The elasticity decomposition is suitable for a separate assessment of changes in purchase incidence probabilities, brand choice probabilities, and purchase quantities while keeping the other components constant. For example, it shows how much the expected number of purchase incidents changes during a promotion for a brand. In addition, it demonstrates how much the conditional choice probabilities change for the promoted and nonpromoted brands during a promotion. Finally, it shows the gross decrease in unit sales for nonpromoted brands if we assume constant category sales. The unit sales decomposition measure complements the elasticity results by considering the net decrease in sales of the nonpromoted

brands. It accounts for the fact that part of the category expansion effect may go to the nonpromoted brands. Thus, the unit sales decomposition shows the net result.

Importantly, this same net decrease should be visible or estimable from (store-level) sales data. Indeed, Van Heerde, Leeflang, and Wittink (2002) on average find comparable secondary demand ratios (33%) for nonparametrically estimated promotion effects in a model of store data. The strikingly different conclusion about the net secondary demand ratio based on both household and store data has important implications for manufacturers and retailers. Although the estimated short-term own-brand sales increase is the same in the two measures, the major source of the increase is different. If three fourths of the promotional sales gain of a brand were due to net sales losses of other brands, retailers might conclude that promotional activities provide little benefit. That is, unless promoted items provide higher margins, the vast majority of the effect would simply be a reallocation of expenditures by households across items within a category. Manufacturers would similarly conclude that most of the effect relates to competition between brands.

Instead, we find that the vast majority of the own-brand unit sales increase consists of primary demand effects. Thus, stockpiling and/or category expansion together comprise the dominant sources of sales effects due to temporary price cuts. Manufacturers may prefer the greatest source to be primary demand. For example, if competitors tend to match each other's promotional activities especially if most of the effect is due to brand switching, secondary demand effects exacerbate the intensity of competition.

Retailers should also prefer primary- to secondary demand effects. One contributing factor is that cross-store effects represent one possible part of the primary demand effect. If a retailer wants to rank order the brands to promote in a category based on primary demand effects in unit sales, the following calculation can be used. The primary demand effect in unit sales is obtained by

multiplying the primary demand ratio by the own sales effect:  $PD_{\text{sales},j} \times \eta_{S_j} \times S_j$  (this is based on a 0-1 promotion dummy). This measure shows that given the magnitude of the promotional sales increase ( $\eta_{S_j} \times S_j$ ), a brand with higher  $PD_{\text{sales},j}$  generates higher primary demand effects.

Our results may imply that promotions are more attractive for managers than has been assumed so far. There are, however, other aspects worth considering. First, the extent to which a primary demand effect represents cannibalization of future sales via stockpiling is an important consideration in the assessment of the effectiveness of sales promotions. In some product categories a substantial component of the primary demand increase may represent enhanced consumption (Ailawadi and Neslin 1998, Sun 2001). But in other categories households are unlikely to accelerate consumption (such as for sugar and bathroom tissue), so that some primary demand effects may just represent inventory management by households. Second, we note that the long-term effects of promotions have been documented to be detrimental (Mela, Gupta, and Lehmann 1997).

#### *CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH*

We show in this paper that the choice elasticity being 74 percent of the total sales elasticity does not imply that if a promoted brand gains 100 units, the other brands together lose 74 units. Instead, we find that on average the net secondary demand effect is only about one third of the total unit sales effect, i.e., the other brands together lose about 33 units. The much higher fraction of secondary demand effects indicated by elasticity decomposition results in the literature arises because it focuses on the gross change in sales for the nonpromoted brands, holding category volume constant. In contrast, our unit sales decomposition focuses on the net change, accounting for increasing category volume, which partly benefits the nonpromoted brands. The answer to the question: “Is 3/4 of the Sales Promotion Bump Due to Brand Switching?” is, therefore that it depends. Yes, if one uses the gross effect. If one uses the net effect, it is 1/3, on average

Researchers who use household data can use the formulas (10) and (11) at the purchase occasion level to convert elasticity results into a unit sales effect decomposition. Alternatively, they can conduct market simulations based on the estimated incidence, choice and quantity effects to derive unit sales decompositions (cf. Vilcassim and Chintagunta 1995).

We note that the unit sales effect decomposition does not restrict the ratio of secondary demand effects to lie between zero and one. We find in our second study that the ratio is negative for two product categories. We do not consider this to be a limitation for two reasons. One, this result just indicates what the elasticity decomposition implies in unit sales terms: other brands may have a net gain in sales from the promotion of the focal brand. This occurs if the incidence effect is so large that the loss for the nonpromoted brands due to a change in conditional brand choice is smaller than the gain from the category expansion that goes to the nonpromoted brands. In fact, a negative secondary demand effect ratio (or, equivalently, a primary demand effect ratio that is larger than one) is diagnostic of this managerially important promotional effect, a signal that the elasticity decomposition does not provide. Two, it only occurs for two of the 16 datasets analyzed in Tables 3 and 4, specifically when we had to use the aggregate approximation formula (14) to create Table 4. To avoid biases in the unit sales decomposition, we recommend the use of exact expressions (10) and (11) at the purchase occasion level. Our use of approximation (14) is restricted to converting aggregate elasticity results reported in the literature to unit sales.

A main finding is that the primary demand effects of promotions are larger than what has been assumed so far: two-thirds in unit sales instead of one quarter in terms of elasticities. One possible direction for future research is to further decompose primary demand effects into increased consumption effects, stockpiling effects (without increased consumption), cross-category effects, and cross-store effects. These effects differ strongly in attractiveness for retailers and

manufacturers, and it is critical to know the magnitudes so as to measure net sales promotion effects for both parties. In addition, it is important, especially for manufacturers, to decompose secondary demand effects into within-brand (cannibalization) and between-brand effects.

Another research avenue is to study category- and brand differences in the ratios of primary and secondary demand effects measured in *unit sales*. It is also of interest to determine how these ratios depend on the support for the promotion (feature and/or display) and the discount magnitude (see Van Heerde et al. 2002). An additional possibility lies in a direct comparison of household purchase and store sales data. Gupta et al. (1996) compared price elasticities, based on equivalent model specifications. They found that the substantive conclusions did not differ dramatically between the two sources of data, as long as the household data were chosen based on “purchase selection”. It will be useful to see how household-model based decompositions compare with corresponding store-model based decompositions. In addition, there is an opportunity to study if and under what conditions nonpromoted brands experience sales increases when a competing brand is promoted. Finally, strategic decisions should depend on the nature of the decomposition of a sales increase due to promotion. In particular, are competitive reaction effects more sensitive to the secondary demand unit sales ratio or to the elasticity ratio?

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APPENDIX: EXPRESSIONS FOR PRIMARY AND SECONDARY DEMAND EFFECTS

We start with the definition of the secondary demand effect in unit sales on a purchase occasion:

$$SD_{\text{sales},j} = \frac{-\sum_{\substack{k=1 \\ k \neq j}}^J \partial S_k / \partial D_j}{\partial S_j / \partial D_j}$$

The numerator equals:

$$\begin{aligned} -\sum_{\substack{k=1 \\ k \neq j}}^J \partial S_k / \partial D_j &= -\sum_{\substack{k=1 \\ k \neq j}}^J \left[ \frac{\partial P(I)}{\partial D_j} P(C_k | I) Q_k + P(I) \frac{\partial P(C_k | I)}{\partial D_j} Q_k + P(I) P(C_k | I) \frac{\partial Q_k}{\partial D_j} \right] \\ &= -\sum_{\substack{k=1 \\ k \neq j}}^J \left[ \eta_{I_j} \frac{P(I)}{D_j} P(C_k | I) Q_k + P(I) \eta_{C_{kj}} \frac{P(C_k | I)}{D_j} Q_k + 0 \right] \\ &= -\sum_{\substack{k=1 \\ k \neq j}}^J \left[ (\eta_{I_j} + \eta_{C_{kj}}) P(I) P(C_k | I) Q_k \frac{1}{D_j} \right]. \end{aligned}$$

Note that we use the result that the effect of brand  $j$ 's promotion on brand  $k$ 's conditional purchase quantity is zero ( $\frac{\partial Q_k}{\partial D_j} = 0$ ), since that is the assumption used in all five major decomposition papers: Gupta (1988), Chiang (1991), Chintagunta (1993), Bucklin, Gupta, and Siddarth (1998), and Bell, Chiang, and Padmanabhan (1999). This assumption is plausible: conditional on choosing a nonpromoted brand, the expected purchase quantity is unchanged. It would be straightforward to allow for non-zero cross-brand quantity effects in the equations, however.

The denominator equals:

$$\frac{\partial S_j}{\partial D_j} = \frac{\eta_{S_j} P(C_j | I) Q_j}{D_j} = (\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}) P(I) P(C_j | I) Q_j \frac{1}{D_j}$$

Hence the ratio equals:

$$(A1) \quad SD_{\text{sales},j} = -\sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}} \right) \left( \frac{Q_k}{Q_j} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right).$$

Equation (A1) represents the exact definition, applicable to each purchase occasion separately. If we have only aggregate elasticities and market shares, we need as an intermediate step a version in which we assume that  $Q_j = Q_k = Q \forall j, k$ . Then (A1) reduces to:

$$(A2) \quad SD_{\text{sales},j} = \frac{\eta_{C_j}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1 - P(C_j | I))}{P(C_j | I)}.$$

Proof:

$$\begin{aligned} SD_{\text{sales},j} &= - \sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}} \right) \left( \frac{Q_k}{Q_j} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right) \\ &= - \sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{S_j}} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right) \\ &= - \left[ \sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{I_j}}{\eta_{S_j}} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right) + \sum_{\substack{k=1 \\ k \neq j}}^J \left( \frac{\eta_{C_{kj}}}{\eta_{S_j}} \right) \left( \frac{P(C_k | I)}{P(C_j | I)} \right) \right] \\ &= - \left[ \left( \frac{\eta_{I_j}}{\eta_{S_j}} \right) \left( \frac{1 - P(C_j | I)}{P(C_j | I)} \right) + \frac{1}{\eta_{S_j} P(C_j | I)} \sum_{\substack{k=1 \\ k \neq j}}^J \frac{\partial P(C_k | I)}{\partial D_{jt}} D_{jt} \right] \\ &= - \left[ \frac{\eta_{I_j}}{\eta_{S_j}} \left( \frac{1 - P(C_j | I)}{P(C_j | I)} \right) + \frac{1}{\eta_{S_j} P(C_j | I)} \frac{\partial (1 - P(C_j | I))}{\partial D_{jt}} D_{jt} \right] \\ &= - \left[ \frac{\eta_{I_j}}{\eta_{S_j}} \left( \frac{1 - P(C_j | I)}{P(C_j | I)} \right) + \frac{1}{\eta_{S_j} P(C_j | I)} (-\eta_{C_j}) P(C_j | I) \right] = \frac{\eta_{C_j}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \left( \frac{1 - P(C_j | I)}{P(C_j | I)} \right). \end{aligned}$$

Both equations (A1) and (A2) are at the purchase occasion level. If we apply (A2) to aggregate-level quantities we obtain an approximate SD sales ratio:

$$(A3) \quad SD_{\text{sales},j}^{\text{aggr}} = \frac{\eta_{C_j}^{\text{aggr}}}{\eta_{S_j}^{\text{aggr}}} - \frac{\eta_{I_j}^{\text{aggr}}}{\eta_{S_j}^{\text{aggr}}} \frac{(1 - ms_j)}{ms_j}.$$

This measure (A3) differs from the exact equation (A1) as follows:

- it assumes non-promotional quantities are equal across brands;
- it approximates conditional choice probabilities by average market shares;
- it first aggregates the elasticities and market shares, and then applies a non-linear formula, instead of applying the nonlinear formula first at the purchase occasion level and then aggregating.

Table 1  
ELASTICITY DECOMPOSITION RESULTS

<i>Study</i> <sup>1</sup>	<i>Category</i> <sup>2</sup>	<i>Brand Switching</i>	<i>Timing Acceleration</i>	<i>Quantity Acceleration</i>
		“Secondary Demand Effect”	“Primary Demand Effect”	
Gupta (1988)	Coffee	0.84	0.14	0.02
Chiang (1991)	Coffee (feature)	0.81	0.13	0.06
	Coffee (display)	0.85	0.05	0.10
Chintagunta (1993)	Yogurt	0.40	0.15	0.45
Bucklin, Gupta, and Siddarth (1998)	Yogurt	0.58	0.19	0.22
Bell, Chiang, and Padmanabhan (1999)	Margarine	0.94	0.06	0.00
	Soft drinks	0.86	0.06	0.09
	Sugar	0.84	0.13	0.03
	Paper towels	0.83	0.06	0.11
	Bathroom tissue	0.81	0.04	0.15
	Dryer Softeners	0.79	0.01	0.20
	Yogurt	0.78	0.12	0.09
	Ice Cream	0.77	0.19	0.04
	Potato Chips	0.72	0.05	0.24
	Bacon	0.72	0.20	0.08
	Liquid Detergents	0.70	0.01	0.30
	Coffee	0.53	0.03	0.45
	Butter	0.49	0.42	0.09
<b>Average</b>		<b>0.74</b>	<b>0.11</b>	<b>0.15</b>

<sup>1</sup> All studies are based on household data.

<sup>2</sup> Different studies may find different decomposition percentages for the same category due to model differences, data differences, and so forth.

Table 2  
INTERPRETATION OF ELASTICITY DECOMPOSITION RESULTS

	Author(s)	Relevant Text extracted from Article
1	Gupta (1988)	The results indicate that more than 84% of the sales increase due to promotions comes from brand switching.
2	Blattberg and Neslin (1990)	The general consensus appears to be that brand switching is a major source of volume (due to sales promotions). ....Gupta (1988) found that switching accounted for 84% of the increase in coffee brand sales generated by promotion. Putting together the facts that sales promotions generate dramatic immediate sales increases and that brand switching accounts for a large percentage of this increase, we can conclude that sales promotions are strongly associated with brand switching.
3	Wheat and Morrison (1990)	Gupta (1998) finds that brand switching accounts for most of the sales increase due to promotion, while stockpiling accounts for only 2%.
4	Bucklin and Srinivasan (1991)	Our approach does not currently incorporate quantity effects of price promotions such as purchase acceleration and stockpiling. (These effects in the coffee category are estimated by Gupta 1988 to be about 16% of the variation in brand volume.)
5	Chiang (1991)	These results are similar to the ones obtained by Gupta (1998, p. 352), where 84% of the increase is attributed to brand switching, 14% by purchase time acceleration and 2% by increases in quantity.
6	Karande and Kumar (1995)	Gupta (1988) showed that 84 percent of the sales increase due to promotion comes from brand switching. Therefore it is important to study the effect of retailer policies on promotional cross-price elasticities.
7	Gupta, Chintagunta, Kaul, and Wittink (1996)	The importance of brand choice is underscored by Gupta's (1988) finding that brand switching accounts for 84% of the overall sales increase due to promotions in the coffee category.
8	Leeflang and Wittink (1996)	Gupta (1988) concluded that the consumer effects of promotion consist almost entirely of brand switching (as opposed to product category expansion or stockpiling).
9	Midgley, Marks, and Cooper (1997)	Indeed, Gupta (1988), in studying consumer panel data from the same time, concluded that increased sales from coffee promotions came more from brand switching than from forward buying or stockpiling.
10	Guadagni and Little (1998)	In an important paper, Gupta (1988) breaks the purchase process down into three separate subprocesses: brand choice, quantity selected, and interpurchase timing. ... Gupta's paper also provides a useful analysis of the incremental sales induced by purchase acceleration and stockpiling.
11	Ainslie and Rossi (1998)	At least for the case of price, it has been documented in the literature that the lion's share of response is in the choice as opposed to quantity or incidence decisions (Gupta 1998).
12	Malhotra, Peterson, and Kleiser (1999)	These results serve to clarify earlier findings that more than 84 percent of the sales increase due to promotion comes from brand switching, while purchase acceleration in time accounts for less than 14 percent, whereas stockpiling due to promotion accounted for less than 2 percent of the sales increase (Gupta 1988).
13	Dekimpe, Hanssens, and Silva-Risso (1999)	Gupta (1988) found that the majority of the promotional volume was due to brand switching.
14	Bell, Chiang, and Padmanabhan (1999)	Gupta (1988) captures these effects in a single model and decomposes a brand's total price elasticity into these components. He reports, for the coffee product category, that the main impact of a price promotion is on brand choice (84%), and that there is a smaller impact on purchase incidence (14%) and stockpiling (2%). In other words, the majority of the effect of a promotion is at the secondary level (84%) and there is a relatively small primary demand effect (16%).
15	Sethuraman, Srinivasan, and Kim (1999)	Bell et al. (1997) report that most of the price elasticity (86%) is due to brand choice. So, we expect the category expansion effects to be small relative to brand switching effects.
16	Van Heerde, Leeflang, and Wittink (2000)	These numbers are consistent with the results from household-level studies, which have found the acceleration effect to vary between 6 and 51%.
17	Ailawadi (2001)	This is exemplified by Gupta's (1988) finding that 84% of the immediate sales promotion bump is due to brand choice.
18	Ailawadi, Neslin, and Gedenk (2001)	In general, the positive associations between brand loyalty and deal use and between storage availability and deal use suggest that a significant role of out-of-store promotions is to induce loyal users to stock up on the brand. This finding is somewhat at odds with the notion that the predominant effect of promotions is on brand switching (e.g., Gupta 1988).
19	Dhar, Hoch, and Kumar (2001)	Other work has shown that despite high brand price elasticities category sales may not change much if promotions and other marketing mix actions primarily lead to brand switching (Gupta 1998) and/or store switching (Kumar & Leone, 1988).
20	Sethuraman and Srinivasan (2002)	Gupta (1988) and Bell, Chiang, and Padmanabhan (1999) have shown that price promotions have a relatively small effect on category expansion compared with brand switching. Therefore, we isolate and study the profitability due to brand switching only.

Table 3  
DECOMPOSITION RESULTS FOR HOUSEHOLD DATA

<i>Yogurt</i>					
Brand	Yoplait	Dannon	Weight Watchers	Hiland	Average
Average purchase incidence elasticity	0.40	0.56	0.14	0.28	0.34
Average conditional choice elasticity	1.99	1.79	2.66	2.25	2.17
Average conditional quantity elasticity	1.35	1.31	1.30	0.91	1.22
Total elasticity	3.74	3.65	4.10	3.44	3.73
$SD_{\text{elast}}$ (equation 5)	0.53	0.49	0.65	0.65	0.58
Average $SD_{\text{sales}}$ (equation 10)	0.33	0.31	0.40	0.28	0.33
Aggregate $SD_{\text{sales}}$ (equation 14)	0.30	0.27	0.32	0.27	0.29
Market share	0.31	0.41	0.10	0.18	
<i>Canned Tuna</i>					
Brand	Chicken of the Sea	Starkist			Average
Average purchase incidence elasticity	0.96	0.89			0.92
Average conditional choice elasticity	1.64	1.90			1.77
Average conditional quantity elasticity	0.92	0.95			0.94
Total elasticity	3.52	3.74			3.63
$SD_{\text{elast}}$ (equation 5)	0.47	0.51			0.49
Average $SD_{\text{sales}}$ (equation 10)	0.22	0.23			0.22
Aggregate $SD_{\text{sales}}$ (equation 14)	0.25	0.22			0.23
Market share	0.55	0.45			
<i>Sugar</i>					
Brand	Control	C&H			Average
Average purchase incidence elasticity	0.40	1.19			0.80
Average conditional choice elasticity	3.82	1.13			2.48
Average conditional quantity elasticity	0.23	0.21			0.22
Total elasticity	4.45	2.53			3.49
$SD_{\text{elast}}$ (equation 5)	0.86	0.45			0.65
Average $SD_{\text{sales}}$ (equation 10)	0.59	0.31			0.45
Aggregate $SD_{\text{sales}}$ (equation 14)	0.62	0.27			0.45
Market share	0.27	0.73			

Table 4  
COMPARISON OF SECONDARY DEMAND EFFECTS:  
ELASTICITY VERSUS UNIT SALES

Category	$SD_{\text{elast}}^1$	$SD_{\text{sales}}^2$
Margarine	0.94	0.51
Soft drinks	0.86	0.36
Sugar	0.84	0.34
Paper Towels	0.83	0.42
Bathroom Tissue	0.81	0.43
Dryer Softeners	0.79	0.36
Yogurt	0.78	0.12
Ice Cream	0.77	-1.64
Potato Chips	0.72	0.35
Bacon	0.72	0.14
Liquid Detergents	0.70	0.31
Coffee	0.53	0.23
Butter	0.49	-0.26
Overall Average	0.75	0.13
Average without Ice Cream and Butter	0.77	0.33

<sup>1</sup> Secondary demand effects based on elasticity decomposition (Bell, Chiang, and Padmanabhan 1999, Table 5)

<sup>2</sup> Secondary demand effects based on approximate unit sales effect decomposition (Equation 14)