* RESEARCH NOTES AND COMMUNICATIONS

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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, approximately 74% on average, is attributed to secondary demand effects (brand switching) and the remainder is attributed to primary demand effects (timing acceleration and quantity increases). The authors 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. The authors offer a complementary decomposition measure based on unit sales. The measure shows the ratio of the current cross-brand unit sales loss to the current own-brand unit sales gain during promotion; the authors report empirical results for this measure. They 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, the authors apply these expressions to previously reported elasticity decomposition results and find that approximately 33% of the unit sales increase is attributable to losses incurred by other brands in the same category.

Is 75% of the Sales Promotion Bump Due to Brand Switching? No, Only 33% Is

A seminal contribution to modeling sales promotion effects is Gupta's (1988) study in which he distinguishes three components of household response: category purchase timing, brand choice, and purchase quantity. In the coffee category, Gupta finds that the percentage of own-brand sales elasticity with respect to a particular promotion that is due to brand-switching elasticity is 84%, that is due to purchase acceleration elasticity is 14%, and that is due to quantity elasticity is 2%. Gupta 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.

Chiang (1991), Chintagunta (1993), and Bucklin, Gupta, and Siddarth (1998) extend Gupta's (1988) approach, which Bell, Chiang, and Padmanabhan (1999) then generalize to many categories and brands. Across these decomposition studies, we find that, on average, secondary demand effects (brand switching) account for the vast majority (approximately 74%) of total elasticity, which leaves 26% for primary demand effects (purchase acceleration and quantity increases). We summarize the elasticity decomposition results in Table 1, in which the percentage of secondary demand effects is never less than 40% (yogurt) and is as high as 94% (margarine).

A frequently used interpretation of this decomposition of a promotional elasticity is that if a brand gains 100 units during a promotion, and 74% of the sales elasticity is attributable to brand switching, other brands in the category (are estimated to) lose 74 units. Several researchers seem to interpret

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Table 1
ELASTICITY DECOMPOSITION RESULTS

		Secondary Demand Effect	*Primary Demand Effect*	
Study	*Category*	*Brand Switching*	*Timing Acceleration*	*Quantity Acceleration*
Gupta (1988)	Coffee	.84	.14	.02
Chiang (1991)	Coffee (feature)	.81	.13	.06
	Coffee (display)	.85	.05	.10
Chintagunta (1993)	Yogurt	.40	.15	.45
Bucklin, Gupta, and Siddarth (1998)	Yogurt	.58	.19	.22
Bell, Chiang, and Padmanabhan (1999)	Margarine	.94	.06	.00
	Soft drinks	.86	.06	.09
	Sugar	.84	.13	.03
	Paper towels	.83	.06	.11
	Bathroom tissue	.81	.04	.15
	Dryer softeners	.79	.01	.20
	Yogurt	.78	.12	.09
	Ice cream	.77	.19	.04
	Potato chips	.72	.05	.24
	Bacon	.72	.20	.08
	Liquid detergents	.70	.01	.30
	Coffee	.53	.03	.45
	Butter	.49	.42	.09
Average		.74	.11	.15

Notes: All studies are based on household data. Different studies may find different decomposition percentages for the same category as a result of model differences, data differences, and so forth.

Gupta's (1988) elasticity decomposition in this way (for a partial listing of such studies, see Table 2). A significant point of our article is that this interpretation is incorrect because 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% of the elasticity is not equal to 74 of 100 units).

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 rather than primary demand effects. To be consistent with the elasticity-based household-level approach, we consider only contemporaneous effects of promotions. On the basis of elasticities, Pauwels, Hanssens, and Siddarth (2002) assess the long-term effects of price promotions on incidence, choice, and quantity.

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 that there is a straightforward unit sales decomposition that is easily obtained from those models. Because 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 approximately 75% of the total effect, translates to a unit sales decomposition in which the cross-brand effect is approximately 33%. 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 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 mathematically show how the elasticity decomposition can be transformed to a unit sales effect decomposition. This transformation gives insight into the nature of the difference between the two decompositions. Second, 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's (1999) study. Both approaches provide convincing evidence that, on average, approximately 33% of the unit sales increase from promotions is attributable to cross-brand effects. We present managerial implications and provide conclusions and directions for further research.

Table 2

INTERPRETATION OF ELASTICITY DECOMPOSITION RESULTS

Authors	*Relevant Text Extracted from Article*
Gupta (1988, p. 342)	The results indicate that more than 84% of the sales increase due to promotions comes from brand switching.
Blattberg and Neslin (1990, pp. 82–83)	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.
Wheat and Morrison (1990, p. 167)	Gupta (1998) finds that brand switching accounts for most of the sales increase due to promotion, while stockpiling accounts for only 2%.
Bucklin and Srinivasan (1991, p. 70)	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.)
Chiang (1991, p. 309)	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.
Karande and Kumar (1995, p. 260)	Gupta (1988) showed that 84% 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.
Gupta et al. (1996, p. 384)	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.
Leeflang and Wittink (1996, p. 103)	Gupta (1988) concluded that the consumer effects of promotion consist almost entirely of brand switching (as opposed to product category expansion or stockpiling).
Midgley, Marks, and Cooper (1997, p. 266)	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.
Guadagni and Little (1998, p. 324)	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.
Ainslie and Rossi (1998, p. 93)	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).
Malhotra, Peterson, and Kleiser (1999, p. 167)	These results serve to clarify earlier findings that more than 84% of the sales increase due to promotion comes from brand switching, while purchase acceleration in time accounts for less than 14%, whereas stockpiling due to promotion accounted for less than 2% of the sales increase (Gupta 1988).
Dekimpe, Hanssens, and Silva-Risso (1999, p. 273)	Gupta (1988) found that the majority of the promotional volume was due to brand switching.
Bell, Chiang, and Padmanabhan (1999, p. 504)	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%).
Sethuraman, Srinivasan, and Kim (1999, p. 31)	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.
van Heerde, Leeflang, and Wittink (2000, p. 393)	These numbers are consistent with the results from household-level studies, which have found the acceleration effect to vary between 6 and 51%.
Ailawadi (2001, p. 305)	This is exemplified by Gupta's (1988) finding that 84% of the immediate sales promotion bump is due to brand choice.
Ailawadi, Neslin, and Gedenk (2001, p. 85)	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).
Dhar, Hoch, and Kumar (2001, p. 166)	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 and Leone 1988).
Sethuraman and Srinivasan (2002, p. 380)	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.

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 begin with the key equation that underlies this decomposition:[1]

$$S_j = P(I)P(C_j|I)Q_j, \tag{1}$$

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,
- $P(C_j|I)$ = probability of choice of brand j given the purchase incidence, and
- Q_j = quantity bought given purchase of brand j.

We 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:

$$\eta_{S_j} = \frac{\partial S_j}{\partial D_j}\frac{D_j}{S_j} = \frac{\partial P(I)}{\partial D_j}\frac{D_j}{P(I)} + \frac{\partial P(C_j|I)}{\partial D_j}\frac{D_j}{P(C_j|I)} + \frac{\partial Q_j}{\partial D_j}\frac{D_j}{Q_j}, \text{ or} \tag{2}$$

$$\eta_{S_j} = \eta_{I_j} + \eta_{C_j} + \eta_{Q_j}, \tag{3}$$

where

- η_{S_j} = sales elasticity of brand j,
- η_{I_j} = elasticity of category purchase incidence with respect to D_j,
- η_{C_j} = elasticity of choice probability of brand j conditional on purchase incidence, and
- η_{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 greatest (74%), followed by purchase quantity (15%) and purchase timing (11%). However, the percentages differ substantially across categories, as Blattberg, Briesch, and Fox (1995) also suggest. 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) define primary demand effect as the sum of the purchase incidence elasticity and the purchase quantity elasticity. Both elasticities reflect previous or larger purchases in the category and result in consumers having higher inventories and/or increased consumption. The distinction between the two types of primary demand effects is only modestly meaningful for managerial purposes, because both may capture stockpiling and consumption. Therefore, we combine them into one measure so that the primary demand percentage of the total effect is as follows (see also Bell, Chiang, and Padmanabhan 1999):

$$PD_{elast,j} = \frac{\eta_{I_j} + \eta_{Q_j}}{\eta_{S_j}}. \tag{4}$$

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

$$SD_{elast,j} = \frac{\eta_{C_j}}{\eta_{S_j}}. \tag{5}$$

Gupta (1988) provides the following example of a feature-and-display elasticity for Folgers 16 oz. coffee: $\eta_S = .248$, $\eta_C = .210$, $\eta_I = .034$, and $\eta_Q = .004$. Thus, $PD_{elast} = (.034 + .004)/.248 = .16$, and $SD_{elast} = .210/.248 = .84$.

Gupta (1988, p. 342) interpreted this percentage 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." This interpretation dominates the marketing literature, as we show in Table 2. We now demonstrate that this interpretation is correct only if category volume is held constant when the cross-brand effect is assessed. The measure for the 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 that Folgers 16 oz. coffee has an initial choice probability of 18% (i.e., its market share in nonpromoted conditions is 18%).[2] Suppose also that 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 other brands are 164 units. If there is a feature-and-display activity in the next week, and $\eta_S = .248$, sales of Folgers 16 oz. will be $1.248 \times 36 = 45.2$ units. From where does the increase of 9.2 units come? 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 $.782 \times 200 = 156.4$ 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.

Category incidence is not constant, because the incidence probability is now $1.034 \times .20 = .207$. This leads to $.207 \times 1000 = 207$ purchase incidents. According to the model, of the 7 additional purchase incidents, 78.2% should result in purchases of nonpromoted brands, leading to an increase of $.782 \times 7 = 5.4$ units. Thus, the net change in sales for the nonpromoted brands equals $-7.6 + 5.4 = -2.2$ units (net total

[1]This equation is specified for a purchase occasion, that is, an occasion when a household has an opportunity to purchase a brand in the category. This is usually operationalized as a shopping trip. We suppressed the subscript for purchase occasion throughout for convenience.

[2]We thank a reviewer for motivating this example.

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., which 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 probability. Although both approaches enable the category to expand during a promotion, the elasticity decomposition keeps the category constant when the brand-switching percentage is calculated (Bucklin, Gupta, and Siddarth 1998, p. 196). In contrast, the unit sales decomposition accounts for the model's enabling 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. In other words, 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 derive the relationship between the elasticity decomposition and the net unit sales effect decomposition formally, we begin with expressions of unit sales and define the following identity equation:[3]

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

where own-brand sales of brand j equal 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) because point elasticities are also based on such changes.[4] An infinitesimal temporary price reduction for brand j is denoted by ∂D_j. The own-brand sales effect due to this promotion is $\partial S_j/\partial D_j$. Using Equation 6, we can write this as the effect on category sales minus the effect on cross-brand sales:

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

We now divide both sides of Equation 7 by the own-brand sales effect ($\partial S_j/\partial D_j$). The left-hand side 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:

$$(8) \quad PD_{sales,j} = \text{primary demand effects ratio} = \frac{\partial \sum_{k=1}^{J} S_k/\partial D_j}{\partial S_j/\partial D_j}.$$

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:[5]

$$(9) \quad SD_{sales,j} = \text{secondary demand effects ratio} = \frac{-\partial \sum_{\substack{k=1 \\ k \neq j}}^{J} S_k/\partial D_j}{\partial S_j/\partial D_j}.$$

The primary and secondary demand effects ratios sum to 1 by definition.

We now show the relationship between the elasticity decomposition (Equations 4 and 5) and the unit sales decomposition (Equations 8 and 9). Beginning with the elasticity decomposition on a purchase occasion, we obtain the following expressions for $SD_{sales,j}$ and $PD_{sales,j}$ (see the Appendix):

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

$$(11) \qquad PD_{sales,j} = 1 - SD_{sales,j},$$

where $\eta_{C_{kj}}$ is the elasticity of choice probability of brand k when j is promoted, conditional on purchase incidence.

Equations 10 and 11, which are central to this article, 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 Equation 10 (see Equation A5, in the Appendix) that obtains if we assume that the nonpromotional purchase quantities are equal across brands ($Q_j = Q_k = Q \forall j,k$):[6]

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

Equation 12 shows that to obtain the secondary demand effects ratio in net unit sales, we must subtract from the gross elasticity-based fraction the amount A, which is the fraction of the sales elasticity attributable to the incidence elasticity multiplied by the inverse of the odds of conditionally choosing brand j: $A = (\eta_{I_j}/\eta_{S_j})\{[1 - P(C_j|I)]/P(C_j|I)\}$. Because 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

[3]This equation is also specified for a household purchase occasion.

[4]We use the framework of derivatives and point elasticities rather than 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, because temporary price cuts are not infinitesimal but are quite large (often more than 10%). However, in practice, we expect the differences between arc and point elasticities to be small.

[5]When defined in this manner, SD_{sales} is appropriately not restricted to lie between 0 and 1. If a promotion for brand j increases the cumulative sales of other brands, SD_{sales} will be negative (and PD_{sales} will be greater than 1). If the promotion reduces the cumulative sales of other brands by an amount greater than the sales gain of brand j, SD_{sales} will be greater than 1 (and PD_{sales} will be less than 0). We do not force SD_{sales} to lie in the interval [0,1] because values out of this range are theoretically possible and managerially relevant. With model-based estimates, there is always a possibility that an out-of-range value is due to estimation inaccuracies.

[6]Note that we do not make the assumption that the quantity elasticity is zero. Furthermore, 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.

two parts: a negative part that is due to decreased conditional choice probabilities and a positive part that is 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 experience a gain from the increased purchase incidence probability reflected in the quantity A.

A mathematical explanation for the quantity A is that because of the promotion for brand j, there is an increase in the overall purchase incidence probability of size $\eta_{I_j}P(I)$. When we keep 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:[7]

$$\text{(13)} \qquad A \equiv \frac{\eta_{I_j}P(I)\left[1 - P(C_j|I)\right]Q}{\eta_{S_j}P(I)P(C_j|I)Q} = \frac{\eta_{I_j}\left[1 - P(C_j|I)\right]}{\eta_{S_j}P(C_j|I)}.$$

Note that Equation 12 does not imply that the smaller the conditional choice probability $P(C_j|I)$, the smaller is the secondary demand effects ratio in net unit sales ($SD_{sales,j}$), because the elasticities are also functions of $P(C_j|I)$. Therefore, the direction of the change in $SD_{sales,j}$ is difficult to predict when $P(C_j|I)$ decreases.[8]

To illustrate our approach, we again consider Gupta's (1988, p. 352) example 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 A7, in the Appendix):

$$\text{(14)} \qquad SD^{aggr}_{sales,j} = \frac{\eta^{aggr}_{C_j}}{\eta^{aggr}_{S_j}} - \frac{\eta^{aggr}_{I_j}}{\eta^{aggr}_{S_j}}\frac{(1 - ms_j)}{ms_j}.$$

Assuming again that Folgers 16 oz. has 18% market share, we estimate the secondary demand effects ratio in unit sales to be $SD_{sales} = .847 - .137 \times [(1 - .18)/.18] = 22.2\%$. This percentage is close to the 24.3% we obtained previously in the numerical example. The difference is due to the use of an arc elasticity in the example, whereas Equation 14 is based on point elasticities. For example, if we use a .001 increase (rather than an increase of 1) in the feature variable in the numerical example, we find SD_{sales} to be 22.2%. The contribution of secondary demand effects based on unit sales is much smaller than the 84% 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 the 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's (1998) study: a latent-class model with nested logit specification for incidence and brand choice and a truncated-at-1 Poisson model for quantity. We find that a three-segment model fits the yogurt data best. The tuna data consist of 17,771 store visits by 270 households in Sioux Falls, S.Dak. Of the visits, 1740 resulted in purchases of one of the following two brands: Chicken of the Sea and StarKist. The product is a 6.5 oz. can of water- or oil-packed chunky tuna. We use the same model for tuna as we do for yogurt, and we find that a three-segment model fits the tuna data best as well. The sugar data consist of 17,492 store visits by 266 households in Springfield, Mo. Of the 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 that a three-segment model fits the sugar data best.

We summarize the results in Table 3. For yogurt, the secondary demand ratio based on elasticities (Equation 5) is, on average, .58, whereas the secondary demand ratio based on unit sales effects (Equation 10) is only .33 (the approximate formula [Equation 14] based on aggregate quantities yields .29). For tuna, the average elasticity-based secondary demand ratio is .49, whereas in unit sales it is .22 (.23 based on the aggregate approximation). For sugar, the elasticity decomposition attributes .65 to secondary demand, whereas in unit sales it is .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 we might have expected on the basis of the elasticity decomposition. On average, across these three categories, the cross-brand effect is 33% of the own-brand effect, but it is 57% in the elasticity decomposition. Furthermore, 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.

STUDY 2: BRAND SWITCHING BASED ON PUBLISHED HOUSEHOLD DECOMPOSITION RESULTS

We now reconsider the decomposition results in Bell, Chiang, and Padmanabhan (1999).[9] In Table 4 (Bell, Chiang, and Padmanabhan's Table 5), we reproduce the secondary demand elasticity ratio for each product category. We also show the secondary demand ratios of unit sales based on Equation 14. The SD_{sales} ratios represent share-weighted averages, as in the work of Bell, Chiang, and Padmanabhan. The differences between Columns 2 and 3 are dramatic. On average, the secondary demand effects ratio

[7]As we pointed out in Note 5, it is possible that the decreased conditional choice probabilities of nonpromoted brands are exactly offset, or even exceeded, by the increased category purchase incidence probability, resulting in $SD_{sales,j}$ being 0 or negative (and $PD_{sales,j}$ being equal to or greater than 1). A reviewer pointed out that this does not mean that the promotion does not have a competitive effect, because the conditional choice probability of the nonpromoted brands decreases. However, this applies to a temporarily increased category incidence probability.

[8]We thank a reviewer for raising this issue.

[9]We thank David Bell for providing the average elasticity results and market shares for all 173 brands. Because he was unable to provide individual-level data, we used the approximate Equation 14 rather than the exact Equation 10.

Table 3
DECOMPOSITION RESULTS FOR HOUSEHOLD DATA

	Yogurt				
Brand	*Yoplait*	*Dannon*	*Weight Watchers*	*Hiland*	*Average*
Average purchase incidence elasticity	.40	.56	.14	.28	.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	.91	1.22
Total elasticity	3.74	3.65	4.10	3.44	3.73
SD_{elast} (Equation 5)	.53	.49	.65	.65	.58
Average SD_{sales} (Equation 10)	.33	.31	.40	.28	.33
Aggregate SD_{sales} (Equation 14)	.30	.27	.32	.27	.29
Market share	.31	.41	.10	.18	

	Canned Tuna		
Brand	*Chicken of the Sea*	*StarKist*	*Average*
Average purchase incidence elasticity	.96	.89	.92
Average conditional choice elasticity	1.64	1.90	1.77
Average conditional quantity elasticity	.92	.95	.94
Total elasticity	3.52	3.74	3.63
SD_{elast} (Equation 5)	.47	.51	.49
Average SD_{sales} (Equation 10)	.22	.23	.22
Aggregate SD_{sales} (Equation 14)	.25	.22	.23
Market share	.55	.45	

	Sugar		
Brand	*Private Label*	*C&H*	*Average*
Average purchase incidence elasticity	.40	1.19	.80
Average conditional choice elasticity	3.82	1.13	2.48
Average conditional quantity elasticity	.23	.21	.22
Total elasticity	4.45	2.53	3.49
SD_{elast} (Equation 5)	.86	.45	.65
Average SD_{sales} (Equation 10)	.59	.31	.45
Aggregate SD_{sales} (Equation 14)	.62	.27	.45
Market share	.27	.73	

based on the elasticity decomposition is .75, whereas it is only .13 based on a unit sales decomposition. However, the .13 is strongly affected by the negative numbers for ice cream and butter. For these categories, the application of Equation 14 generates negative values for SD_{sales} (corresponding to values for PD_{sales} that are greater than 1). This is a theoretically feasible result (see Note 5). For example, the promotion of a brand of butter or ice cream may stimulate households to buy nonpromoted brands as well. The negative result occurs if the incidence effect is so great 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.

Note that cases of positive net cross-brand effects of price promotions (negative ratios in Table 4) are consistent with Sethuraman, Srinivasan, and Kim's (1999, p. 30) findings. On the basis of a meta-analysis of cross-price elasticities, they find that approximately 10% are negative. In Table 4, the –1.64 for SD_{sales} for ice cream (corresponding to PD_{sales} = 2.64) means that if a brand promotes and gains 100 units, the other brands together gain 164 units. There are 11 ice cream brands; thus, on average, the 10 other brands gain 16.4 units, which is not an implausible result. For example, the promotion of a brand may trigger consideration of the category with positive effects for nonpromoted brands if brand preferences are strong. For butter, SD_{sales} = –.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; thus, 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 Equation 14 is also an imperfect approximation of the actual ratio based on Equation 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 .33, which happens to be the same as the average across the three categories in Table 3. No matter how the

Table 4

COMPARISON OF SECONDARY DEMAND EFFECTS: ELASTICITY VERSUS UNIT SALES

Category	SD_{elast}[a]	SD_{sales}[b]
Margarine	.94	.51
Soft drinks	.86	.36
Sugar	.84	.34
Paper towels	.83	.42
Bathroom tissue	.81	.43
Dryer softeners	.79	.36
Yogurt	.78	.12
Ice cream	.77	–1.64
Potato chips	.72	.35
Bacon	.72	.14
Liquid detergents	.70	.31
Coffee	.53	.23
Butter	.49	–.26
Overall average	.75	.13
Average without ice cream and butter	.77	.33

[a]Secondary demand effects based on elasticity decomposition (Bell, Chiang, and Padmanabhan 1999, Table 5).

[b]Secondary demand effects based on approximate unit sales effect decomposition (Equation 14).

average is computed in Table 4, the ratio of brand switching over unit sales is not nearly as great as it is for elasticity. For example, the lowest elasticity percentage is .49 (butter, Column 1), and the highest unit sales ratio is .51 (margarine, Column 2). The implication is clear: Secondary demand effects based on unit sales are far smaller than might be concluded 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 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 the other components are kept 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 constant category sales are assumed. The unit sales decomposition measure complements the elasticity results by considering the net decrease in sales of the nonpromoted brands. It accounts for the possibility that part of the category expansion effect goes to nonpromoted brands. Thus, the unit sales decomposition shows the net result.

Notably, this same net decrease should be visible or estimable from (store-level) sales data. Indeed, van Heerde, Leeflang, and Wittink (2002) 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 75% of the promotional sales gain of a brand are 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 reallocation of households' expenditures across items in a category. Manufacturers would similarly conclude that most of the effect is related to competition between brands.

In contrast, 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 constitute 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 one another'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 demand effects to secondary ones. A contributing factor is that cross-store effects represent a 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 $PD_{sales,j} \times \eta_{S_j} \times S_j$ (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 $PD_{sales,j}$ generates greater primary demand effects.

Our results suggest that promotions are more attractive for managers than has been assumed thus far. However, there are other aspects worth consideration. First, the extent to which a primary demand effect represents cannibalization of future sales as a result of 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). However, in other categories, households are unlikely to accelerate consumption (e.g., for sugar or bathroom tissue); thus, some primary demand effects may represent households' inventory management. Second, note that the long-term effects of promotions have been documented as detrimental (Mela, Gupta, and Lehmann 1997).

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

In this article, we show that a choice elasticity of 74% 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 approximately 33% of the total unit sales effect; that is, the other brands together lose approximately 33 units. The much higher percentage 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, when category volume is held 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 75% of the sales promotion bump due to brand switching? is, It depends. Yes, if the gross effect is used; or 33% if the net effect is used.

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

Note that the unit sales effect decomposition does not restrict the ratio of secondary demand effects to lie between 0 and 1. In our second study, we find that the ratio is negative for two product categories. We do not consider this a limitation for two reasons. First, this result 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 great 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. A negative secondary demand effect ratio (or, equivalently, a primary demand effect ratio that is greater than 1) is diagnostic of this managerially important promotional effect, a signal that the elasticity decomposition does not provide. Second, it only occurs for 2 of the 16 data sets analyzed in Tables 3 and 4, specifically when we had to use the aggregate approximation Equation 14 to create Table 4. To avoid biases in the unit sales decomposition, we recommend the use of the exact expressions, Equations 10 and 11, at the purchase-occasion level. Our use of Equation 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 greater than what has been assumed so far: 66% in unit sales rather than 25% in terms of elasticities. A possible direction for further research is to 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 would also be worthwhile to determine how these ratios depend on the support for the promotion (feature and/or display) and the discount magnitude (see van Heerde, Leeflang, and Wittink 2002). An additional possibility is a direct comparison of household purchase and store sales data. Gupta and colleagues (1996) compare price elasticities based on equivalent model specifications. They find that the substantive conclusions did not differ dramatically between the two sources of data as long as the household data were chosen on the basis of "purchase selection." It would be useful to know how household-model-based decompositions compare with corresponding store-model-based decompositions. In addition, there is an opportunity to study whether 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?

APPENDIX: EXPRESSIONS FOR PRIMARY AND SECONDARY DEMAND EFFECTS

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

$$\text{(A1)} \qquad SD_{sales,j} = \frac{-\sum_{k=1, k\neq i}^{J} \partial S_k/\partial D_j}{\partial S_j/\partial D_j}.$$

The numerator equals

$$\text{(A2)} \quad -\sum_{k=1, k\neq j}^{J} \partial S_k/\partial D_j = -\sum_{k=1, k\neq j}^{J}\left[\frac{\partial P(I)}{\partial D_j} P(C_k|I)Q_k + P(I)\frac{\partial P(C_k|I)}{\partial D_j}Q_k + P(I)P(C_k|I)\frac{\partial Q_k}{\partial D_j}\right],$$

$$= -\sum_{k=1, k\neq j}^{J}\left[\eta_{I_j}\frac{P(I)}{D_j}P(C_k|I)Q_k + P(I)\eta_{C_{kj}}\frac{P(C_k|I)}{D_j}Q_k + 0\right], \text{ and}$$

$$= -\sum_{k=1, k\neq j}^{J}\left[(\eta_{I_j} + \eta_{C_{kj}})P(I)P(C_k|I)Q_k\frac{1}{D_j}\right].$$

Note that we use the result that the effect of brand j's promotion on brand k's conditional purchase quantity is zero ($\partial Q_k/\partial D_j = 0$), because that is the assumption used in all five major decomposition articles (Bell, Chiang, and Padmanabhan 1999; Bucklin, Gupta, and Siddarth 1998; Chiang 1991; Chintagunta 1993; Gupta 1988). This assumption is plausible: Conditional on a nonpromoted brand being chosen, the expected purchase quantity is unchanged. However, it would be straightforward to allow for nonzero cross-brand quantity effects in the equations.

The denominator equals

$$\text{(A3)} \qquad \frac{\partial S_j}{\partial D_j} = \frac{\eta_{S_j}P(C_j|I)Q_j}{D_j}$$

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

Thus, the ratio equals

$$\text{(A4)} \quad SD_{sales,j} = -\sum_{k=1, k\neq j}^{J}\left(\frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}}\right)\left(\frac{Q_k}{Q_j}\right)\left[\frac{P(C_k|I)}{P(C_j|I)}\right].$$

Equation A4 represents the exact definition, applicable to each purchase occasion separately. If only aggregate elasticities and market shares are available, a version in which it is assumed that $Q_j = Q_k = Q \forall j,k$ is needed as an intermediate step. Then, Equation A4 reduces to

$$\text{(A5)} \qquad SD_{sales,j} = \frac{\eta_{C_j}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \frac{[1 - P(C_j|I)]}{P(C_j|I)}.$$

Proof:

$$\text{(A6)} \qquad SD_{sales,j} = -\sum_{\substack{k=1 \\ k \neq j}}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{I_j} + \eta_{C_j} + \eta_{Q_j}}\right)\left(\frac{Q_k}{Q_j}\right)\left[\frac{P(C_k|I)}{P(C_j|I)}\right],$$

$$= -\sum_{\substack{k=1 \\ k \neq j}}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}}}{\eta_{S_j}}\right)\left[\frac{P(C_k|I)}{P(C_j|I)}\right],$$

$$= -\left\{\sum_{\substack{k=1 \\ k \neq j}}^{J} \left(\frac{\eta_{I_j}}{\eta_{S_j}}\right)\left[\frac{P(C_k|I)}{P(C_j|I)}\right] + \sum_{\substack{k=1 \\ k \neq j}}^{J} \left(\frac{\eta_{C_{kj}}}{\eta_{S_j}}\right)\left[\frac{P(C_k|I)}{P(C_j|I)}\right]\right\},$$

$$= -\left\{\left(\frac{\eta_{I_j}}{\eta_{S_j}}\right)\left[\frac{1 - P(C_j|I)}{P(C_j|I)}\right] + \frac{1}{\eta_{S_j} P(C_j|I)} \sum_{\substack{k=1 \\ k \neq j}}^{J} \frac{\partial P(C_k|I)}{\partial D_{jt}} D_{jt}\right\},$$

$$= -\left\{\frac{\eta_{I_j}}{\eta_{S_j}}\left[\frac{1 - P(C_j|I)}{P(C_j|I)}\right] + \frac{1}{\eta_{S_j} P(C_j|I)} \frac{\partial[1 - P(C_j|I)]}{\partial D_{jt}} D_{jt}\right\}, \text{ and}$$

$$= -\left\{\frac{\eta_{I_j}}{\eta_{S_j}}\left[\frac{1 - P(C_j|I)}{P(C_j|I)}\right] + \frac{1}{\eta_{S_j} P(C_j \mid I)} (-\eta_{C_j}) P(C_j|I)\right\}$$

$$= \frac{\eta_{C_j|I}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}}\left[\frac{1 - P(C_j|I)}{P(C_j|I)}\right].$$

Equations A4 and A5 both are at the purchase-occasion level. If Equation A5 is applied to aggregate-level quantities, an approximate SD sales ratio is obtained:

$$\text{(A7)} \qquad SD^{aggr}_{sales,j} = \frac{\eta^{aggr}_{C_j}}{\eta^{aggr}_{S_j}} - \frac{\eta^{aggr}_{I_j}}{\eta^{aggr}_{S_j}} \frac{(1 - ms_j)}{ms_j}.$$

Equation A7 differs from the exact Equation A4 because it (1) assumes that nonpromotional quantities are equal across brands; (2) approximates conditional choice probabilities by average market shares; and (3) aggregates the elasticities and market shares and then applies a nonlinear formula, instead of applying the nonlinear formula at the purchase-occasion level and then aggregating.

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