M A R K E T I N G   S C I E N C E   I N S T I T U T E

The Brand Switching Fraction of Promotion Effects: Unit Sales versus Elasticity Decompositions

Harald J. van Heerde, Sachin Gupta, and Dick R. Wittink

WORKING PAPER • REPORT NO. 02-116 • 2002

W O R K I N G   P A P E R   S E R I E S

The Brand Switching Fraction of Promotion Effects: Unit Sales versus Elasticity Decompositions

Harald J. van Heerde, Sachin Gupta, and Dick R. Wittink

W O R K I N G P A P E R • R E P O R T N O. 0 2 - 1 1 6 • 2 0 0 2

The authors thank the editor, three anonymous reviewers, Don Lehmann, and Tammo Bijmolt for useful comments, and David Bell and ACNielsen (USA and The Netherlands) for data.

The Brand Switching Fraction of Promotion Effects: Unit Sales versus Elasticity Decompositions

Harald J. van Heerde, Sachin Gupta, and Dick R. Wittink

A number of studies have examined the effects of sales promotions via decomposition of sales elasticities. In general, they find that the majority of the sales promotion elasticity, about 74 percent on average, can be attributed to secondary demand effects (brand switching) and the remainder to primary demand effects (timing acceleration and quantity increases). This result has commonly been interpreted to imply that if a brand gains 100 units in sales during a promotion, the other brands in the category are estimated to lose 74 units.

In this study, authors van Heerde, Gupta, and Wittink argue that such an interpretation is incorrect, and that the other brands lose far less than commonly assumed. They show that the transformation of an *elasticity* decomposition to a *unit sales* decomposition provides a very different assessment of sales promotion effects: on average, brand switching is only about one-third of the total unit sales effect.

The elasticity approach does not account for the fact that part of the increased purchase incidence probability favors the non-promoted brands, the authors note. Their model, in contrast, considers the *net* sales decrease of the other brands, which they argue is the bottom-line quantity for managers since it shows the total result after all calculations. Further, this same net decrease should be estimable from (store-level) sales data.

Their findings have important implications for manufacturers and retailers. If three-fourths of sales promotions' effect were due to other brands' losses, retailers might conclude that promotional activities provide little benefit and manufacturers that promotional activities primarily enhance competition between brands. If, however, the vast majority of the effect consists of stockpiling and/or category expansion, as this study suggests, manufacturers and retailers alike may find promotional activities to be beneficial.

Harald J. van Heerde is Assistant Professor at the Department of Marketing, Faculty of Economics, Tilburg University. Sachin Gupta is Associate Professor of Marketing at the Johnson Graduate School of Management, Cornell University. Dick R. Wittink is the General George Rogers Clark Professor of Management and Marketing at the Yale School of Management, and Professor of Marketing and Marketing Research, Faculty of Economics, University of Groningen, The Netherlands.

Contents

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 own-brand sales elasticity with respect to a specific promotion can be decomposed into brand switching (84 percent), purchase acceleration (14 percent), and quantity (2 percent) elasticities. He notes that such a decomposition may be used to compare the effectiveness of alternative promotional offerings and to determine the most suitable and effective promotion.

Gupta's approach was extended in the 1990s by Chiang (1991), Chintagunta (1993), and Bucklin, Gupta, and Siddarth (1998). Most recently, the result was 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, whereas primary demand effects (purchase acceleration and quantity increases) are relatively modest (about 26 percent). We summarize the elasticity decomposition results in Table 1. In this table the fraction of secondary demand effects is never less than 40 percent (yogurt) and is as high as 94 percent (margarine).

A common 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. An important point of our paper is that the elasticity decomposition does not allow the results to be interpreted in terms of unit sales: other brands lose far less than 74 units. To assess how widespread the misinterpretation is in the marketing literature, we conducted a review via the *Web of Science* (Institute for Scientific Information 2002) and found 145 references to Gupta (1988). Of these, we were able to access 135 articles. Twenty-three of these made direct reference to the decomposition of promotional response. In Table 2 we list these articles along with the relevant text extracted from the papers. We find that 16 of the 23 articles (70 percent) incorrectly interpret Gupta's decomposition, i.e., the interpretation explicitly refers to incremental *sales volume* resulting from a promotion. Four studies do not literally interpret the decomposition in this way, although they nearly do so (studies 7, 9, 13, and 19). Only Bucklin, Gupta, and Siddarth (1998) and Kim and Staelin (1999) emphasize that the correct interpretation is in terms of elasticities, although they do not mention that a unit sales effect decomposition might be different. Neslin (2002) raises the important question of whether the elasticity decomposition is interpretable in terms of percentages with respect to a promotional sales bump.

Table 1. Elasticity Decomposition Results

Study[1]	Category[2]	"Secondary Demand Effect"	"Primary Demand Effect"	
		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

[1]All studies are based on household data.

[2]Different studies may find different decomposition percentages for the same category due to model differences, data differences, and so forth.

In this paper we demonstrate that the decomposition of the promotional elasticity *does not* imply an equivalent decomposition of unit sales increases. Instead we find that the elasticity decomposition reported in the literature translates to a unit sales decomposition in which the cross-brand component is much smaller than 74 percent. We clarify the interpretation of an elasticity decomposition and we show how it can be transformed into a decomposition of unit sales effects. The latter is instructive for researchers who use models of purchase incidence, brand choice, and quantity, because there is no straightforward unit sales decomposition directly available from those models. Since the literature includes many elasticity decomposition results, and since an elasticity decomposition is the common approach for household models, our transformation can be applied to derive substantively useful results from models of household data. We show that the transformation of elasticity decomposition to unit sales decomposition provides a very different assessment of the attractiveness of a sales promotion activity. It also changes the ordering of product categories in Bell, Chiang, and Padmanabhan (1999) in terms of relative desirability for sales promotion based on the fraction of secondary demand effects.

Table 2. Interpretation of Elasticity Decomposition Result in Gupta (1988)

	Article Title	Journal	Year	Author(s)	Relevant Text Extracted from Article	Interpreted as Contribution to Unit Sales Effect?
1.	"Impact of Sales Promotion on When, What, and How Much to Buy"	*Journal of Marketing Research*	1988	Gupta	"The results indicate that more than 84% of the sales increase due to promotions comes from brand switching."	Yes
2.	"Sales Promotion: The Long and the Short of It"	*Marketing Letters*	1990	Blattberg and Neslin	"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."	Yes
3.	"Assessing Purchase Timing Models—Whether or Not Is Preferable to When"	*Marketing Science*	1990	Wheat and Morrison	"Gupta (1998) finds that brand switching accounts for most of the sales increase due to promotion, while stockpiling accounts for only 2%."	Yes
4.	"Determining Interbrand Substitutability Through Survey Measurement of Consumer Preference Structures"	*Journal of Marketing Research*	1991	Bucklin and Srinivasan	"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.)"	Yes
5.	"A Simultaneous Approach to the Whether, What, and How Much to Buy Questions"	*Marketing Science*	1991	Chiang	"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."	Yes
6.	"Sales Response of Elderly Consumers to Point-of-Purchase Advertising"	*Journal of Advertising Research*	1992	Greco and Swayne	"In a study of the impact of price and display promotions on coffee, Gupta (1988) underscored the importance of brand-switching behavior by providing empirical evidence from scanner panel data that indicated more than 84 percent of the sales impact due to promotion comes from brand-switching as opposed to purchase time acceleration or stockpiling."	Yes
7.	"Asymmetric Response to Price in Consumer Brand Choice and Purchase Quantity Decisions"	*Journal of Consumer Research*	1992	Krishnamurthi, Mazumdar, and Raj	"Gupta (1988) finds that a significant proportion of brand switching in coffee purchase is promotion induced."	Nearly
8.	"A Model for Optimizing the Refund Value in Rebate Promotions"	*Journal of Business Research*	1994	Ali, Jolson, and Darmon	"An empirical analysis of IRI scanner panel data suggests that brand switching rather than purchase acceleration accounts for most of the incremental sales due to promotion (Gupta 1988)."	Yes

Table 2. continued

9. "Contextual and Temporal Components of Reference Price"	*Journal of Marketing*	1994	Rajendran and Tellis	"For scanner data on coffee, Gupta (1988) found that price discounts had only a small effect on consumers' timing and quantity of purchases but a strong effect on brand choices; therefore, price differences could lead consumers to switch brands more than change how much or when they buy."	Nearly
10. "The Effect of Brand Characteristics and Retailer Policies on Response to Retail Price Promotions: Implications for Retailers"	*Journal of Retailing*	1995	Karande and Kumar	"Also, 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."	Yes
11. "Do Household Scanner Data Provide Repres-entative Inferences from Brand Choices: A Comparison with Store Data"	*Journal of Marketing Research*	1996	Gupta, Chintagunta, Kaul, and Wittink	"The importance of brand choice is underscored by Gupta's (1988) finding that brand switching accounts for 84% of the overall sales increases due to promotions in the coffee category."	Yes
12. "Breeding Competitive Strategies"	*Management Science*	1997	Midgley, Marks, and Cooper	"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."	Yes
13. "When and What to Buy: A Nested Logit Model of Coffee Purchase"	*Journal of Forecasting*	1998	Guadagni and Little	"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."	Nearly
14. "Similarities in Choice Behavior across Product Categories"	*Marketing Science*	1998	Ainslie and Rossi	"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)."	Yes
15. "Determining Segmentation in Sales Response across Consumer Purchase Behaviors"	*Journal of Marketing Research*	1998	Bucklin, Gupta, and Siddarth	"The overall price elasticity can be decomposed into the sum of choice, incidence, and quantity elasticities for that segment (e.g., Gupta 1988, Appendix B)."	No
16. "Marketing Research: A State-of-the-Art Review and Directions for the Twenty-First Century"	*Journal of the Academy of Marketing Science*	1999	Malhotra, Peterson, and Kleiser	"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 accounts for less than 2% of the sales increase (Gupta 1988)."	Yes
17. "Manufacturer Allowances and Retailer Pass-Through Rates in a Competitive Environment"	*Marketing Science*	1999	Kim and Staelin	"Gupta (1998) estimates that 85% of a brand's promotional elasticity is due to brand switching while the rest is due to changes in the quantity normally purchased or in the frequency of purchase, i.e., purchase incidence."	No

Table 2. continued

18. "Long-run Effects of Price Promotions in Scanner Markets"	*Journal of Econometrics*	1999	Dekimpe, Hanssens, and Silva-Risso	"Gupta (1988) found that the majority of the promotional volume was due to brand switching."	Yes
19. "The Decomposition of Promotional Response: An Empirical Generalization"	*Marketing Science*	1999	Bell, Chiang, and Padmanabhan	"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%)."	Nearly
20. "The Retailer Power-Performance Conundrum: What Have We Learned?"	*Journal of Retailing*	2001	Ailawadi	"This is exemplified by Gupta's (1988) finding that 84% of the immediate sales promotion bump is due to brand choice."	Yes
21. "Pursuing The Value-Conscious Consumer: Store Brands Versus National Brand Promotions"	*Journal of Marketing*	2001	Ailawadi, Neslin, and Gedenk	"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)."	Yes
22. "Effective Category Management Depends on the Role of the Category"	*Journal of Retailing*	2001	Dhar, Hoch, and Kumar	"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)."	Yes
23. *Sales Promotion*	Marketing Science Institute monograph	2002	Neslin	"While, strictly speaking, the above findings pertain to choice, incidence, and quantity, it is logical to interpret these as switching, acceleration or consumption, and quantity stockpiling respectively. The findings would then suggest that the primary effect of promotions is brand switching rather than stockpiling or consumption" (p. 30). "However, recent methodological and empirical evidence suggests that this conclusion might be overstated" (p. 62). 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 of promotions as well as the competitive impact" (p. 62-63).	No

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. We use the resulting transformation equations to infer unit sales effects from elasticity results for three categories for which we estimate household-level decomposition models (Study 1). We also present an equation that approximates the fraction of secondary demand effects if only *aggregate* elasticities are available. We apply the latter equation to the elasticity decomposition results in Bell, Chiang, and Padmanabhan (1999) (Study 2). Both studies provide convincing evidence that far less than 74 percent of the unit sales increase due to promotions comes from cross-brand sales. In the final section, we present managerial implications, conclusions, and directions for future research.

Transforming Elasticity Decomposition to Unit Sales Decomposition

For the decomposition of sales promotion effects into secondary and primary demand effects based on *elasticities*, we start with the key equation underlying this decomposition:[1]

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

where:

S_j	=	expected 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
$P(C_j \mid I)$	=	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:

$$\eta_{S_j} = \frac{\partial S_j}{\partial D_j}\frac{D_j}{S_j} = \frac{\partial P(I)}{\partial D_j}\frac{D_j}{P(I)} + \frac{\partial P(C_j \mid I)}{\partial D_j}\frac{D_j}{P(C_j \mid I)} + \frac{\partial Q_j}{\partial D_j}\frac{D_j}{Q_j} \tag{2}$$

or

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

where:

η_{S_j}	=	sales elasticity of brand j
η_{I_j}	=	elasticity of category purchase incidence with respect to D_j

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

$\eta_{Q_j|I,C_j}$ = 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 the 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 and consumption. Therefore we also combine them into one measure so that the primary demand fraction out of the total effect is (see also Bell, Chiang, and Padmanabhan 1999):

$$\mathrm{PD}_{\mathrm{elast,j}} = \frac{\eta_{I_j} + \eta_{Q_j|I,C_j}}{\eta_{S_j}} \tag{4}$$

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:

$$\mathrm{SD}_{\mathrm{elast,j}} = \frac{\eta_{C_j|I}}{\eta_{S_j}} \tag{5}$$

Gupta (1988) provides the following example of a feature-and-display elasticity for Folgers 16-ounce coffee: η_S = .248; $\eta_{C|I}$ = .210; η_I = .034; and $\eta_{Q|C,I}$ = .004. Hence, $\mathrm{PD}_{\mathrm{elast}}$ = (.034 + .004/.248 = .16 and $\mathrm{SD}_{\mathrm{elast}}$ = .210/.248 = .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 . . ." (1988, p. 342). This interpretation dominates the marketing literature, as we show in Table 2. We now demonstrate the correct interpretation.[2] Suppose Folgers 16-ounce has an initial choice probability of 18 percent (i.e., its overall market share is 18 percent). And suppose the initial purchase incidence probability in a given week is 20 percent while the number of purchase occasions is 1,000. Then category sales in that week are 200 units, sales of Folgers 16-ounce are 36 units, and sales of the other brands are 164 units. If there is a feature and display, and η_S = .248, sales of Folgers 16-ounce change to 1.248 * 36 = 45.2 units. Where does this increase of 9.2 units come from? The incidence probability goes up to 1.034 * 20% = 20.7%. The choice probability for Folgers 16-ounce increases to 1.210 * 18% = 21.8%, so that the other brands together have 78.2 percent choice probability. Sales of the other brands equal .207 * .782 * 1,000 = 161.8 units, representing a 2.2 unit decline. This decline represents only 24.3 percent of the 9.2 unit sales increase for Folgers 16-ounce.

The key difference between the percentage attributable to brand switching according to the elasticity decomposition (84 percent) and the unit sales decomposition (24 percent) lies in the way the approaches treat the category expansion induced by the increase in the purchase incidence probability. The elasticity decomposition holds the category constant to assess the brand switching fraction (Bucklin, Gupta, and Siddarth 1998, p. 196). If we hold the category constant at 200 units, then under this promotion the other brands together sell .782 * 200 = 156.4 units. This represents a *gross* decline of 7.6 units from the original sales of 164 units, which is exactly 84 percent of the 9.2 unit sales increase for Folgers 16-ounce. However, another relevant component is the increase in the purchase incidence probability. The other brands gain 5.3 units from this category expansion, so that their *net* sales loss equals (approximately) 2.2 units. This is the number used in the unit sales decomposition to yield 24.3 percent of the sales increase. We argue that this net decrease in sales of the non-promoted brands is the bottom-line quantity of interest to retailers, to brand managers of the non-promoted brands, and to brand managers of the promoted brands, since it represents the sales loss for the non-promoted brands after all calculations have been made. In the literature, the net unit sales interpretation of the elasticity decomposition dominates, as indicated in Table 2, although the numbers represent a gross sales loss. As a consequence, we need equations to transform the elasticity decomposition into a net unit sales effect decomposition.

To achieve this, we start with expressions of unit sales and define the following identity equation:[3]

$$S_j = \sum_{k=1}^{J} S_k - \sum_{\substack{k=1 \\ k \neq j}}^{J} S_k \tag{6}$$

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 the sales promotion variable, i.e., temporary price cuts, since 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 $\partial S_j / \partial D_j$.[5] Using Equation 6, we can write this as the effect on category sales minus the effect on cross-brand sales:

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

We now divide both sides of Equation 7 by the own-brand sales effect ($\partial S_j \mid \partial D_j$). The left-hand side then equals 1, and the right-hand side consists of two terms. The first term represents the fraction of the own-brand sales increase due to primary demand effects, since it expresses the effect of the promotion on category sales as a fraction of the own-brand sales effect:

$$\mathrm{PD}_{\text{sales},j} = \text{Fraction Primary Demand Effects in Sales of brand } j = \frac{\partial \sum_{k=1} S_k / \partial D_j}{\partial S_j / \partial D_j} \tag{8}$$

The second term represents the fraction of the own-brand unit sales increase due to secondary demand effects (decreases in unit sales of other brands), since it is the ratio of minus the cross-brand sales effect (loss) over the own-brand sales change:[6]

$$\mathrm{SD}_{\text{sales},j} = \text{Fraction Secondary Demand Effects in Sales of brand } j = \frac{-\partial \sum_{\substack{k=1 \\ k \neq j}}^{J} S_k / \partial D_j}{\partial S_j / \partial D_j} \tag{9}$$

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

We now show the relationship between the elasticity decomposition (equations 4 and 5) and 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 $\mathrm{SD}_{\text{sales},j}$ and $\mathrm{PD}_{\text{sales},j}$:

$$\mathrm{SD}_{\text{sales},j} = -\sum_{\substack{k=1 \\ k \neq j}}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}|I}}{\eta_{I_j} + \eta_{C_{jj}|I} + \eta_{Q_{jj}}} \right) \left(\frac{Q_k}{Q_j} \right) \left(\frac{P(C_k \mid I)}{P(C_j \mid I)} \right) \tag{10}$$

and

$$\mathrm{PD}_{\text{sales},j} = 1 - \mathrm{SD}_{\text{sales},j} \tag{11}$$

where η_{I_j} is the elasticity of category purchase incidence, $\eta_{C_{kj}|I}$ is the elasticity of choice probability of brand k when j is promoted, conditional on purchase incidence, and $\eta_{Q_{jj}}$ is the elasticity of purchase quantity of brand j, conditional on purchase incidence and choice of brand j, each with respect to D_j.

In Study 1 (to follow), we apply equations 10 and 11, which are central to this paper, to three household-level datasets. The intuition behind Equation 10 is easier to see if we use a simplified version of Equation 10 ([A2] in the appendix) that obtains if we assume that the non-promotional purchase quantities are equal across brands ($Q_j = Q_k = Q \forall j, k$):

$$\mathrm{SD}_{\mathrm{sales},j} = \frac{\eta_{C_j|I}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1-P(C_j \mid I))}{P(C_j \mid I)} = \mathrm{SD}_{\mathrm{elast},j} - A \tag{12}$$

Equation 12 shows that to obtain the fraction of secondary demand effects 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*:

$$A = \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1-P(C_j \mid I))}{P(C_j \mid I)}$$

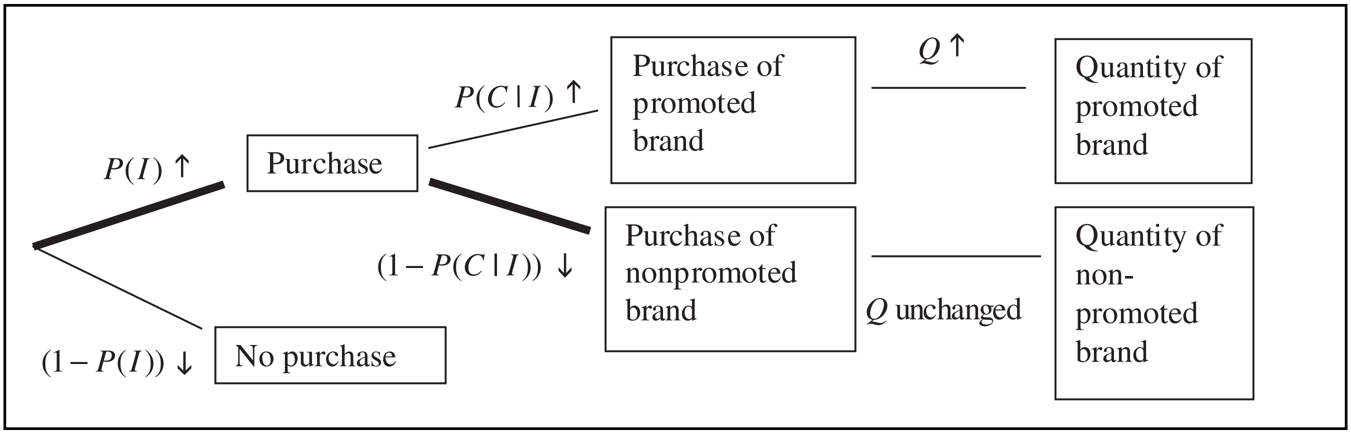
Since *A* is ordinarily a positive quantity, Equation 12 shows that in the *unit sales* decomposition, the secondary demand effect fraction will decrease relative to the elasticity decomposition.

The change in sales of non-promoted brands consists of two parts: a *positive* part due to an increase in the category purchase incidence probability, and a *negative* part due to decreased conditional choice probabilities. This is illustrated in Figure 1 by the two bold lines. The first bold line shows that a temporary price cut for a brand may increase the purchase incidence probability. A large part of this favors the promoted brand. However, the non-promoted brands may also benefit according to the model specification. That is, even though their conditional choice probabilities tend to decrease, other brands may experience a partly offsetting gain from the increased purchase incidence probability. The quantity *A* reflects this gain.

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 non-promoted brands of size $\eta_{I_i} P(I)(1-P(C_j \mid I))Q$. When we express this sales increase relative to the sales increase of brand *j*, we obtain *A*:

$$\frac{\eta_{I_j} P(I)(1-P(C_j \mid I))Q}{\eta_{S_j} P(I) P(C_j \mid I) Q} = \frac{\eta_{I_j} (1-P(C_j \mid I))}{\eta_{S_j} P(C_j \mid I)} \equiv A \tag{13}$$

Figure 1. Changes in Probabilities and Quantities Due to a Sales Promotion



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

$$\mathrm{SD}^{\mathrm{aggr}}_{\mathrm{sales},j} = \frac{\eta^{\mathrm{aggr}}_{C_j|I}}{\eta^{\mathrm{aggr}}_{S_j}} - \frac{\eta^{\mathrm{aggr}}_{I_j}}{\eta^{\mathrm{aggr}}_{S_j}} \frac{(1-ms_j)}{ms_j} \tag{14}$$

Assuming again 18 percent market share for Folgers 16-ounce, we estimate the fraction of secondary demand effects in unit sales to be: $\mathrm{SD}_{\mathrm{sales}}$ = .847 – .137 * ((1 – .18)/.18) = 22.2%. 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 Equation 14 is based on point elasticities. For example, if we use a .01 increase (instead of an increase of 1) in the feature variable in the numerical example, we would find $\mathrm{SD}_{\mathrm{sales}}$ to be 22.2 percent. Importantly, this estimated percentage secondary demand effect in *unit sales* is much smaller than the 84 percent based on the *elasticities*.

Study 1: Brand Switching Based on Household Data

We use the transformations to obtain unit sales decompositions from three household panel datasets: yogurt, tuna, and sugar. The yogurt data consist of 28,720 store visits by 223 households in Springfield, Missouri. Of these trips, 2,424 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, South Dakota. Of these trips, 1,740 resulted in purchases of one of the following two brands: Chicken of the Sea and StarKist. The product is a 6.5-ounce 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, Missouri. Of these trips, 1,824 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 fraction of secondary demand based on elasticities (Equation 5) is on average .58. However, the fraction of secondary demand based on unit sales effects (Equation 10) is quite a bit lower, .33. The approximate formula (Equation 14) based on aggregate quantities yields .29, which is reasonably close to .33. For tuna, the average elasticity-based secondary demand fraction is .49, whereas in unit sales it is .22 or, based on the aggregate approximation, .23. 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 brand switching contributes far less to the own-brand unit sales effect than what one might believe based on the elasticity decomposition. On average across these three categories, it is only 33 percent, whereas the elasticity decomposition suggests 57 percent. Further, the aggregate approximation formula provides results close to the average results from the purchase-occasion-level transformation. This suggests that we can apply the aggregate approximation formula to published results for which we do not have individual data.

Table 3. Decomposition Results for Household Data

Brand—Yogurt	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	
Brand—Canned Tuna	**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			
Brand—Sugar	**Control**	**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			

Study 2: Brand Switching Based on Published Household Decomposition Results

We now reconsider the decomposition results in Bell, Chiang, and Padmanabhan (1999).[7] We reproduce in Table 4 for each product category the fraction of secondary demand *elasticity* (Bell et al.'s Table 5). Next to those fractions we present the fraction of secondary demand *unit sales* based on Equation 14. The SD_{sales} fractions 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 fraction based on the elasticity decomposition is .75, whereas it is only .13 based on a unit sales decomposition. However, the number .13 is affected by the negative numbers for ice cream and butter. For these categories, the application of Equation 14 results in negative values of SD_{sales}. As discussed in note 5, this is a theoretically feasible result. It means that the promotion of one brand of butter or ice cream can stimulate households to also buy non-promoted brands. A factor that may contribute to this empirical finding is the possible occurrence of zero inventory for promoted items. The negative result occurs if the incidence elasticity is so large that the loss in conditional brand choice is offset by the gain in category demand.

Table 4. Comparison of Secondary Demand Effects: Elasticity versus Unit Sales

Category	SD_{elast}[1]	SD_{sales}[2]	Attractiveness for sales promotion	
			based on elasticity decomposition	based on unit sales effect decomposition
Margarine	.94	.51	13	13
Soft drinks	.86	.36	12	9
Sugar	.84	.34	11	7
Paper towels	.83	.42	10	11
Bathroom tissue	.81	.43	9	12
Dryer softeners	.79	.36	8	10
Yogurt	.78	.12	7	3
Ice cream	.77	–1.64	6	1
Potato chips	.72	.35	5	8
Bacon	.72	.14	4	4
Liquid detergents	.70	.31	3	6
Coffee	.53	.23	2	5
Butter	.49	–.26	1	2
Overall average	.75	.13		
Average without ice cream and butter	.77	.33		

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

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

Specifically, the number –1.64 for ice cream 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 non-promoted brands if brand preferences are strong. For butter, –.26 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.

If these two categories have especially strong brand preferences, they may be susceptible to such cross-brand effects. However, we note that the aggregate formula (Equation 14) is an imperfect approximation of the real fraction based on Equation 10, and any errors may also contribute to this result for ice cream and butter.

We obtain perhaps a more realistic estimate for the secondary demand fraction by excluding these two categories. In that case the secondary demand fraction is .33, which happens to be the same as the average across three categories in Table 3. Importantly, no matter how we compute the average in Table 4, brand switching in unit sales is not nearly as strong as it is in elasticity. For example, the lowest elasticity fraction is .49 (butter in column 1), whereas the highest unit sales fraction is .51 (margarine in column 2). The implication is clear: secondary demand effects are far less important than what has been claimed.

We note that although the ice cream and bacon categories have very similar elasticity patterns, the unit sales decompositions are quite different. This result is caused by differences in (average) market shares for the brands in these categories. In the ice cream category, there are 11 brands versus 6 in the bacon category. As a consequence, the average market share in the ice cream category is much lower, leading to lower secondary demand effects based on Equation 14. The intuition for this result is that, ceteris paribus, there is less switching in a diversified category with many items, which may be related to the existence of heterogeneous consumer preferences.

Managerial Implications

The current literature, based on models of household data, suggests that the vast majority of the sales increase due to promotional activities is attributable to brand switching (see Table 1). Bell, Chiang, and Padmanabhan (1999) find that on average, across various categories, secondary demand effects account for about 75 percent of the sales elasticity. We show that this result does not imply that if a promoted brand gains 100 units, the other brands together lose 75 units. To arrive at a substantively interpretable decomposition, we express the results in terms of comparable unit sales effects. We find that on average the secondary demand effect is only about one-third of the total unit sales effect. One interpretation of the difference from the elasticity fraction is that our decomposition considers the *net* sales decrease of the other brands, whereas the elasticity decomposition considers the *gross* decrease. That is, the elasticity approach does not account for the fact that part of the increased purchase incidence probability favors the non-promoted brands, according to the model specification. We argue that the net sales decrease is the bottom-line quantity for managers, since it shows the total result after all calculations have been done. Importantly, this same net decrease should be visible or estimable from (store-level) sales data. These findings may help managers reconcile inconsistencies between their own experiences ("there is little switching") and academic research that suggests brand switching tends to be the predominant source of the promotional bump.

The strikingly different brand switching contribution has important implications for manufacturers and retailers. Although the estimated short-term own-brand sales increase is the same, the major source of the increase is different. If three-fourths of the sales effect were due to 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 conclude that most of the effect enhances competition between brands. Instead, we find that the vast majority of the *sales* effect consists of primary demand effects. Thus, stockpiling and/or category expansion together appear to be the dominant sources of sales effects due to temporary price cuts. Manufacturers may prefer the greatest source to be primary demand, assuming that competitors tend to match each other's promotional activities especially if most of the effect is due to brand switching. Retailers should also prefer primary demand to secondary demand effects, since store switching is one possible part of the primary demand effect.

Apart from the large difference between the two decompositions in the average proportion of the sales increase attributable to secondary demand effects, it is useful to order product categories according to this proportion. To illustrate, we show in the last two columns of Table 4 the rank order from the most attractive category (lowest fraction of secondary demand effects = 1) to the least attractive category (highest fraction of secondary demand effects = 13), based on the elasticity decomposition in the third column, and based on the unit sales decomposition in the fourth column.[8] We find, for instance, that whereas ice cream is the sixth-most-attractive category for sales promotions based on the elasticity decomposition, it is first based on the unit sales effect decomposition. Similarly, yogurt becomes relatively much more attractive to promote: instead of seventh it is third, and its brand switching fraction changes from 78 percent to 12 percent!

Our results may imply that promotions are more attractive for managers than has been assumed so far. There are, however, two 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

Our main conclusion is that although the decomposition of sales promotion effects based on elasticities is mathematically correct, its commonly used interpretation (see Table 2) is incorrect. We find that secondary demand effects represent, on average, a third of the unit sales effect. Our unit sales decomposition answers the question: What part of own-brand sales gains due to a sales promotion is attributable to losses for other brands, and what part is attributable to primary demand effects? To accomplish this, the composite term (unit sales effect) and the decomposition terms (primary and secondary demand effects) are expressed in exactly the same units. The elasticity decomposition is in itself correct, but it must be interpreted with care: it gives insight in each of the three promotion effects, holding the other two effects constant (Bucklin, Gupta, and Siddarth 1998, p. 196). Researchers who use household data can use the formulas we provide 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 so as to derive unit sales decompositions (cf. Vilcassim and Chintagunta 1995).

We note that the unit sales effect decomposition does not restrict the fraction of secondary demand effects to lie between 0 and 1. We find in our second study that the fraction 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. The unit sales outcome is directly linked to the elasticity result, and, as a consequence, any result that one might consider (im)plausible is due to the (im)plausibility of the elasticity decomposition results. Two, it only occurs for 2 of the 16 datasets analyzed in tables 3 and 4, specifically when we had to use an approximation formula (Table 4).

The misinterpretation of the decomposition result that has prevailed for more than a decade in the literature is due to the use of elasticities instead of absolute sales effects. This observation is similar to claims made by Sethuraman, Srinivasan, and Kim (1999). They argue that the use of non-comparable elasticities has led to support for theories of asymmetric switching behavior between brands (Blattberg and Wisniewski 1989). That is, this asymmetry may not hold if one uses an absolute measure of cross-price effects. Sethuraman, Srinivasan, and Kim (1999) show that asymmetries in cross-price elasticities tend to favor a high-priced brand because of scaling effects. Thus, it is clear that elasticities must be interpreted with great care so as to avoid improper comparisons.

One possible direction for future research is to study category differences in the fractions of primary and secondary demand effects measured in *unit sales*. In addition, it is of interest to explore cross-category effects (Song and Chintagunta 2001) for promotions. For example, categories may experience asymmetric effects, such as margarine losing sales to butter but butter not losing to margarine, if an item in either category is promoted. Another possibility lies in a direct comparison of household purchase and store sales data. Gupta, Chintagunta, Kaul, and Wittink (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". If managers tend to prefer store-level data for decision-making purposes, it would be of interest to see how proper household-model-based decompositions compare with corresponding store-model-based decompositions. Finally, it would be useful to determine whether the nature of the decomposition of a sales increase due to promotion matters to manufacturers and retailers. For example, are competitive reaction effects sensitive to the secondary demand fraction?

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:

$$\mathrm{SD}_{\mathrm{sales},j} = \frac{-\sum_{\substack{k=1 \\ k \neq i}}^{J} \partial S_k / \partial D_j}{\partial S_j / \partial D_j}$$

The numerator equals:

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

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

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

Note that we use the result that the effect of brand *j*'s promotion on brand *k*'s conditional purchase quantity is zero ($\frac{\partial Q_k}{\partial D_j} = 0$), 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 non-promoted 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:

$$\frac{\partial S_j}{\partial D_j} = \frac{\eta_S P(I)P(C_j \mid I)Q_j}{D_j} = (\eta_{I_j} + \eta_{C_{jj}\mid I} + \eta_{Q_{jj}})P(I)P(C_j \mid I)Q_j \frac{1}{D_j}$$

Hence the ratio equals:

$$\mathrm{SD}_{\mathrm{sales},j} = -\sum_{\substack{k=1 \\ k\neq j}}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}\mid I}}{\eta_{I_j} + \eta_{C_{jj}\mid I} + \eta_{Q_{jj}}} \right) \left(\frac{Q_k}{Q_j} \right) \left(\frac{P(C_k \mid I)}{P(C_j \mid I)} \right) \qquad \text{(A1)}$$

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 Equation A1 reduces to:

$$\mathrm{SD}_{\mathrm{sales},j} = \frac{\eta_{C_j\mid I}}{\eta_{S_j}} - \frac{\eta_{I_j}}{\eta_{S_j}} \frac{(1 - P(C_j \mid I))}{P(C_j \mid I)} \qquad \text{(A2)}$$

Proof:

$$\mathrm{SD}_{\mathrm{sales},j} = -\sum_{\substack{k=1 \\ k\neq j}}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}\mid I}}{\eta_{I_j} + \eta_{C_{jj}\mid I} + \eta_{Q_{jj}}} \right) \left(\frac{Q_k}{Q_j} \right) \left(\frac{P(C_k \mid I)}{P(C_j \mid I)} \right)$$

$$= -\sum_{i\neq j}^{J} \left(\frac{\eta_{I_j} + \eta_{C_{kj}\mid I}}{\eta_{S_j}} \right) \left(\frac{P(C_k \mid I)}{P(C_j \mid I)} \right)$$

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

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

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

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

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

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

$$\mathrm{SD}^{\mathrm{aggr}}_{\mathrm{sales},j} = \frac{\eta^{\mathrm{aggr}}_{C_j \mid I}}{\eta^{\mathrm{aggr}}_{S_j}} - \frac{\eta^{\mathrm{aggr}}_{I_j}}{\eta^{\mathrm{aggr}}_{S_j}} \frac{(1 - ms_j)}{ms_j} \tag{A3}$$

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 no linear formula, instead of applying the nonlinear formula first at the purchase-occasion level and then aggregating.

Notes

1. 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.

2. We thank an anonymous reviewer for providing the impetus for this example.

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

4. 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. For example, for linear models, arc elasticities are exactly the same as point elasticities, while for nonlinear models arc elasticities are very close to point elasticities evaluated at some representative (average) value of the predictor variables.

5. To be consistent with the elasticity household-level approach, we only consider contemporaneous effects of promotions. Thus, we do not consider dynamic (short- or long-term) effects.

6. Note that 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. Also, 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 larger than 1.

7. We thank David Bell for providing the average elasticity results and market shares for all 173 brands. Unfortunately, he was unable to give us the individual-level data, and therefore, we had to use an approximate formula (Equation 14) instead of the exact formula (Equation 10).

8. Of course, this measure is not sufficiently representative of the attractiveness of promotions within a category. Other important factors include: margins, overall sales levels, importance of the category for the store image, and the extent to which primary demand effects represent increased consumption.

References

Ailawadi, Kusum L. (2001), "The Retail Power-Performance Conundrum: What Have We Learned?" *Journal of Retailing* 77 (3), 299-318.

Ailawadi, Kusum L., and Scott A. Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming It Faster." *Journal of Marketing Research* 35, 390-8.

Ailawadi, Kusum L., Scott A. Neslin, and Karen Gedenk (2001) "Pursuing the Value-Conscious Consumer: Store Brands Versus National Brand Promotions." *Journal of Marketing* 65 (1), 71-89.

Ainslie, Andrew, and Peter E. Rossi (1998), "Similarities in Choice Behavior across Product Categories." *Marketing Science* 17 (2), 91-106.

Ali, Abdul, Marvin A. Jolson, and Rene Y. Darmon (1994), "A Model for Optimizing the Refund Value in Rebate Promotions." *Journal of Business Research* 29 (3), 239-45.

Bell, David R., Jeongwen Chiang, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization." *Marketing Science* 18 (4), 504-26.

Blattberg, Robert C., Richard Briesch, and Edward J. Fox (1995), "How Promotions Work." *Marketing Science* 14 (3, Part 2 of 2), G122-32.

Blattberg, Robert C., and Scott A. Neslin (1990), "Sales Promotion: The Long and the Short of It." *Marketing Letters* 1 (1), 81-97.

Blattberg, Robert C., and Kenneth J. Wisniewski (1989), "Price-Induced Patterns of Competition." *Marketing Science* 8 (4), 291-309.

Bucklin, Randolph E., Sunil Gupta, and S. Siddarth (1998), "Determining Segmentation in Sales Response across Consumer Purchase Behaviors." *Journal of Marketing Research* 35 (May), 189-97.

Bucklin, Randolph E., and V. Srinivasan (1991), "Determining Interbrand Substitutability Through Survey Measurement of Consumer Preference Structures." *Journal of Marketing Research* 28 (1), 58-71.

Chiang, Jeongwen (1991), "A Simultaneous Approach to the Whether, What, and How Much to Buy Questions." *Marketing Science* 10 (4), 297-315.

Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice, and Purchase Quantity Decisions of Households." *Marketing Science* 12 (2), 184-208.

Dekimpe, Marnik, Dominique M. Hanssens, and Jorge M. Silva-Risso (1999) "Long-run Effects of Price Promotions in Scanner Markets." *Journal of Econometrics* 89 (1-2), 269-91.

Dhar, Sanjay K., Stephen J. Hoch, and Nanda Kumar (2001), "Effective Category Management Depends on the Role of the Category." *Journal of Retailing* 77 (2), 165-84.

Greco, Alan J., and Linda E. Swayne (1992), "Sales Response of Elderly Consumers to Point-of-Purchase Advertising." *Journal of Advertising Research* 32 (5), 43-53.

Guadagni, Peter M., and John D. C. Little (1998), "When and What to Buy: A Nested Logit Model of Coffee Purchase." *Journal of Forecasting* 17 (3-4), 303-26.

Gupta, Sachin, Pradeep K. Chintagunta, Anil Kaul, and Dick R. Wittink (1996), "Do Household Scanner Data Provide Representative Inferences from Brand Choices: A Comparison with Store Data." *Journal of Marketing Research* 33 (November), 383-98.

Gupta, Sunil (1988), "Impact of Sales Promotion on When, What and How Much to Buy." *Journal of Marketing Research* 25 (November), 342-55.

Institute for Scientific Information (2002), *ISI Web of Science*, http://isi6.isiknowledge.com/portal.cgi/wos.

Karande, Kiran W., and V. Kumar (1995) "The Effect of Brand Characteristics and Retailer Policies on Response to Retail Price Promotions: Implications for Retailers." *Journal of Retailing* 71 (3), 249-78.

Kim, Sang Yong, and Richard Staelin (1999), "Manufacturer Allowances and Retailer Pass-Through Rates in a Competitive Environment." *Marketing Science* 18 (1), 59-76.

Krishnamurthi, Lakshman, Tridib Mazumdar, and S. P. Raj (1992), "Asymmetric Response to Price in Consumer Brand Choice and Purchase Quantity Decisions." *Journal of Consumer Research* 19 (3), 387-400.

Malhotra, Naresh K., Mark Peterson, and Susan B. Kleiser (1999), "Marketing Research: A State-of the-Art Review and Directions for the Twenty-first Century." *Journal of the Academy of Marketing Science* 27 (2), 160-83.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice." *Journal of Marketing Research* 34, 248-61.

Midgley, David F., Robert E. Marks, and Lee G. Cooper (1997), "Breeding Competitive Strategies." *Management Science* 43 (3), 257-75.

Neslin, Scott A. (2002), *Sales Promotion*. Cambridge, Mass: Marketing Science Institute.

Rajendran, K. N., and Gerard J. Tellis (1994) "Contextual and Temporal Components of Reference Price." *Journal of Marketing* 58 (1), 22-34.

Sethuraman, Raj, V. Srinivasan, and Doyle Kim (1999), "Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations." *Marketing Science* 18 (1), 23-41.

Song, Inseong, and Pradeep K. Chintagunta (2001), "Investigating Cross-Category Effects of a Retailer's Marketing Activities: Application of a Random Coefficients Choice Model with Aggregate Data." Chicago, Ill.: University of Chicago, Graduate School of Business, Working paper.

Sun, Baohung (2001), "Promotion Effects on Category Sales with Endogenized Consumption and Promotion Uncertainty." Pittsburgh, Penn.: Carnegie Mellon University, Graduate School of Industrial Administration, Working paper.

Vilcassim, Naufel J., and Pradeep K. Chintagunta (1995), "Investigating Retailer Product Category Pricing from Household Scanner Panel Data." *Journal of Retailing* 71 (2), 103-28.

Wheat, Rita D., and Donald G. Morrison (1990), "Assessing Purchase Timing Models—Whether or Not Is Preferable to When." *Marketing Science* 9 (2), 162-70.

MARKETING SCIENCE INSTITUTE
1000 Massachusetts Avenue
Cambridge, MA 02138 USA
Phone: 617.491.2060
www.msi.org