RAJ SETHURAMAN*

Drawing on a consumer preference distribution structure postulated in analytical modeling research, the author develops a Separate Effects Model that separates the total discount effect of a competing high-priced brand on the sales of the focal low-priced brand into discount effect in the region where price of the competing brand is (1) above the price of the focal brand, (2) equal to the price of the focal brand, and (3) below the price of the focal brand. The author applies the model to store-level data on fabric softener and illustrates the steps involved in the estimation and usefulness of model results. In particular, he shows that the Separate Effects Model can (1) identify the source of the discount effect observed in the conventional model, (2) uncover discount effects not detected in the conventional model, and (3) guide managers' decisions related to discount sizes and provide some insights about brand strength. An interesting substantive finding from the empirical analysis is that the leading national brand can draw sales from competing brands without reducing its price below the price of the other brands.

A Model of How Discounting High-Priced Brands Affects the Sales of Low-Priced Brands

Price promotions in the consumer packaged goods market have been growing rapidly in the last decade (Blattberg and Neslin 1990). In the current market, in which consumers are becoming more value conscious, higher-priced brands (e.g., premium national brands) are facing increased competition from lower-priced brands (e.g., low-priced national brands and private labels). In the short term, higher-priced brands attempt to stem the sales growth of lower-priced brands through temporary price discounts. To make appropriate price promotion decisions, managers of these brands must understand the impact of their price cuts on low-priced competitors' sales.

In this context, Blattberg and Wisniewski (1989) propose a distribution of consumer preferences, which suggests that when the higher-priced, higher-quality brands price promote, consumers of the lower-priced, lower-quality brands will switch to the promoted higher-quality brand. However, when the lower-priced, lower-quality brands price promote, few consumers of the higher-priced, higher-quality brands will switch to the promoted lower-quality brand because they would perceive a large quality difference. The implication of this price-tier theory for aggregate sales is that when higher-priced brands price promote, they will draw sales from lower-priced brands, but not vice versa. They apply this theory to understand asymmetries in aggregate cross-price effects in store-level data on four product categories.

My study is similar in spirit to Blattberg and Wisniewski's (1989) in that I use a consumer preference distribution structure as the basis for understanding aggregate cross-promotion effects. However, whereas Blattberg and Wisniewski address the question of whether discounts by high-priced brands affect the sales of low-priced brands, I propose a model that can enable researchers to further refine their understanding of the discount effect. In particular, I address the following question: Does the effect of a price discount of a high-priced brand on the sales of a low-priced brand depend on whether the discounted price is above, equal to, or below the price of the cheaper brand?

The motivation for addressing this question comes broadly from the consumer preference distributions postulated in analytical modeling research (e.g., Lal 1990; Narasimhan 1988; Raju, Srinivasan, and Lal 1990) and specifically from the consumer preference distribution used in Rao's (1991) study. Briefly, Rao's model suggests that the effect of a

*Raj Sethuraman is an assistant professor, Department of Marketing, College of Business Administration, University of Iowa. The author is grateful to the Marketing Science Institute for providing funds for this project and to Information Resources, Inc. for providing the data. He thanks Don Lehmann, Forrest Nelson, Randall Schultz, Doyle Weiss, and Andrew Daughety for their comments and suggestions on an earlier version of this article; Vijay Mahajan and three anonymous *JMR* reviewers for their valuable suggestions; and Doyle Kim and Alexandru Degeratu for their comments and assistance in data analysis.

Journal of Marketing Research
Vol. XXXIII (November 1996), 399–409

change in a competitor's price on the focal brand's sales can be meaningfully separated into three effects due to three types of consumer segments: (1) the effect due to those consumers who would pay a positive premium for the competitor brand (competitor brand preferrers), (2) the effect due to those who would not pay a premium for either brand (price shoppers), and (3) the effect due to those who would pay a premium for the focal brand (focal brand preferrers). Drawing on this distribution structure, I develop an econometric model that separates the total discount effect of a competing high-priced brand on the sales of the focal low-priced brand into (1) discount effect in the region where price of the competing brand is above the price of the focal brand, that is, the effect arising from competitor brand–preferrer segment, (2) discount effect at the point where the price of the competing brand equals the price of the focal brand, that is, the effect arising from the price-shopper segment, and (3) discount effect in the region where price of the competing brand is below the price of the focal brand, that is, the effect arising from focal brand–preferrer segment. I call this model the *Separate Effects Model.*

Estimating these separate effects can guide managers' decisions related to the size of discounts to be offered and help them understand the nature of competition between the brands. Several studies have computed cross-promotional elasticities at the store level (e.g., Bemmaor and Mouscheaux 1991; Blattberg and Wisniewski 1989; Mulhern and Leone 1991; Sethuraman 1995) and the consumer level (e.g., Chintagunta, Jain, and Vilcassim 1991; Kamakura and Russell 1989). Recent studies have provided some empirical generalizations regarding promotion effects (Blattberg, Briesch, and Fox 1995; Rao, Arjunji, and Murthi 1995). However, I am not aware of studies that have attempted to estimate cross-promotional effects in different regions of the discount range.

The article is divided as follows: First, I develop the Separate Effects Model and discuss its usefulness. Second, I illustrate its application, using store-level scanner data for fabric softeners. Third, I provide the conclusions.

MODEL DEVELOPMENT

I describe the consumer preference distribution structure adapted from Rao's (1991) study. From this distribution, I generate the separate discount effects and discuss their implications. Then, I develop the econometric model for estimating the separate effects.

Consumer Preference Distribution

Let c denote the competing brand that attempts to draw sales from the focal brand f through price changes. Let p_c and p_f represent the prices of the competing and focal brands, respectively. Assume a consumer k would buy the competing brand if $p_c - p_f \leq \delta^k$ and the focal brand if otherwise. The price premium that consumer k is willing to pay for the competing brand over the focal brand is δ^k. Broadly, I can divide the consumers who would switch between the two brands into three segments: (1) those who would pay a positive premium for the competing brand (competitor brand–preferrer segment—$\delta^k > 0$), (2) those who would not pay a premium for either brand (price-shopper segment—$\delta^k = 0$), and (3) those who would pay a positive premium for the focal brand (focal brand–preferrer segment—$\delta^k < 0$).

When the competing brand is the strong (national) brand and the focal brand is the weak (store) brand, Rao (1991) postulates that a certain proportion (P) of consumers belongs to the price-shopper segment, with $\delta^k = 0$. The remaining proportion (1 – P) of consumers belong to the competitor brand–preferrer segment—in this segment, consumer k buys the strong brand if the price differential is greater than or equal to δ^k, where δ^k is distributed uniformly between 0^+ and δ_u;[1] 0^+ can be thought of as some small positive number above zero, and δ_u is the upper limit (a relatively large number) of the premium that switchers from focal brand to competing brand would pay. Expanding on this structure, in Figure 1, I present a more general consumer preference distribution that allows for preferrer segments for both brands. This consumer preference distribution forms the basis for developing the aggregate separate effects discount model used to study the effect of a discount on a high-priced brand on the sales of a low-priced brand.

Separate Effects—Description and Implications

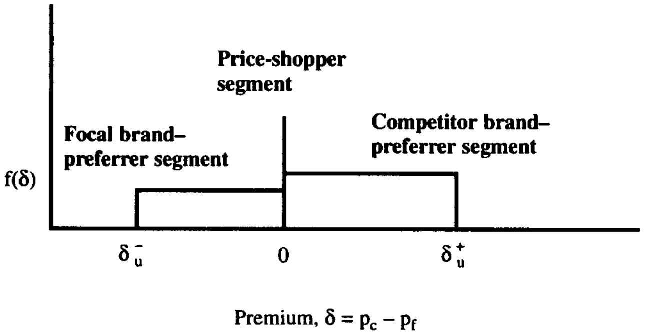
Consider a competing high-priced brand with a regular price p_{rc} that is attempting to draw sales from a low-priced focal brand, which is priced at p_f. Let the competing brand discount by d_c dollars to p_c (= $p_{rc} - d_c$). The effect of the discount on sales can be decomposed into three separate effects (see Figure 2):

1. Discount effect in the region where the price of the competing brand is above the price of the focal brand, that is, the effect arising from the competitor brand–preferrer segment (Figure 1)—I denote this effect as λ.
2. Discount effect at the point where the price of the competing brand equals the price of the focal brand, that is, effect arising from the price-shopper segment—I denote this effect as θ.
3. Discount effect in the region where price of the competing brand is below the price of the focal brand, that is, the effect arising from focal brand–preferrer segment—I denote this effect as μ.

Why is it useful to estimate the discount effect in terms of these separate effects? Compared to a model that does not separate the effects, the Separate Effects Model can provide useful information about the nature of price competition (based on aggregate effects) and help in making better discount decisions. In Table 1, I present the discount size implications arising from differences in the strengths of these separate effects. For illustration, take Case 2 in Table 1, in which the discount effects λ and θ are strong, whereas discount effect μ is weak. In this case, the competing high-priced brand can offer a discount to draw sales from the low-priced brand; however, it need not discount to a price below that of the focal brand. Although my focus is to refine the understanding of aggregate discount effects, because the model is developed from a distribution of consumer preferences, I can make some inferences about the distribution of premiums among consumers who switch from the focal brand to the competing brand. These inferences also are presented in Table 1. Case 2 corresponds to the distribution posited in Rao's (1991) study. The scenario implies that consumers who switch from the focal brand to the discounting

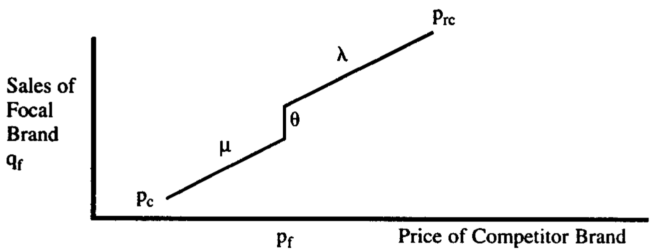
[1] I use the uniform distribution to motivate the discussion of the separate effects. However, it is not a necessary condition for the general specification of the Separate Effects Model. In the application section, I consider nonlinear functional forms, which can arise from nonuniform distributions.

Figure 1
CONSUMER PREFERENCE DISTRIBUTION



p_f = price of focal brand.
p_c = price of competitor brand.

Figure 2
SEPARATE EFFECTS



λ = Discount effect above focal brand price, which is due to competitor brand–preferrer segment.
θ = Discount effect at focal brand price, which is due to price shopper segment.
μ = Discount effect below focal brand price, which is due to focal brand–preferrer segment.
p_{rc} = Regular price of competitor brand.
p_c = Discounted price of competitor brand.

competitor brand would predominantly pay a positive or zero premium for the competitor brand.

Specification of Econometric Model

The development of the Separate Effects Model can be viewed as a sequence of successively refined models. Consider the simple case with one high-priced competitor brand and one focal brand. Start with the simple linear price model, which can be written as follows:

$$(1) \qquad q_f = \alpha - \beta\, p_f + \gamma\, p_c + \text{error},$$

where

q_f = unit sales of the focal (low-priced) brand,
p_f = actual price of focal brand, and
p_c = actual price of competing (high-priced) brand.

Both the competing brand and the focal brand are likely to offer temporary price discounts, d_c and d_f, from their regular prices, p_{rc} and p_{rf}, respectively (i.e., $p_c = p_{rc} - d_c$ and $p_f = p_{rf} - d_f$). The effects due to these discounts are likely to differ from the effects due to changes in regular price (Blattberg and Wisniewski 1989; Mulhern and Leone 1991). To capture these differences in effects, refine Model 1 as follows:[2]

$$(2) \qquad q_f = \alpha - \beta'\, p_{rf} + \beta''\, d_f + \gamma'\, p_{rc} - \gamma''\, d_c + \text{error},$$

where

d_f = discount size for focal brand = $p_{rf} - p_f$, and
d_c = discount size for competing brand = $p_{rc} - p_c$.

My focus is on the effect of competitor discount d_c or γ''. The Separate Effects Model decomposes the cross-deal effect γ'' into the three effects described in Figure 2. In the scenario when all discounting by the high-priced brand reduces its price from a level above the focal brand price to a level below the focal brand price (as described in Figure 2), the econometric model that estimates the separate effects can be written as follows:

$$(3) \quad q_f = \alpha - \beta'\, p_{rf} + \beta''\, d_f + \gamma'\, p_{rc} - \lambda\, d_{\lambda c} - \theta\, I_{\theta c} - \mu\, d_{\mu c} + \text{error},$$

where

$d_{\lambda c}$ = discount in the region where price of discounting brand is above price of focal brand,

$$d_{\lambda c} = \begin{cases} p_{rc} - p_f \text{ if } p_{rc} > p_f \text{ and } p_c \le p_f \\ 0 \text{ otherwise,} \end{cases}$$

$I_{\theta c}$ = indicator variable for measuring price-shopper effect,

$$I_{\theta c} = \begin{cases} 1 \text{ if } p_{rc} > p_f \text{ and } p_c \le p_f \\ 0 \text{ otherwise,} \end{cases}$$

$d_{\mu c}$ = discount in the region where price of discounting brand is below price of focal brand, and

$$d_{\mu c} = \begin{cases} p_f - p_c \text{ if } p_{rc} > p_f \text{ and } p_c \le p_f \\ 0 \text{ otherwise.} \end{cases}$$

Coefficient λ measures the discount effect in the region where the price of the competing brand is above the price of the focal brand. Coefficient θ measures the discount effect at the point where the price of the high-priced competing brand equals the price of the focal brand. Coefficient μ measures the discount effect in the region where price of the competing brand is below the price of the focal brand. Note that when $\lambda = \mu = \gamma''$ and $\theta = 0$, Equation 3 reduces to Equation 2, the model without the separate effects.

In the real world, not all discounts are situations in which the discounted price of the high-priced brand goes below the price of the low-priced brand. Furthermore, a predominantly high-priced brand may be a low-priced brand in some weeks. In Figure 3, I provide the various discount scenarios and the effects that can be estimated under each scenario for this more general setting. Scenario 1a is the one described in Figure 2 and Equation 3—the high-priced brand discounts and goes below the price of the focal brand ($p_{rc} > p_f$ and $p_c < p_f$), and all three effects can be estimated. Scenario 1b, for example, is a situation in which the high-priced brand discounts to a price equal to that of the low-priced brand ($p_{rc} >$

[2]Blattberg and Wisniewski (1989) separate the regular price effect and discount effect for own price but not for competitor price. I separate the two effects for both.

Table 1
IMPLICATIONS OF SEPARATE DISCOUNT EFFECTS

Case	*λ Effect*	*θ Effect*	*μ Effect*	*Implications for Discount Size*	*Inferences About Consumer Premium Distribution*
1	Strong	Strong	Strong	Competing brand can offer discount to curtail sales of focal brand. Discount of any size within the normal discounting range would be useful in decreasing focal brand sales.	Brand premiums for consumers who switch from focal brand to competing brand because of discounting appear to be widely distributed.
2	Strong	Strong	Weak	Discounting by the competing brand up to the point where its price equals the price of the focal brand is effective in decreasing focal brand sales. Any further discounting would not be useful.	Consumers who switch from focal brand to competing brand would pay a positive or zero premium for the competing brand.
3	Strong	Weak	Strong	Discount of any size within the normal discounting range would be useful in decreasing focal brand sales (same as Case 1 except there is no price-shopper effect).	Brand premiums are widely distributed. However, there are few price-shoppers.
4	Strong	Weak	Weak	Discounting by the competing brand up to the point where its price equals the price of the focal brand is effective in decreasing focal brand sales. Any further discounting would not be useful (same as Case 2 except there is no price-shopper effect).	Consumers who switch from focal brand to competing brand would pay a positive premium for the competing brand.
5	Weak	Strong	Strong	Competing brand should offer discount so that its price is at least on par with the focal brand.	Consumers who switch from focal brand to competing brand would pay a positive or zero premium for the focal brand.
6	Weak	Strong	Weak	Competing brand should offer discount so that its price is on par with the focal brand. However, further discounting would not be useful.	Consumers who switch from focal brand to competing brand would not pay a premium for either brand.
7	Weak	Weak	Strong	Competing brand should offer discount so that its price is below the price of focal brand.	Consumers who switch from focal brand to competing brand would pay a positive premium for the focal brand.
8	Weak	Weak	Weak	Discounting would not be useful for decreasing focal brand sales.	Consumers of focal brand do not switch to the competing brand when it discounts.

p_f and $p_c = p_f$). In this situation, λ and θ can be estimated, but not μ. The general econometric model based on the extended scenarios can be written as follows:

$$(4)\quad q_f = \alpha - \beta' p_{rf} + \beta'' d_f + \gamma' p_{rc} - \lambda d_{\lambda c} - \theta I_{\theta c} - \mu d_{\mu c} + \text{error},$$

where

$d_{\lambda c}$ = discount in the region where price of discounting brand is above price of focal brand,

$$d_{\lambda c} = \begin{cases} p_{rc} - p_f \text{ if } p_{rc} > p_f \text{ and } p_c \leq p_f \text{ (Scenarios 1a and 1b in Figure 3)} \\ p_{rc} - p_c \text{ if } p_{rc} > p_f \text{ and } p_c > p_f \text{ (Scenario 1c in Figure 3)} \\ 0 \text{ otherwise,} \end{cases}$$

$I_{\theta c}$ = indicator variable for price-shopper effect,

$$I_{\theta c} = \begin{cases} 1 \text{ if } p_{rc} > p_f \text{ and } p_c \leq p_f \\ 0 \text{ otherwise,} \end{cases}$$

$d_{\mu c}$ = discount in the region where price of discounting brand is below price of focal brand, and

$$d_{\mu c} = \begin{cases} p_f - p_c \text{ if } p_{rc} \geq p_f \text{ and } p_c < p_f \text{ (Scenarios 1a and 2a in Figure 3)} \\ p_{rc} - p_c \text{ if } p_{rc} < p_f \text{ and } p_c < p_f \text{ (Scenario 3a in Figure 3)} \\ 0 \text{ otherwise.} \end{cases}$$

My interest is in separating the discount effect of a high-priced brand on the sales of a low-priced brand into the three effects—λ, θ, and μ. Let C be the set of all brands competing with the focal brand (f) and Ω be the subset of competitor brands relative to the focal brand (f), in which the three separate effects can be estimated. Then, the general model in a multibrand situation can be written as

$$(5)\quad q_f = \alpha - \beta' p_{rf} + \beta'' d_f + \sum_{c\in C} \gamma' p_{rc} - \sum_{c\in\Omega} \lambda d_{\lambda c} - \sum_{c\in\Omega} \theta I_{\theta c} - \sum_{c\in\Omega} \mu d_{\mu c} - \sum_{c\notin\Omega} \phi d_{\phi c} + \sum_{j} v_j Z_j + \text{error},$$

where

$d_{\phi c}$ = discount for brands when separate effects are not estimated = $p_{rc} - p_c$, and
Z_j = covariates.

Equation 5 represents the general linear Separate Effects Model. Note that an increase in competitor discount should decrease focal brand sales, hence I expect λ and μ to be nonnegative. Similarly, when the discounted price equals the focal brand price, I expect a drop in focal brand sales, and hence θ should be nonnegative. A more general model that accounts for nonlinearities while maintaining the separablility of the discount effects can be written as

(6) $q_f = f\,(p_{rf}, d_f, p_{rc}, d_{\lambda c}, I_{\theta c}, d_{\mu c}, d_{\phi c}, Z_j, \text{error})$.

The underlying assumptions in Model 6 are (1) the effects due to $d_{\lambda c}$, $I_{\theta c}$, $d_{\mu c}$ are separable and (2) competitor sales are a continuous function of $d_{\lambda c}$ and $d_{\mu c}$. I subsequently illustrate the application of the model to understanding discount effects by using store-level data on five brands of fabric softener.

APPLICATION

I describe the data and then the econometric models and estimation procedure. Finally, I present and discuss the results.

Data

The data are store-level supermarket scanner data for fabric softener sheets obtained from Information Resources. The data set contains weekly information on unit sales by item, price by item, whether the item was discounted, deal size, and display and feature. Data are available for 104 weeks during 1991–93. Because my focus is mainly on describing the market rather than on predicting sales, I use all 104 observations for the analysis. The product is sold in three package sizes: 20-count, 40-count, and 60-count fabric softener sheets. The 40-count pack is the dominant one, accounting for over 65% of unit volume sales. I focus on the sales of one package size (40-count pack) but introduce the prices of brands in other package sizes as potential covariates in the model. There are five brands of 40-count fabric softener sold in the store: Arm & Hammer (AH), Bounce (BO), Downy (DO), Private Label (PL), and Snuggle Soft (SS). The average regular prices and discount data for these brands are given in Table 2. The general ordering of regular prices during this period was as follows: BO ≥ DO ≥ SS ≥

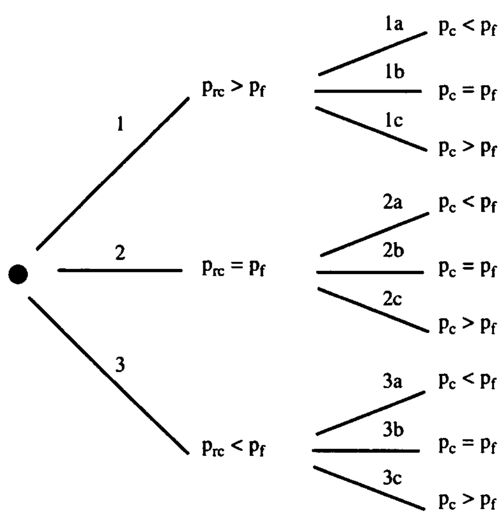
Table 2
DESCRIPTIVE STATISTICS

Brand	*Average Regular Price ($)*	*Unit Market Share (%)*	*Frequency of Deals (%)*[a]	*Average Discount (%)*[b]
Arm & Hammer	2.28	4.3	26	8.8
Bounce	2.58	38.8	60	18.9
Downy	2.52	22.8	31	13.7
Private Label	2.08	14.3	6	12.3
Snuggle	2.43	19.8	21	11.8

[a] $\frac{\text{Number of weeks on discount}}{\text{Total number of weeks (104)}} \times 100$

[b] $\frac{\text{Regular price} - \text{Discounted price}}{\text{Regular price}} \times 100$

Figure 3
DISCOUNT SCENARIOS AND ESTIMABLE EFFECTS[a]



Estimable Effect		
λ	θ	μ
Y ($p_{rc} - p_f$)	Y ($I_{\theta c}$)	Y ($p_f - p_c$)
Y ($p_{rc} - p_f$)	Y ($I_{\theta c}$)	N
Y ($p_{rc} - p_c$)	N	N
N	N	Y ($p_f - p_c$)
NP	NP	NP
NP	NP	NP
N	N	Y ($p_{rc} - p_f$)
NP	NP	NP
NP	NP	NP

[a]Relevant discount terms are in parentheses.
Note:
Y = Estimable.
N = Not estimable.
NP = Scenario not possible.
p_{rc} = Regular price of competing (discounting) brand.
p_c = Discounted price of competing brand.
p_f = Actual price of focal brand.
$I_{\theta c}$ = Indicator variable for price-shopper effect.

Table 3

DETAILS OF OBSERVATIONS FOR ESTIMATING SEPARATE EFFECTS

			$\lambda (d_{\lambda c})$		$\theta (I_{\theta c})$	$\mu (I_{\mu c})$	
Competing Brand	*Focal Brand*	*Notation*	*Number of Observations > 0*	*Range ($)*	*Number of Observations = 1*	*Number of Observations > 0*	*Range ($)*
Bounce	Arm & Hammer	BO→AH	62	0.0–.5	56	52	0.0–.4
Bounce	Downy	BO→DO	55	0.0–.46	44	51	0.0–.64
Bounce	Private Label	BO→PL	62	0.0–.54	42	37	0.0–.2
Bounce	Snuggle	BO→SS	44	0.0–.44	40	36	0.0–.5
Downy	Arm & Hammer	DO→AH	32	0.0–.44	15	15	0.0–.2
Downy	Private Label	DO→PL	32	0.0–.44	12	0	0.0
Downy	Snuggle	DO→SS	32	0.0–.44	23	23	0.0–.20
Snuggle	Arm & Hammer	SS→AH	22	0.0–.40	14	12	0.0–.20

AH ≥ PL. Bounce discounted most heavily both in terms of frequency and depth of discount. Bounce was also the leading brand with the highest market share. Arm & Hammer had the least market share and appeared to be more of a niche brand.

For these five brands, 20 (5 × 4) cross-deal effects can be estimated. I focus on the following effects of discounting by higher-priced brands on sales of lower-priced brands: Effects of Bounce on Arm & Hammer (BO→AH), Downy (BO→DO), Private Label (BO→PL), and Snuggle (BO→SS); effects of Downy on Arm & Hammer (DO→AH), Private Label (DO→PL), and Snuggle (DO→SS); effects of Snuggle on Arm & Hammer (SS→AH) and Private Label (SS→PL); effect of Arm & Hammer on Private Label (AH→PL). Discounting by Arm & Hammer and Snuggle did not result in the prices of these brands becoming equal to or less than the price of Private Label, so the separate effects could not be estimated. Thus, there are eight brand-pairs that belong to the set Ω in which the separate effects can be estimated. These eight pairs, along with the number of nonzero observations used for the estimation, are given in Table 3. There appear to be a sufficient number of observations for estimating the separate effects in all cases except that of DO→PL, in which there are no observations to estimate μ.

Table 4

OWN- AND CROSS-DEAL EFFECTS: BASE MODEL

Change in Discount of	*Affects Sales of* BO	DO	SS	AH	PL
BO	–75.6[a]**	15.0[b]**	9.92**	3.63**	1.77
	(4.4)	(3.65)	(3.81)	(1.65)	(2.00)
DO	27.9**	–54.5**	7.27	–.59	2.83
	(9.9)	(7.76)	(8.06)	(3.33)	(3.65)
SS	–10.2	12.6*	–77.7**	2.92	12.4**
	(10.4)	(8.0)	(8.81)	(3.74)	(4.46)
AH	1.02	17.6*	–17.3	–12.2**	–2.75
	(15.3)	(11.4)	(11.6)	(5.14)	(5.79)
PL	7.88	14.6*	10.5	3.27	–64.8**
	(12.9)	(10.2)	(10.7)	(4.75)	(5.74)

Note: The brands are arranged in the order of their average regular prices. Standard errors are given in parentheses.

[a]When Bounce discounts (decreases its price) by $1, its own sales increases by 75.6 units.

[b]When Bounce discounts by $1, Downy's sales decreases by 15 units.

*Significant at the 10% level.

**Significant at the 5% level (one-tail test).

Model Estimation

I estimate the Separate Effects Model using the linear as well as several nonlinear functional forms. In the application, the linear model performs as well as or better than the other models, and the basic results do not change. Hence, I focus on the linear Separate Effects Model. I start by estimating the base linear brand sales model (Equation 2) without the separate effects. The covariates used in the model are display and feature indicators for the estimation brand, as well as competitors' brands. The display (feature) indicator for a brand takes a value 1 if the brand is displayed (featured) during that week, and 0 otherwise. In addition, actual prices of brands in other package sizes are used as covariates.[3]

There are five brand sales equations to be estimated. To account for interdependencies in error structures across equations, I estimate this system of equations using the Seemingly Unrelated Related Regression (SUR) method (Zellner 1962). Because of the time-series nature of the data, I allow for first-order autocorrelation in the error term by using the procedure suggested by Parks (1967).[4] The regular prices of Arm & Hammer, Downy, and Private Label changed once during the time frame and all at the same time. Therefore, this was treated as a structural change and a dummy variable was introduced to account for the change. The own- and cross-deal effects from the base model are presented in Table 4. The system-weighted R^2 is .78.

Then, I estimate the linear Separate Effects Model (Equation 5) by using the same estimation procedure. The system-weighted R^2 is .81. The coefficients of the separate effects for the eight brand-pairs in which the effects were estimated are presented in Table 5.

Tests for Robustness of Results

Several diagnostic tests and tests for robustness and predictive validity were performed. These tests are now briefly described.

[3]However, to improve efficiency and increase error degrees of freedom, I include only prices of those brands in other package sizes whose coefficients are statistically significant in the base model.

[4]Autocorrelation was accounted for by first estimating the AR(1) coefficient ρ separately for each brand sales equation and creating new variables $X^* = X_t - \rho X_{t-1}$ and $Y^* = Y_t - \rho Y_{t-1}$, where X and Y are the independent and dependent variables, respectively.

Table 5
SEPARATE EFFECTS—ESTIMATES[a]

Brand Pair	Base Model	Full Model λ	Full Model θ	Full Model μ	Reduced Models λ^b	Reduced Models θ^c	Reduced Models μ^b
BO→AH	3.63** (1.65)	26.6** (6.9)	–4.2 (2.7)	2.27 (4.41)	8.51** (2.77)	1.97 (2.20)	–3.89 (3.10)
BO→DO	15.0** (3.65)	64.1** (12.3)	3.45 (3.14)	–5.24 (6.85)	66.8** (12.0)	1.13 (3.38)	.58 (4.46)
BO→SS	9.92** (3.81)	21.9* (14.8)	.82 (4.8)	3.99 (10.3)	24.6** (10.7)	.04 (2.22)	2.57 (5.98)
BO→PL	1.77 (2.00)	–3.29 (4.3)	3.85* (2.4)	1.99 (12.3)	.85 (2.80)	4.09** (2.28)	7.08 (9.9)
DO→AH	–.59 (3.33)	–8.38 (5.38)	1.38 (1.96)	5.72 (13.0)	–1.33 (4.1)	.73 (1.97)	9.59 (9.29)
DO→ SS	7.27 (8.06)	–30.3 (17.9)	10.8** (4.57)	1.63 (26.2)	1.45 (13.2)	12.3** (4.32)	9.6 (22.8)
DO→PL	2.83 (3.65)	3.86 (4.51)	.22 (2.08)	—	3.47 (3.93)	.07 (2.05)	—
SS→AH	2.92 (3.74)	6.38 (5.2)	–4.81 (2.75)	68.8** (29.4)	–1.45 (4.7)	2.6 (2.03)	45.2** (19.6)

[a]Standard Errors are given in parentheses.
[b]Estimate from model with $I_{\theta c}$ excluded ($\theta = 0$).
[c]Estimate from model with d_c instead of $d_{\lambda c}$ and $d_{\mu c}$ ($\lambda = \mu$).
*Significant at the 10% level.
**Significant at the 5% level (one-tail test).

Multicollinearity. I investigated the extent and location of the collinearity problem through analysis of variance inflation factors, condition indices, and eigenvalue decomposition (Belsley, Kuh, and Welsh 1980; Mason and Perrault 1991).[5] Collinearity is present in some cases and arises mainly because of the high correlation (> .6) of the competitor discount term, $d_{\mu c}$, with the price-shopper indicator, $I_{\theta c}$. This high correlation can occur because both $d_{\mu c}$ and $I_{\theta c}$ take positive values when $p_{rc} > p_f$ and $p_c < p_f$.

To test if the collinearity changes the nature of the results, I estimate the following alternate models. Note that the Separate Effects Model has two refinements: (1) differences in effects due to $d_{\lambda c}$ and $d_{\mu c}$ ($\lambda \neq \mu$) and (2) existence of a price-shopper effect due to $I_{\theta c}$ (θ). I incorporate these refinements individually. That is, first I estimate λ and μ in a model with no price-shopper indicator $I_{\theta c}$ ($\theta = 0$). Second, I estimate the price-shopper effect θ in a model with no slope difference ($\lambda = \mu$) by replacing $d_{\lambda c}$ and $d_{\mu c}$ with d_c These alternate models decrease the extent of collinearity. The estimates from these alternate reduced models are also presented in Table 5.

Six of twenty-three coefficients have (unexpected) negative signs in the full Separate Effects Model. In the alternate reduced models (Table 5, Columns 6–8), in which I separately estimate the refinements λ and μ with $\theta = 0$, and θ with $\lambda = \mu$, there are negative signs for just three coefficients and their magnitudes are small. These findings suggest that the correlation of $d_{\lambda c}$ and $d_{\mu c}$ with $I_{\theta c}$ may be causing some negative signs. However, despite the potential collinearity problem in some cases, the results pertaining to the statistical significance and relative magnitudes of the separate effects are similar.

Functional form. To test the robustness of the results with respect to functional form, I estimate several nonlinear functional forms. First, I estimate a semi-log model with the dependent variable as log(sales) instead of absolute sales, as in Blattberg and Wisniewski's (1989) and Mulhern and Leone's (1991) studies.[6] The system-weighted R^2 is .73. In addition, I estimate models in which the competitor discount terms $d_{\lambda c}$ and $d_{\mu c}$ take either the square root form $\sqrt{d_{\lambda c}}$ and $\sqrt{d_{\mu c}}$, or the quadratic form $d_{\lambda c}^2$ and $d_{\mu c}^2$.[7] The R^2 for these models are .79 and .80, respectively. The results are not different from the linear model.[8]

Price-shopper effect. In the BO→PL case (Table 4), the base model indicates that discounting by Bounce has little impact on sales of Private Label. In the Separate Effects Model (Table 5), λ and μ are nonsignificant, whereas θ is significant, at least at the 10% level in the full model and alternate models. That is, there is evidence indicating that Bounce is "effective" in drawing Private Label sales only when its discounted price equals that of Private Label (Case 6 of Table 1). A similar but stronger result (price-shopper effect) is obtained for the effect of discount by Downy on sales of Snuggle (DO→SS).

As a further test of the price-shopper effect in the BO→PL pair, I assessed whether there is a drop in (residual) pri-

[5]The details are summarized in an appendix, which is available from the author.

[6]The results from this model are in the author's appendix.

[7]The results from these models also are presented in the author's appendix.

[8]I ran several additional models besides the ones reported in the author's appendix (e.g., reduced models for the semi-log functional form, constrained models, where all coefficients with unexpected [negative] signs were set to zero, and so on). The broad results pertaining to the strengths of the separate effects do not change.

vate label sales near the region where the price of Bounce equals the price of Private Label.[9] I reestimated the sales model for Private Label after omitting the variables related to Bounce's discount. The residual from this model should reflect the effect of discount by Bounce and other (random or omitted) factors. I plotted this residual against the discount size of Bounce. However, because the discount observations are not continuous, I cannot precisely measure the drop in sales at the point where the discounted price of Bounce equals the price of Private Label. Therefore, I defined two regions in the neighborhood of that point and found that there was an average 1.02 units drop in (residual) sales when Bounce discounts, so that its price goes from a level slightly above Private Label price to a level slightly below Private Label price. Similar analysis of residuals was performed for the DO→SS case. A drop of 5.9 units was found when the price of Downy decreased from a level slightly above the price of Snuggle to a level below the price of Snuggle.

Predictive validity. I also compared the performance of the Separate Effects Model with the conventional model in terms of predictive validity. For this specific purpose, I used the first 90 weeks as the estimation sample and the last 14 weeks as the holdout sample. Based on the mean squared residual measure, the Separate Effects Model performed as well as or better than the conventional model for four brands—Arm & Hammer (6.7 versus 37.2), Bounce (412.4 versus 415.4), Downy (33.4 versus 34.6), and Private Label (197.1 versus 197.7). The performance was slightly lower for Snuggle (73.2 versus 72.3). The total mean squared residual for the Separate Effects Model (141.6) was approximately 6.5% lower than the residual for the base model (151.4).

In summary, the Separate Effects Model performs as well as or slightly better than the conventional model and the broad results pertaining to the statistical significance and relative strengths of the separate effects are robust.

Discussion of Results and Managerial Implications

I discuss the results from the base model and how the Separate Effects Model helps refine the understanding of the discount effects and enables researchers to make better discount decisions.

Results from base model. The own-deal effects (Table 4) are all negative and significant, as would be expected. My interest is in the cross-deal effects. Discount by Bounce, the leading brand, significantly affects the sales of other national brands (Downy, Snuggle, and Arm & Hammer); that is, the cross-deal effect is significantly greater than zero at the 5% level. The implication would be that Bounce can discount to draw sales from these brands. It is also interesting to note that the greatest impact in terms of effect size and t-statistic is with the next highest priced competitor (Downy). This is consistent with the observation made by Rao (1991, p. 139) that promotion competition is probably the highest with other brands with neighboring price points. The effect of Bounce's discount on Private Label sales (BO→PL) is not significant, which suggests that discounting is not effective in drawing Private Label sales.

Discounting by Downy significantly affects its immediately higher-priced brand (Bounce) and to some extent (though nonsignificant) its neighboring lower-priced brand (Snuggle), which again is consistent with Rao's (1991) observation of neighboring relations in promotion competition. The key implication is that Downy can discount to draw sales from Bounce but not other brands.

Snuggle has a marginally significant impact on its neighboring higher-priced brand. It has a significant impact, leaving out Arm & Hammer, which appears to be a small-share niche brand, on its neighboring lower-priced brand: Private Label. This observation is also consistent with Sethuraman's (1995) finding that, all things being equal, Private Label sales are affected not so much by the discounts of the highest-priced brands, but by the brands which are closer in price to Private Label.

Discounting by Arm & Hammer has a marginally significant impact on Downy but not on the others. The effects of Private Label discount on other national brands also are not statistically significant except in the one case (Downy) when it is marginally significant. This finding would be consistent with the theory and empirical findings of Blattberg and Wisniewski (1989).

It is also interesting to note that besides Downy, Bounce's neighboring lower-priced brand, none of the other brands affected the sales of the leading brand, Bounce. This finding suggests that discounts by leading brands can affect the sales of other brands, but the sales of leading brands are less affected by discounts of other brands (Sethuraman 1995).

Results from the Separate Effects Model. How can the results from the Separate Effects Model improve our understanding of the discount effects and help managers make better discount decisions? In Table 6, I present the discount implications for the brand pairs whose separate effects were estimated. Now consider the discount implications for Bounce. The base model (Table 4) indicates that discounting by Bounce has a significant impact on sales of Arm & Hammer, Downy, and Snuggle. The results from the Separate Effects Models (Table 5) indicate that λ is relatively large and significant, and θ and μ are small, negative, or nonsignificant, which corresponds to Case 4 of Table 1. That is, the dominant discount effect occurs in the region where the discounted price of Bounce is above the prices of these brands. Thus, though the base model suggests that discounting is useful, the Separate Effects Model suggests that Bounce can discount up to the point that its price equals the prices of these brands. Further discounting would not be useful. The inference regarding consumer premium distribution is that consumers who switch from these brands to Bounce would pay a positive premium for Bounce. In this sense, Bounce can be deemed the strong brand.

In the BO→PL case, the base model indicates that discounting by Bounce has little impact on sales of Private Label. In the Separate Effects Model, λ and μ are nonsignificant, whereas θ is significant—at least at the 10% level in the full model and alternate models. That is, there is evidence indicating that Bounce is "effective" in drawing Private Label sales only when its discounted price equals that of Private Label (Case 6 of Table 1). The inference regarding consumer distribution is that there are few switchers between Bounce and Private Label, and most of them appear to be price-shoppers. A possible explanation may be that Private Label consumers are typically the more price-sensitive consumers and would switch only if the price of the high-priced brand were at least the same as the Private Label price.

[9]The details are in the author's appendix.

Table 6
IMPLICATIONS OF SEPARATE DISCOUNT EFFECTS—FABRIC SOFTENER

Pair	*λ Effect*	*θ Effect*	*μ Effect*	*Case (Table 1)*	*Implications for Discount Size*	*Inferences About Premium Distribution*
BO→AH	Strong	Weak	Weak	4	Bounce can discount up to the point where its price equals the price of Arm & Hammer. Further discounting would not be useful	Consumers who switch from Arm & Hammer to Bounce would pay a positive premium for Bounce.
BO→DO	Strong	Weak	Weak	4	Bounce can discount up to the point where its price equals the price of Downy. Further discounting would not be useful.	Consumers who switch from Downy to Bounce would pay a positive premium for Bounce.
BO→SS	Strong	Weak	Weak	4	Bounce can discount up to the point where its price equals the price of Snuggle. Further discounting would not be useful	Consumers who switch from Snuggle to Bounce would pay a positive premium for Bounce.
BO→PL	Weak	Strong (Marginal)	Weak	6	Bounce should offer discount so that its price is on par with Private Label. However, further discounting would not be useful.	Consumers who switch from Private Label to Bounce would not pay a premium for either brand.
DO→AH	Weak	Weak	Weak	8	Discounting by Downy would not be useful for decreasing Arm & Hammer sales.	Consumers of Arm & Hammer do not switch to Downy when it discounts.
DO→PL	Weak	Weak	?	8	Discounting by Downy would not be useful for decreasing Private Label sales.	Consumers of Private Label do not switch to Downy when it discounts.
DO→SS	Weak	Strong	Weak	6	Downy should offer a discount so that its price is on par with Snuggle. However, further discounting would not be useful	Consumers who switch from Snuggle to Downy would not pay a premium for either brand.
SS→AH	Weak	Weak	Strong	7	Snuggle should discount so that its price is below that of Arm & Hammer	Consumers who switch from Arm & Hammer to Snuggle would pay a premium for Arm & Hammer.

For Downy, the base model indicates that discount by Downy does not significantly affect sales of Snuggle. The Separate Effects Models indicate that the slope effects (λ and μ) are small, negative, or nonsignificant, whereas the price-shopper effect (θ) is significant. The observed significance of the price-shopper effect in all alternate models suggests that the result is robust. That is, Downy should discount to a level equal to the price of Snuggle to draw sales from Snuggle. Note that from Table 2 the price and market share of Downy and Snuggle are close to each other, which suggests that they have more or less equal quality and attractiveness. In this situation, it is possible that consumers will switch from Downy to Snuggle only when the price of Downy equals the price of Snuggle.

In the case of SS→AH, coefficient μ is large and significant in all models, which suggests a strong effect in the region where the discounted price of Snuggle is below the price of Arm & Hammer (Case 7). The implication is that Snuggle should discount to a price below that of Arm & Hammer to draw sales. One possible reason is as follows: Arm & Hammer has relatively low market share (Table 2) in the fabric softener market. The brand that is a leader in the baking soda category is generally associated with health and cleanliness. It is likely that it is operating in a niche segment. So, consumers of Arm & Hammer might not switch to Snuggle unless the price were lower.

Together, these results provide an interesting set of implications. The highest-priced leading brand, Bounce, needs to discount only above the price of competitive national brands to draw sales. The second highest priced brand, Downy, needs to equal the price of its close competitor (Snuggle) to attract sales, and the third highest priced brand (Snuggle) needs to discount below the price of Arm & Hammer to draw sales. Rao (1991, Figure 3) observes in three product categories that on average the brand with the highest regular price has a promotion price just below the regular price of the brand with the next highest regular price and so on. Our analysis of fabric softeners suggests that, in this case, the highest priced brand does not need to reduce its price below the second highest priced brand; the second highest priced brand should discount so that its price is on par with the third-highest priced brand; the third highest priced brand should have a promotion price that is below the fourth highest priced brand.

CONCLUSION

I develop a model that can enable researchers to gain a better understanding of the effect of price discounts by high-priced brands on the aggregate sales of low-priced brands. The study is motivated by the consumer premium distributions postulated in analytical modeling research, especially by Rao (1991). These models suggest that consumers who switch between two brands can be divided into those who would pay a premium for one of the brands and those who would not pay a premium for either brand. Building on this distribution structure, I develop a Separate Effects Model that separates the total discount effect of a competing high-priced brand on the sales of the focal low-priced brand into (1) discount effect in the region where the price of the competing brand is above the price of the focal brand, (2) discount effect at the point where the price of the competing brand equals the price of the focal brand, and (3) discount effect in the region where the price of the competing brand is below the price of the focal brand. I apply the model to store-level data on fabric softeners and illustrate the steps involved in the estimation of the model and the usefulness of the model results. In particular, the Separate Effects Model can provide the following additional insights, compared to a conventional (base) model that does not separate the effects:

1. *It can identify the source of the discount effect observed in the conventional model:* For example, the base model indicates that discounting by Bounce significantly decreases the sales of Downy. The Separate Effects Model suggests that the dominant discount effect is in the region where the discounted price of Bounce is above the price of Downy.
2. *It can uncover discount effects not detected in the conventional model:* For example, the base model indicates that discount by Downy does not affect the sales of Snuggle. The Separate Effects Model indicates a strong price-shopper effect.
3. *The model can guide managers' decisions related to discount sizes and provide some insights about their brand strength as it relates to aggregate consumer switching:* For example, an interesting substantive finding is that the leading brand, Bounce, attracts sales from three other national brands by discounting. However, its major impact is in the region where its price is above the price of competing brands. So, to compete with these national brands, it does not need to discount its price to a level below the price of the other brand. The inference is that switchers would pay a premium for Bounce. In this sense, Bounce appears to be the strong brand. Downy, on the other hand, does not significantly affect two of three lower-priced brands and has an impact on a third brand only when its price equals that of the focal brand. Thus, Downy can be deemed as a weaker brand relative to Bounce.

Limitations

There are some limitations in estimating and interpreting the econometric model developed. First, there must be a sufficient number of observations to estimate the separate effects. That is, the high-priced brand should discount fairly often, and on several occasions its discounted price should go below the price of the cheaper brand so that all three effects could be estimated. I do not foresee this aspect as a problem for heavily discounted brands or for brands that are not priced much higher than the cheaper brands. Second, because a single discount effect is separated into three components, collinearity among these three components may pose a problem. The issue suggests the need for assessing the extent of collinearity and testing the robustness of model results with alternate models that mitigate the problem. In the case of fabric softeners, the broad results are robust. Third, the inferences regarding consumer premium distributions are based on aggregate data. Household level data may yield different results.

A pertinent question at this point is whether the model insights could be obtained more efficiently or more accurately by estimating the parameters in a flexible manner by using nonparametric regression. Nonparametric regression is superior in some ways to conventional regression because it does not assume any functional form and it relaxes other standard assumptions of regression, such as nonnormality and homoscedasticity (Rust 1988). It makes possible unique local coefficients for each point on the regression surface and would be ideal here if the effect of a high-priced brand's discount on sales of the focal brand at each discount point could be estimated and the results interpreted. Unfortunately, the nonparametric regression falls short on both counts of ability to be implemented and description power. Nonparametric regressions suffer from the "curse of dimensionality" in that a large sample is required when the number of dimensions becomes higher—casual review of the marketing literature suggests that applications of nonparametric regression are restricted to situations in which there are no more than three marketing variables and three brands (Abe 1991, 1995; Rust 1988). Here, there are several marketing variables and five brands. Furthermore, my interest is not in identifying the entire response function but more in assessing if the discount effects are different in three specific regions so that some managerial implications can be generated, such as in Table 1. The nonparametric regression method lacks this descriptive capability (Abe 1995).

There are also limitations in the interpretation of the results. Although the results suggest that it is not optimal for Bounce to decrease its price below the price of the focal brands (Arm & Hammer, Downy, Snuggle), its price does go below the prices of these brands. (In fact, the existence of these nonoptimal observations is what permits me to estimate the separate effects.) Given the model results, this occurrence may be because Bounce's manager is pricing incorrectly. Or, he or she may be charging a lower price (1) to compete with other brands (e.g., Private Label) and (2) to increase sales from its own customers. My recommendations are valid in the specific situation when the competing high-priced brand is discounting to draw sales from a particular low-priced brand.

Further Research

My objective has been to develop a model to better understand aggregate cross-deal effects. I use a consumer premium distribution that is postulated in analytical research as the behavioral foundation for developing an aggregate sales model that can potentially add greater insights into the cross-deal effects and help in making better discount decisions. I want to know whether a high-priced brand should discount so that its price is above, equal to, or below the price of the cheaper brand to draw sales from the low-priced brand. Store-level data are commonly used for guiding such managerial decisions (Bemmaor and Mouscheaux 1991; Blattberg and Wisniewski 1989; Bolton 1989; Mulhern and Leone 1991).

Recognize, however, that an important area of further research is to understand consumer-level response and then aggregate the responses to estimate market-level response. In this regard, I explore whether existing methodologies using consumer panel data can provide the insights sought here. Two types of related studies are discussed: (1) studies on market segmentation and market structure and (2) studies that incorporate consumer heterogeneity.

Several recent consumer studies have segmented the market on the basis of brand preferences and price sensitivity. For example, Grover and Srinivasan (1992) segment consumers on the basis of brand-choice probabilities, whereas Kamakura and Russell (1989) segment consumers on the basis of brand preferences and price sensitivity. Segments are defined on the basis of a vector of choice probabilities. A segment can be identified as Brand X segment if the choice share for Brand X in that segment is higher relative to the choice share for other brands. Market structure also can be understood from the distribution of choice shares within segments. If two brands have relatively high within-segment choice probabilities, then consumers in the segment are believed to be switching between those two brands. Although these studies have provided valuable insights, to the best of my knowledge, they have not separated the consumers into the three segments described here. That is, they do not identify in a two-brand context how many consumers prefer the focal brand or the competitor brand and how many are price-shoppers.

Studies that incorporate consumer heterogeneity can potentially provide the insights sought here, namely, a distribution of premiums in a two-brand context (premium consumers are willing to pay for one brand over the other). Consumers are willing to pay a premium for Brand A over Brand B because their "intrinsic" value (say V) for Brand A is greater than that for Brand B. That is, premium $\delta = f(V_A - V_B)$. Previous studies (e.g., Guadagni and Little 1983) have incorporated heterogeneity in brand preferences through purchase history. Recently, researchers have captured brand preference by including a constant for each brand and household and estimating its coefficient. Heterogeneity in brand preferences is estimated by using a variation of the random effects model that assumes some probability distribution of the brand preference parameter across households (Chintagunta, Vilcassim, and Jain 1991; Kamakura and Russell 1989) or a fixed effects model that estimates the parameter for each household (Rossi and Allenby 1993). However, to the best of my knowledge, these studies do not translate the distribution of brand preferences (distribution of V_A and V_B) into a distribution of consumer premium δ [(f $(V_A - V_B)$]. This aspect is an interesting and useful area for further research.

There are several other interesting substantive questions that can be addressed by separating the effects proposed here. I find that the discount effect of Bounce, the leading national brand, is stronger when the discounted price is above or equal to the price of the lower-priced brand. The finding suggests that those who switch from Bounce to the lower-priced brands would pay a positive or zero premium for the higher-priced brand. This finding is consistent with what has been postulated in analytical modeling research about strong brands. It would be of interest to test if the same result holds for other leading brands in other product categories. Additional research also can ascertain if there are systematic variations in the separate effects across product categories. For instance, would there be greater price-shopper effect in the case of less-differentiated products, such as margarine and flour?

REFERENCES

Abe, Makato (1991), "A Moving Ellipsoid Method for Nonparametric Regression and its Applications to Logit Diagnostics Using Scanner Data," *Journal of Marketing Research*, 28 (3), 339–46.

——— (1995), "A Non-Parametric Density Estimation Method for Brand Choice Using Scanner Data," *Marketing Science*, 14 (3), 300–325.

Belsley, D. A., E. Kuh, and R. E. Welsh (1980), *Regression Diagnostics*. New York: John Wiley & Sons.

Bemmaor, Albert C. and Dominique Mouscheaux (1991), "Measuring the Short Term Effect of In-Store Promotion and Retail Advertising on Brand Sales: A Factorial Experiment," *Journal of Marketing Research*, 28 (1), 202–14.

Blattberg, Robert, Richard Briesch, and Edward Fox (1995), "How Promotions Work," *Marketing Science*, 14 (3, part 2), G122–32.

——— and Scott A. Neslin (1990), *Sales Promotion: Concepts, Methods, and Strategies*. Englewood Cliffs, NJ: Prentice Hall.

——— and Kenneth J. Wisniewski (1989), "Price Induced Patterns of Competition," *Marketing Science*, 8 (Fall), 291–309.

Bolton, Ruth N. (1989), "Relationship Between Market Characteristics and Promotional Price Elasticities," *Marketing Science*, 8 (Spring), 153–69.

Chintagunta, Pradeep K., Dipak C. Jain, and Naufel J. Vilcassim (1991), "Investigating Heterogeneity in Brand Preferences in Logit Models for Panel Data," *Journal of Marketing Research*, 28 (November), 417–28.

Grover, Rajiv and V. Srinivasan (1992), "Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments," *Journal of Marketing Research*, 29 (1), 76–89.

Guadagni, Peter M. and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 3 (Summer), 203–38.

Kamakura, Wagner and Gary Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26 (November), 379–90.

Lal, Rajiv (1990), "Manufacturer Trade Deals and Retail Price Promotions," *Journal of Marketing Research*, 27 (November), 428–44.

Mason, Charlotte H. and William D. Perrault (1991), "Collinearity, Power, and Interpretation of Multiple Regression Analysis," *Journal of Marketing Research*, 28 (August), 268–80.

Mulhern, Francis J. and Robert P. Leone (1991), "Implicit Price Bundling of Retail Products: A Multiple Product Approach to Maximizing Store Profitability," *Journal of Marketing*, 55 (4), 63–76.

Narasimhan, Chakravarti (1988), "Competitive Promotional Strategies," *Journal of Business*, 61 (4), 427–49.

Parks, Richard (1967), "Efficient Estimation of a System of Regressions When Disturbances Are Both Serially and Contemporaneously Correlated," *Journal of the American Statistical Association*, 62 (June), 500–509.

Raju, Jagmohan, V. Srinivasan, and Rajiv Lal (1990), "The Effect of Brand Loyalty on Competitive Price Promotional Strategies," *Management Science*, 36 (March), 276–304.

Rao, Ram C. (1991), "Pricing and Promotions in Asymmetric Duopolies," *Marketing Science*, 10 (Spring), 131–44.

———, Ramesh Arjunji, and B. P. S. Murthi (1995), "Game Theory and Empirical Generalizations Concerning Competitive Promotions," *Marketing Science*, 14 (3, part 2), G89–100.

Rossi, Peter E. and Greg M. Allenby (1993), "A Bayesian Approach to Identifying Household Parameters," *Journal of Marketing Research*, 30 (May) 171–82.

Rust, Roland T. (1988), "Flexible Regression," *Journal of Marketing Research*, 25 (1), 10–24.

Sethuraman, Raj (1995), "A Meta-Analysis of National Brand and Store Brand Cross-Promotional Price Elasticities," *Marketing Letters*, 6 (4), 275–286.

Zellner, Arnold (1962), "An Efficient Method of Estimating Seemingly Unrelated Regression and Tests of Aggregation Bias," *Journal of the American Statistical Association*, 57 (June), 343–68.