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The impact of marketing policy on promotional price elasticities and baseline sales

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Looking across studies on the ability of price promotions to increase a brand's sales, one sees that the power of that instrument varies across brands, categories, retail chains, and markets. These differences in promotional *price elasticities* have been shown to be systematically related to marketing policy. We add to this body of research in two ways. First, we broaden the focus to also consider the relationships between marketing policy and *baseline sales*. Second, we use an analytical multi-segment model of market response to develop hypotheses about the likely relationships between marketing policy and promotional price elasticities and baseline sales. Using weekly store sales data for three cleaning product categories, we find coefficients consistent with the hypothesized relationships. Interestingly, for almost all elements of the marketing mix we find that those elements that tend to be associated with higher levels of promotional price response tend also to be associated with lower levels of baseline sales. National advertising share of voice is the *only* element that does not follow this pattern. Higher levels of national advertising tend to be associated with higher levels of promotional price response *and* higher levels of baseline sales. Managerial implications are discussed. © 1998 Elsevier Science Ltd

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1. Introduction

Economic and marketing theory tells us that, in allocating a budget across the marketing mix, a manager should invest more in instruments with higher elasticities than he or she invests in instruments with lower elasticities. (Carpenter *et al.*, 1988; Dorfman and Steiner, 1954; Gatignon and Hanssens, 1987; Jagpal and Brick, 1982; Lambin, 1970). Such advice assumes (1) that elasticities and unpromoted 'baseline' sales levels are fixed, i.e. 'exogenous constants' and (2) that the particular budget allocation chosen has no impact on future response.

However, these assumptions are likely to be incorrect. Both the elasticity of a brand and the baseline sales at the aggregate level are a function of (1) the distribution of price elasticities across consumers who buy the brand, and (2) the number of consumers who consider the brand for choice. The premise of this study is that marketing policy (i.e. the level of promotional and advertising support for the brand) affects these determinants of elasticities and baseline sales. Hence, elasticities and baselines are are assumed to be neither exogenous nor fixed but rather are a function of marketing policy.

We focus our study on promotional price elasticities.[1] These elasticities are typically quite large in absolute value. Associated sales increases may range from three-fold to seven-fold (Blattberg and Neslin, 1990,p. 351). Further, these elasticities differ across brands, categories, and markets (Blattberg and Wisniewski, 1987; Wittink *et al.*, 1987) and differences between elasticities are related to manufacturers' and retailers' marketing policies (Bolton, 1989).

Our contribution to this evolving literature is two-fold. First, we provide a causal framework to explain the relationships between manufacturers' and retailers' marketing policies on the one hand and *promotional price elasticities* on the other. Second, we also use that framework to consider the relationships between these marketing policies and unpromoted, *baseline sales levels*. The insights from this theoretical analysis could cause reconsideration of the traditional budget allocation process. For instance, if marketing actions taken today cause the structure of response to change such that unpromoted, full margin,

[1] Promotional price elasticities reflect response to short term price reductions that are accompanied by retailer promotional support: a feature advertisement in the retailer's weekly ad, a special display (sign at point of purchase, free-standing platforms/bins, end of aisle shelves, etc.), or a coupon. It is important to note that most price changes that occur in supermarkets today are promotional price changes.

baseline sales are diminished in the future, those marketing actions may bear reconsideration. Finally, secondary contributions of our paper are (1) that, in contrast to Bolton (1989), we estimate the impact of policy variables on elasticities using a single stage estimation procedure and (2) that our larger database, combined with the single stage estimation allows us more precision in estimation than Bolton had.

We study the impact of marketing policy on the evolving pattern of market response through a three step process. First, we specify a cross-sectional, time series model of the general form $Q = \alpha P^{\beta}$, where both β, promotional price elasticity, and α, a surrogate for baseline sales, are functions of brand and category descriptors that are manifestations of manufacturers' and retailers' marketing policies.

In the second step, we specify directional hypotheses for the coefficients of brand and category descriptors in the $\alpha(\cdot)$ and $\beta(\cdot)$ functions. We use a consumer response framework to derive analytical expressions for a brand's expected promotional price elasticity and expected baseline sales. The signs of derivatives of these expressions with respect to relevant parameters yield directional hypotheses for the coefficients in the $\alpha(\cdot)$ and $\beta(\cdot)$ functions.

In the final step, we estimate the parameters of the $\alpha(\cdot)$ and $\beta(\cdot)$ functions with 52 weeks of scanner data from 15 stores for brands in three categories of cleaning products. The signs of estimated coefficients are consistent with hypotheses suggested by the analytical model. We find that for most elements of the marketing mix, those actions which tend to increase the degree of promotion response tend to also lower the level of baseline sales. Only national advertising breaks this pattern. Increased use of national advertising is associated with higher levels of promotional price response *and* higher levels of baseline sales.

In what follows we present, in Section 2, the empirical model and, in Section 3, the analytical model used to generate hypotheses about signs of parameters in the empirical model. We then report the empirical findings in Section 4.1. We subsequently discuss, in Section 5, the managerial implications of our study and conclude, in Section 6, with directions for future research and the limitations of our study.

2. Empirical model

While we cannot directly observe manufacturers' and retailers' marketing policies during the period relevant to our data, we can observe manifestations of those policies. We focus on policy manifestations at the brand level and at the category level. At the brand level we consider a brand's average price, market share, the frequency and depth of its price cuts, the frequency with which it is displayed,[2] and its share of voice in national advertising. At the category level we look across all brands in the category and consider the frequency and depth of price cuts and the frequency with which the category is displayed.

We propose that marketing policies at one point in time can affect the structure of market response at a later point in time. Ideally, then, we would take manifestations of marketing policies at one point in time and relate them to promotional price elasticities and baselines estimated at a later point in time. Because of data limitations we are forced to relate policy manifestations for the 52-week period of our data to elasticities and baselines estimated with the same 52 weeks of data (see, eg Bolton, 1989, for a similar approach). We assume that the marketing policies are reasonably stable during the relevant periods of time and that the estimated elasticities and baselines have impounded these policies. Because our analysis is cross-sectional as well as time serial we get the variability needed to identify relationships by looking across brands, categories, and stores.

Following the general structure developed by Bolton (1989) in her study of the relationship between marketing policies and promotional price elasticities, we propose the following structure for the empirical model[3].

$$\log(Q_{irt}) = \alpha(i,r,c) + \beta(i,r,c)\cdot\log(P_{irt}) + \delta \cdot D_{irt} + \xi_{irt} \quad (1)$$

where:

Q_{irt}	= unit sales of item i in store r at time t
P_{irt}	= price of item i at store r at time t
D_{irt}	= dummy variable indicating that item i was displayed in store r at time t
$\alpha(i,r,c)$	$= a_0 + a_1\cdot(\text{PRICE}_{ir}) + a_2\cdot(\text{SHARE}_{ir}) + a_3\cdot(\text{B - ACTIVITY}_{ir}) + a_4\cdot(\text{B - DISPLAY}_{ir}) + a_5\cdot(\text{B - MADVTG}_i) + a_6\cdot(\text{C - ACTIVITY}_{cr}) + a_7\cdot(\text{C - DISPLAY}_{cr}) + a_{7+r}\cdot(\text{STORE}_r) + a_{23+c}\cdot(\text{CATEGORY}_c)$
$\beta(i,r,c)$	$= b_0 + b_1\cdot(\text{PRICE}_{ir}) + b_2\cdot(\text{SHARE}_{ir}) + b_3\cdot(\text{B - ACTIVITY}_{ir}) + b_4\cdot(\text{B - DISPLAY}_{ir}) + b_5\cdot(\text{B - MADVTG}_i) + b_6\cdot(\text{C - ACTIVITY}_{cr}) + b_7\cdot(\text{C - DISPLAY}_{cr}) + b_{7+r}\cdot(\text{STORE}_r) + b_{23+c}\cdot(\text{CATEGORY}_c)$
PRICE_{ir}	= average price for item i in store r, divided by the weighted average price for all items in i's category in store r (weights are market shares)
SHARE_{ir}	= log of i's market share in store r times the number of SKUs in i's category in store r
B-ACTIVITY_{ir}	= coefficient of variation for i's price in store r
B-DISPLAY_{ir}	= percentage of weeks that item i was on display in store r
B-MADVTG_i	= LNA share of voice for item i
C-ACTIVITY_{cr}	= weighted average of the coefficients of variation of price for items in category c in store r (weights are market shares)
C-DISPLAY_{cr}	= percentage of weeks that category c was on display in store r
STORE_r	= dummy variable indicating rth store
CATEGORY_c	= dummy variable indicating cth category

[2] Our data also contain information on feature advertising in the retailers' weekly ads. Unfortunately, the occurrence of these feature ads is highly correlated with in-store displays. The correlation between feature and display is 0.44 at the brand level, and 0.77 at the category level. To avoid problems of multicollinearity we dropped the data on features.

[3] We follow Bolton in the definition of the variables of the empirical model.

Model (1) has the property that the coefficient of $\log(P_{irt})$, $\beta(\cdot)$, is the promotional price elasticity.[4] Further, the function $\alpha(\cdot)$ can be interpreted as a surrogate for baseline sales. While the exact value of $\alpha(\cdot)$ will not necessarily correspond to the exact value of baseline sales, changes in $\alpha(\cdot)$ should correspond directionally to changes in baseline sales.

The term $\delta \cdot D_{irt}$ in model (1) is included to control for the impact of display, leaving $\beta(\cdot)$ to capture uncontaminated measures of response to promotional price cuts. If the effects of promotional display versus promotional price cut were not disentangled, then the incremental sales increase caused by displaying a brand when its price is cut would be captured in b_4, biasing its value toward greater negativity (see, eg Inman *et al.*, 1990).

To develop hypotheses regarding the likely signs of parameters a_1–a_7 and b_1–b_7, we develop, in contrast to Bolton (1989), a single analytical framework that suggests the ways in which the policy manifestations might be related to baselines and promotional price elasticities.

3. An analytic framework

Using disaggregated shopping data from nearly 20 000 households, Leo Burnett USA identified a set of generic shopping strategies and used it to exhaustively classify those households' purchase patterns in more than 25 product categories (Olson and McQueen, 1995; Progressive Grocer, 1995). Setting aside the 'Light User' strategy,[5] we reorganize the Leo Burnett shopping strategies to yield:

— *Not Promotion Sensitive*: These consumers may find only one brand in a category acceptable (a Leo Burnett 'Long Loyal'), or they may find several different brands in a category acceptable (a Leo Burnett not promotion sensitive 'Rotator'). These consumers do not react to promotional offers. The 'Rotators' buy different brands to accommodate different family members, occasions, or purposes.

— *Promotion Sensitive*: These consumers let promotional offers determine which of the acceptable brands will be chosen (a Leo Burnett 'Promotion Sensitive Rotator'). If no acceptable brand is promoted, these consumers will pay full price for one of the acceptable brands.

— *Store Brand Buyers*: These consumers typically buy store brands. They may, however, buy a national brand if it is on promotion (a Leo Burnett 'Price-Driven').

To model expected promotional sales and expected unpromoted sales, for a particular national brand, B_1, we build from the three segments described above. We represent these segments with three prototypical consumers: a regular buyer of national brands who is not promotion sensitive, a regular buyer of national brands who is promotion sensitive, and a store brand buyer who may be induced by promotion to buy a national brand.

For tractability we assume that there are two national brands, B_1 and B_2. We represent preferences for B_1 and B_2 by π and $(1-\pi)$ respectively ($0<\pi<1$); and assume that, in the absence of promotion, consumers choose between brands with probabilities proportional to preferences (Luce, 1959). We assume that the prototypical consumer in the second segment responds to promotion by restricting her choice to promoted acceptable brands, and that she chooses according to her preferences if both national brands are promoted simultaneously. Finally, we assume that a prototypical consumer in the third segment will consider national brand B_1 only if B_1 is on promotion. This consumer will never buy any national brand, including B_1, if that national brand is not promoted.

3.1. Expected baseline sales and expected percentage sales increase due to promotion

We translate the behavior of these prototypical consumers into expectations of sales response by assuming that each segment is made up of many replicas of its prototypical consumer.[6] Next we derive expressions for the level of sales that brand B_1 can expect when it is not promoted and the percentage sales increase that it can expect when it is promoted. This latter measure is an oppositely signed surrogate for elasticity. We denote the number of consumers in the loyal, the promotion sensitive segment and the store-brand segment by N_1, N_2, and N_3, respectively.

Focusing on brand B_1, we note that its demand is conditional on whether brand B_2 is promoted or not. If B_2 is promoted, the brand B_1 has a baseline sales of $\pi \cdot N_1$, i.e. B_1 does not sell to any consumers in the promotion sensitive segment. If B_2 is not promoted, B_1's baseline sales will equal $\pi \cdot (N_1+N_2)$.Assuming that the occurrence of B_2's promotions follow a Bernouilli process with parameter p, expected baseline sales of B_1 is thus equal to:

$$EBS = E[B_1\text{'s Baseline Sales} = p \cdot \pi \cdot N_1 + (1-p) \cdot \pi \cdot (N_1 + N_2) \quad (2)$$

If B_1 promotes, its sales will once more be conditional on B_2's promotional status. Specifically, when B_2 also promotes, B_1 will sell $\pi \cdot (N_1+N_2+N_3)$. When B_2, does not promote, B_1 will sell $\pi \cdot N_1+N_2+N_3$. Thus, taking the

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[4] Our choice of a fixed model form represents a departure from Bolton, who estimated both (1) and a strictly linear model on each brand. Bolton then selected the model form which provided the best fit to the estimation data. Approximately one-half of Bolton's elasticity estimates were derived from the linear model. It should be noted that elasticity estimates from the linear model are point specific, ie they will differ at different levels of price. While there is some debate over the relative merits of linear versus multiplicative models (Brodie and deKluyver, 1984; Ghosh *et al.*, 1984; Leeflang and Reuyl, 1984; Naert and Weverbergh, 1985), we chose to adopt the multiplicative constant elasticity model (1) because it obviates the need to specify evaluation levels of the independent variable and because it allows us to perform single stage estimation.

[5] We set this segment aside because it is not a shopping strategy.

> Light Usage is not a buying strategy, per se; it is a reflection of limited category interaction...[These light users] generally should be removed from analysis so clearer patterns can emerge. (Progressive Grocer, 1995, p. 138)

[6] By assuming a fixed number, N_i, of consumers in segment i, we mask any changes in primary demand and any effects of seasonality. We consider those complexities beyond the scope of this paper.

appropriate expectations, the expected percentage sales increase of B_1, when B_1 is promoted, is equal to:

$$\text{EPSI} \equiv E\left[\frac{B_1\text{'s Promotional Sales Peak} - B_1\text{'s Baseline}}{B_1\text{'s Baseline}}\right]$$

$$= p \cdot \left(\frac{N_2 + N_3}{N_1}\right) + (1-p) \cdot \left(\frac{(1-\pi) \cdot N_2 + N_3}{\pi \cdot (N_1 + N_2)}\right) \quad (3)$$

3.2. *Hypotheses*

SHARE. To see the impact of market share on expected baseline sales we consider the derivatives of *Equation 2* with respect to π.

$$\frac{\partial(\text{EBS})}{\partial \pi} = N_1 + N_2 \cdot (1-p) > 0 \quad (4)$$

As one would expect, brands with higher market shares should expect higher baselines.

To see the impact of market share on expected promotional price elasticities, we use an oppositely signed surrogate for elasticities, namely the expected percentage increase in sales when B_1 is promoted. We consider the derivative of *Equation 3* with respect to π.

$$\frac{\partial(\text{EPSI})}{\partial \pi} = -(1-p) \left[\frac{N_2}{\pi \cdot (N_1 + N_2)} + \frac{[(1-\pi) \cdot N_2 + N_3] \cdot (N_1 + N_2)}{[\pi \cdot (N_1 + N_2)]^2}\right] < 0 \quad (5)$$

Higher market share brands should get smaller percentage increases in sales when they are promoted (i.e. their elasticities should be less negative).

PRICE. We assume that, all else held constant, consumers who choose brands that are positioned as high priced brands are less price sensitive than those consumers who choose lower priced brands. Therefore higher priced brands should tend to have more Segment 1 (not promotion sensitive consumers) and lower priced brands should tend to have more Segment 2 (promotion sensitive consumers, see also Blattberg and Wisniewski (1989)). To see the impact of price on baselines, we look at the derivative of *Equation 2* with respect to N_1, holding the total number of consumers in segments 1 and 2 constant at $N=N_1+N_2$.

$$\frac{\partial(\text{EBS})}{\partial N_1}\bigg|_{N_1 = N - N_2} = p \cdot \pi > 0 \quad (6)$$

Hence, higher priced brands should be expected to have higher baselines, ie the sales of higher priced brands are less sensitive to price promotions of others brands all else equal.[7]

Similarly, to see the impact of price on promotional price elasticities, we look at the derivative of *Equation 3* with respect to N_1, holding the total number of consumers in Segments 1 and 2 constant.

$$\frac{\partial(\text{EPSI})}{\partial N_1}\bigg|_{N_1 = N - N_2} = -\left[\frac{p \cdot (N_3 + N)}{N_1^2} + \frac{[(1-\pi) \cdot (1-p)]}{\pi \cdot N}\right] < 0 \quad (7)$$

Hence higher priced brands should expect to have smaller percentage increases in sales when promoted, which corresponds to less negative promotional price elasticities.

B-DISPLAY and B-ACTIVITY. We expect that more frequently displayed brands will tend to draw more Segment 2 (promotion sensitive) consumers and fewer Segment 1 (not promotion sensitive) consumers. Therefore, to look at the impact of display frequency (B-DISPLAY) and the volatility of prices (B-ACTIVITY) on baseline sales and promotional price elasticities we consider the derivative of *Equation 2* with respect to N_2, holding $N_1+N_2=N$ constant. To look at the impact of these variables on promotional price elasticities, we consider the derivative of *Equation 3* with respect to N_2, holding $N_1+N_2=N$ constant.

Since $N_2=N-N_1$, we refer to the analysis above that considered the derivative of *Equation 2* and *Equation 3* with respect to N_1, and predict that brands that are displayed more frequently and that have more volatile prices should have lower baselines and larger percentage increases in sales due to promotion (more negative promotional price elasticities).

C-DISPLAY and C-ACTIVITY. These two category descriptors reflect the extent to which a category receives promotional support. We believe that those consumers who buy brands from highly promoted categories are more promotion sensitive than consumers who buy brands from categories that are infrequently promoted.[8] To investigate the impact of these variables on baseline sales and promotional price elasticities we would once again look at the derivatives of equations and with respect to N_2, holding $N_1+N_2=N$ constant and conclude that higher values of these variables should be associated with lower baselines and higher percentage increases in sales due to promotion (more negative promotional price elasticities.)

B-MADVTG. National advertising can have two different effects (Mitra and Lynch, 1995): differentiation effects (Bain, 1956; Boulding *et al.*, 1992) and information effects (Erdem and Keane, 1996; Stigler, 1961). The differentiation effect suggests that advertising insulates a brand from competitors' marketing activities by making consumers less sensitive to those actions. We capture this 'market power' effect in our framework by assuming that some of the promotion sensitive consumers are converted to non

[7] We are not hypothesizing that higher priced brands have positive price elasticities. Instead, higher priced brands are assumed to signal higher quality and will under *ceteris paribus* conditions have less price sensitive consumers. Thus price promotions of other brands should have less impact on the baseline sales of higher priced brands.

[8] It happens that a category is frequently promoted in one store and almost never promoted in another. We suggest that more promotion sensitive consumers will tend to buy this category in stores that promote the category more frequently.

promotion sensitive consumers. (N_2 grows smaller, holding $N=N_1+N_2$ constant.) As shown above, this leads to higher baselines and smaller percentage increases in sales due to promotion.

The information effect or consideration set effect suggests that advertising can cause some consumers who do not have the advertised brand in their acceptable set to consider it when promoted (Hauser and Wernerfelt, 1989; Mitra and Lynch, 1995). Within our framework this can be modeled as a sales increase stemming from Segment 3, those consumers who were previously not considering B_1. Notice that this effect differs from effects described earlier in that (1) it applies only to promotion periods, and (2) the increase in the size of the promotion sensitive segment is not offset by a parallel decrease in the size of the promotion insensitive segment.

To examine the impact of the consideration set effect on baselines and promotional price elasticities we look at the derivative of *Equation 3* with respect to N_3, the number of consumers in the store brand segment.

$$\frac{\partial(EBS)}{\partial N_3} = 0 \tag{8}$$

,and

$$\frac{\partial(\mathrm{EPSI})}{\partial N_3} = \frac{p}{N_1} + \frac{1-p}{\pi \cdot N} > 0 \tag{9}$$

We see that the two roles of advertising drive elasticities in different directions. Market power tends to dampen elasticity, while consideration tends to enhance elasticity. *Table 1* summarizes the hypothesized effects.

4. Estimation

4.1. Data and estimation procedure

Fifty-two weeks of scanner sales data were drawn from 16 stores representing five different chains in a Midwestern market. Three different categories were selected: two household cleaning product categories and one personal care product category. National advertising share of voice data was drawn from Bar LNA.

We do not aggregate items to the brand level because preliminary investigation revealed that promotional activity was often size-specific. This results in 27 brand-size items of Household Cleaning Product 1, 64 brand-size items of Household Cleaning Product 2, and 25 brand-size items of the Personal Care Product. In total, we have 1243 store-brand-size combinations (ie 1243 series of 52 weeks of data). All items are nationally marketed, ie there are no store brands in these data.

Table 1 Hypothesized sign of the coefficients of the variables in this study

Variable	in $\alpha(\cdot)$	in $\beta(\cdot)$
	Brand-specific covariates	
PRICE_{ir}	+	+
SHARE_{ir}	+	+
	Brand specific policy variables	
$\mathrm{B\text{-}DISPLAY}_{ir}$	-	-
$\mathrm{B\text{-}ACTIVITY}_{ir}$	-	-
$\mathrm{B\text{-}MADVTG}_{i}$	+	±
	Category specific policy variables	
$\mathrm{C\text{-}DISPLAY}_{ir}$	-	-
$\mathrm{C\text{-}ACTIVITY}_{ir}$	-	-

4.2. Empirical results[9]

The estimation results in *Table 2* are consistent with our hypotheses. High share brands tend to have higher baselines (positive coefficients in the $\alpha(\cdot)$ function) and less elastic demand (positive coefficients in the $\beta(\cdot)$ function) than low share brands. The same holds for high priced brands, where the high price positioning of these brands is presumably related to higher levels of quality. We also hypothesized that increased promotional activity affects the mix of consumers for a brand. More specifically, the higher levels of promotional activity will tend to be associated with brands that have a higher percentage of promotion sensitive consumer in their franchises. This will cause lower baseline sales and more elastic demand than brands that promote less. We indeed find that the effect of promotion (DISPLAY and ACTIVITY variables) on baseline sales and price elasticities is negative.

For advertising (B-MADVTG), we hypothesized that baseline sales should be higher for advertised than for unadvertised brands, and, indeed, see that the coefficient of B-MADVTG in the $\alpha(\cdot)$ expression is positive. The relationship between B-MADVTG and elasticity could have gone either way; the market power effect dampens elasticity while the consideration set effect heightens elasticity. For this data, we see that the consideration effect dominated and that higher levels of advertising are associated with higher degrees of elasticity (the coefficient of B-MADVTG in the $\beta(\cdot)$ expression is negative).

5. Discussion

Because our empirical analysis is cross-sectional, we cannot directly test the causal hypotheses generated in "3.2. Hypotheses". Our correlational findings are nonetheless all consistent with the causal hypotheses.

It is, however, possible that the direction of causation goes both ways. We consider two cases explicitly. First, for the DISPLAY and ACTIVITY variables, opposite causality may be consistent with certain implications of normative economic theory. Brands that are more promotion price elastic should promote more frequently. Further, since frequent price promotion might lead to lower average prices, this normative link between elasticity and promotion frequency might also in part drive the

[9] We will not discuss comparisons with the Bolton (1989) analysis in depth. One difference with Bolton (1989) that should be mentioned though is that while Bolton's work gave inconclusive (insignificant) results about the role of C-ACTIVITY, B-MADVTG, B-DISPLAY and C-DISPLAY, our larger data set, exploited with single stage estimation, shows strong significant effects of these four latter variables and an additional one (B-ACTIVITY).

Table 2 Estimation results[a]

		Effect on baselines sales, (t-ratios)		Effect of promotional price elasticity, (t-ratios)	
Constant		a_0	0.000 [d]	b_0	-0.908 (-8.87)
PRICE		a_1	1.581 (44.53)	b_1	0.030 (1.69) [ns]
SHARE		a_2	0.913 (202.34)	b_2	0.034 (19.07)
B-ACTIVITY		a_3	-0.148 (-11.34)	b_3	-0.028 (-5.01)
B-DISPLAY		a_4	-0.873 (-14.29)	b_4	-0.234 (-10.35)
B-MADVTG		a_5	0.919 (20.09)	b_5	-0.343 (-14.22)
C-ACTIVITY		a_6	-2.808 (-8.13)	b_6	-1.259 (-4.68)
C-DISPLAY		a_7	-0.060 (-0.82) [ns]	b_7	-0.123 (-2.96) [b]
Store Dummies	1	a_8	-0.340 (-8.51)	b_8	-0.008 (-0.38) [ns]
	2	a_9	-0.589 (-14.71)	b_9	-0.005 (-0.23) [ns]
	3	a_{10}	-0.124 (-2.95)[b]	b_{10}	-0.008 (-0.37) [ns]
	4	a_{11}	-0.519 (-16.42)	b_{11}	-0.020 (-1.25) [ns]
	5	a_{12}	-0.020 (-0.52) [ns]	b_{12}	-0.020 (-0.96) [ns]
	6	a_{13}	-0.752 (-24.14)	b_{13}	-0.068 (-3.99)
	7	a_{14}	-0.767 (-19.95)	b_{14}	-0.046 (-2.38) [c]
	8	a_{15}	-0.560 (-19.91)	b_{15}	-0.020 (-1.15) [ns]
	9	a_{16}	-0.962 (-46.05)	b_{16}	-0.055 (-4.57)
	10	a_{17}	-0.761 (-28.88)	b_{17}	0.060 (2.91) [b]
	11	a_{18}	-0.311 (-16.33)	b_{18}	-0.048 (-6.09)
	12	a_{19}	-0.784 (-44.14)	b_{19}	-0.019 (-2.48) [c]
	13	a_{20}	-0.654 (-24.58)	b_{20}	-0.025 (-2.45) [c]
	14	a_{21}	-1.366 (-62.39)	b_{21}	-0.067 (-7.49)
	15	a_{22}	-2.161 (-86.84)	b_{22}	-0.095 (-9.42)
	16	a_{23}	0.000[d]	b_{23}	0.000 [d]
Category dummies					
	1	a_{24}	5.290 (80.15)	b_{24}	-0.774 (-8.24)
	2	a_{25}	-3.548 (-21.99)	b_{25}	-0.788 (-8.43)
	3	a_{26}	0.430 (2.95) [b]	b_{26}	0.000 [d]
			Main sales effect		
DISPLAY	δ		0.872 (51.23)		

[a] R^2=0.758, n=48 614, all parameters are significant at the 0.0001 level unless noted. Note that the elasticities are negatively signed. Hence negatively signed coefficients enhance the elasticities.
[b] Significant at the 0.01 level.
[c] Significant at the 0.05 level.
[d] Fixed to zero to set a metric.
[ns] Not significant.

hypothesized relationship between price and elasticity. On the other hand, we argue that frequently promoted brands draw a more promotion sensitive consumer base and that therefore promotion price elasticity is enhanced by the frequency of promotion itself. Subsequently, this more negative elasticity may attract a larger portion of the marketing budget to support even more frequent promotions. Hence, most likely causation goes both ways in the link between promotional price elasticities and promotion frequencies.

The rational of opposite causation for advertising variables is less clearly sensible. Should brands that are more promotion price sensitive be more heavily advertised? The Dorfman–Steiner theorem suggests the opposite, ie it predicts that we need to observe lower price sensitivities with higher levels of advertising (see also Boulding *et al.*, 1992; Carpenter *et al.*, 1988; Dorfman and Steiner, 1954). Thus, we believe that reverse causation can not be a strong argument to explain our empirical results with respect to the advertising effects.

In a descriptive sense, our results bear an interesting interpretation of asymmetric promotion effects. Blattberg and Wisniewski (1989) argue that the asymmetry in promotion effects is due to heterogeneity in willingness to pay for higher quality. They find that consumers who normally buy higher priced national brands rarely switch down when lower priced store brands are promoted, while consumers who buy lower priced store brands often switch up to promoted national brands.

Assuming that brands in higher priced tiers are more frequently advertised than brands in lower priced tiers, our results indicate that advertising may very well offer an alternative explanation for the asymmetric switching effects discovered by Blattberg and Wisniewski. Namely, within the confines of our data, brands that are advertised have higher baselines and more negative elasticities. This means that these brands (1) do not portray a large sensitivity to promotions of other brands, and (2) are successful in attracting consumers from other brands.

6. Conclusion

Promotional price elasticities are typically larger, in absolute value, than elasticities for other elements of the marketing mix. Following the economic framework of Dorfman and Steiner (1954), a marketer would therefore allocate a disproportionate percentage of his or her marketing budget to promotional price cuts. A quantity that is not considered in the traditional economic analysis is baseline sales. According to our framework, a brand's baseline sales is smaller in the face of a marketing policy that allocates large percentages of the budget to promotional activity. Hence, the traditional allocation rule's blindness to the impact of the allocation rule on future response can lead to a policy that drives out high margin, unpromoted sales. This implication is powerfully reflected in the following quote from Business Week:

> [I]n category after category, brand managers are scrambling to boost quarterly sales instead of investing in image advertising to nurture brands for the long haul. To pump sales, they're shifting marketing dollars from ads into promotions...Many marketing experts believe that such strategies—carried to an extreme—run the risk of damaging valuable brand franchises that enable marketers to price their products at a premium. (Landler *et al.*, 1991)

We have attempted to model the effects of marketing policy on promotional price elasticities and baseline sales. Due to data limitations and pending unresolved issues in intertemporal aggregation, we have not been able to test our framework with time-ordered descriptors of causes and effects. This is a potential limitation of our study because cross sectional associations between variables do not rule out reverse causation or constant elasticities. However, in this paper, we offer theoretical support for why elasticities should vary with policy variables. Further, the pattern of effects we obtain empirically follow our predictions and can not be reconciled with the normative implications of constant elasticities. Nonetheless, more research is warranted.

For instance, a limitation of our study is that we assume marketing mix variables to be exogenous. Recent research in economics and marketing suggests that this may lead to biased estimates of market response (Berry *et al.*, 1995; Villas-Boas and Winer, 1996). Given the cross-sectional nature of part of our data, we can not test for endogeneity. Further, it is not likely that shifts in demand will have instantaneous effects on, for instance, advertising or pricing given observation lags and coordination issues in the retail channel. The existence of such response and observation lags and the lack of knowledge about their distribution makes the analysis of the endogeneity problem difficult to attain in the current context as the inferred cause and effect relationships will be sensitive to the causal ordering one assumes (see, eg Dekimpe and Hanssens, 1996). Finally, we are investigating relatively stable and mature categories of which it could be argued that the selling parties charge relatively stable regular prices.

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