Relating Price Sensitivity to Retailer Promotional Variables and Pricing Policy: An Empirical Analysis

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There is substantial evidence for variation in price sensitivity of products across stores and chains. Understanding the relationships between price sensitivity and promotional variables (such as price cut, feature advertising, and display), and between price sensitivity and pricing policy (Everyday Low Pricing [EDLP] and High Low Pricing [HLP]) is particularly important to retailers. We develop hypotheses on the relationships between regular price elasticity and retailer promotional variables, and between regular price elasticity and retailer pricing policy. We test these hypotheses by analyzing the variation of regular price elasticity of a frequently purchased consumer packaged brand across stores, both within and across chains, through a multistage regression analysis. In the first stage of our analysis, we use a mixed double-log model to estimate the sales response function for the brand in each store using time series data. In the second stage, we explain the differences in the estimated regular price elasticities across stores within a chain by a process function model. In the final stage, the differences across all stores and chains are explained through an aggregate process function model. We extend the literature by separating regular (long-run) price elasticity from promotional (short-run) elasticity, and by studying the influence of both strategic and tactical retailer variables on regular price elasticity in a single framework within and across chains. Our results for the brand analyzed show that a higher level of display and feature advertising together is associated with a lower level of regular price elasticity in EDLP stores and that an EDLP policy is associated with a higher level of regular price elasticity, whereas an HLP policy is related to a lower level of regular price elasticity.

INTRODUCTION

Price sensitivity varies across brands, stores, chains, and markets for most consumer packaged goods (Blattberg and Neslin, 1990). In addition, price sensitivities for such products are often intertwined with sensitivities to promotional variables such as price cut, feature

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advertising, and display. A clearer understanding of the variation in price sensitivity will help manufacturers and retailers formulate better promotional and pricing decisions.

Understanding the relationships between price sensitivity and promotional decisions and between price sensitivity and pricing decisions is particularly important to retailers. Decisions facing retailers can be viewed as strategic or tactical. Strategic decisions are decisions on product mix, pricing policy and the like. Of these decisions, the pricing policy decision is particularly significant. Typically, retailers are faced with two alternative pricing policies, an Everyday Low Pricing (EDLP) policy or a High-Low Pricing (HLP) policy. Tactical decisions include decisions on retailer promotional variables such as price cut, feature advertising, and display.

In this paper, we study the influence of retailer pricing policy as well as the influence of retailer tactical variables such as price cut, feature advertising and display, on regular price elasticity. We develop hypotheses on the relationships between regular price elasticity and retailer promotional variables, and between regular price elasticity and retailer pricing policy. We test these hypotheses by investigating the variation of regular price elasticity of a frequently purchased consumer packaged brand across stores, both within and across chains, through a multistage regression analysis. In the first stage of our analysis, we use a mixed double-log model to estimate the sales response function for the brand in each store using time series data. In the second stage, we use a process function model to explain the differences in the estimated regular price elasticities across stores within a chain. In the final stage, we explain the differences across all stores and chains through an aggregate process function model.

We extend prior research on the variation in price sensitivity in three ways. First, prior research on the relationship between price elasticity and promotional variables has produced conflicting results. While Bolton (1989a) found that increased feature advertising in the category is related to a higher level of price elasticity, Allenby and Ginter (1995), Bucklin and Lattin (1991) and Lattin and Bucklin (1989) found a negative relationship between brand feature advertising and price elasticity. These studies essentially treated regular price (long-run) and price cut (short-run) effects together under price elasticity, although there are strong theoretical reasons in favor of separating their effects (Blattberg and Neslin, 1989). We separate regular price elasticity from price cut (deal) response and analyze the relationship between regular price elasticity and promotional variables.

Second, previous research did not examine the relationship between retailer pricing policy (in terms of EDLP or HLP) and price elasticity, which we do in our paper. By analyzing both the relationships together in a single framework, we can better understand the appropriate influence of both strategic and tactical decisions of the retailer on regular price elasticity. Third, prior research on price elasticity variation has restricted its focus to variation across stores or geographical territories (Bolton, 1989a; Wittink, 1977). Price elasticities of brands, however, have been found to vary among stores within a chain, as well as across different chains (Blattberg and George, 1991). We study the systematic variation of regular price elasticity both within and across chains, providing additional insights.

Our analysis shows two important results for one brand in a particular category. First, we find that a higher level of display and feature advertising together is associated with a lower level of regular price elasticity in stores that follow an EDLP policy. Second, we show that an EDLP policy is associated with a higher level of regular price elasticity, whereas an HLP policy is related to a lower level of regular price elasticity.

The rest of the paper is organized as follows. The next section reviews the literature on the relationship between price sensitivity and advertising. In section three, we develop hypotheses on the relationship between price sensitivity and retailer promotional variables, and between price sensitivity and retailer pricing policy. Sections four and five describe the data and the model formulation respectively. The model estimation and results are presented in section six. The paper ends with a section on discussion, managerial implications, limitations, and future research.

ADVERTISING-PRICE SENSITIVITY RELATIONSHIP

We first examine the relationship between advertising and price sensitivity and will apply the theoretical reasoning in the advertising-price sensitivity literature to examine the influence of tactical variables such as feature advertising and display on regular price sensitivity in the retail context. Although factors such as availability of close substitutes, and availability of information about brands and their prices may also influence price sensitivity in addition to advertising, we focus on advertising because it is a key decision variable of managerial interest in our context. The advertising-price sensitivity relationship has been explored by many researchers in different settings (for a detailed review, please see Kaul and Wittink, 1995).

Two theories are used to explain the effects of advertising on price elasticity. The first theory, *the market power theory of advertising*, postulates that advertising reduces price elasticity primarily by increasing brand loyalty (Comanor and Wilson, 1979). The second theory, *the information theory of advertising*, contends that advertising increases price elasticity by exposing consumers to information about alternative brands (Nelson, 1974, 1975).

A number of marketing studies on the effects of advertising on price sensitivity are summarized in Table 1. Our interest is in the generalizability of the results in these studies to the retailing context of our study. We highlight certain key aspects of these studies that may be relevant to our context.

From Table 1, we can see that some studies support the market power theory, while others are consistent with the information theory. Although it appears that the effect of *price* advertising on price sensitivity may support information theory and that of *nonprice* advertising may support market power theory (Kaul and Wittink, 1995), this does not explain the results of Prasad and Ring (1976) and Eskin and Baron (1977), who found the effect of nonprice advertising to support the information theory. It is difficult to draw a general conclusion from the studies because of several significant differences among the studies. First, the dependent variable is different in nearly every study. Second, the price measure also varies across the studies. For example, although Krishnamurthi and Raj (1985), Prasad and Ring (1976), and Wittink (1977) use relative price as the price measure, it is operationalized differently in their studies. Third, the level of data aggregation is different across the studies, varying from household level data as in Kanetkar, Weinberg and Weiss (1992) and Krishnamurthi and Raj (1985), to store level data as in Eskin and Baron (1977), and territory

TABLE 1

Effect of Advertising on Price Sensitivity

Authors	*Dependent Variable*	*Experiment*	*Product Category*	*Type of Advertising*	*Results*	*Explanation*
Prasad & Ring (1976)	Weekly panel market share	Yes; TV advertising; experimental & control panel	Grocery, food item	Non-price; product class TV advertising	Price sensitivity higher in high advertising condition than low advertising	Supports "information theory"
Lambin (1976)	Brand price elasticity	No; data on European markets	Variety of consumer packaged goods	TV, radio and newspaper advertising	Brands with high advertising intensities have low price elasticities	Supports "market power theory"
Eskin & Baron (1977)	Monthly unit retail sales	Yes; store-level; price and advertising changed	3 food, 1 non-food; all new products	Non-price; attribute oriented TV adv.	Negative advertising price interaction	Supports "information theory"
Wittink (1977)	Brand price elasticity	No; data from sales territories	Unspecified; major frequently purchased national brand	Unspecified but TV advertising	Price elasticity higher in territories with high advertising levels	Supports "information theory"
Sawyer et al. (1979)	Product choice	Lab experiment; 5 price levels; with or without product information	Maple syrup	Non-price information	Higher purchase prob. at high price levels when information is provided	Supports "market power theory"
Gatignon (1984)	Price sensitivity	No; data on airline routes	Air travel	Unspecified; TV and print advertising	Price sensitivity higher under high adv. levels and high comp. reactions	Supports "information theory"

Krishnamurthi & Raj (1985)	Household weekly purchase	Yes; split cable TV advertising experiment; experimental and control groups	Unspecified; dominant established brand in frequently purchased category	Non-price mood oriented TV advertising	Price elasticity unchanged in ctl. panel, decreased when advertising was increased in exp. panel	Supports "market power theory"
Popkowski & Rao (1990)	Brand price elasticity	No; supermarket data	Unspecified; mature consumer packaged good	Local and national advertising; print and TV	Local advertising increases price elasticity; national adv. decreases it	Supports both theories
Kanetkar et al. (1992)	Household brand choice	No; single source Nielsen scanner data	Aluminum foil, dry dog food	Unspecified TV advertising	Higher choice price sensitivity with increased advertising exposures	Supports "information theory"
Mitra & Lynch (1995)	Price elasticity	Yes: lab experiments	Candy bars	Unspecified	Advertising increases price elasticity in memory based environment; decreases elasticity in stimulus based environment	Supports both theories
Kalra & Goodstein (1995)	Price sensitivity	Yes; 3 types; value, celebrity, comparative	High involvement categories	Print	Value advertising increases brand price sensitivity; unique attribute and differentiation advertising lower price sensitivity	Supports both theories

level data as in Wittink (1977). Fourth, six of the eleven studies summarized in the table use experimental data, whereas the others use archival data. Fifth, the type of advertising is different in different studies, e.g., TV vs. print, national vs. local, and price vs. nonprice. Sixth, all the studies investigated established products except for Eskin and Baron (1977) who studied new products. Some of these differences could have contributed to the support for both the theories on advertising-price sensitivity relationship.

Some studies attempt to reconcile both the theories (Gatignon, 1984; Kalra and Goodstein, 1995; Mitra and Lynch, 1995; Popkowski and Rao, 1990). Gatignon (1984) suggests that the relationship between advertising and price elasticity may be moderated by competitive reactions in the market. Kalra and Goodstein (1995) show that the advertising-price sensitivity relationship depends on brand positioning strategies.

Mitra and Lynch (1995) suggest that the effect of advertising on price sensitivity is mediated by two constructs, namely, size of the consideration set and relative strength of preference. If advertising increases (decreases) the consideration set size it may lead to a higher (lower) price sensitivity. At the same time, advertising could increase the relative strength of preference for the brand, resulting in a lower price sensitivity. The observed result of the impact of advertising on price sensitivity would thus be a net result of the effects of these two mediating constructs.

Popkowski and Rao (1990) find that local advertising increases price elasticity whereas national advertising decreases it. Local advertising is typically price oriented advertising whereas national or manufacturer advertising is typically nonprice advertising.

Our study shares the following operational details with some of the studies in Table 1: it focuses on the retail environment as in Eskin and Baron (1977), examines feature advertising in newspapers and display advertising in stores as in Popkowski and Rao (1990), evaluates price elasticity of a leading brand as in Krishnamurthi and Raj (1985), and follows the multistage modeling approach first adopted by Wittink (1977). Our study, however, does not consider manufacturer advertising because our focus is on retailer decisions and because our data are at the retailer level.

CONCEPTUAL DEVELOPMENT AND HYPOTHESES

We now examine the relationship between price elasticity and retailer tactical variables such as feature advertising, display and price cut, and the link between price elasticity and a retailer strategic variable such as pricing policy.

Price Elasticity and Retailer Promotional Variables

Consider first, the relationship between price sensitivity and feature advertising and display. The results from studies relating feature advertising and display to price sensitivity are mixed. Some studies support the information theory, while the others are consistent with the market power theory.

In an extensive study of four product categories, Bolton (1989a) examined the promotional price elasticity of a brand as a function of the frequency with which the brand and its category were featured and were on display. She found that brands with high *category* feature frequency had a higher price elasticity than those with low category frequency, supporting the information theory for the impact of category feature activity. Interestingly, *brand* feature advertising activity did not have any significant effect on price elasticity. In contrast, display frequency (category and brand) had the opposite effect on price elasticity, consistent with the market power theory, although at a lower statistical significance level than category feature frequency. An explanation for the opposite effects of feature and display may lie in the differential nature of exposure to feature and display. Frequent exposure to *category* feature advertising (which is typically local in scope) occurs at home, and such advertising can induce consumers to compare prices of brands within the category and increase their price sensitivity, consistent with the findings of Popkowski and Rao (1990). In contrast, repeated exposure to displays which occurs in the store, may influence consumers to focus more on the displayed brand, lowering their price sensitivity.[1]

Bucklin and Lattin (1991) and Lattin and Bucklin (1989) found a positive interaction between price and promotion (defined as feature advertising *or* display) while studying markets for crackers and ground coffee respectively. This interaction implies that the effect of price is less substantial in the presence of feature or display, i.e., feature or display tends to be associated with lower price elasticity. Allenby and Ginter (1995), in an analysis of canned tuna, also found that brand level in-store display and feature activities serve to decrease household price sensitivity. These results support market power theory, which differs from Bolton's (1989a) findings with regard to the influence of category feature on price sensitivity.

Three possible explanations can be offered for the different findings. They are based on (1) level of feature activity (category or brand); (2) the treatment of the feature advertising and the display variables; and (3) the type of price elasticity analyzed. First, Bolton's (1989a) result is based on *category* feature activity, whereas the results of the other studies are based on *brand* feature activity. Category feature activity will likely induce more price comparison than brand feature activity. Second, Bolton (1989a) treated feature and display separately, whereas both Bucklin and Lattin (1991) and Lattin and Bucklin (1989) combined the two into a single variable. The use of a combined variable would reflect the net impact of both feature and display which could be positive or negative depending on the separate influences of feature and display. Third, Bolton (1989a) studied quantity elasticity, while Allenby and Ginter (1995), Bucklin and Lattin (1991), and Lattin and Bucklin (1989) examined choice elasticity. There is empirical evidence to show that the direction of change in these two types of elasticities may not be the same (Krishnamurthi and Raj, 1988).

These studies used actual/promoted price as the price measure, and did not treat the effects of regular price and price cut separately. This failure to separate regular price and price cut effects on sales response may have confounded the impact of price and promotion in the existing literature. There are strong theoretical reasons to expect consumers to behave differently to changes in regular price and price cuts, that underscore the need to separate the effects of regular price and price cuts (Blattberg and Neslin, 1989). First, changes in regular price typically lasts for a longer period of time than temporary price cuts. This difference implies different consumer transactional utilities for price cuts vis-a-vis regular price changes. Second, consumers may stockpile on price cuts/deals, but not on regular price reduction because price cuts last for a much shorter duration than regular price reduction. Third, a change in regular price, may not be signaled, but may have to be inferred by consumers, unlike a price cut which could be accompanied by feature advertising and/or display. Therefore, there is less anticipatory consumer response to regular price changes, unlike the case of price cuts. Furthermore, several price-promotion models include regular price and price cut as separate independent variables (Blattberg and George, 1991; Guadagni and Little, 1983). Therefore, it is important to separate the effects of regular price and price cut on brand sales in studying variation in price sensitivity.

We study quantity elasticity, operationalize feature and display separately, separate the effects of changes in regular price from that of price cuts, and focus our investigation on the variation of *regular* price elasticity. In a managerial sense, regular price elasticity can be viewed as the long-run price elasticity, whereas price cut/deal elasticity can be regarded as the short-term price elasticity. Promotional price elasticity includes the effect of price cuts, which are temporary, and, is therefore, more representative of short-run price elasticity. From a managerial standpoint, regular price elasticity is a better indicator of the *long term* strength of the brand than either price cut or promotional price elasticity.

The relationship between feature or display and regular price elasticity could be explained in terms of whether they highlight brand salience or price salience. If feature and display increase brand salience more than price salience, they tend to differentiate the brand from the rest of the brands in the category. By increasing the salience of the brand, feature and display may serve to increase the relative preference of the brand over other brands. Increased relative preference of the brand will likely lead to a lower regular price elasticity (Mitra and Lynch, 1995).

If feature and display increase brand salience, they could also reduce the consideration set or the number of alternatives that consumers are likely to process. Typically, consumers choose brands based either on their memory or on marketing stimuli or both. Mitra and Lynch (1995) argue that information from stimuli such as feature and display strongly control the size of the consideration set in a stimulus-based environment such as that for consumer packaged goods. When feature and display increase brand salience, the consideration set size is reduced. A decrease in consideration set size will, in turn, reduce price comparisons of the featured and displayed brand with other brands in the category, resulting in a lower regular price elasticity for the displayed and featured brand, consistent with market power theory.

Essentially, by serving as credible signals of brand differentiation and of reduction in consideration set size, higher levels of feature and display may obviate the need for the consumer to compare brand prices.[2] By decreasing the price comparisons they make, consumers are more likely to choose the highlighted brand, resulting in a lower regular price elasticity for the brand.

On the other hand, if feature and display increase price salience more than brand salience, they tend to induce the consumers to compare prices of different brands within the category. Frequent price comparisons could heighten consumers' sensitivity to prices. Consequently, one would expect a higher regular price elasticity to be associated with higher levels of feature and display, consistent with information theory.

Brand feature and display could increase brand or price salience depending on the level of consumer involvement in the category. The signaling power of brand feature and display in differentiating the brand and in making it more salient, may be particularly high in relatively low involvement product categories (Allenby and Ginter, 1995). In such categories, increased levels of brand feature and display may serve to reduce cognitive efforts involved in brand choice. This enables the featured and displayed brand to be perceived as differentiated from the rest of the brands, leading to a lower regular price elasticity. Conversely, brand feature and display may serve to increase regular price elasticity in high involvement categories.

Summarizing from the above discussion, we can formulate the following hypothesis.

> **H1**: *Low involvement brands at stores with higher incidence of feature and display are expected to have lower regular price elasticity, regardless of whether they are EDLP stores or HLP stores, all else equal.*

For high involvement brands, on the other hand, the predicted relationship in **H1** will likely be in the opposite direction.

Consider next the relationship between regular price elasticity and the average depth of price cut in the store. This relationship is important from a retailer's standpoint because average depth of price cut may have an important bearing on the timing of consumer purchases. If a store offers deep price cuts on average, its customers may stockpile or accelerate their purchases by buying primarily when there are deep price cuts. Over a period of time, they may become conditioned to expect deep price cuts, and buy predominantly when such price cuts are offered. Frequent or deep price cuts may also result in a lower reference price for the brand (Blattberg and Neslin, 1989). Because regular price is closely related to consumer reference price, this situation implies a lower perceived regular price. Consequently, consumers may tend not to respond much when regular price is actually reduced. This reasoning suggests that stores with deeper average level of price cut are likely to exhibit lower regular price elasticities. As in the case of **H1**, we expect this to be the case, regardless of the pricing policy of the store. This leads us to the following hypothesis.

> **H2**: *Brands at stores with higher average depth of price cut are expected to have lower regular price elasticity, regardless of whether they are EDLP or HLP stores, all else equal.*

Price Elasticity and Retailer Pricing Policy

The relationship between regular price elasticity and retailer pricing policy can be predicted on the basis of consumer self-selection.

Consumer Self-Selection of Stores

A store's pricing strategy serves to draw a certain type of customer to that store. Different stores have different customer profiles. Heterogeneity exists not only in consumer demographics, but also in consumers' response to a strategic marketing variable such as the pricing policy of a store or chain. A price conscious consumer will likely choose an EDLP store over an HLP store because he/she can be relatively certain that, on average, he/she will find lower prices for a basket of items. It has been documented that the incidence of regular price of a brand at an EDLP store being equal to or greater than that in an HLP store is very rare (regular prices in EDLP stores were on average about 11% below those in HLP stores; see Hoch, Dreze and Purk, 1994). Although the actual price for any one item at an EDLP store may not be lower than that for a corresponding item at an HLP store in any given week, the *effective* price for a basket of items at an EDLP store is likely to be lower than that at an HLP store, if one were to include search costs of locating the store with the lowest actual price for each item in the consumer's shopping basket. One would expect the search cost of identifying stores with the lowest actual price for each item in the consumer's basket to be high, especially for time sensitive consumers.[3] Since an EDLP store offers the assurance of lower average regular prices on a basket of items, price sensitive consumers can hedge their search costs by leaning more toward purchase in an EDLP store. Thus, an EDLP store is most likely to draw consumers with high regular price sensitivity. In contrast, HLP stores will likely appeal to consumers who respond more to price cuts than they do to changes in regular price.

These arguments are summarized by the following hypothesis.

> **H3**: *Regular price elasticity is expected to be higher for brands in EDLP stores than in HLP stores, all else equal.*

DATA

We test the hypotheses using store level data from A.C. Nielsen for a leading brand-size of mouthwash, a relatively low involvement supermarket product category, for a single metropolitan market. The dataset represents a maximum of 104 weekly observations per store on store-level variables such as sales, regular price,[4] and promotional variables such as price cut, feature, and display. Price cut, also known as temporary price reduction, is the difference between regular price and actual price for a given week. Regular price, actual price, and price cut are available directly from the data.[5]

The brand-size selected for investigation was the most widely sold brand-size across all stores and chains. Other brand-sizes were not sold in a significant number of stores in the market. Furthermore, among all the brand-sizes in the category, the selected brand-size also had the highest variability in regular price and promotional variables that could permit a detailed analysis of regular price variation. Therefore, the leading brand-size was chosen for analysis. Among twelve chains that the product category was sold in, two chains collectively generated about 70% of the unit sales for the brand-size. Other chains were made up of only two to four stores. Therefore, only the top two chains were chosen for further analysis. Chain 1 comprised 20 stores and chain 2 was composed of 18 stores.

Chain 1 was classified as an EDLP chain and chain 2 an HLP chain by the data provider based on knowledge of these chains in that metro market. To verify this notion for the product category analyzed by us, we computed the means and the variances of regular price and price cut of the selected brand-size for each store within each chain and compared the two chains. Our analysis of the two chains provides two important results, supporting the notion that chain 1 is indeed more of an EDLP chain and chain 2 is more of an HLP chain. First, the mean of the average regular prices of stores in chain 1 (304.9) is significantly lower ($p < 0.01$) than that in chain 2 (322.9). This is consistent with the finding reported in Hoch et al. (1994, p. 17) that EDLP store prices are, on average, lower than HLP store prices on an everyday basis.

Second, chain 1 is characterized by higher variance in regular prices relative to the variance in price cuts, when compared to chain 2. This is consistent with one's expectation that an EDLP store will have a greater variation in its regular price compared to an HLP store, which tends to have a more stable regular price, but has greater variation in price cuts. A summary of the means and standard deviations of regular price and price cut variables, and the ratio of the standard deviation of price cut to that of regular price (relative standard deviation) is provided in Table 2. The relative standard deviation is less than one for most stores in chain 1. In chain 2, on the other hand, it is greater than one for all stores, and is greater than two in most stores.

Stores in chain 1 offer promotions in the form of price cut, feature, and display. Although this observation may run counter to the popular belief that EDLP stores do not offer promotions, it supports Hoch et al. (1994)'s assertion that EDLP is best seen as a continuum. Hoch et al. (1994, p. 17) argue "that a pure EDLP strategy characterized by constant prices (no temporary price cuts) is apparently not pursued widely in practice. Even Food Lion, an acknowledged EDLP limited assortment chain with over 1000 outlets, offers hundreds of temporary price reductions each week." Therefore, we conclude that chain 1 is more of an EDLP chain, whereas chain 2 is more of an HLP chain in the pricing policy continuum.

Feature and display levels varied across the stores in chain 1, suggesting that some stores make independent promotional decisions, consistent with the practice of zone promotions found in many chains (see Blattberg and George, 1991). In contrast, the feature levels did not vary as much across the stores in chain 2 as in chain 1. There were no incidence of displays in the stores in chain 2. The relative levels of display are consistent with the finding of Information Resources, Inc. (IRI)'s report (1993) that EDLP stores use displays more often than HLP stores.

MODEL FORMULATION

To test the hypotheses, we develop the models in three stages. First, we estimate regular price elasticity for each store using an appropriate sales response model. Second, we formulate a model relating regular price elasticity with retailer level strategic and tactical variables across stores *within* each chain. Third, we develop a similar model linking regular price elasticity *across* chains.

For the sales response model, we selected unit sales as the dependent variable and regular price (which is the focal variable), price cut, feature, display, highest competitive price cut,

TABLE 2

Means and Variances of Regular Price and Price Cut

	Mean Regular Price (cents)			*SD Regular Price*			*Meance Price Cut (cents)*			*SD Price Cut*			*Relative SD*		
Chain	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*	*Min*	*Max*	*Mean*
1	301.1	322.4	304.9	12.0	14.4	13.1	9.9	20.1	12.6	6.7	16.9	9.7	0.6	1.2	0.8
2	314.1	340.5	322.9	6.4	19.2	9.2	9.3	31.8	23.1	16.3	30.2	23.1	1.2	4.2	2.8

and lagged dependent variable, as the explanatory variables. Unit sales is most commonly used in sales response models for store level scanner data (Blattberg and George, 1991). Market share does not appear to be an appropriate choice for the dependent variable when weekly data are used because of the dramatic expansion and contraction of category volume due to promotions. The operationalization of regular price and promotional variables is consistent with the operationalizations used by Guadagni and Little (1983), Gupta (1988), and Neslin, Henderson and Quelch (1985).

To model the response function, a mixed double-log model was selected. The model is double-log with respect to regular price, price cut, and competitive price cut. It is semi-log with respect to the indicator variables such as feature, display and feature and display together. Although alternative models such as linear and semi-log models were also tried, the mixed double-log model was selected because: (1) regular price elasticity is directly provided by the estimated parameters, consistent with a well accepted behavioral explanation that consumers respond to percentage changes in price; (2) it provided better fits in terms of lowest sum of squared error for a greater number of stores; and (3) overstatement of elasticity estimates if any, is lowest for the double-log form when compared to linear and semi-log forms (Bolton, 1989b).

Thus, the following model is used for the sales response function for each store in the first stage of analysis.

$$LS_{ijt} = \beta_{0ij} + \beta_{1ij}LPR_{ijt} + \beta_{2ij}LPCR_{ijt} + \beta_{3ij}FT_{ijt} + \beta_{4ij}DP_{ijt} + \beta_{5ij}FTDP_{ijt} + \beta_{6ij}LCPC_{ijt} + \beta_{7ij}LS_{ij(t-1)} + \varepsilon_{ijt} \quad (1)$$

where $i = 1, 2, \ldots n_j$ denotes the store, $j = 1, 2$ the chain, t the week of observation, and

LS_{ijt} = Logarithm of unit sales
LPR_{ijt} = Logarithm of regular price in cents
$LPCR_{ijt}$ = Logarithm of price cut ratio
= $\log(1 + PCR_{ijt})$
PCR_{ijt} = (Price Cut/Regular Price)
FT_{ijt} = Presence or absence of feature advertising only
= 0 (absence)
= 1 (presence)
DP_{ijt} = Presence or absence of display only
= 0 (absence)
= 1 (presence)
$FTDP_{ijt}$ = Presence or absence of display and feature together
= 0 (absence)
= 1 (presence)
$LCPC_{ijt}$ = Logarithm of highest price cut ratio of competitive brands
= $\log(1 + CPC_{ijt})$
CPC_{ijt} = Highest price cut ratio among competitive brand-sizes
β_{0ij} = Intercept term
β_{1ij} = Regular price elasticity of the brand in store i, chain j

$\beta_{2ij},\ldots \beta_{7ij}$ = Coefficients of other variables in store i, chain j

ε_{ijt} = Stochastic disturbance term assumed to be independent and identically distributed normal with mean 0 and variance $\sigma^2_{\varepsilon ij}$.

The effect of price cut is captured through the price cut ratio variable $(1 + PCR_{ijt})$. We use this variable, and not magnitude of price cut, because of the following reasons. The price cut ratio variable (PCR_{ijt}) captures consumer behavior better than the magnitude of price cut since consumers typically respond more to price cuts relative to the original price, than they do to the absolute magnitude of price reductions. For example, a price cut of 20 cents on product A with a regular price of $1 is more attractive than a price reduction of 30 cents on product B with a regular price of $3, although the price cut on product A is less than that on product B in magnitude. We modify the price cut ratio by adding one to it to mitigate the problem that may arise in estimation of a double log model when price cut ratio is zero. Our operationalization of price cut is consistent with that used by Blattberg and Wisnewski (1988).

The competitive promotional effect is captured through the variable $LCPC_{ijt}$. This operationalization recognizes that the competitive brand-size with the highest price cut ratio (CPC_{ijt}) during any given week should have the maximum competitive impact on the brand-size studied.[6] The modified competitive price cut is consistent with the operationalization of own price cut ratio.

In addition to having feature and display as independent variables, an interaction variable was also chosen consistent with prior studies. Since display is an in-store promotional vehicle for the brand, the joint effect of display and feature should serve as a reinforcement for those consumers already exposed to the feature advertisement, thereby increasing their likelihood of purchase. We operationalize display, feature, and the joint effect of feature and display as three separate variables representing *display only, feature only, and feature and display together.*

The lagged dependent variable $LS_{ij(t-1)}$ is included to capture the dynamics of sales response and to eliminate residual serial correlation (see Blattberg and George, 1991).

In the second stage of analysis, we formulate a process function model to explain variation in price elasticity across stores *within* a chain. The regular price elasticity becomes the dependent variable in this stage of analysis. The possible factors influencing cross-sectional variability in price elasticity include marketing variables, consumer characteristics and environmental variables (Wittink, 1977). Because we want to relate retailer promotional variables to regular price elasticity and we do not have data on consumer characteristics or environmental variables, we choose the following variables as the independent variables for this stage of analysis: average depth of price cut, and proportions of incidence of feature advertising only, display only, and feature and display together.

The following process model is formulated separately at the chain level.

$$\beta_{1ij} = \gamma_{0j} + \gamma_{1j}MPC_{ij} + \gamma_{2j}PFT_{ij} + \gamma_{3j}PDP_{ij} + \gamma_{4j}PFTDP_{ij} + u_{ij} \tag{2}$$

Notice that we have included an error term u_{ij} in Equation 2 to allow for unexplained cross-sectional variation in β_{1ij}. Regular price elasticity estimated from Equation 1 is given by:

$$\hat{\beta}_{1ij} = \beta_{1ij} + \omega_{ij} \tag{3}$$

From Equations 2 and 3, we get:

$$\hat{\beta}_{1ij} = \gamma_{0j} + \gamma_{1j}MPC_{ij} + \gamma_{2j}PFT_{ij} + \gamma_{3j}PDP_{ij} + \gamma_{4j}PFTDP_{ij} + e_{ij} \tag{4}$$

where $\hat{\beta}_{1ij}$ is the estimated regular price elasticity for store i in chain j, and

MPC_{ij} = Mean price cut in cents
PFT_{ij} = Proportion of weeks with feature advertising only
PDP_{ij} = Proportion of weeks with display only
$PFTDP_{ij}$ = Proportion of weeks with both display and feature
$\gamma_{1j}, \ldots \gamma_{4j}$ = Coefficients of the above variables
γ_{0j} = Intercept term
e_{ij} = Mixed heteroscedastic error consisting of a homoscedastic error u_{ij}, i.i.d. normal with mean 0 and variance σ_u^2, and a heteroscedastic error ω_{ij} from the estimated $\hat{\beta}_{1ij}$ with variance $\sigma_{\omega ij}^2$.

To examine the significance of the effect of retail pricing policy on price elasticity, we use a final stage model in which the estimated regular price elasticity is pooled for all stores across chains. In the final stage, we express estimated regular price elasticity of each store as a linear function of the mean levels of the promotional variables as in the second stage. In addition, we make the intercept and the coefficients of the mean level of promotional variables a linear function of a chain dummy variable, to reflect the impact of the type of pricing policy (EDLP or HLP) on regular price elasticity with chain 1 as the base model. The process model for the final stage is as follows:

$$\hat{\beta}_{1ij} = \delta_0 + \delta_1 MPC_{ij} + \delta_2 PFT_{ij} + \delta_3 PDP_{ij} + \delta_4 PFTDP_{ij} + v_{ij} \tag{5}$$

where:

$$\delta_k = \delta_{k1} + \delta_{k2} * DUM, \qquad k = 0, \ldots, 4 \tag{6}$$

DUM = Dummy variable for chain 2
= 1 (for chain 2 stores)
= 0 (otherwise)
δ_{01}, δ_{02} = Intercept term and incremental intercept for chain 2
$\delta_{11}, \ldots \delta_{42}$ = Coefficients of the explanatory variables
v_{ij} = Error with the same properties as e_{ij}, but with different variance

ESTIMATION AND RESULTS

Estimation

We estimate the models in three stages. First, we estimate regular price elasticity in the sales response Model 1. Second, we estimate Model 4, and finally Model 5. We estimate the models in multiple stages rather than in a single stage to account for the *mixed heteroscedasticity* in the error terms of Models 4 and 6, consistent with the approach of Wittink (1977). In the second and final stage models, the estimate of regular price elasticity obtained from the first stage serves as the dependent variable. This variable is subject to a mixed heteroscedastic error (a combination of homoscedastic and heteroscedastic components) and the estimation procedure should capture this stochastic uncertainty. It can be shown that Ordinary Least Squares (OLS) estimates for the second and final stage models will not be efficient, although they will still be unbiased. By using information about the estimated variance of the sampling error (ω_{ij}) in the dependent variable from Equation 3, it is possible to obtain more efficient parameter estimates than those of OLS, using a multistep estimation process (Hanushek, 1974). Because the homoscedastic error (u_{ij}) from Equation 2, unlike the error (ω_{ij}) in Equation 3, is unknown and cannot be directly estimated, we cannot efficiently estimate the regular price elasticity (β_1) in a single stage, without making restrictive assumptions on the estimates of the error component u_{ij}. We, therefore, use the multi-stage analysis to estimate the second stage and final stage process models (for details, see Hahn, Park, Krishnamurthi and Zoltner, 1994; Wittink, 1977).

We estimate the first stage model for each store using OLS. We examined the correlation matrix of independent variables for each store to check for any problems of multicollinearity. There were only three instances of high correlation (above 0.6) among the independent variables in Equation 1. Therefore, the correlations were not seriously high enough to warrant further analysis of multicollinearity.

Results

The results of the first stage of analysis are provided in Table 3. Table 3 shows the estimated regular price elasticities for different stores classified under their respective chains, together with the response coefficients of the promotional variables.

The first stage model fits the data well for most stores in chain 1 (17 out of 20 stores have R^2 of 0.5 and above). The signs of regular price elasticity and own promotional variables, where significant, are also intuitive. Regular price is significant in 90% of the stores in chain 1 (18 out of 20). Price cut is significant in 75% of the stores (15 out of 20). Feature advertising only is significant in 25% of the stores and display only is significant in 45% of the stores. On the other hand, the joint effect of feature and display is significant in all stores, where present. A major reason for this finding is that the average frequency of feature and display together is greater than the average frequency of either feature only or display only in chain 1. Competitive price cut is insignificant in all but one of the stores. Lagged dependent variable is significant only in 20% of the stores. Analysis of Durbin *h*-statistic for test of serial correlation in the presence of a lagged dependent variable (Johnston, 1984, p. 318) showed that serial correlation is not a serious problem in the data.[7]

The results of the first stage model for chain 2 are broadly similar to those for chain 1. Regular price is negative and significant in 94% of the stores (17 out of 18), price cut is significant in 83% of the stores (15 out of 18), feature advertising only is significant in 17% of the stores (3 out of 18), and competitive price cut is significant in only one store. The

TABLE 3

Summary of Estimated Slope Parameters for Store-Level Models

Store	*Regular Price*	*Price Cut*	*Feature Only*	*Display Only*	*Feature and Display*	*Competitive Price Cut*	*Lagged Dependent Variable*	R^2	*Number of Weeks#*
					Chain 1 (EDLP)				
1	−4.24**	1.20*	−0.01	0.13	1.39**	−0.24	0.25**	0.62	104
2	−5.10**	0.04	0.30	0.31*	1.43**	−0.31	0.31**	0.60	104
3	−3.45**	1.43**	0.57*	0.61	1.74*	0.21	−0.00	0.75	82
4	−4.05**	0.99*	0.00	0.32	1.44**	−0.21	0.03	0.67	104
5	−6.24**	0.18	0.84**	—	—	0.22	0.31**	0.54	66
6	−7.93**	1.87**	−0.01	0.48**	1.19**	0.49	−0.05	0.77	103
7	−3.40**	1.97**	0.29	0.09	1.75**	0.23	0.08	0.68	104
8	−5.26**	1.53*	0.56**	0.11	1.51**	0.57	0.15	0.52	104
9	−1.03	1.84**	−0.08	0.43	1.61**	0.70	0.02	0.60	104
10	−6.45**	0.91*	0.00	0.39**	1.29**	−0.05	0.01	0.76	104
11	−5.46**	1.51**	0.23	0.48**	1.59**	0.44	0.05	0.70	104
12	−3.20**	0.39	0.58*	0.09	0.87**	−0.10	0.44**	0.51	104
13	−5.82**	1.44**	−0.23	−0.09	0.95**	−0.44	0.10	0.67	104
14	−6.94**	1.01	0.81**	0.35**	1.45**	0.43	0.07	0.46	104
15	−6.10**	2.77**	0.48	−0.27	1.20**	0.28	0.17	0.48	90
16	−1.26	1.73**	0.02	0.28*	1.30**	−0.03	−0.05	0.51	104
17	−6.49**	1.54*	0.30	0.46**	1.11**	−0.46	0.17	0.53	104
18	−4.54**	0.86	−0.07	0.15	1.28**	−0.37	0.14	0.65	104
19	−3.71**	1.70**	0.24	0.39*	1.10**	0.44	−0.05	0.47	93
20	−5.81**	1.67**	−0.05	0.23*	0.92**	−0.73*	0.12	0.70	104
					Chain 2 (HLP)				
1	−3.59**	1.37*	0.31	—	—	−0.35	0.28**	0.54	104
2	−3.76**	3.40**	-	—	—	0.77	0.02	0.36	92
3	−5.15**	2.49**	0.21	—	—	0.05	0.23**	0.76	104
4	−4.45**	1.17	0.32	—	—	−0.67	−0.07	0.28	103
5	−2.15**	3.83**	0.01	—	—	0.62	0.08	0.45	104
6	−3.59**	4.17**	—	—	—	0.73	0.32**	0.46	103
7	−4.18**	2.92**	−0.01	—	—	−0.05	0.23**	0.46	104
8	−4.69**	2.90**	0.20	—	—	0.41	0.06	0.60	104
9	−4.05	5.11**	−0.41	—	—	−1.15	0.05	0.32	58
10	−1.00*	1.46	0.62**	—	—	0.25	0.36**	0.50	104
11	−5.13**	3.23**	0.12	—	—	−0.06	0.08	0.58	104
12	−7.83**	2.93**	—	—	—	−0.51	0.19*	0.60	90
13	−3.25**	1.77*	0.30	—	—	−0.21	0.23*	0.63	104
14	−8.37**	4.19**	−0.09	—	—	0.72	0.09	0.53	89
15	−3.77**	3.06**	0.10	—	—	0.26	0.35**	0.61	104
16	−3.54**	3.08**	0.10	—	—	−0.05	0.10	0.54	104
17	−0.85*	1.63*	0.55**	—	—	0.11	0.40**	0.53	104
18	−1.62*	1.43	0.55*	—	—	1.05*	0.16	0.31	100

Notes: *Significant at 0.05 level.
** Significant at 0.01 level.
— Indicates absence of the variable.
Stores with number of weeks less than 104 either did not stock the brand during certain weeks, or were not included in the data.

differences are that the fit of the models in chain 2 are worse than in chain 1 with only 11 out of 18 stores having an R^2 of 0.5 and above. The lagged dependent variable is significant in a greater number of stores (50% vs. 20%). Unlike chain 1, where feature and display together had a significant positive effect on sales, in chain 2, there were no instances of the brand being featured and displayed together. The key differences are that the average price cut (deal) response parameter is about twice as large in the HLP chain 2 than in the EDLP chain 1 (2.72 vs. 1.33) and the average magnitude of the regular price elasticity is lower in the HLP chain 2 than in the EDLP chain 1 (3.94 vs. 4.83).

Before proceeding with the second and final stages of regression analysis, we tested for homogeneity of regular price elasticity across the stores using the Chow test (Chow, 1960). The null hypothesis that regular price elasticity is equal across the stores was rejected separately in chain 1 ($p < 0.001$) and in chain 2 ($p < 0.001$). We, therefore, concluded that the regular price elasticity is indeed different across stores within each chain.

The significance and signs of the parameters in Models 4, 5 and 6 are of central interest to us in testing the hypotheses. To test **H1**, we examine the parameters of feature only, display only, and feature and display in the process models for chains 1 and 2, and in the final stage model, as appropriate. To test **H2**, we check the parameter for mean price cut in the second stage and the final stage models. Finally, to test **H3**, we examine the incremental intercept parameter in the final stage model.

Table 4 shows the results of the estimated process model for chain 1. From table 4, we observe that feature and display together is a significant determinant of regular price elasticity ($p < 0.01$). Feature advertising only is also significant, although at a lower significance level ($p < 0.05$). Display only, however, is not significant. The results imply that higher levels of feature and display together and feature alone are associated with a lower regular price elasticity. Because mouthwash is a relatively low involvement product cate-

TABLE 4

Second Stage Process Model of Regular Price Elasticity[a] in Chain 1 (Adjusted R^2 = 0.47; RMSE = 4.71; df = 15)

Parameter	*Value (Std. Error)*
Intercept (γ_{01})	25.12**
	(6.39)
Price cut parameter (γ_{11})	−0.20
	(0.18)
Feature only parameter (γ_{21})[b]	−223.71*
	(110.75)
Display only parameter (γ_{31})	14.36
	(15.36)
Feature and Display parameter (γ_{41})	−215.18**
	(63.10)

Notes: a. For ease of interpretation, the dependent variable in the second stage regression is the absolute value of the regular price elasticity.
b. It may be noted that feature only, display only and feature and display together are measured in proportion of weeks.
** Significant at 0.01 level.
* Significant at 0.05 level.

gory, our result supports **H1**. With respect to **H2**, depth of price cut is not a significant determinant of regular price elasticity. Thus, **H2** is not supported for chain 1.

No store in chain 2 had any instance of display only or display and feature together during the period of data. Therefore, **H1** could only be partially tested (for the relationship of regular price elasticity with feature only). The absence of these variables and the lack of adequate variance in the other two promotional variables, viz., price cut and feature advertising, across stores within chain 2 resulted in the process model for chain 2 to be insignificant. This precluded explanation of variation in regular price elasticity for chain 2. Thus, both **H1** and **H2** are not supported for chain 2.

To test **H3**, the third stage regression was done by pooling the stores under chains 1 and 2 after including an incremental intercept and incremental parameters for the promotional variables as shown in Equation 6.[8] Incremental parameters were not included for display only and feature and display together because these variables were absent in chain 2. Results of the third stage are shown in Table 5. The incremental intercept of chain 2 is negative (−19.83) and significant ($p < 0.05$), indicating that stores in chain 2 (an HLP chain) tend to have lower regular price elasticities on average than stores in chain 1 (an EDLP chain), all else equal, supporting **H3**.[9]

The results in Table 5 also support the results from the second stage models. Neither price cut nor display only is a significant determinant of regular price elasticity, as in the second stage model. Although the feature only parameter for chain 1 is negative (−202.51) and significant ($p < 0.05$), the incremental feature only parameter for chain 2 is positive (243.14)

TABLE 5

Final Stage Process Model of Regular Price Elasticity[a]
(Adjusted R^2 = 0.57; RMSE = 3.83; df = 30)

Parameter	*Value (Std. Error)*
Intercept (δ_{01})	24.32** (7.01)
Price cut parameter (δ_{11})	−0.18 (0.15)
Feature only parameter (δ_{21})	−202.51* (96.54)
Display only parameter (δ_3)	12.71 (13.24)
Feature and display parameter (δ_4)	−204.41* (58.07)
Incremental intercept of chain 2 (δ_{02})	−19.83* (9.36)
Incremental price cut parameter of chain 2 (δ_{12})	0.05 (0.11)
Incremental feature only parameter of chain 2 (δ_{22})	243.14** (110.89)

Notes: a. Again, as in Table 3, for ease of interpretation, the absolute magnitude of the regular price elasticity is used as the dependent variable.
** Significant at 0.01 level.
* Significant at 0.05 level.

and significant ($p < 0.05$) indicating that higher incidence of feature advertising only is related to a lower level of regular price elasticity, only in stores of chain 1. Similarly, the coefficient of feature and display together is negative (–204.41) and significant ($p < 0.01$), consistent with the result of the second stage model.

DISCUSSION, MANAGERIAL IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

The result on the joint effect of display and feature on regular price elasticity in EDLP stores is consistent with **H1** and the market power theory. This relationship, however, could not be verified in the case of HLP stores.

The result on the effect of brand feature and display can be explained by the dominance of brand salience over price salience as noted in section three. Frequent incidence of feature and display of a brand serve to narrow the consideration set of the consumers and direct their attention to the featured or displayed brand. Frequent incidence of feature and display of a brand may indeed lead to an automatic inclusion of the brand in the consumer's consideration set, and to a lesser focus on its regular price. Over a period of time, brand feature and display may serve more as a signal of differentiation of the brand from the rest of the brands, rather than increase consumer attention to price. Reduced consideration set and increased brand differentiation may help create a greater relative preference for the featured and displayed brand, resulting in lower regular price elasticity (Mitra and Lynch, 1995).

Brand salience could also be high in cases where consumers use an elimination-by-aspects model to choose their brands (Fader and McAlister, 1990). By eliminating certain brands that are not featured or displayed, consumers reduce the size of their consideration sets. Repeated exposures to featured and displayed brands may serve to restrict their consideration set, lowering their price sensitivity.

While *brand* feature and display serve to decrease regular price elasticity, *category* feature and display, on the other hand, may have an opposite effect. Higher incidence of category feature and display may serve to highlight multiple brands over different weeks. This may lead to an increase in size of the consumer's consideration set, making the consumer compare brands. Promotional activities such as feature and display can expand consideration set to include displayed and featured brands (Siddarth, Bucklin and Morrison, 1995). If multiple brands are featured or displayed over time, increased consideration set size could contribute to an increase in regular price elasticity (Mitra and Lynch, 1995). This reasoning may explain why Bolton (1989a) found that category feature increased price sensitivity, whereas she did not find the same for brand feature advertising.

Although average depth of price cut was hypothesized to be negatively related to regular price elasticity, it did not turn out to be a significant determinant of regular price elasticity for both types of stores. A possible reason is the lack of adequate variance in average depth of price cut across stores within each chain. If a chain adopts price cuts that exhibit greater variance across its different stores on a weekly basis, perhaps we can study the relationship between price cut and regular price elasticity in greater detail.

The results on the relationship between regular price elasticity and retailer pricing policy are consistent with **H3**. An EDLP chain attracts more price sensitive consumers, contributing to the higher level of regular price elasticity in the chain. In contrast, an HLP chain draws consumers who are not as price sensitive as those of the EDLP chain. Therefore, we find lower regular price elasticities in HLP stores. On the other hand, based on the results from the first stage model, HLP stores are likely to attract more deal-sensitive consumers, some of whom may be "cherry pickers," actively searching for the lowest actual prices in several items on their shopping lists.

Our results have two interesting managerial implications. First, they can help managers better allocate resources among the different promotional variables (price cuts vs. feature and display) at the retail level. The relationship between regular price elasticity and feature and display, and the link between regular price elasticity and average depth of price cuts can enable a retailer fine tune her/his mix among promotional variables. A retailer could be interested in maintaining a low regular price elasticity for most brands because of the ability to extract price premiums that may improve her/his profitability in the long run. For the brand analyzed in our study, if an EDLP retailer's objective is to maintain a low regular price elasticity, the results suggest that the retailer can achieve this by allocating more expenditure to feature advertising and display than by allocating more to deeper price cuts. In addition, the significant effect of feature and display together on regular price elasticity suggests that a retailer may achieve a low regular price elasticity by running feature and display together rather than by running them separately.

Second, the results also reflect manufacturers' dependence on retailers who can influence the price elasticity for manufacturers' brands with their pricing policies. For instance, if the manufacturer of the brand analyzed in the study seeks a lower regular price elasticity, she/he can better achieve her/his objective through HLP retailers than EDLP retailers. The manufacturer, however, may find higher response to price cuts in HLP stores. From the retailer's standpoint, on the other hand, an EDLP policy may not be optimal. For instance, Hoch, Dreze and Purk (1994) found that an HLP strategy was more profitable for a retailer than an EDLP strategy.

Methodologically, our study builds on the research of Bolton (1989a) and Wittink (1977) in two ways. First, while Bolton (1989a) and Wittink's (1977) studies analyzed price elasticity variation in two stages, we analyze regular price elasticity variation in three stages that include a final stage at the chain level. Second, unlike Bolton's (1989a) study of cross-sectional variation of price elasticity across stores, we allow for mixed heteroscedastic errors in the estimated regular price elasticities in the higher stages of regression analysis.

Our study has certain limitations which can be addressed by future research. First, due to data limitations, our study focused on one brand-size in a single product category. Another limitation in our data is the absence of display in the HLP chain. With additional data, our study could be extended to multiple brands across multiple product categories with greater variation in promotional variables. Second, our analysis has been confined to variation in regular price elasticity. With additional promotional data, it would also be interesting to understand the variation in promotional elasticities. Third, disaggregate consumer panel data for the same set of stores and chains on which aggregate data are available, would enhance our understanding of consumer store choice and purchase behavior. Fourth, we could relax our assumption that regular price and price cut decisions are exogenous, adding to the complexity of analysis. Fifth, we have not addressed the issue of zone pricing. A store located in a highly competitive geographical market may have a pricing policy that is different from that of its parent chain. Hoch, Kim, Montgomery and Rossi (1995) found that competitive characteristics were significant in the variation of price elasticity. With availability of store location data, we can include zone pricing in our analysis of retail competition.

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NOTES

1. We thank an anonymous reviewer for this explanation.
2. We recognize that feature and display together could actually serve to heighten response to price cuts because they may remind consumers to seek bargains.
3. We thank an anonymous reviewer for this explanation.
4. Regular price is the depromoted price (shelf price) that is made available in the Nielsen dataset. According to the data provider, this measure of regular price is reliable and has been successfully used by them for analyzing many categories. It is consistent with the definitions used by Guadagni and Little (1983) and Gupta (1988).
5. Actual price does not include the effect of coupons because coupon data were unavailable.
6. We tested for the possibility that the brand studied could have competed only with a subset of all the brands due to the competitive market structure prevalent in mouthwash. We tested an unrestricted version of our model that included as independent variables, the price cut of each brand separately with different parameters. The parameters were not significant in most stores, suggesting that it is unlikely that different competing brands may have different effects on the brand studied.
7. Test of Durbin h-statistic was not significant for 18 out of 20 stores in chain 1 and 15 out of 18 stores in chain 2.
8. It must be noted that a test of pooling across chains (homogeneity of slopes and intercepts, Chow, 1960) would not be very insightful because Model 4 did not turn out to be significant for chain 2. We, however, allow for differences between chains by including incremental parameters for chain 2 as in Model 6.
9. A simple t test of the difference between the regular price elasticity of chain 2 and chain 1 (–3.94 vs. –4.83) provides a t value of 1.43 which is significant at $p < 0.08$ (one-tailed).

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