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The authors examine the long-term effects of promotion and advertising on consumers' brand choice behavior. They use 8 1/4 years of panel data for a frequently purchased packaged good to address two questions: (1) Do consumers' responses to marketing mix variables, such as price, change over a long period of time? (2) If yes, are these changes associated with changes in manufacturers' advertising and retailers' promotional policies? Using these results, the authors draw implications for manufacturers' pricing, advertising, and promotion policies. The authors use a two-stage approach, which permits them to assess the medium-term (quarterly) effects of advertising and promotion as well as their long-term (i.e., over an infinite horizon) effects. Their results are consistent with the hypotheses that consumers become more price and promotion sensitive over time because of reduced advertising and increased promotions.

The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice

Trade promotions account for 50% of the $70 billion budget of consumer packaged goods manufacturers (*Progressive Grocer* 1995). Almost 70% of the firms have increased their trade promotions between 1990 and 1995. *Forbes* (1991) also reports an increase in consumer and trade promotional spending for consumer packaged goods manufacturers—from 50% to 75% of marketing budgets during 1985–90. It suggests that this increase induced a loss of 8–15% in the share of the top three brands in categories as diverse as popcorn, dishwashing detergent, cat food, barbecue sauce, and prepared dishes. The article goes on to cite several marketing managers who blame couponing and promotions for reduced brand loyalty. *Business Week* (1991) also contends that a shift of marketing dollars from advertising to promotions is to be blamed for the drop in the number of consumers that buy only well-known brands from 77% in 1975 to 62% in 1990.

In light of this, some companies now believe that promotions have made consumers more price sensitive, which consequently has lowered the effective price companies can charge (*BrandWeek* 1993). As a result of this belief, Colgate-Palmolive, Ralston Purina, Quaker Oats, and Procter & Gamble (P&G) recently have curtailed the frequency of their price promotions (*Wall Street Journal* 1996).

However, support for value pricing strategy is not universal. There is an uncertainty in both industry and academia about the long-term impact of promotion and advertising on brand performance. Some companies such as Heinz have emphasized their continued reliance on promotions as their main marketing vehicle (*Wall Street Journal* 1992). Others cite such cases as that of Hi-C, which tried to switch away from promotion in the early 1980s and lost significant share (*Business Week* 1992). The empirical evidence to date is limited and mixed. Although many previous studies examine the short- and long-term effects of advertising (e.g., Clarke 1976), few focus on the long-term effects of promotions. As Blattberg and Neslin (1989, p. 93) note, "Almo no re has been conducted on the long term effe of promotions. Yet, it is critical to a brand's strategy." In summary, understanding whether promotion and advertising hurt or help a brand in the long run appears to be relevant, important, and underresearched.

We empirically examine the long-term effects of promotion and advertising on consumers' brand choice decisions in mature product categories (i.e., we do not focus on changes due to the product life cycle factors). Specifically, we address the following two questions: (1) Does consumers' responsiveness to marketing mix elements change over time? For example, are consumers becoming more price sensitive over time? Is the price-sensitive segment of consumers growing over time? (2) If such changes as increasing price sensitivity occur, what factors affect these changes? For example, is the reduction in advertising expenditures and/or increase in promotions influencing consumers' price sensitivity to the product?

Investigation of these issues not only will enable us to better understand the changes in consumer behavior over the

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long run, but also will provide useful marketing implications for manufacturers' pricing, advertising, and promotion policies. To ensure consistent interpretation of *long term* throughout this article, we begin by defining it.

What Is Long Term?

Similar to Fader and colleagues (1992), we characterize the effect of marketing actions on consumers' choice behavior as follows:

1. *Short-term effects*: This is the immediate (e.g., weekly) effect of promotion or advertising on the sales or share of a brand. Most recent studies focus on these effects. These studies generally find very strong short-term effects of promotion but very weak or insignificant effects of advertising on brand share (e.g., Guadagni and Little 1983; Gupta 1988; Tellis 1988a).
2. *Medium-term effects*: Some studies attempt to go beyond week-by-week effects of promotions. Most of these studies use a 4- to 16-week time frame. For example, Davis, Inman, and McAlister (1992) study the impact of promotions on consumer attitudes; Ehrenberg, Hammond, and Goodhardt (1994) examine promotion effects on brand shares; and Kim and Lehmann (1993) study changes in consumer sensitivities due to promotions. Although many of these studies draw implications about the long-term effects of promotions, we believe that effects of advertising and promotion in the following 4- to-16 weeks qualify as medium-term rather than long-term effects. Here, we define the impact of a current period's advertising/promotion on sales, share, or consumers' sensitivities of the subsequent 13 weeks (or quarter) as the medium-term effect of advertising/promotion.
3. *Long-term effects*: Previous studies find that advertising has a substantial carryover effect. The long-term effect of advertising (or promotion) is the cumulative effect on consumers' brand choice behavior, lasting over several years. One approach to capture the long-term impact of advertising is the distributed lag model (e.g., Clarke 1976). We use a similar approach here.
4. *Effects of changes in marketing strategy*: P&G's move from high-low pricing to everyday low pricing is a good example of a change in marketing strategy. An important task for marketing managers is to assess the impact of these strategy changes on brand share or sales. Notice the distinction between long-term effects and effects of a policy change. If a company changes its advertising in one period only and evaluates its cumulative effect in future periods, it is measuring long-term effects of advertising. Conversely, if the company cuts its advertising expenditure in half in all periods and studies its effect on consumer choice, it is evaluating the effect of strategy change.

Our focus here is to study the long-term effects of promotions and advertising on consumers' price and promotion sensitivities. We proceed as follows: We start with a brief review of the relevant literature and development of hypotheses. We then describe our modeling approach. This is followed by data, variables, and results sections. We discuss managerial implications of these results and conclude with the contributions and limitations of this study.

LITERATURE REVIEW AND HYPOTHESES

Long-Term Effects of Advertising

Economists have developed two theories that predict opposite effects of advertising on consumers' price sensitivity. The first theory suggests that advertising leads to product differentiation, thereby reducing consumers' price sensitivity (Comanor and Wilson 1974). The second theory states that advertising increases competition by providing information to consumers that is likely to make consumers more price sensitive (Nelson 1974). Mitra and Lynch (1995) reconcile these conflicting theories by suggesting that advertising affects price elasticity through its influence on two moderating constructs: Advertising can increase price elasticity by increasing the number of brands considered; it also can decrease price elasticity by increasing the relative strength of brand preference.

Kaul and Wittink (1995) provide an excellent review of the studies examining the impact of advertising on price sensitivity. They also suggest that the apparently conflicting results of many studies might be indicative of the different aspects of the problem on which the researchers inadvertently focus. For example, Eskin and Baron (1977) study new products, for which more advertising might attract additional consumers who are more price sensitive, and Krishnamurthi and Raj (1985) analyze a constant set of households. Researchers seem to agree that if the advertising message is non–price-oriented and brand building, then it lowers consumers' price sensitivity, whereas a price-oriented message could increase consumers' price sensitivity.

In our application, we use a product category in which five of the nine brands advertise, all using a non-price advertising message. Furthermore, the price of these five brands is, in general, higher than the price of the remaining four brands that do not advertise. According to Boulding, Lee, and Staelin (1994), who use price as a proxy for the advertising message of a brand, firms charging higher-than-average price have a natural inclination to have a non-price message in their advertising. Therefore,

H_1: Non–price-oriented advertising is expected to reduce consumers' price sensitivity in the long run.

Few studies, even those using disaggregate data, involve conducting analysis at the segment level. A notable exception is Krishnamurthi and Raj (1985), who find that the impact of advertising on consumers' price sensitivity is stronger for the more price-sensitive (or nonloyal) segment, and this effect is marginal for the less price-sensitive (or relatively loyal) segment. This suggests a "floor" effect: If the loyal segment is completely price insensitive, increased advertising will have no effect on this segment's price sensitivity. On the basis of these findings, we expect the following:

H_2: The long-term impact of advertising on consumers' price sensitivity is likely to be stronger for nonloyal consumers than for relatively loyal (and less price-sensitive) consumers.

Although several studies address the issue of how advertising affects price sensitivity, almost none focus on the effect of advertising on consumers' sensitivity to promotions. To understand advertising's effect on consumers' promotion sensitivity, we believe that promotions should be categorized into two groups: price-oriented and non–price-oriented promotions.[1] Advertising that makes consumers less price sensitive also should make these consumers less sensitive to price-oriented promotions that primarily focus on price cues. Conversely, advertising should increase consumers' response to non–price-oriented promotions that

[1]We use the word *promotions* for all sales and trade promotions such as temporary price reductions, feature, coupon, display, and so on.

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enhance the awareness and visibility of a brand without focusing on price.

H_3: In the long run, advertising will reduce consumers' sensitivity to price-oriented promotions.

H_4: In the long run, advertising will increase consumers' sensitivity to non–price-oriented promotions.

H_5: In general, these effects are likely to be stronger for the nonloyal segment than for the loyal segment.

As advertising is expected to reduce consumers' price sensitivity and build loyalty, it is reasonable to expect that it also will reduce the size of the nonloyal segment.

H_6: Advertising will reduce the size of the nonloyal segment.

Long-Term Effects of Promotion

Several theories suggest a negative long-term effect of promotion on consumers' attitude and behavior. Self-perception theory implies that consumers who buy on promotions are likely to attribute their behavior to the presence of promotions and not to their personal preference for the brand (Dodson, Tybout, and Sternthal 1978). Increased promotion in a category is likely to lead to a perception that the key differentiating feature of brands is the price (Sawyer and Dickson 1983). This simplifying heuristic then can lead to increased reliance on sales promotions for choosing brands. Operant conditioning principles also suggest that frequent dealing in a category can condition consumers to look for promotions in the future, thereby making them more promotion prone.

There are some theories that predict an opposite effect of promotion. For example, learning theory suggests that promotions can help a brand through increased familiarity and experience. However, this effect is likely to be small for mature and stable product categories (like the one used in our study), in which consumers have been familiar with almost all of the brands for a long period of time.

Empirical research in the area of promotions typically focuses on identifying the short-term effects of promotions (e.g., Guadagni and Little 1983; Gupta 1988; Kamakura and Russell 1989). These studies show that promotions have a large short-term effect on consumers' brand choice. Few recent studies examine the medium-term effect (over 4–16 weeks) of promotion on brand share, brand evaluations, and consumers' price sensitivity. Using data from four weeks before and four weeks after major promotions, Ehrenberg, Hammond, and Goodhardt (1994) conclude that consumer promotions for established brands have no noticeable effect on either subsequent sales or brand loyalty. Davis, Inman, and McAlister (1992) use a controlled experiment over three months to conclude that promotions have no negative effect on brand evaluations. However, these studies do not address whether promotions make consumers more sensitive to short-term (weekly) price and promotion activities. Kim and Lehmann (1993) examine this issue using a four-month time frame and suggest that promotions do make consumers more price sensitive.

Two studies discuss the long-term effect of advertising and promotions. Johnson (1984) analyzes 20 product categories to examine changes in brand loyalty over the period 1975–83. He finds no significant changes in a brand's share of requirements. However, if promotions have increased over time, then it is difficult to say if a brand's share is high because of consumer loyalty for the brand or increased brand promotions. Boulding, Lee, and Staelin (1994) use PIMS data at the business unit level to conclude that advertising decreases and promotion increases consumers' price sensitivity for large brands.

Consumer behavior theories, empirical studies, and the previous discussion about advertising suggest that over the long run, price-oriented promotions will make consumers more price sensitive by focusing their attention on price cues. Non–price-oriented cues therefore will become less important to consumers. The opposite is likely to hold with increasing non–price-oriented promotions, which are likely to work like advertisements (consistent with the empirical generalizations of Kaul and Wittink 1995). Therefore,

H_7: Over the long run, price-oriented promotions will (a) increase consumers' price sensitivity, (b) increase consumers' sensitivity to price-oriented promotions, and (c) decrease consumers' sensitivity to non–price-oriented promotions.

H_8: Over the long run, non–price-oriented promotions will (a) decrease consumers' price sensitivity, (b) decrease consumers' sensitivity to price-oriented promotions, and (c) increase consumers' sensitivity to non–price-oriented promotions.

Are results likely to be the same across the nonloyal and loyal segments? Some studies suggest that promotion signals that do not carry price information (e.g., displays) can have a dual effect. According to Inman, McAlister, and Hoyer (1990), these promotion signals have a positive impact on the choice behavior of "low need for cognition" people. However, high-need-for-cognition people react to a promotion signal only when it is accompanied by a substantive price reduction. By definition, loyal consumers are more habitual buyers and respond less to price and promotions. Therefore, it is reasonable to expect that, like the low need for cognition consumers examined by Inman, McAlister, and Hoyer (1990), loyal consumers will be less motivated to process non–price-oriented promotion information actively. This suggests that non–price-oriented promotions are likely to divert the attention of loyal consumers away from price but in fact might make the nonloyal consumers focus on price even more. Inman and McAlister (1993) support this view by suggesting that some consumers think of promotion signals as price-oriented promotions (probably the nonloyals), whereas others think of them as a non-price promotion (probably the loyals). Therefore,

H_9: Non–price-oriented promotions will decrease the price sensitivity of loyal consumers and increase the price sensitivity of nonloyal consumers.

Consistent with our previous discussion, we expect price promotions to reduce consumers' loyalty by making them more sensitive to price and price promotions. Therefore we expect these promotions to increase the size of the nonloyal segment. However, the effect of non–price-oriented promotions on consumers' brand loyalty and price sensitivity is expected to be mixed (depending on the loyal or the nonloyal segment), which makes it hard to assess their impact on segment sizes. Therefore,

H_{10}: Price-oriented promotions are likely to increase nonloyal segment size.

These hypotheses are summarized in Table 1.[2]

[2]Price sensitivity is generally negative, indicating that higher prices reduce brand choice probability. Therefore a positive sign in this table indicates reduction in price sensitivity.

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Table 1
SUMMARY OF HYPOTHESES

Long-Term Impact of	Impact on Consumer Sensitivity to: Price	Price Promotions	Non-price Promotions	Nonloyal Segment Size
Advertising	+	–	+	–
Price Promotions	–	+	–	+
Non-price Promotions	+/–*	–	+	?

*This effect is expected to be positive for loyal consumers and negative for nonloyal consumers.

MODELING APPROACH

We begin by briefly describing the multinomial logit model we used to capture the impact of short-term (weekly) price and promotion activities on consumers' brand choice behavior. We then extend this model to a segment-level logit model, which allows for consumer heterogeneity in response parameters (Kamakura and Russell 1989). Next, we suggest that the slope or first derivative of the logit model with respect to, for example, price is a better measure of consumers' sensitivity to short-term marketing activities than are the response parameters or elasticities. This is followed by a discussion of the distributed lag model used to capture changes in consumers' sensitivities over time as a function of quarterly marketing activities such as advertising. Finally, we discuss estimation issues.

Modeling Consumers' Brand Choice Behavior

Single-segment logit. The probability that household h buys brand i at occasion t is captured by the multinomial logit model (Guadagni and Little 1983):

$$(1) \qquad P_{it}^h = \frac{\exp(V_{it}^h)}{\Sigma_j \exp(V_{jt}^h)},$$

where the deterministic part of the utility is

$$(2) \qquad V_{it}^h = \beta_{0i} + \beta \mathbf{X}_{it}^h.$$

The vector $\mathbf{X}_{it}^h$ includes short-term (weekly) marketing variables such as price and promotion, as well as household-specific variables such as brand loyalty. The parameter β_{0i} is a brand-specific constant, and β is a vector of parameters for variables $\mathbf{X}_{it}^h$. One of our key objectives here is to test explicitly whether consumers' sensitivities to short-term marketing activities (which are a function of β parameters) change over time and if these changes are correlated with marketing activity such as advertising over the long run. Because some long-term marketing variables are reported (at least in our data set) on a quarterly basis, we estimate β for each quarter q. This is consistent with previous research (e.g., Moore and Winer 1987) and the managerial judgment of the company that provided us the data. (In the Estimation section, we provide more details about the choice of a quarter as the time period of analysis.)

Multiple-segment logit. We allow for consumer heterogeneity in response parameters by using segment-level logit models. Instead of specifying these segments a priori, we use the latent class or mixture modeling approach advocated by Kamakura and Russell (1989):

$$(3) \qquad P_{it}^h = \sum_{s=1}^{S} \pi_s P_{ist}^h,$$

where

π_s = share of the sth segment, $0 < \pi_s \leq 1$, $\Sigma \pi_s = 1$ and
P_{ist}^h = probability that household h in segment s buys brand i at time t.

The segment-level choice probability is a logit model:

$$(4) \qquad P_{ist}^h = \frac{\exp(\beta_{0iqs} + \beta_{qs}\mathbf{X}_{it}^h)}{\Sigma_i \exp(\beta_{0iqs} + \beta_{qs}\mathbf{X}_{it}^h)},$$

where β_{0jqs} and β_{qs} are segment-specific parameters estimated for each quarter q.

Although the marketing response parameters, β_{qs}, are not brand specific *within* a segment, the net effect of the marketing activity of a brand is a convex combination of segment-level response parameters. The weights in this convex combination depend on within-segment brand shares, which typically differ substantially across brands and segments (Kamakura and Russell 1989). This approach allows for brand-specific responses and consumer heterogeneity without making the number of model parameters very large. In our application, estimating brand-specific response parameters does not provide better fit or insights.

When the segment-level logit parameters and segment sizes are estimated, we can obtain a household's posterior probability (w_{qs}^h) of belonging to a segment s in quarter q by Bayes' rule:

$$(5) \qquad w_{qs}^h = \frac{\pi_{qs} L_{qs}^h}{\Sigma_s \pi_{qs} L_{qs}^h},$$

where L_{qs}^h is the likelihood of household h's purchase history given that it belongs to segment s in quarter q.

A Measure of Consumers' Sensitivities to Short-Term Marketing Activities

The segment specific parameters, β, represent consumers' response to weekly price and promotion activities of brands. We could use these parameters, which vary over time (quarters), to capture changes in consumers' *sensitivities* to short-term marketing activities. However, logit models pose a special problem because the logit parameters are identified only up to a scale constant (Ben-Akiva and Lerman 1985). This scale constant is inversely proportional to the variance of the error in the utility function. Therefore, comparison of β parameters across time or models is not desirable because the comparison is confounded by the error variances (Swait and Louviere 1993).

It is possible to use *elasticities* instead of model parameters as measures of consumers' sensitivities to short-term marketing variables. Unlike the elasticities in multiplicative models (Krishnamurthi and Raj 1985), the elasticities in logit models are scaled by brand choice probabilities. This scaling implies that low-share brands will tend to have high elasticities, though consumers are not necessarily more responsive to the marketing actions of small-share brands (Guadagni and Little 1983). Scaling also introduces asymmetry into cross-elasticities, even though there might be no underlying asymmetry in consumer response (Russell, Bucklin, and Srinivasan 1993).

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We therefore use first derivatives or slopes as our measure of consumers' sensitivities. The first derivative represents change in brand share for one unit change in an independent variable, such as price. In the logit model, for segment s the first derivative of market share of brand i in quarter q with respect to one unit change in an independent variable X_i is given by

$$(6) \qquad Y_{iqsx} = \frac{\Sigma_h \Sigma_t \beta_{qsx} w^h_{qs} P^h_{ist}(1 - P^h_{ist})}{\Sigma_h \Sigma_t w^h_{qs}}.$$

For discrete (0,1) independent variables, such as promotion, the discrete analog of the first derivative is

$$(7) \qquad Y_{iqsx} = \frac{\Sigma_h \Sigma_t w^h_{qs} \Delta P^h_{ist}}{\Sigma_h \Sigma_t w^h_{qs}},$$

where ΔP^h_{ist} is the change in purchase probability due to change in the X_i variable from 0 to 1 (e.g., from no promotion to promotion scenario).

Note that there are three important features of this measure. First, it does not suffer from the scaling problems mentioned previously. Second, for a given value of β_{qsx}, this measure is the highest when $P^h_{ist} = .5$. This is intuitively appealing because it suggests that consumers have the highest response to price and promotion when they have the highest level of uncertainty of whether to choose a particular brand. Third, even if all brands have the same β_{qsx} parameters, brands will have different responses to their marketing activities as measured by the first derivatives.

In summary, in the first stage of our model, we estimate segment-level logits and then compute first derivatives with respect to price, price-oriented promotion, and non–price-oriented promotion for each quarter of the data.

Modeling the Long-Term Impact of Advertising and Promotion

The second stage of our model captures the impact of quarterly marketing variables, such as advertising, on quarterly sensitivity (first derivative) estimates using a distributed lag model. These models (e.g., the Koyck model and the partial adjustment model) have been used extensively in marketing to capture the carryover effects of advertising (e.g., Clarke 1976). The Koyck model, for example, makes the assumption that the advertising effect has a geometric decay over time. The partial adjustment model assumes that in the short run consumers adjust their behavior only partially to changes in the environment. For example, frequent promotions can lead consumers to expect promotions in the future, thereby making them more price sensitive. However, this shift in price sensitivity is likely to be gradual, as consumers slowly adjust their behavior to the new market environment. These assumptions lead to the following model[3]:

$$(8) \qquad Y_{iqsx} = \alpha_{is} + \lambda_{is} Y_{i(q-1)sx} + \gamma_{is} Z_{iq} + \delta_s C_q + \epsilon_{iqs},$$

where

Y_{iqsx} = consumer response in quarter q for brand i in segment s, with respect to short-term marketing variable X, such as price;
$Y_{i(q-1)sx}$ = last quarter's response value, that is, lag term;
Z_{iq} = vector of quarterly marketing variables, such as advertising, for brand i, quarter q;
C_q = control variables, such as economy, for quarter q;
$\alpha_{is}, \lambda_{is}, \gamma_{is}, \delta_s$ = parameters to be estimated; and
ϵ_{iqs} = error term.

This model has several important features. First, the model parameters (γ) represent the medium-term (quarterly) impact of advertising and promotion on consumers' sensitivities. Second, the decay parameter (λ) indicates how long the effect of advertising and promotion on consumers' sensitivities last. Third, the cumulative long-term effects (over infinite time horizon) of marketing activities, such as advertising, are captured by $\theta = \gamma/(1 - \lambda)$. When the estimates and the variance-covariance of γ and λ are obtained, the variance of the long-term effect θ can be estimated using Cramer's theorem, which enables us to test for the significance of θ[4]:

$$(9) \qquad \mathrm{Var}(\theta) = \frac{1}{(1-\lambda)^2}\mathrm{Var}(\gamma) + \frac{2\gamma}{(1-\lambda)^3}\mathrm{Cov}(\lambda, \gamma) + \frac{\gamma^2}{(1-\lambda)^3}\mathrm{Var}(\lambda).$$

An implicit assumption of the model in Equation 8 is that the decay parameter λ is identical for all quarterly marketing variables such as advertising and promotion. Although this makes the model parsimonious, it potentially is a very restrictive assumption. In other words, if the long-term effects of advertising last for several years but the long-term effects of promotions last for only a few quarters, then this assumption can lead to erroneous conclusions. Following Johnston (1984, p. 347), we test whether advertising, price promotion, and non-price promotion have different lag structures.

Estimation

The model is estimated in two stages. In stage one, we estimate the segment-level logit model by maximum likelihood (Kamakura and Russell 1989). From this stage of the analysis we obtain parameter estimates for each quarter. We chose a quarter as the appropriate window or interval length for several reasons. First, we have 8¼ years of data, which suggests that a larger window (e.g., 1 year) will leave us with few observations for the second stage of the analysis; second, because the median interpurchase time in our application is approximately six weeks, a shorter window (e.g., a month) will leave us with few observations and unstable coefficients in the first stage of the analysis; third, information on some of the marketing variables (e.g., advertising) is available on a quarterly basis; and fourth, the managers of

[3]Both the Koyck and the partial adjustment models' formulations are similar to Equation 8. However, in the Koyck model, errors are serially correlated, whereas these errors are independent in the partial adjustment model (Johnston 1984). We test for error correlation in our estimation.

[4]$\mathrm{Var}(\theta) = \dot{\mathbf{g}}'\Sigma\dot{\mathbf{g}}$ where $\dot{\mathbf{g}}$ is the vector of first derivatives of the function $\mathbf{g}$ that defines the relationship between θ and γ, λ (i.e., $\theta = g(\gamma, \lambda) = \gamma/(1 - \lambda)$), and Σ is the variance-covariance matrix for the parameter estimates γ and λ. This implies that

$$\mathrm{Var}(\theta) = \begin{bmatrix} \frac{\partial\theta}{\partial\gamma} \\ \frac{\partial\theta}{\partial\lambda} \end{bmatrix} \begin{bmatrix} \mathrm{Var}(\gamma) & \mathrm{Cov}(\gamma, \lambda) \\ \mathrm{Cov}(\gamma, \lambda) & \mathrm{Var}(\lambda) \end{bmatrix} \begin{bmatrix} \frac{\partial\theta}{\partial\gamma} & \frac{\partial\theta}{\partial\lambda} \end{bmatrix}.$$

Appropriate substitution then leads to Equation 9.

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the company that provided us the data believe that most significant marketing decisions are made on a quarterly basis.

Our initial attempt at estimating segment-level logit models on quarterly data indicates that even a quarter is too short a period to obtain stable parameter estimates. Given this dilemma (i.e., a desire to have quarterly parameter estimates so that we have enough observations for the second stage analysis, while needing a longer time interval to obtain more stable parameter estimates in the first stage), we use a rolling three-quarter window for estimating the segment-level logit. Specifically, we assume the parameter estimates for data covering quarters 1, 2, and 3 to represent quarter 2, estimates from quarters 2, 3, and 4 to represent quarter 3, and so on. Although this procedure could smooth out some of the quarterly fluctuations in coefficients, it also will smooth out random error. In the spirit of moving averages, this procedure captures the overall trend in coefficients in the 8¼ years of data. More important, it provides us with more stable parameter estimates, which are essential for drawing meaningful conclusions.[5]

When we obtain quarterly estimates of β parameters, we then can compute first derivatives with respect to independent variables (such as price and promotion) as per Equation 6 or 7. We then use these first derivatives as dependent variables in Equation 8, which is estimated by ordinary least squares.

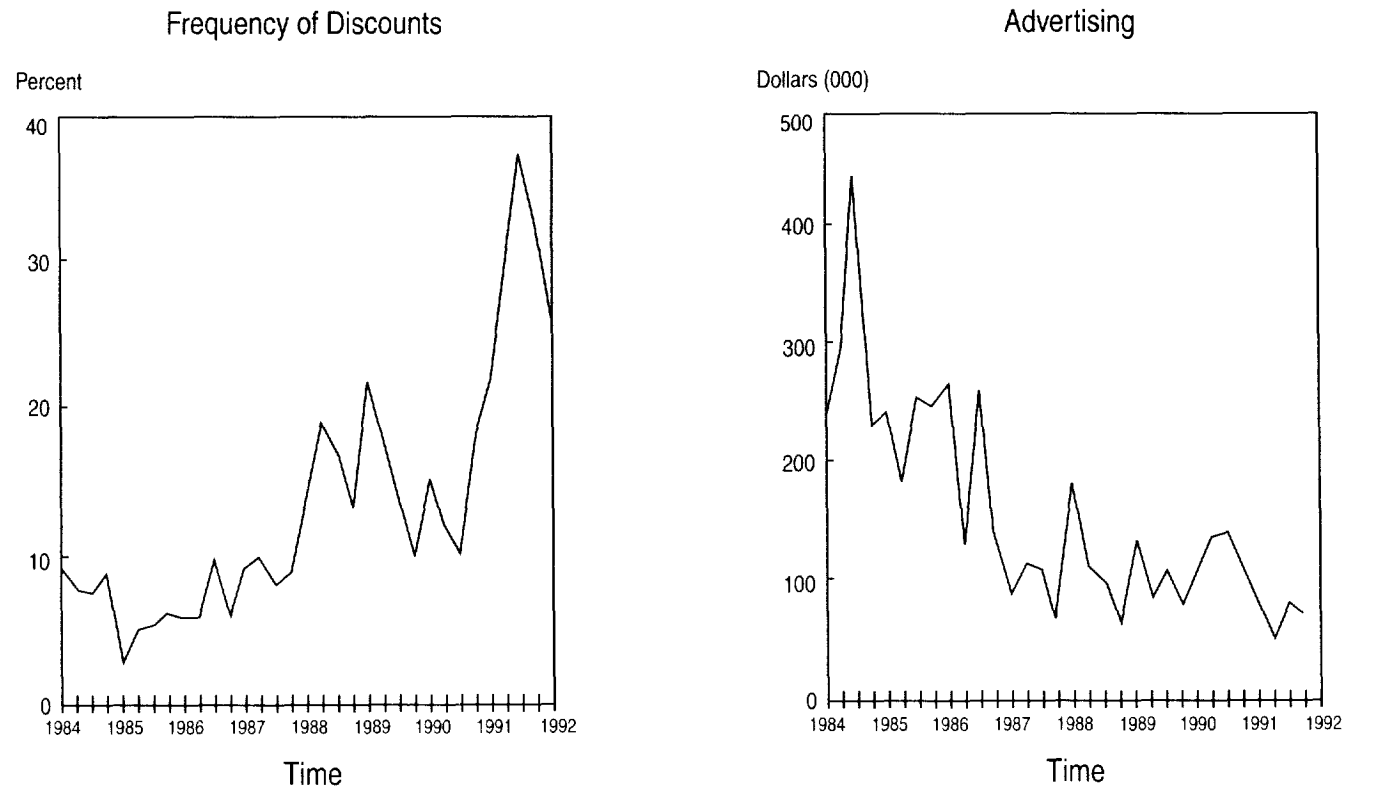
[5]We conducted an extensive sensitivity analysis for our choice of the "window" length of three quarters. Using a sub-sample of the data, we compared the coefficients of the three-quarter window with the coefficients from one-quarter and five-quarter windows. The results were not statistically significantly different across these scenarios. We acknowledge that using the three-quarter window parameters could inflate the lag parameter in Equation 8.

DATA

The data and managerial input for our application were provided by a major consumer packaged goods company and Information Resources, Inc. The data contain panel, store, and demographic information for a consumer nondurable category in one market area for 8¼ years, from January 1984 to March 1992. The sponsoring company also provided quarterly advertising expenditures for all brands. Because scanner data began to proliferate approximately ten years ago, it is only now that researchers can use this information to make long-term inferences regarding changes in consumer behavior. Our study is one of the first to utilize this long a period of disaggregate data.

We cannot reveal the product category or the brands. The category is a household nonfood product. The median interpurchase time is 6 weeks, and the mean is 12 weeks. The category has several characteristics that make it particularly suitable for our application. First, like most other consumer packaged goods, advertising in this category has declined over time relative to promotion (Figure 1). This enables us to examine the effects of these changes, if in fact they exist. Second, this is a mature product category. Therefore, our results will not be confounded by changes over the product life cycle (Sethuraman and Tellis 1991; Tellis 1988b). Final-

Figure 1
CHANGES IN CATEGORY MARKETING ACTIVITY



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ly, there were no major brand entries or exits during the period to complicate the analysis of advertising and promotional effects.

The category consists of eight major brands that account for approximately 85% of the market. We consider all other brands, along with private-label and generic brands, to constitute a ninth brand. There are four major sizes, and there is a great deal of switching among sizes. The two medium sizes represent approximately three-quarters of the market share, and the largest and smallest account for approximately one-eighth each. There are 11 stores in this particular market. The panel data include 1590 households making 54,731 product purchases over 8¼ years, that is, 33 quarters. The demographics of the panelists roughly match the demographics of the United States on age, family size, education, and children; though the panelists in our study had slightly higher incomes. Approximately 92% of households purchased more than one brand during the period of the study. Households did not enter or exit the panel during the study period. The lack of entry or exit could raise questions of maturation or mortality, however, any disaggregate long-duration study will suffer from this limitation.[6] By having the same households, we are uniquely able to monitor exposure to promotions and track concurrent changes in behavior. As we mentioned previously, conflicting results about the impact of advertising on consumers' price sensitivity can be explained partially by whether advertising is attracting new price-sensitive consumers (Eskin and Baron 1977) or reducing the price sensitivity of existing consumers (Krishnamurthi and Raj 1985). By having a fixed set of households, we avoid this potential confounding. Table 2 provides some descriptive statistics of the data.

Although most brands in our product category have four sizes, our unit of analysis is a brand, not brand size. This choice was made for the following reasons: First, with nine brands and four sizes, even a single-segment logit model will have a large number of parameters. This problem increases dramatically in a multi-segment logit model. Second, a model with 36 brand-size combinations is likely to violate the IIA property of the logit model. Third, management believes that most marketing actions in this category (e.g., advertising, feature) are brand oriented rather than designed specifically for a brand size. Previous studies use brand, instead of brand size, for similar reasons (Krishnamurthi and Raj 1991).

[6]In the spirit of cohort analysis, we checked our data to see if the percentage of purchases on discount or brand switching for three different age groups of panelists differed over time. We found no significant differences.

VARIABLES

Short-Term (Weekly) Variables

We include the following short-term variables $\mathbf{X}_{it}^{h}$ (for household h, brand i, occasion t) in the logit model.

Price. Price for a brand is the actual shelf price in dollars per ounce, net of all discounts. The existence of multiple brand sizes poses a problem for creating a price variable for competing brands. We use *minimum* shelf price per ounce across different sizes of a brand as the price for that brand for several reasons. First, in our data the average unit price differential among the three largest brand sizes, which constitute the bulk of purchases, is approximately 3%. Second, the average price differences across brands are far greater than are the average price differences across sizes of the same brand. Third, and most important, a weighted average price formulation is likely to underestimate the true price variation in the marketplace. For example, if a retailer offers a 15% discount on the largest size of a brand that accounts for, say, one-eighth of the volume, then the weighted average percent discount will be (.15 × 1/8), or less than 2%. Given size switching in this category, such averaging will understate price effects. Fourth, consumers switch heavily among sizes, which suggests that minimum price per ounce more accurately reflects their price search behavior.

Price promotions. We classify three types of promotions as price promotions: (1) temporary price reduction (TPR), (2) feature, and (3) coupon. Temporary price reduction and coupons always are accompanied by price discounts and are therefore clearly price-promotion signals to consumers. Features almost always are accompanied by prominent pricing information with little product information.

We define a brand to be on feature or TPR, or as offering a coupon if any size of that brand is on feature or TPR or offering a coupon. Although the data provide information about coupon *redemption*, there is no information about the recency of coupon *drop*. Therefore, we assume a coupon drop for a brand occurred in a week if the total number of redemptions for that brand by all households in the panel data exceed one standard deviation higher than the average

Table 2
DESCRIPTIVE STATISTICS OF THE DATA

	Market Share		*Price ($/ounces)*		*Advertising ($000)*		*TPR*[1]		*Feature*		*Display*		*Coupon*	
Brand	*1984*	*1991*	*1984*	*1991*	*1984*	*1991*	*1984*	*1991*	*1984*	*1991*	*1984*	*1991*	*1984*	*1991*
1	.38	.38	.057	.060	393	128	.27	.55	.04	.09	.08	.19	.07	.10
2	.07	.10	.054	.059	142	30	.12	.40	.07	.03	.05	.14	.12	.04
3	.19	.13	.057	.063	225	57	.12	.43	.01	.04	.00	.12	.14	.04
4	.04	.10	.052	.056	144	0	.10	.54	.01	.04	.04	.19	.00	.04
5	.08	.07	.057	.062	278	44	.08	.42	.00	.05	.02	.15	.05	.15
6	.09	.06	.049	.049	0	0	.03	.15	.00	.01	.02	.05	.14	.04
7	.04	.03	.029	.034	0	0	.04	.08	.00	.01	.00	.02	.25	.06
8	.00	.04	.061	.054	0	0	.08	.28	.00	.02	.00	.05	.00	.42
9	.11	.10	.024	.030	0	0	.18	.21	.01	.01	.02	.06	.06	.04

[1]TPR (temporary price reduction), Feature, Display, and Coupon variables represent the proportion of times the category was discounted, featured, displayed, or couponed in that year.

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weekly redemption for that brand across the entire period of the study. In other words, a significant increase in coupon redemption is assumed to be an indicator of a recent coupon drop.

Non-price promotions. We classify display as the non-price promotion variable. Typically price is not the dominant focus of displays. Similar to features and TPR, we define display as a binary (0,1) variable that is 1 if any size of the brand is on display, 0 otherwise.

Brand loyalty. To control for observed differences in households' purchasing patterns, we include a brand loyalty variable (e.g., Guadagni and Little 1983). A household's loyalty for a brand is defined as that brand's share in the last four purchases of that household (on average four purchases represent one year of purchase history in this category). Previous studies use similar or even fewer purchases to assess brand loyalty (e.g., Chiang 1991 used four weeks of coffee purchases). Our measure enables a household's loyalty for a brand to change over time, that is, we do not assume that brand loyalty for a household remains constant over eight years.[7]

Quarterly Variables

Quarterly variables (Z_{iq}) for each brand i and quarter q are operationalized as follows:

Advertising. Advertising is the total advertising expenditure (in inflation adjusted dollars) for brand i in quarter q in the market area.[8]

Price promotions. Once again, the intensity of price promotion by a brand in a quarter is captured by three types of promotions: (1) TPR, (2) feature, and (3) coupon. Specifically, we define the feature activity for brand i in quarter q (F_{iq}) as the proportion of times brand i is on feature across all stores and all weeks of that quarter. Similarly, we define frequency of price discounts as the proportion of times a brand is on TPR in a quarter. Finally, coupon intensity for brand i in quarter q is defined as the proportion of times that brand uses coupons in that quarter. Quarterly price promotion is defined as a simple average of quarterly feature, TPR, and couponing activity of a brand.

Non-price promotions. Our non-price promotion variable is the proportion of times a brand is on display across all stores and all weeks of that quarter, operationalized similar to the long-term feature variable.

RESULTS

We first present the results of the first stage analysis, in which we calibrate segment-level logit models to obtain quarterly parameter estimates and consumers' sensitivities. Next, we discuss results from the second stage analysis, in which we use quarterly marketing variables to explain changes in consumers' sensitivities. These results provide a test of our hypotheses.

Stage One: Estimating Segment-Level Logit Models

Choosing the number of segments. For each time period, we calibrated the single-segment choice model and then proceeded to fit multi-segment models for two and three segments.[9] We used the Bayesian Information Criterion (BIC) and segment interpretability as guidelines to select the appropriate number of segments (Bucklin and Gupta 1992). For all time periods, the BIC values favored a two-segment solution over a single-segment solution. Three-segment solutions were occasionally better, and often worse, than the two-segment solutions. Across time periods, the average and maximum gain in BIC in going from two to three segments were .30 and 23, respectively. Even the maximum gain in going from a two-segment to a three-segment solution represented a percentage gain of only .5% in the BIC for that period, at the expense of 15 additional parameters. Because a constant number of segments over time facilitates interpretation (Moore and Winer 1987), we chose a two-segment solution for all time periods.

The two segments appeared to be relatively loyal and nonloyal segments, which is consistent with the conceptualization of Krishnamurthi and Raj (1991), Bucklin and Gupta (1992), and others.

Average sensitivities of consumers across all time periods were as follows:

Consumer Sensitivity to	*Loyal Segment*	*Nonloyal Segment*
Price	−.28	−1.70
Price promotion	.02	.04
Non-price promotion	.03	.09

These results show that, as expected, consumers in the nonloyal segment are more price and promotion sensitive than are consumers in the loyal segment. The price sensitivity (or slope) estimates are equivalent to price elasticities of −.51 for the loyal segment and −1.02 for the nonloyal segment. These estimates are somewhat lower than the average of −1.76 reported by Tellis (1988b), who used a meta-analysis of several product categories.

Consumers' sensitivities over time. Over the 29 quarters of the calibration period, in addition to segment size and brand-specific constants, we estimated 348 response parameters in the first stage of our analysis.[10] Of these, 316 coefficients were significant and correctly signed (e.g., the price parameter was negative, as expected), 8 were significant and incorrectly signed, and 53 were insignificant. Notice that under the null hypothesis of zero parameter value, using a 5% significance level would yield $348 \times .05 = 17$ co-

[7]Results were insensitive to slightly different operationalizations of brand loyalty. Also, response parameters in the first stage were similar for models with or without the brand loyalty variable.

[8]Because β parameters are estimated for a quarter, it could be unreasonable to suggest that advertising for the *entire* current quarter (including end-of-quarter advertising) affects consumers' sensitivities for that quarter (which include consumer response at the beginning of the quarter as well). Therefore, the quarterly advertising variable was created by *phase-shifting* advertising by half a quarter. In other words, for the current quarter of April–June, advertising was defined as half the advertising expenditure for April–June plus half the advertising expenditure for January–March. We also defined the lag terms accordingly. Once again, this adjustment did not affect the empirical results. We obtained similar results for other quarterly variables.

[9]We also compared a single-segment model with brand-specific parameters for price, promotion, and so on with a single-segment model in which the parameters for short-term marketing variables were constrained to be the same across brands. Using Bayesian Information Criterion (which penalizes a model for estimating additional parameters), a model with the same parameters for brands performed better than did a model with brand-specific parameters. Moreover, this constrained model was found to be more stable over time.

[10]For each quarter we estimated 12 response parameters: 6 parameters for each of the two segments. Therefore for the 29 quarters, we get $6 \times 2 \times 29 = 348$ coefficients.

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efficients as significant, by chance. In other words, it is possible to obtain approximately 8 coefficients as significant and correctly signed, and 8 coefficients as significant and incorrectly signed, by chance.

Next, we used these estimates of parameters and segment sizes and Equations 6 and 7 to compute consumer sensitivities to price, price promotion, and non-price promotion for each quarter q.[11] We performed a simple trend analysis for each brand and segment by regressing quarterly sensitivities against time. To control for exogenous macroeconomic factors, we used recession (0,1) as a covariate because consumers could become more price sensitive during a recession period. Consistent with the economics literature, we define a quarter to be in recession if it was a period of three or more consecutive quarters with negative growth in gross domestic product. Two interesting results emerged from this analysis. First, consumers in the nonloyal segment became more price sensitive over time, whereas loyal consumers showed little change in their price behavior. Second, the nonloyal consumers also demonstrated increasing sensitivity to price promotions and reduced sensitivity to non-price promotions, though these effects were weaker than were the effects for price. The promotion effects for the loyal consumers were in the same direction as for the nonloyal consumers, though the brand-level coefficients were not significant.

We also conducted a trend analysis for the nonloyal segment size (π) with $\ln(\pi/1-\pi)$ as the dependent variable, and trend and recession as the independent variables. This regression showed a significant increase in the size of the nonloyal segment over time, which indicates that an increasing proportion of consumers have become more price and promotion sensitive over time.

Pooling across brands. It is possible that consumer sensitivities for most brands could show a positive but insignificant trend. However, if we conclude from these results that consumer sensitivities are not changing over time, we may be making a Type II error by not appropriately pooling information across brands (Dutka 1984). Pooling results across brands also can be thought of as a "meta-analysis" across several brands.

One possibility is to run a *category*-level regression, which gives us a single-trend parameter for the category rather than separate trend parameters for the nine brands. Although this approach increases the sample size and pools the information across brands, it also could lead to erroneous results if the parameters for brands are so far apart that pooling across brands increases the variance of the category-level parameter, making it insignificant. Treating the results from different brands as independent replications, we use Fisher's pooling test (Fisher 1948; Rosenthal 1978). Pooled results that are based on this test are summarized in Table 3.

These results suggest that the answer to our first question—"Are consumers' sensitivities to marketing variables changing over time?"—is a resounding yes.[12] Of special interest is the result that price and price promotion sensitivities are increasing over time. Our findings have important implications for managers and researchers who attempt to draw empirical generalizations using meta-analysis or to compare the results of two or more studies conducted over different time periods. For example, Tellis (1988b) and Sethuraman and Tellis (1991) find average price elasticity to be around −1.7. However, our results suggest that these averages are likely to change over time. We next examine the reasons for these changes.

Table 3
CHANGE IN CONSUMERS' SENSITIVITIES OVER TIME

Consumers' Sensitivity to	*Changes Over Time*	*Significance Level*
1. Loyal Segment		
Price	Increase	$p < .001$
Price Promotion	Increase	$p < .001$
Non-price Promotion	Decrease	$p < .05$
2. Nonloyal Segment		
Price	Increase	$p < .001$
Price Promotion	Increase	$p < .001$
Non-price Promotion	Decrease	$p < .05$
Nonloyal Segment Size	Increase	$p < .05$

Stage Two: Impact of Marketing Activity on Consumers' Sensitivities

The purpose of the second stage analysis is to test explicitly if advertising and promotion affect consumers' price and promotion sensitivities over the long run. We used the distributed lag model described in Equation 8, in which consumers' sensitivities (i.e., first derivatives) to weekly price, price promotion, and non-price promotion activities for each brand and segment were the dependent variables, and quarterly advertising, price promotion, and non-price promotion of that brand were the independent variables along with the lagged dependent variable. We also included recession as an independent variable to control for exogenous macroeconomic factors. We first ran Durbin's test to check for serial correlation of errors in a distributed lag model (Johnston 1984, p. 318). Out of 54 regressions (2 segments × 3 dependent variables × 9 brands), 47 regressions had no correlation in the errors. Therefore, our formulation seems to be consistent with the partial adjustment model. Next, we performed a test as per Johnston (1984, p. 347) to see if the decay parameter λ is different for advertising, price promotion, and non-price promotion. For all nine brands, we could not reject the null hypothesis that all of the decay parameters are the same.

[11]To obtain consumers' sensitivity to price promotion, we used a simple average of consumers' sensitivity to TPR, feature, and coupons. Results were not sensitive to different weighting schemes.

[12]To confirm further whether the long-term series of consumers' sensitivities to price and promotion is evolving, for all nine brands we performed the unit root test suggested by Dekimpe and Hanssens (1995a). We found strong evidence of evolving sensitivities in the nonloyal segment and somewhat weaker evidence for the loyal segment. We also found the advertising and promotion variables to have unit roots. We thank Marnik DeKimpe for making the necessary program available for this test.

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Using this brand- and segment-specific regression, we estimated the γ parameters associated with each of the quarterly variables (see Equation 8). These parameters reflect the quarterly (medium-term) effect of advertising and promotion on consumers' response sensitivities. Results from these brand-specific regressions were pooled according to Fisher's method. We estimated the long-term impact of advertising and promotion on consumers' sensitivities [$\theta = \gamma/(1-\lambda)$] and its variance for each brand and segment. We then pooled brand-level results using Fisher's method.

Finally, we also regressed the size of the nonloyal segment (π) against quarterly marketing variables. Specifically, we used $\log(\pi/1-\pi)$ for each quarter as the dependent variable and quarterly advertising, price promotion, non-price promotion, and recession as independent variables along with the lagged dependent variable. Because the segment sizes were not brand specific, we used the mean category level variables (e.g., average category advertising) as our independent variables. The purpose of this regression was to see if, for example, decreased advertising expenditure made consumers less brand loyal.

The Long-Term Effects of Advertising and Promotions

Results of both the medium-term (over one quarter) and long-term (over infinite horizon) impact of advertising and promotion on consumers' price and promotion sensitivities are given in Table 4. To facilitate comparison and discussion, we have also included the hypothesized signs for these effects. Overall, we found support for many of our hypotheses. Although some of the results were insignificant, none were significant in the wrong direction.

1. *Advertising.* Consistent with several previous studies (e.g., Krishnamurthi and Raj 1985), we find that a reduction in advertising makes consumers more price sensitive and that most of this effect is on the nonloyal consumers.[13] Furthermore, we find that less advertising helps to increase the size of the nonloyal segment. This dual effect (i.e., a reduction in advertising leading to an increase in the size of the nonloyal segment and making consumers more price sensitive) shows a powerful role of advertising in reinforcing consumer preferences for brands. Table 4 also shows that reduction (increase) in advertising reduces (increases) consumers' sensitivity to non-price promotion for the nonloyal consumers. In other words, advertising makes non-price promotions such as displays more effective. Moreover, our results indicate that if a market has a large "loyal" segment, then using an unsegmented model can lead to insignificant and/or substantially smaller advertising effects. This might explain partially the inability of many researchers to find any advertising effects in scanner data.
2. *Price promotions.* As expected, in the long run price promotions make consumers more price sensitive in both the loyal and nonloyal segments. They also train nonloyal consumers to look for promotions, thereby making them more sensitive to price promotions.
3. *Non-price promotions.* Non-price promotions have significant effects only on consumers' price sensitivities. Consistent with our hypotheses, these promotions make loyal consumers less price sensitive and make the nonloyal consumers much more price sensitive. These results are consistent with prior literature that suggests opposite effects of certain promotions for different consumers.

Several additional insights emerge from our analyses. First, the results are identical for the medium-term and long-term effects of advertising and promotion (except for the

[13]Although our data show advertising expenditures to be declining over time, we expect our results to be bidirectional (i.e., we expect an increase/decrease in advertising expenditure to reduce/increase consumers' price sensitivity). Also, when the price parameter (which is negative) is used as a dependent variable, a positive coefficient for advertising implies that advertising reduces price sensitivity.

Table 4
HYPOTHESES AND RESULTS

Loyal Segment				*Nonloyal Segment*				
	Impact on Consumer Sensitivity to				*Impact on Consumer Sensitivity to*			
Long-Term Impact of	*Price*	*Price Promotions*	*Non-price Promotions*	*Long-Term Impact of*	*Price*	*Price Promotions*	*Non-price Promotions*	*Nonloyal Segment Size*
1. Hypothesized Signs								
Advertising	+	−	+	Advertising	+	−	+	−
Price Promotions	−	+	−	Price Promotions	−	+	−	+
Non-price Promotions	+	−	+	Non-price Promotions	−	−	+	?
2. Results for Medium-Term Effects								
Advertising	*ns*	*ns*	*ns*	Advertising	+	*ns*	+	−
Price Promotions	−	*ns*	*ns*	Price Promotions	−	+	*ns*	*ns*
Non-price Promotions	+	*ns*	*ns*	Non-price Promotions	−	*ns*	*ns*	*ns*
3. Results for Long-Term Effects								
Advertising	*ns*	*ns*	*ns*	Advertising	+	*ns*	+	−
Price Promotions	−	*ns*	*ns*	Price Promotions	−	+	*ns*	*ns*
Non-price Promotions	+	*ns*	*ns*	Non-price Promotions	−	*ns*	*ns*	*ns*

Note: Price sensitivity is generally negative. Therefore, a positive sign (e.g., ad-price) indicates a decrease in price sensitivity. Significance is based on pooled Fisher test with $p < .05$.

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Table 5
AVERAGE EFFECT OF ADVERTISING AND PROMOTION ON CONSUMERS' SENSITIVITIES
REGRESSION RESULTS FROM SECOND-STAGE ANALYSIS[1]

	Loyal Segment			*Nonloyal Segment*			
Impact of	*Price Sensitivity*	*Price-Promotion Sensitivity*	*Non-price-Promotion Sensitivity*	*Price Sensitivity*	*Price-Promotion Sensitivity*	*Non-price-Promotion Sensitivity*	*Nonloyal Segment Size*
Lag (λ)	.384*	.461*	.410*	.516*	.285*	.389*	.639*
Advertising	.0007	.000	.000	.008*	.000	.0003*	−.0001*
Price Promotion	−.374*	−.023	−.006	−1.207*	.080*	.011	.059
Non-price Promotion	.349*	.041	.011	−4.368*	.020	−.029	−.047
Recession	−.106*	−.003	−.012*	−.015	.005	−.001	−.001
R^2	.29	.32	.39	.56	.35	.27	.74

[1]Numbers in this table are weighted averages of the parameters from brand-level regressions, where weights are proportional to inverse of the parameter variances (R^2 is a simple, not weighted average across brands). Therefore, they represent medium-term effects of advertising and promotion on consumers' sensitivities. Parameters with $p < .05$ based on pooled Fisher test are represented by an asterisk.

"effect size," which we discuss subsequently). Second, the average R^2 for the second stage analysis is .37 ($\bar{R}^2 = .26$). The model fit is slightly poorer for the loyal segment (average $R^2 = .34$, $\bar{R}^2 = .21$) than for the nonloyal segment (average $R^2 = .39$, $\bar{R}^2 = .30$). This is an intuitively appealing result, which suggests that long-term marketing variables can explain better the changes in the behavior of nonloyal consumers, who by definition are affected by marketing variables more than are loyal consumers. This is also reflected in more significant signs for the nonloyal segment than for the loyal segment. Third, the decay parameter λ varies from .29 to .52 with an average of .41 (see Table 5). This indicates that on average the long-term effects of advertising and promotion are $1/(1 - .41)$, or 1.7, times their medium-term (quarterly) effects. The decay parameter also suggests that 90% of the cumulative effect of advertising and promotion on consumers' sensitivities occurs within three quarters, which is similar to the result obtained by Clarke (1976). Finally, though recession had no impact on consumers' sensitivities in the nonloyal segment, it increased consumers' price sensitivity and reduced their non-price promotion sensitivity in the loyal segment.

How Large Are the Long-Term Effects of Advertising and Promotions?

Our previous discussion indicates the directional effects of advertising and promotions. It is also useful to assess the magnitude of these effects. We estimated the medium- and long-term effect sizes as follows.

To estimate the medium-term impact, γ, we note from Equation 8 that the parameter $\gamma = \partial Y/\partial Z$ represents the change in consumers' sensitivity (Y) for one unit change in the quarterly variable Z. Therefore, $(\gamma/Y) \times 100$ is the percent change in consumers' sensitivity for one unit change in Z.[14] We use the average Y and Z values to arrive at the effect size in the medium term for each of the two segments.[15] The long-term effect size is then simply the medium-term effect size divided by $(1 - \lambda)$, where λ is the decay parameter.

We give the effect sizes in Table 6. Three key results emerge from this table: First, consistent with previous research, advertising effects are generally smaller than promotion effects; second, long-term effect sizes are approximately 1.5 to 2 times larger than medium-term effect sizes; and third, the changes in price sensitivities are greater than the changes in promotion sensitivities.

Summary of Results

In summary, our results suggest the following:

- Advertising helps a brand in the long run by making consumers (especially nonloyal ones) less price sensitive as well as by reducing the size of the nonloyal segment.
- In the long run, price promotions make both loyal and nonloyal consumers more sensitive to price. An increased use of such promotions also trains consumers (especially nonloyal ones) to look for deals in the marketplace. On average, we find these effects to be almost four times larger for nonloyal consumers than for relatively loyal consumers.
- As expected, we found that non-price promotions have different effects for loyal and nonloyal consumers. Although these promotions act like advertising for loyal consumers, making them less price sensitive, they make the nonloyal consumers focus even more on prices. In other words, these promotions reduce the price sensitivity of loyal consumers but significantly increase the price sensitivity of nonloyal consumers. The effects for nonloyals are almost 12 times larger than the effects for loyals.

To the extent that increased price and promotion sensitivity of consumers can be considered undesirable outcomes, our results confirm the conventional wisdom that in the long run, advertising has "good" effects and promotions have "bad" effects on consumers' brand choice behavior. Note, however, that these results are based on the analysis of only one category in one market.

[14]Because price elasticity $\eta = \dfrac{\partial \text{Share Price}}{\partial \text{Price Share}} = Y \dfrac{\text{Price}}{\text{Share}}$ it is easy to show that under certain conditions, $(\gamma/Y) \times 100$ also represents percent change in η for one unit change in Z.

[15]Strictly speaking, we should evaluate changes in Y for each brand, segment, and quarter. However, our "aggregate" approach should provide us with a good approximation. For example, in the context of discrete choice models, Ben-Akiva and Lerman (1985) indicate that errors due to aggregation across consumers are relatively small if all consumers have the same choice set.

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Issues of Causality

This study is correlational in nature. It is possible that changes in consumer behavior have led to changes in marketing activity rather than changes in marketing activity leading to changes in behavior. We empirically tested for causality by running a simultaneous equation model as follows:

Price sensitivity = f(Lag price sensitivity, Ad, PP, NPP, Recession)
PP sensitivity = f(Lag PP sensitivity, Ad, PP, NPP, Recession)
NPP sensitivity = f(Lag NPP sensitivity, Ad, PP, NPP, Recession)
Ad = f(Lag Ad of brand, Competitive Ad, Price sensitivity, PP sensitivity, NPP sensitivity)
PP = f(Lag PP of brand, Competitive PP, Price sensitivity, PP sensitivity, NPP sensitivity)
NPP = f(Lag NPP of brand, Competitive NPP, Price sensitivity, PP sensitivity, NPP sensitivity),

where PP is price promotion and NPP is non-price promotion. The first three equations represent our second-stage analysis and the last three equations capture the reverse causality (i.e., the effect of changes in consumers' sensitivities on marketing activities). We estimated these equations at a brand and segment level using two-stage least squares. We then pooled the results across brands using Fisher's procedure, as indicated previously.

Of the seven significant results obtained in Table 4, four show causality only in the proposed direction at $p < .05$, and three show bidirectional effects (and two of them have p-values that are almost ten times smaller in the proposed direction than in the reverse direction). Although these results do not rule out reverse causality completely, they do lend support for the proposed causal effects.

Competitive Reaction

Recent articles by Lal and Padmanabhan (1995) and DeKimpe and Hanssens (1995a, b) suggest that market shares are stationary (i.e., not evolving over the long run) for a majority of product categories. Lal and Padmanabhan (1995) also find the long-term effect of promotions on market shares to be largely insignificant.

In contrast, we find long-term effects of advertising and promotions on consumers' *sensitivities* to price and promotions, not on the *market shares* of various brands. We conjecture that our findings are consistent with those of Lal and Padmanabhan (1995) and DeKimpe and Hanssens (1995a, b) for the following reasons. Increasing promotion and reduced advertising makes consumers more price and promotion sensitive. This leads firms to offer even more price promotions to obtain short-term gains. However, all firms engage in this action. This form of competitive action has two effects: First, it makes the overall promotional intensity in the category higher, thereby making consumers even more price sensitive over time (as we find); and second, competitive matching of promotional spending leaves the relative promotion across firms to be largely the same, thereby having little effect on their market share. In other words, it is conceivable that though consumers are becoming more price sensitive because of increased promotional activities of various firms, "the offsetting competitive activity plays a role in the maintenance of what appears to be stationary and zero order behavior" (Bass et al. 1984, p. 284), leading to stationary market shares. This highlights the importance of studying the long-term effects of promotion and advertising on not only the changes in market share or sales, but also on changes in consumer behavior.

CONCLUSION

Our purpose was to develop and empirically test a model to understand the long-term impact of advertising and promotion on consumers' brand choice behavior. Specifically, we set out to find if consumers' responsiveness to marketing mix variables changes over time and, if so, why. To address these issues we used a unique data set that includes store environment and purchase history of more than 1500 household for 8¼ years for one frequently purchased consumer packaged good in one market.

At least in our data set, consumers have become more price and promotion sensitive over time. We found two segments of consumers—loyal, or relatively less price-sensitive consumers, and nonloyal, or price-sensitive consumers. Our results show that the size of the nonloyal segment has grown over time. In other words, a larger number of consumers have become increasingly more price and promotion sensitive over time.

We used quarterly advertising and promotion policies of brands to help explain these changes in consumer behavior. Our results confirm the conventional wisdom that in the long run, advertising reduces consumers' price sensitivity and promotions increase consumers' price and promotion sensi-

Table 6

MEDIUM- AND LONG-TERM EFFECTS OF ADVERTISING AND PROMOTION ON CONSUMERS' SENSITIVITIES[1]

	Loyal Segment *% Change in Consumers' Sensitivity to*			*Nonloyal Segment* *% Change in Consumers' Sensitivity to*		
1% Increase in	*Price*	*Price Promotion*	*Non-price Promotion*	*Price*	*Price Promotion*	*Non-price Promotion*
Medium-Term Effects						
Advertising	*ns*	*ns*	*ns*	.15	*ns*	.10
Price Promotion	−.37	*ns*	*ns*	−1.20	.08	*ns*
Non-price Promotion	.35	*ns*	*ns*	−4.37	*ns*	*ns*
Long-Term Effects						
Advertising	*ns*	*ns*	*ns*	.30	*ns*	.15
Price Promotion	−.61	*ns*	*ns*	−2.50	.11	*ns*
Non-price Promotion	.57	*ns*	*ns*	−9.02	*ns*	*ns*

[1]We focus on only significant effects ($p < .05$). Note that negative numbers for price imply increase in price sensitivity.

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tivity. These effects were found to be significantly larger for nonloyal consumers than for loyal consumers. In general, compared with the "good" effects of advertising, promotions were found to have significantly larger "bad" effects on consumers' price and promotion sensitivities. We also conjecture that though increased promotional spending could make consumers more price sensitive over time, market shares of brands may not see any long-term trends becaue of offsetting competitive activities.

Although this study provides some managerial insights about the relative roles of advertising and promotions, additional research is required before we can make such general recommendations to managers such as to increase advertising and reduce promotions. Specifically, the results of this study are limited by the fact that we only studied one product category in one market. Generalization of these results across several markets and categories will be a useful area of further research. Moreover, it will be useful to compare the short- and long-term changes in brand shares due to different advertising and promotion policies. It is possible that the large, positive short-term benefits of promotions outweigh their relatively small, negative long-term effects. The study also can be extended by focusing on sales and profits instead of shares. It is conceivable that negative long-term effects of price promotion on consumers' brand choice are significantly mitigated or even reversed by promotions' positive long-term effects on consumers' purchase timing or purchase quantity decisions. Therefore, understanding the long-term effects of advertising and promotion on other components of consumers purchase behavior, such as purchase incidence and quantity, is a fruitful area of further research. Here we have speculated about the competitive reactions; however, a better understanding of the competitive dynamics over time is certainly needed. In summary, we believe that understanding the long-term effects of marketing variables on brand share, sales, and competition is a useful and rich area of academic research and managerial relevance. We hope our study sparks interest in this direction.

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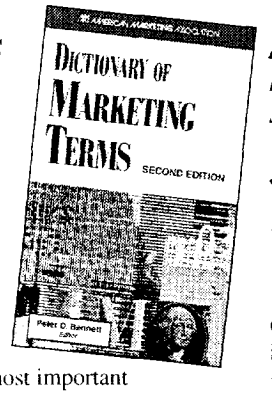

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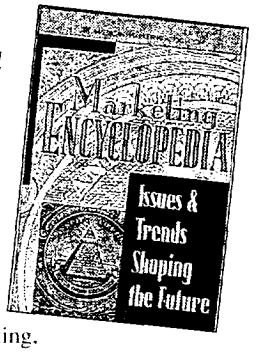

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