# Explaining the Variation in Short-Term Sales Response to Retail Price Promotions

V. Kumar and Arun Pereira

*Journal of the Academy of Marketing Science* 1995; 23; 155
DOI: 10.1177/0092070395233001

# Explaining the Variation in Short-Term Sales Response to Retail Price Promotions

**V. Kumar**
*University of Houston*

**Arun Pereira**
*St. Louis University*

*This study focuses on the short-term sales response to price promotions in retail grocery stores and attempts to explain its variation using frequency of price promotions and the consecutive scheduling of price promotions. Retail managers' expectations and tenets from behavioral theories provide the basis for the hypotheses that the frequency of price promotions and consecutive scheduling of price promotions affect short-term response to price promotions. The hypotheses are tested on three frequently purchased product categories, using store-level data from retail chains in three major markets. The analysis is validated with additional data on the same product categories and markets. A variety of managerial implications are drawn from the results and suggestions for future research are offered.*

Manufacturers spend huge sums of money in the attempt to influence retailer support of their brands with retail promotions (e.g., Curhan and Kopp 1986; Hardy 1986). However, because retailers are not legally required to "pass through" these trade incentives as retail promotions, the retail promotional support for a brand varies across retailers. Consider the following comments, made by two managers of major grocery store chains in St. Louis, Missouri, with respect to price promotions.

**Journal of the Academy of Marketing Science.**
**Volume 23, No. 3, pages 155-169.**


The manager in charge of retail promotions for grocery products at a chain of 14 grocery stores in St. Louis said

> Manufacturers continuously attempt to entice us into offering their brands on price promotions with trade incentives such as volume discounts. Whether we actually pass these incentives to the customer will depend on issues such as how often we have promoted the brand in the past. Our intention is to "excite" the customers with a price discount promotion; and we cannot get customers excited if we discount often.

In contrast, the general manager of another chain of 8 grocery stores said

> We pass through manufacturers' trade incentives to the customer close to 100% of the time. We do not take into consideration how often we discounted the brand in the past nor how well it performed during the past promotions. Because of the large number of trade promotions offered to us, we have very frequent price promotions. Further, this policy of frequent price promotions means that the sales generated during our price promotions are less than that generated during promotions of other retailers who are more selective in offering price promotions.

Our interviews with retail managers in New York, Chicago, Los Angeles, and Houston found them echoing the words of the St. Louis managers. A question of interest to managers and researchers is, What are the implications of having a brand supported by price promotion policies that vary among retailers? Will the short-term sales response to a given price promotion vary among retailers based on promotion policies that differ from one retail store to another? As discussed in the following section, we would expect this to be the case, given that the frequency of price promotion support received by the brand can vary from one store to another. Further, even if frequency of promotion is similar, the type of promotion schedule—such as consecutive scheduling—can vary. This would mean that the "excitement" generated for a given price promotion will depend on frequency and scheduling of price promotions in the store, affecting the short-term sales response to the price promotion.

This issue is important because the examples given are not isolated ones, but rather, reflect a larger phenomenon. For example, according to Information Resources Inc. (IRI) data, the frequency with which a major brand of saltine crackers was price promoted in a recent 52-week period among the retail chains in the Chicago market varied from a low of 4 weeks in one retail chain to a high of 17 weeks in another. The IRI data reveal similar variation in the frequency of price promotions across retail chains for other frequently purchased products in other cities including Los Angeles and New York. The data indicate that the price promotion support received by the brand varies extensively by retail chains within each city and across cities. This variance in frequency of price promotions (see also Blattberg and Neslin 1990, pp. 344-5) is particularly relevant because all retail chains in a city typically receive the same amount of trade incentives by manufacturers (as required by law).

From a research perspective, the above issue is important because retail managers recognize that the short-term sales impact of a particular price promotion will depend on the frequency of price promotions in the store, as described earlier. However, no research has explicitly addressed this issue or attempted to analyze the scheduling of price promotions. Only Krishna (1994a, 1994b) has attempted to discuss the effect of deal timing pattern on consumer purchase behavior using a normative model. The lack of research attention in this area is surprising because the implications of varying price promotion policies across retailers may mean that all retail chains are not "equal" in terms of being effective price promoters of brands. As such, research is required to help manufacturers better understand the effects of the price promotion policies of retailers, as well as help retailers understand the effects of their price promotion decisions.

First, we offer definitions of key variables used in the study, followed by sections on the theoretical underpinnings of frequency and scheduling, hypotheses, data, and methodology. The final sections are devoted to discussion of the results, managerial implications, and suggestions for future research.

## FREQUENCY AND SCHEDULING

Short-term sales (as opposed to long term) in a retail promotion context is defined as "the sales volume that is generated in the promotion week, in the promoting store, that is incrementally related to the promotion, and is incremental to 'normal' sales in that store during that week that would have occurred if the promotion had not been run" (Abraham and Lodish 1993, p. 250). Short-term sales response is defined in this study as the effect of a retail price promotion in generating the short-term sales.

Interviews with retail managers indicate that they expect the frequency of price promotions to affect the short-term sales response to price promotions. The sales response to price promotions for a given brand in a given store is expected to vary depending on how frequently price promotions are offered (for that brand and competing brands) in that store. This expectation of the effect of frequency of price promotions can be explained by concepts such as purchase acceleration and brand switching and substantiated by theories such as operant conditioning theory and reference price theory (see following section). However, the direction of the effect (e.g., does frequency of price promotions have a positive or negative effect on a given promotion?) is not clear. The present study examines this area by analyzing frequency of promotions and its effect on the short-term sales response to promotions, and by introducing the issue of scheduling of price promotions. Although Krishna (1991) has studied the effect of dealing patterns on consumer perceptions of deal frequency and willingness to pay, no published study to date has focused on the effect of frequency and scheduling of price promotions on short-term sales response.

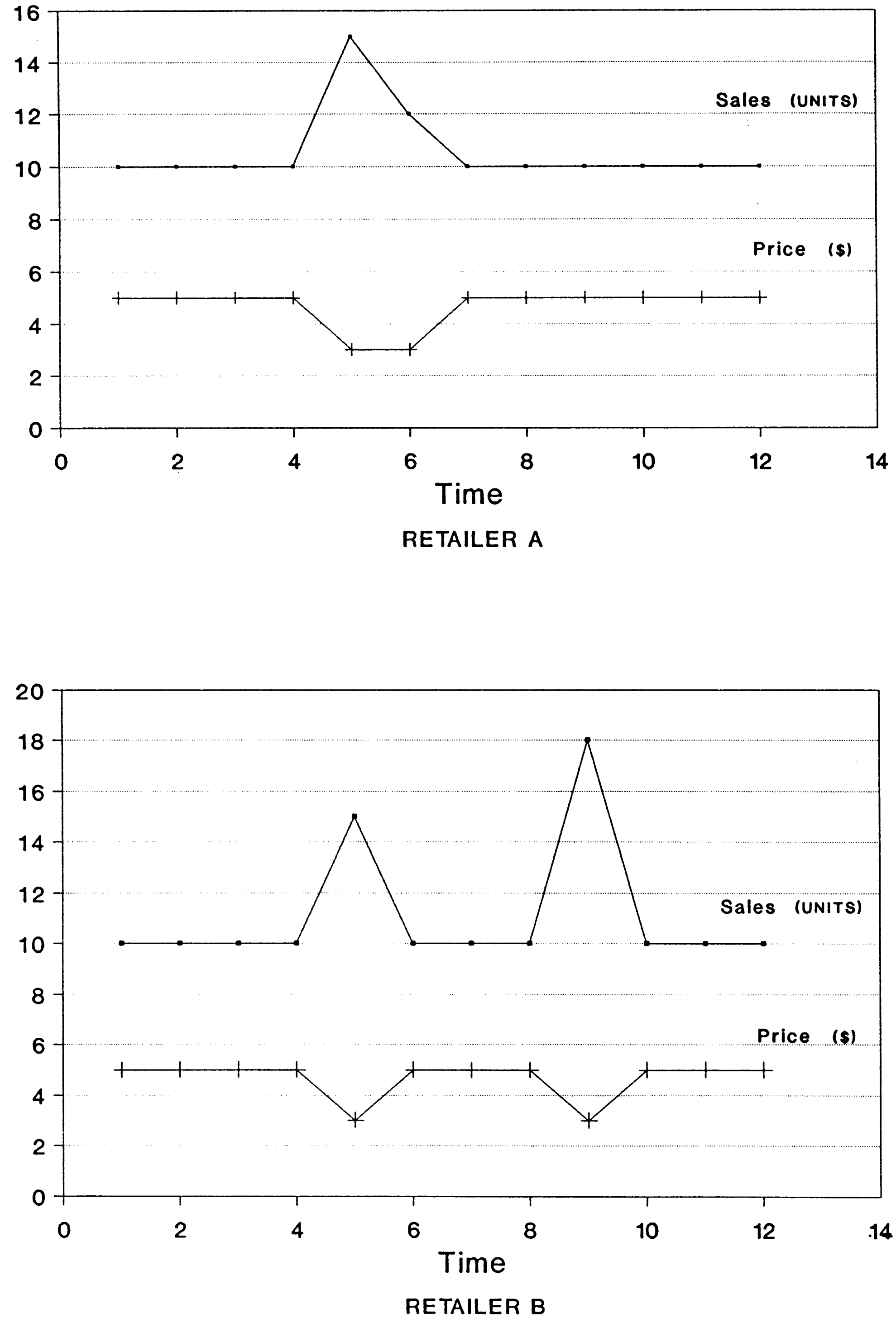
Specifically, we focus on price promotion schedules, where one week of price promotion systematically follows another (e.g., Brand A is price promoted for a week immediately following a week of competing Brand B's price promotion, or immediately following Brand A's own week of price promotion). As such, we focus on *consecutive scheduling*—whereby a brand's price promotion runs consecutive to a competing brand's price promotion or its own price promotion. Our objective is to explain the variation in sales response to price promotions using frequency and consecutive scheduling. Price promotions are defined in this study as the following: temporary price discounts, temporary price discount with feature, and temporary price discount with display, where "temporary" is defined as a week. In this study, 2 weeks of price promotion for the same brand in a store is considered as a consecutive schedule of two price promotions (each lasting for a week) for the same brand.

## CONCEPTUAL FOUNDATIONS AND HYPOTHESES

### An Example

We expect frequency of price promotions, consecutive scheduling of price promotions, and the interaction between the two to affect the short-term sales response to a given price promotion. To illustrate the effect of consecutive scheduling, let us first assume that two retail chains (A and B) have identical frequency of price promotions for

**FIGURE 1**
**The Effect of Different Price Promotion Schedules**




a given brand (Brand X). As an example, assume that each retailer will offer Brand X on price promotion on two occasions (i.e., a frequency of two); however, Retailer A schedules the price promotions in consecutive weeks (time periods 5 and 6) and Retailer B schedules them far apart (time periods 5 and 9) (see Figure 1).

In such a case, the short-term sales response to the price promotions for Brand X (over the two price promotions) can vary between the two retailers. Brand X may generate a different (lower) sales response at Retailer A than at Retailer B because of the possibility of purchase acceleration. *Purchase acceleration*, as defined by Blattberg and

Neslin (1990), refers to consumers buying different quantities or purchasing at different times than they would have had a promotion not been available (see Blattberg and Neslin 1990, p. 128, for a comprehensive discussion of purchase acceleration and summary of empirical evidence). Customers at Retailer A can purchase more units than they normally do during the first price promotion and stockpile the extra units. In this situation, they have little need to take advantage of another price promotion until they have exhausted their home inventory. Thus the second price promotion at Retailer A will have a lower sales impact than the second promotion at Retailer B. This means that the overall sales response (over the two promotions) for Brand X will be smaller at Retailer A than at Retailer B (as illustrated in Figure 1).

The same effect will be expected for another competing brand (e.g., Brand Y) if the second price promotion at both Retailers A and B is not of Brand X, but of competing Brand Y. We would expect the overall sales response for Brand Y to be lower at Retailer A than at Retailer B. This expectation is based on the combined phenomena of brand switching and purchase acceleration. *Brand switching*, as defined by Blattberg and Neslin (1990), occurs when consumers are induced to purchase a different brand from one that would have been purchased had the promotion not been available (see Blattberg and Neslin 1990, p. 112, for a detailed discussion and empirical evidence associated with brand switching). That is, regular customers of Brand Y switch to Brand X and stockpile Brand X; thus the customers have little need to take advantage of the price promotion of Brand Y when it consecutively follows the price promotion of Brand X. The degree of brand switching due to price promotions in a product category will depend on the extent of differentiation (or the lack of differentiation) between brands, as well as other issues such as price tier competition (Kumar and Leone 1988), utility, and attitude (Blattberg and Neslin 1990). Thus if Brands X and Y are close competitors, the more often Brand Y's price promotions are consecutively scheduled after Brand X, the more likely that the short-term sales response for Brand X is larger than the short-term sales response for Brand Y.

Further, in the example, we assumed a fixed frequency of price promotions; however, in reality the frequency of price promotions (and the scheduling of these promotions) is not expected to be fixed across retailers, and is instead expected to vary among them. As such, we have two variables, frequency and scheduling (and specifically in this study, consecutive scheduling), that can vary across retailers and affect the short-term sales response to a given price promotion.

In summary, because of possible purchase acceleration and brand switching, the short-term sales response to price promotions for a brand can be expected to vary from one store to another depending on frequency. Further, the degree to which frequency affects the sales response will depend on scheduling of these price promotions. In this study we focus on the particular case of consecutive scheduling. Thus we expect an interaction between frequency and consecutive scheduling to affect the sales response to price discounts. Also, this effect is expected to occur regardless of whether the consecutive scheduling is of "own" brands or competing brands. In either case, consecutive scheduling will affect the short-term sales response to a price promotion. Before we offer our hypotheses, we provide a theoretical basis to our expectations.

## Frequency and Scheduling of Price Promotions: Theoretical Expectations

This section focuses on operant conditioning theory, which lends itself to an understanding of the combined effects of frequency and scheduling of price promotions. It is followed by a brief discussion of other theories that address the specific issue of frequency of price promotions.

As postulated by Skinner (1938), the basic tenet of operant conditioning theory is that reinforced behavior is likely to persist, with frequency and the associated scheduling of reinforcement (continuous or intermittent) playing an integral role (Blattberg and Neslin 1990, p. 24) in persistence of the behavior. However, according to the theory, once reinforcement is removed, the likelihood of behavior continuing will decrease and may become "extinct." The challenge is to use frequency and scheduling such that reinforcement builds behavior, and prevents the extinction effect.

In the context of retail price promotions, the relevance of operant conditioning is that price promotions can reward in the form of monetary savings and hence reinforce purchase behavior. However, more than one reinforcer can reward a single behavior (Blattberg and Neslin 1990), and in the above case, more than one reinforcer can influence brand choice. Product performance and satisfaction after consumption of the brand can be a reinforcer, independent of other reinforcers such as monetary savings. Blattberg and Neslin (1990) distinguish between primary and secondary reinforcers. Primary reinforcers are rewards that have intrinsic utility as opposed to the indirect utility of secondary reinforcers. Obviously, managers would like to have the consumption experience of the brand as the primary reinforcer, with the money saving playing a secondary role. In that case, the price promotion can be stopped, and brand choice behavior will continue to persist.

However, it is unlikely that many of today's brands have performance and satisfaction acting as primary reinforcers, given the lack of differentiation in most product categories and the proliferation of "parity" products in today's markets. In this context, the monetary saving may be a primary reinforcer (Blattberg and Neslin 1990) and purchase behavior becomes extinct very quickly once the price promotions are withdrawn—particularly because customers can accelerate purchases and/or switch brands when there are monetary savings available.

Thus, according to operant conditioning theory, when the frequency of price promotions increases, the monetary savings can become the primary motive in purchase behavior. This theoretical expectation has received research interest. For example, when the frequency of price promotions increases, customers learn to buy only during price promotions (Krishna, Currim, and Shoemaker 1991). This means that incremental sales during promotions (the difference between promotional sales and regular or "baseline" sales) are high; however, regular sales (baseline sales) are depressed because customers tend to buy only during price promotions (Krishna 1992). Thus frequency can have a positive main effect on short-term sales response to price promotions. However, the monetary savings can do little to influence purchase behavior if purchase acceleration and brand switching has taken place and the home inventory has not been exhausted. The extent to which purchase acceleration and brand switching may be a factor depends on the scheduling of the price promotions, particularly consecutive scheduling.

As the frequency of price promotions increases, the effect of the frequency on short-term sales response depends on whether the promotions are consecutively scheduled. For example, for a frequency of two promotions, the effect on short-term sales response would vary between consecutive scheduling and staggered scheduling. However, if the frequency is raised to four promotions, the effect would again be different between consecutive scheduling and staggered scheduling. But the differential effect in the latter case could be smaller because consumers cannot take advantage of many promotions when they are sequenced together. Therefore, we can expect an interaction between frequency and consecutive scheduling to affect the short-term response to price promotions.

## The Specific Case of Frequency

If we focus on frequency exclusively (without the issue of scheduling), a variety of theories offer a conceptual basis for the understanding of its effects. However, these predicted effects are often in the direction opposite to that indicated by researchers such as Krishna, Currim, and Shoemaker (1991). For example, theories such as adaptation-level theory (Helson 1964) and the associated concept of reference price would predict that frequency of price promotions will have a negative impact on sales response to price promotions. According to the theory, past stimuli that a person has been exposed to will determine the "adaptation level"; as such, the adaptation level can change as stimuli that the person has been exposed to changes. The adaptation level or the standard used to judge the price of a particular item is called the *reference price*. The reference price can be shaped by previous prices paid for an item or similar items. As such, when the frequency of price promotions increases, the reference price is perceived to be relatively low, and hence another price promotion is not as attractive as it would have been if frequency of price promotions had been low. There is empirical evidence that reference prices do exist and affect purchase behavior (Winer 1986; Kalwani et al. 1990; Kamen and Toman 1970; Nagle 1987). Thus adaptation-level theory would predict that because of reference prices, frequency of price promotions will negatively affect the short-term response to price promotions.

## Hypotheses

The expectations of retail managers in conjunction with concepts such as purchase acceleration and brand switching, as well as tenets of operant conditioning theory, reference price theory, and past research, lead us to expect that the frequency of price promotions, the consecutive scheduling of price promotions, and their possible interaction will affect the sales response to a given price promotion. Operant conditioning theory and past research (e.g., Krishna, Currim, and Shoemaker 1991) would indicate that as frequency of price promotions increases, customers learn to buy only during price promotions, resulting in a positive effect for frequency. Alternatively, other theories such as adaptation-level theory and the associated concept of reference price would predict that as frequency increases, price promotions will have a negative impact on sales response to price promotions. As such, the directionality of the main effect of frequency is not clear, and we accommodate this by offering nondirectional hypotheses regarding the frequency main effect.

As stated earlier, regardless of the frequency of price promotions, the monetary savings of the promotion can do little to influence purchase behavior if purchase acceleration and brand switching has taken place and the home inventory has not been exhausted. The extent to which purchase acceleration and brand switching may be a factor depends on the scheduling of the price promotions, particularly consecutive scheduling. As such, we can expect an interaction between frequency and consecutive scheduling to affect the short-term response to price promotions. We also expect the interaction to negatively affect the short-term sales response to price promotions. A negative effect for consecutive scheduling and its interaction with frequency is hypothesized because of the expectation that consecutive scheduling is not preferable. Consumers may not have depleted the inventory and therefore would not take advantage of a promotion that followed immediately.

The need to examine each of the types of price promotions separately is based on past literature (see Blattberg and Neslin 1990, p. 356 for a discussion). Past theoretical and empirical research indicates the existence of different effects for the following: price discounts, price discounts with feature, and price discounts with display. Price discount with feature means that the price discount is "announced" (feature is local advertising). Similarly, price discount with display is also an announcement, albeit an in-store announcement. The two announcements work differently: the feature announcement can draw customers to the store, the display can draw customers to the product once they are in the store. In contrast, the price discount (without feature/display) has no such announcement.

#### Price Discount

**H1a:** Frequency of price discount promotions affects the short-term sales response to price promotions.

**H1b:** The scheduling of price discount promotions consecutive to either competing brands' promotions and/or own promotions negatively affects the short-term sales response to price promotions.

**H1c:** The interaction of frequency and consecutive scheduling of price discount promotions negatively affects the short-term sales response to price promotions.

#### Price Discount with Feature

**H2a:** Frequency of price discount with feature promotions affects the short-term sales response to price promotions.

**H2b:** The scheduling of price discount with feature promotions consecutive to either competing brands' promotions and/or own promotions negatively affects the short-term sales response to price promotions.

**H2c:** The interaction of frequency and consecutive scheduling of price discount with feature promotions negatively affects the short-term sales response to price promotions.

#### Price Discount with Display

**H3a:** Frequency of price discount with display promotions affects the short-term sales response to price promotions.

**H3b:** The scheduling of price discount with display promotions consecutive to either competing brands' promotions and/or own promotions negatively affects the short-term sales response to price promotions.

**H3c:** The interaction of frequency and consecutive scheduling of price discount with display promotions negatively affects the short-term sales response to price promotions.

The fourth possibility, price discount accompanied by feature *and* display, is not included among the hypotheses because the data used for the study do not include enough data points on such a promotion situation.

## DATA AND METHODOLOGY

### Data

Information Resources Inc.'s INFOSCAN store-level data were used for this analysis. Data on three product categories were analyzed: saltine crackers, baking chips, and disposable diapers. The product categories represented frequently purchased products that varied in price from approximately \$2-\$10. The brands chosen for analysis in each category were dominant national brands that together accounted for at least 85% share of the market. The sizes chosen for the product categories were one-pound boxes for crackers and baking chips, and medium size for the diapers. For better generalizability, the analysis was performed on 52 weeks of store-level data from three urban markets: New York, Chicago, and Los Angeles. Data included for the study were drawn from a sample of stores from each retail chain in each market. Two years of data (one year for model estimation and the subsequent year for checking the consistency of results) were used.

### Methodology

#### Variable Operationalization

When operationalizing the variables and testing the hypotheses, it was more relevant to draw conclusions and implications at the retail chain level because managerial decisions for manufacturers (dealing with the trade) and for retailers (price promotion decisions) are made at the retail chain level. However, we would be overlooking rich information if we ignored demand activity at the store level because stores within a retail chain may have served different demographic/socioeconomic groups based on their geographic locations. Hence promotion sensitivity can vary between stores of the same retail chain. To ensure that we preserve the richness of store-level data and drew managerial implications at the chain level, we operationalize the relevant variables below.

#### Short-Term Sales Response to Price Promotions

Short-term sales response to price promotion (SSR) was estimated for each brand at the store level. A key variable was $BaseSales_{it}$, the baseline sales for a given brand in a given store. Baseline sales are the sales that would have occurred for the brand in the given week if the promotion had not been run. By dividing a brand's total sales in a given week by its baseline sales, we were attempting to focus only on the incremental sales generated by the retail promotion. This is important because baseline is affected by variables that are different from those affecting the incremental sales (Abraham and Lodish 1993). Baseline sales are affected by distribution, the brand's regular price, and advertising, whereas the incremental sales are affected by retail promotion decisions (temporary price cuts, displays, and features), which are of interest to this study. $BaseSales_{it}$ was calculated for each brand/size/flavor combination for each store in the database using the PROMOTIONSCAN methodology (see the appendix and Abraham and Lodish [1993] for a complete description of the methodology). For obtaining the baseline estimates, an additional 2 years of data (prior to the data used for estimating the proposed model in this study) were used.

In terms of other details, price discounts are reductions of 5% or more versus recent prices. A price reduction generally does not last more than 6 weeks. We used volume sold as the unit of analysis. However, because we divided sales by base sales, the analysis was in dimensionless percentage change. Price is in dollars per equivalent volume. Our categories were chosen so there was minimal cross-size competition. Virtually all saltine crackers were one-pound size. Diaper sizes are not substitutes in general. We used the most promoted size (e.g., medium size) in modeling diaper sales. Most baking chips sales are in a single size.

Given that observations used to estimate SSR include all price promotion periods (i.e., periods with price discount only, price discount with feature, and price discount with display), the right-hand side of equation (1) includes discounted price relative to base price (average price during nonprice promotion periods), feature, display, and Feature × Display interaction. The feature and display variables in (1) are specified as dummy variables, taking a value of 1 in the event of a feature and/or display, and 0 otherwise. Equation (1) is estimated for each brand in a product category at the store ($i$) level. For a given brand in store $i$,

$$\log \frac{\text{Sales}_{it}}{\text{BaseSales}_{it}} = a_i + \text{SSR}_i \cdot \log \frac{\text{Price}_{it}}{\text{BasePrice}_{it}} + \theta_{1i} \cdot \text{F}_{it} + \theta_{2i} \cdot \text{D}_{it} + \theta_{3i} \cdot (\text{F} \cdot \text{D})_{it} + e_{it} \quad (1)$$

where

$\text{Sales}_{it}$ = sales of a brand in store $i$ at time $t$
$\text{Price}_{it}$ = promoted price of a brand in store $i$ at time $t$
$\text{F}_{it}$ = feature for a brand in store $i$ at time $t$
$\text{D}_{it}$ = display for a brand in store $i$ at time $t$
$a_i$ = intercept term
$\theta_{ki}$ = parameter estimates
$e_{it}$ = error term
$\text{BaseSales}_{it}$ = baseline sales (using PROMOTIONSCAN methodology)
$\text{BasePrice}_{it}$ = baseline price during nonprice promotion periods in store $i$
$\text{SSR}_i$ = short-term sales response for a brand in store $i$.

### Frequency of Price Promotion

The frequency of each type of price promotion relevant to this study (i.e., price discount, price discount with feature, price discount with display) of a brand is the actual count of number of times (weeks) the brand is offered on price promotion in the retail store. Thus, for each brand in each store, we computed the number (frequency) of price discounts only (F(P)), price discounts with feature (F(F)), and price discounts with display (F(D)).

### Consecutive Scheduling of Price Promotions

To operationalize the consecutive scheduling of price promotions, a Consecutive Scheduling Index (CSI) was computed. This index was based on the methodology adapted from Naert and Leeflang (1978) and was used successfully by other researchers such as Gatignon (1984) and, more recently, by Reddy and Holak (1991) in other contexts. CSI was computed for each brand in each store. This index attempts to measure the extent to which a brand's price promotions (in a given time period) are consecutive to other price promotions (competing brands' or own brands' price promotions). Further, because past research (e.g., McAlister 1985) has illustrated the differential impact of price promotions of large market share brands versus small market share brands, the index takes into account the market share of the brand whose price promotion preceded the given brand's price promotion. In summary, CSI is a measure that incorporates the following:

1. The consecutive nature of price promotions. The extent to which weekly[1] price promotions for a brand in a retail chain are consecutive (i.e., promotions are consecutive to own brand promotions or competing brands' promotions). This measure is calculated as the consecutive schedule coefficient using a logistic regression procedure (see equation [2]).
2. The effect of market share of the brand that was price promoted in the first week (of the 2 consecutive weeks). This is taken into account by weighting the consecutive schedule coefficient by the market share of the brand that is promoted in the first week of the consecutive weeks of price promotion (see equation [3]).

CSIs were computed for every type of price promotion: price discount only (CSI(P)), price discount with feature (CSI(F)), and price discount with display (CSI(D)).

### Calculating CSI: An Example

We describe below the computation of CSI(P), the specific case of Consecutive Scheduling Index for price discount only. In the first step, a brand's (Brand $j$) price promotion periods are identified and operationalized as a dummy variable (1 = *any type of price promotion*, 0 = *otherwise*; $R_{jt}$ in equation [2]). $R_{jt}$ is modeled using a logistic regression procedure against dummy variables for the preceding week's price-discount-only promotion for all brands (see $\text{P}_{k,\,t-1}$ for brand $k$ in equation [2]). The logistic regression model is used to estimate the consecutive schedule coefficient as shown in (2). This consecutive schedule coefficient can be interpreted as a measure of association between a brand's price promotion in one week and its own or competing brands' price promotions in the previous week. Thus, in a given store, the probability that any type of price promotion in week $t$ ($R_{jt}$) following a price discount only in week $t-1$ ($\text{P}_{k,\,t-1}$ for brand $k$) is

$$\text{P}[R_{jt} = 1] = \frac{1}{1 + \exp(-\delta_j - \Sigma_k \tau_{pkj} \cdot \text{P}_{k,t-1})} \quad (2)$$

where

$R_{jt}$ = any promotion (price discount, price discount with feature, and price discount with display) dummy variable for a brand $j$ at time $t$ in a given store
$\delta_j$ = intercept term
$\tau_{pkj}$ = consecutive schedule coefficient for any price promotion of brand $j$ to previous week's price discount of brand $k$ in a given store
$\text{P}_{k,\,t-1}$ = price discount dummy variable for a brand $k$ at time $t-1$ in a given store.

In other words, the consecutive schedule coefficient for any type of price promotion of brand $j$ in a given week was estimated (using [2]) against the previous week's price discount dummy variable for each brand included in the study. For example, if there are three brands ($k$ = 1 to 3 in equation [2]), then three consecutive schedule coefficients are estimated ($\tau_{p1j}$, $\tau_{p2j}$, and $\tau_{p3j}$). In the case of feature with price discount, $P_{k,\,t-1}$ in (2) was replaced with $F_{k,\,t-1}$, the feature with price discount dummy variable, and in the case of display with price discount, the relevant dummy variable used was $D_{k,\,t-1}$.

Given the consecutive schedule coefficient, the CSI for price discount CSI(P) is computed by weighting the coefficient with the market share of the relevant brands and summing across all brands within a store:

$$\mathrm{CSI(P)}_j = \frac{\Sigma m_k \cdot \tau_{Pkj}}{k} \tag{3}$$

where

$\mathrm{CSI(P)}_j$ = Consecutive Schedule Index for price discount for brand $j$ in a given store

$m_k$ = average market share (in percentages) of brand $k$ during the 52-week period in a given store, or

$$= \frac{1}{T}\sum_{t=1}^{\tau} m_{kt}$$

$\tau_{pkj}$ = consecutive schedule coefficient for any promotion of brand $j$ to previous week's price discount of brand $k$ in a given store.

Similarly, CSIs for price discount with feature ($\mathrm{CSI(F)}_j$) and price discount with display ($\mathrm{CSI(D)}_j$) can be calculated in a given store.

## Analysis

First, as described above, CSIs for each brand were calculated for each type of price promotion (price discount only (P), price discount with feature (F), and price discount with display (D)). Frequency of price promotions were calculated in this step as well. Thus, for each brand in each store, we have weeks of price discounts only (F(P)), price discounts with feature (F(F)), and price discounts with display (F(D)).

Next, a brand's short-term sales response to price promotions (SSR) in each store was modeled as a function of frequency of price discount only (F(P)), price discount with feature (F(F)), and price discount with display (F(D)), the three Consecutive Scheduling Indexes, and their interaction.

In other words,

$$\begin{aligned}\mathrm{(SSR)}_i = {} & \mu + \alpha_1\mathrm{F(P)}_i + \alpha_2\mathrm{F(F)}_i + \alpha_3\mathrm{F(D)}_i + \beta_1\mathrm{CSI(P)}_i \\ & + \beta_2\mathrm{CSI(F)}_i + \beta_3\mathrm{CSI(D)}_i + \gamma_1\mathrm{F(P)}_i \\ & \cdot \mathrm{CSI(P)}_i + \gamma_2\mathrm{F(F)}_i \cdot \mathrm{CSI(F)}_i \\ & + \gamma_3\mathrm{F(D)}_i \cdot \mathrm{CSI(D)}_i + \varepsilon_i\end{aligned} \tag{4}$$

where

$\mathrm{(SSR)}_i$ = short-term sales response to price promotions for brand in store $i$

$\mathrm{F(P)}_i$ = frequency of a brand's promotions that are price discounts only in store $i$

$\mathrm{F(F)}_i$ = frequency of a brand's promotions that are price discount with feature in store $i$

$\mathrm{F(D)}_i$ = frequency of a brand's promotions that are price discount with display in store $i$

$\alpha_1$, $\alpha_2$, and $\alpha_3$ = effect of frequency of a brand's price discounts, price discount with feature, and price discount with display on $\mathrm{(SSR)}_i$ in store $i$, respectively

$\beta_1$, $\beta_2$, and $\beta_3$ = effect of consecutive scheduling of a brand's price discounts, price discount with feature, and price discount with display on $\mathrm{(SSR)}_i$ in store $i$, respectively

$\gamma_1$, $\gamma_2$, and $\gamma_3$ = effect of the interaction of frequency and consecutive scheduling of a brand's price discounts, price discount with feature, and price discount with display on $\mathrm{(SSR)}_i$ in store $i$, respectively

$\mu$ = intercept term

$\varepsilon_i$ = error term.

However, to correctly estimate the model parameters, equation (4) is substituted back in the original equation (1). Thus the final model[2] estimated (substituting [4] in [1]) is

$$\begin{aligned}\log\{\mathrm{Sales}_{it}/\mathrm{BaseSales}_{it}\} = {} & a_i + \{\mu + \alpha_1 \cdot \mathrm{F(P)}_i \\ & + \beta_1\mathrm{CSI(P)}_i + \gamma_1 \cdot \mathrm{F(P)}_i \cdot \mathrm{CSI(P)}_i \\ & + \alpha_2 \cdot \mathrm{F(F)}_i + \beta_2\mathrm{CSI(F)}_i + \gamma_2 \cdot \mathrm{F(F)}_i \cdot \mathrm{CSI(F)}_i \\ & + \alpha_3 \cdot \mathrm{F(D)}_i + \beta_3\mathrm{CSI(D)}_i + \gamma_3 \cdot \mathrm{F(D)}_i \\ & \cdot \mathrm{CSI(D)}_i + \varepsilon_i\} \cdot \log\{\mathrm{Price}_{it}/\mathrm{BasePrice}_{it}\} \\ & + \theta_{1i} \cdot F_{it} + \theta_{2i} \cdot D_{it} + \theta_{3i} \cdot (F \cdot D)_{it} + e_{it}.\end{aligned} \tag{5}$$

Because the major managerial decisions are made at the retail chain level, model (5) (specified at the store level) was estimated at the retail chain level by stacking information from each store one below the other.[3] Model (5) parameters were estimated using an estimation procedure appropriate for analyzing cross-sectional time series data. Because some of the model parameters were functions of other exogenous variables, the generalized least squares procedure (Hsiao 1986) was used to estimate the parameters of model (5).[4]

By estimating model (5) as specified, we were essentially attempting to partial out the effect of SSR, the short-term sales response to price promotion, into its component parts and estimate each part. As per our earlier discussion, the variance in SSR can be explained by the frequency of promotion, the consecutive scheduling of promotion, and the interaction of frequency and consecutive scheduling of price promotion. However, the overall effect of frequency of price promotions was given by the sum of the main effect of frequency ($\alpha_1$) and the product of the interaction effect ($\gamma_1$) of frequency and Consecutive Scheduling Index of price promotions and the value for the corresponding CSI (i.e., $\alpha_1 + \gamma_1 \cdot \mathrm{CSI(P)}$). A similar overall effect for consecutive scheduling of price promotions can be calculated.

**TABLE 1**
**Means for the Predictor Variables in the Cracker Category (standard deviations in parentheses)[a]**

| | | Consecutive Schedule Index | | | Frequency | | |
|---|---|---|---|---|---|---|---|
| *Market* | *Brand* | *CSI(P)* | *CSI(F)* | *CSI(D)* | *F(P)* | *F(F)* | *F(D)* |
| New York ($n$ = 180) | 1 | 15.11 | 7.12 | 3.97 | 11.2 | 5.8 | 4.4 |
| | | (9.89) | (7.92) | (4.33) | (2.8) | (2.2) | (2.9) |
| | 2 | 20.11 | 3.89 | 1.97 | 15.6 | 4.1 | 1.8 |
| | | (15.70) | (4.57) | (3.08) | (2.5) | (2.3) | (1.3) |
| | 3 | 18.13 | 9.70 | 18.52 | 9.1 | 6.9 | 6.7 |
| | | (14.01) | (8.81) | (14.92) | (3.5) | (2.9) | (3.6) |
| Chicago ($n$ = 126) | 1 | 20.77 | 6.75 | 6.81 | 8.6 | 4.9 | 3.8 |
| | | (11.96) | (5.51) | (7.10) | (2.1) | (0.8) | (2.3) |
| | 2 | 11.82 | 4.63 | 4.35 | 10.8 | 4.8 | 3.7 |
| | | (10.22) | (6.47) | (6.93) | (2.9) | (1.8) | (3.0) |
| | 3 | 21.41 | 11.98 | 11.25 | 10.1 | 5.1 | 6.2 |
| | | (10.79) | (8.51) | (5.73) | (2.4) | (1.4) | (1.8) |
| Los Angeles ($n$ = 200) | 1 | 3.98 | 1.45 | 10.86 | 8.4 | 3.4 | 8.4 |
| | | (7.62) | (2.05) | (21.01) | (5.1) | (2.5) | (5.9) |
| | 2 | 7.12 | 1.78 | 2.57 | 10.8 | 3.4 | 6.2 |
| | | (7.79) | (2.39) | (2.79) | (3.8) | (0.6) | (3.8) |
| | 3 | 3.78 | 4.04 | 24.01 | 5.3 | 3.9 | 6.9 |
| | | (4.20) | (4.08) | (17.22) | (1.9) | (1.3) | (3.1) |

a. The mean value is computed across all stores and all chains in the market.

**TABLE 2**
**Means for the Predictor Variables in the Baking Chip Category (standard deviations in parentheses)[a]**

| | | Consecutive Schedule Index | | | Frequency | | |
|---|---|---|---|---|---|---|---|
| *Market* | *Brand* | *CSI(P)* | *CSI(F)* | *CSI(D)* | *F(P)* | *F(F)* | *F(D)* |
| New York ($n$ = 180) | 1 | 19.01 | 10.72 | 13.98 | 6.8 | 6.9 | 5.8 |
| | | (16.06) | (8.99) | (10.98) | (1.3) | (2.3) | (2.0) |
| | 2 | 22.72 | 1.13 | 3.96 | 14.7 | 2.1 | 1.1 |
| | | (17.50) | (1.60) | (9.59) | (3.0) | (2.1) | (1.6) |
| | 3 | 6.40 | 1.52 | 1.31 | 15.0 | 3.3 | 1.2 |
| | | (9.51) | (2.99) | (2.63) | (2.1) | (1.8) | (0.8) |
| Chicago ($n$ = 126) | 1 | 21.96 | 8.20 | 6.16 | 10.0 | 5.1 | 5.9 |
| | | (8.99) | (4.34) | (6.07) | (3.2) | (2.6) | (4.1) |
| | 2 | 11.78 | 4.72 | 1.60 | 12.7 | 3.4 | 3.0 |
| | | (7.43) | (4.53) | (2.49) | (1.9) | (1.3) | (2.6) |
| | 3 | 9.49 | 0.56 | 0.08 | 7.7 | 8.3 | 2.7 |
| | | (7.91) | (1.77) | (0.25) | (9.7) | (9.5) | (1.3) |
| Los Angeles ($n$ = 200) | 1 | 10.93 | 6.46 | 21.08 | 4.9 | 4.3 | 11.3 |
| | | (10.15) | (6.71) | (19.09) | (2.7) | (2.5) | (3.3) |
| | 2 | 16.70 | 2.85 | 5.20 | 13.2 | 4.2 | 10.4 |
| | | (6.05) | (3.12) | (10.60) | (3.9) | (3.0) | (15.1) |
| | 3 | 8.36 | 3.73 | 8.73 | 6.8 | 4.3 | 7.5 |
| | | (5.24) | (3.29) | (10.16) | (4.7) | (2.4) | (5.2) |

a. The mean value is computed across all stores and all chains in the market.

The number of observations used to estimate the above model varied for each brand depending on the market (New York, Los Angeles, or Chicago) and retail chain in question. In general, the number of observations (Number of Stores × Number of Time Periods) varied from 300 to 480 depending on the brand, chain, and the market. In the New York market (with 12 retail chains and an average of 15 stores per chain), 108 models (12 Chains × 3 Brands × 3 Product Categories) were estimated. For the Los Angeles (with 10 retail chains and an average of 20 stores per chain) and Chicago (with 7 chains and 18 stores per chain) markets, the number of models were 90 (10 × 3 × 3) and 63 (7 × 3 × 3), respectively. The hypotheses can be tested by evaluating the significance of the coefficient terms in (5).

## RESULTS AND DISCUSSION

The descriptive statistics for each product category in Tables 1, 2, and 3 illustrate the varying levels of consecu-

**TABLE 3**
**Means for the Predictor Variables in the Disposable Diaper Category (standard deviations in parentheses)[a]**

| | | Consecutive Schedule Index | | | Frequency | | |
|---|---|---|---|---|---|---|---|
| *Market* | *Brand* | *CSI(P)* | *CSI(F)* | *CSI(D)* | *F(P)* | *F(F)* | *F(D)* |
| New York ($n$ = 180) | 1 | 3.01 | 28.35 | 4.15 | 2.8 | 16.2 | 1.2 |
| | | (3.87) | (13.10) | (8.15) | (1.2) | (1.7) | (0.1) |
| | 2 | 2.04 | 17.37 | 3.21 | 3.9 | 12.9 | 0.6 |
| | | (1.58) | (14.76) | (6.27) | (1.7) | (1.7) | (0.1) |
| | 3 | 2.55 | 24.58 | 1.34 | 2.9 | 13.9 | 3.6 |
| | | (4.65) | (14.39) | (2.71) | (0.9) | (1.2) | (2.9) |
| Chicago ($n$ = 126) | 1 | 2.62 | 36.15 | 15.63 | 1.2 | 14.6 | 6.4 |
| | | (2.01) | (19.01) | (6.47) | (0.7) | (0.6) | (2.7) |
| | 2 | 2.97 | 21.12 | 5.52 | 4.1 | 10.2 | 5.4 |
| | | (6.30) | (14.79) | (6.17) | (2.3) | (1.8) | (2.2) |
| | 3 | 3.18 | 27.07 | 9.86 | 1.6 | 9.5 | 3.7 |
| | | (5.81) | (18.04) | (6.07) | (2.4) | (12.1) | (2.8) |
| Los Angeles ($n$ = 200) | 1 | 10.15 | 16.31 | 6.90 | 6.7 | 9.1 | 2.7 |
| | | (7.02) | (8.10) | (7.57) | (1.9) | (3.1) | (2.2) |
| | 2 | 8.76 | 2.91 | 1.70 | 6.6 | 8.5 | 2.5 |
| | | (12.80) | (4.18) | (3.58) | (4.7) | (3.2) | (2.0) |
| | 3 | 4.81 | 16.05 | 4.00 | 4.1 | 10.9 | 3.7 |
| | | (4.04) | (9.50) | (3.30) | (0.9) | (2.8) | (2.4) |

a. The mean value is computed across all stores and all chains in the market.

tive scheduling of price promotion experienced by brands, and the extent of the variation in the frequency of price promotion support received by them. It is obvious that different brands experience different levels of consecutive scheduling of promotion and this varies substantially within a market, as well as across markets. For example, in the cracker category (see Table 1), Brand 1 in the New York market had a mean CSI(P) of 15.11, and a mean CSI(D) of 3.97. In contrast, Brand 3 had approximately equal means (CSI(P) = 18.13, CSI(D) = 18.52). Further, Brand 1 had a low CSI(P) of 3.98 in the Los Angeles market compared with New York (15.11) and Chicago (20.77). Such variance was observed in general for the other two brands. Also, the frequency of price promotion support received by brands differed substantially within the markets. For example, the mean frequency of price discounts for crackers varied from 9.1 for Brand 3 to 15.6 for Brand 2 in the New York market. These figures by themselves provide substantial cause for research attention because of their effects in the marketplace.

## Frequency Effect

In general, the coefficients for the main effect of frequency of the three types of price promotion variables were significant (the majority of the coefficients were significant at the .05 level) and positive for all three product categories in all the markets. Table 4 shows the results for the three product categories investigated (sampling three retail chains in every market).[5] As shown in the cracker category in Table 4, the coefficients for the frequency of price promotions for the three brands in a chain in three markets (3 Brands × 3 Markets × 3 Types of Price Promotions) were all positive and significant with the exception of three coefficients, which were negative and significant. Similarly, of the 27 significant coefficients for baking chips, 24 were positive and 3 were negative. Among the 27 significant coefficients for diapers, 22 were positive and 5 were negative.

Overall, out of the possible 108 coefficients (12 Chains × 3 Brands × 3 Types of Price Promotions) for the cracker category in the New York market, 98 (84 positive and 14 negative) coefficients were significant. Of 63 coefficients (7 Chains × 3 Brands × 3 Types of Price Promotions) in the Chicago market, 56 (48 positive and 8 negative) coefficients were significant. Of the possible 90 (10 Chains × 3 Brands × 3 Types of Price Promotions) in Los Angeles, the number of significant coefficients was 82 (71 positive and 11 negative).

Overall, for the frequency main effect, about 90% of all the estimated coefficients were significant for crackers, 87% for baking chips, and 92% for diapers. These results indicate support for Hypotheses 1a, 2a, and 3a.

## Consecutive Scheduling Effect

The hypotheses proposed a negative effect for consecutive scheduling. Most of the coefficients for the main effect of consecutive scheduling were negative and significant (the majority of the coefficients were significant at the .05 level). As shown in the cracker category in Table 4, 19 of 27 coefficients were significant (17 negative and 2 positive) and 8 were not significant. Among the 27 coefficients for baking chips, 22 were significant (19 negative and 3 positive). Similarly, of 27 coefficients for diapers, 24 (19 negative and 5 positive) were significant. The positive

**TABLE 4**
**Sample of Results[a]**

| Market (Chain) | Brand | Frequency Effect F(P) $\alpha_1$ | F(F) $\alpha_2$ | F(D) $\alpha_3$ | Consecutive Scheduling Effect CSI(P) $\beta_1$ | CSI(F) $\beta_2$ | CSI(D) $\beta_3$ | Frequency × Scheduling Effect CSI(P) · F(F) $\gamma_1 (\times 10)$ | CSI(F) · F(D) $\gamma_2 (\times 10)$ | CSI(D) · F(P) $\gamma_3 (\times 10)$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Crackers | | | | | | | | | | |
| New York | 1 | 0.012* | 0.140 | 0.024* | –0.092 | 0.008* | *ns* | –0.035 | 0.060 | *ns* |
| (K = 2) | 2 | 0.024* | 0.221 | 0.008* | –0.121 | *ns* | *ns* | –0.10 | –0.055 | –0.100 |
| | 3 | 0.076 | 0.181 | 0.073 | –0.114 | –0.010* | –0.090 | –0.05 | –0.039 | –0.028* |
| Chicago | 1 | 0.054 | 0.202 | 0.072 | –0.148 | –0.102 | –0.118 | 0.026* | –0.047 | –0.040* |
| (L = 2) | 2 | 0.017* | 0.151 | 0.095 | –0.042* | 0.007* | *ns* | –0.050 | –0.022* | *ns* |
| | 3 | 0.046 | 0.112 | 0.021* | –0.141 | –0.051 | –0.038 | –0.055 | –0.025* | –0.145 |
| Los Angeles | 1 | 0.018* | –0.054 | –0.026* | –0.014* | *ns* | –0.073 | –0.105 | –0.078 | –0.039* |
| (V = 2) | 2 | –0.027* | 0.079 | 0.069 | –0.029* | *ns* | *ns* | –0.120 | –0.045 | *ns* |
| | 3 | 0.147 | 0.164 | 0.208 | *ns* | –0.018* | –0.181 | *ns* | –0.040* | –0.059 |
| Baking Chips | | | | | | | | | | |
| New York | 1 | 0.124 | 0.171 | 0.105 | –0.162 | –0.068 | –0.071 | –0.041 | –0.029* | –0.070 |
| (K = 2) | 2 | 0.019* | 0.179 | 0.153 | –0.194 | 0.011* | –0.019* | –0.178 | 0.022* | –0.014* |
| | 3 | –0.018* | 0.151 | 0.113 | –0.044 | *ns* | *ns* | –0.110 | –0.047 | *ns* |
| Chicago | 1 | 0.052 | 0.026 | 0.046 | –0.181 | –0.082 | –0.066 | –0.065 | –0.105 | –0.009* |
| (L = 2) | 2 | 0.101 | 0.007* | 0.075 | –0.135 | –0.051* | *ns* | –0.037* | –0.079 | *ns* |
| | 3 | 0.117 | 0.171 | –0.188 | 0.097 | *ns* | –0.052 | 0.023 | –0.016* | –0.211 |
| Los Angeles | 1 | 0.012* | 0.218 | –0.007* | –0.107 | –0.074 | –0.161 | –0.167 | –0.039 | –0.089 |
| (V = 2) | 2 | 0.076 | 0.297 | 0.072 | –0.128 | *ns* | –0.041* | –0.03 | *ns* | –0.035 |
| | 3 | 0.112 | 0.289 | 0.118 | –0.084 | –0.018* | 0.096 | –0.023* | –0.058 | 0.057 |
| Disposable Diapers | | | | | | | | | | |
| New York | 1 | –0.009* | 0.027 | 0.090 | –0.007* | –0.212 | –0.018 | –0.155 | –0.130 | –0.455 |
| (K = 2) | 2 | 0.124 | 0.406 | 0.354 | *ns* | –0.174 | –0.012 | *ns* | –0.035 | –0.027* |
| | 3 | 0.158 | –0.015* | –0.059 | 0.008* | –0.196 | *ns* | 0.086 | –0.115 | *ns* |
| Chicago | 1 | 0.027* | 0.186 | 0.070 | –0.013* | –0.246 | –0.163 | –0.045 | –0.020* | –0.210 |
| (L = 2) | 2 | 0.108 | 0.343 | 0.242 | –0.024 | –0.183 | –0.052 | –0.016* | –0.094 | –0.028* |
| | 3 | 0.049* | 0.150 | 0.144 | 0.019* | –0.201 | 0.098 | 0.070 | –0.040 | 0.045 |
| Los Angeles | 1 | –0.021* | 0.060 | –0.007* | –0.097 | –0.131 | –0.048 | –0.231 | –0.063 | –0.126 |
| (V = 2) | 2 | 0.104 | 0.322 | 0.237 | –0.076 | –0.019* | *ns* | –0.039 | –0.024* | *ns* |
| | 3 | 0.119 | 0.092 | –0.016* | 0.047 | 0.118 | –0.021* | 0.017* | 0.068 | –0.090 |

a. All coefficients significant at least at the 0.05 level, unless otherwise noted.
*Denotes significance at the .10 level. *ns* = not significant.

coefficients may result from the fact that brands promoted prior to the concerned brand may not be in direct competition with the concerned brand. For example, both Kumar and Leone (1988) and Blattberg and Wisniewski (1989) have shown the existence of price tier effects (i.e., a high-priced brand will not be affected by the promotion of a low-priced brand because consumers do not tend to switch from a high-priced brand to a low-priced brand).

Overall, of 108 coefficients for the cracker category in the New York market, 73 were significant (65 negative and 8 positive). Of 63 coefficients in the Chicago market, 43 were significant (38 negative and 5 positive), and in Los Angeles, 62 (56 negative and 6 positive) of 90 were significant.

Overall, about 70% of the estimated coefficients were significant for crackers, 77% for baking chips, and 84% for diapers. These results provide support for Hypotheses 1b, 2b, and 3b.

## The Frequency × Consecutive Scheduling Interaction Effect

In general, we found support for Hypotheses 1c, 2c, and 3c as illustrated by the significant interaction effects ($\gamma_1$, $\gamma_2$, and $\gamma_3$) of Frequency of Price Promotions × Consecutive Schedule Indexes (the majority of the coefficients were significant at the .05 level). As hypothesized, we observed predominantly negative interaction effects for all the brands in every chain, market, and product category (see Table 4). Of 27 coefficients in the cracker category (3 Brands × 3 Markets × 3 Types of Price Promotions), 21 were negative and significant, 2 were positive, and 4 were not significant. Similarly, of 27 coefficients for baking chips, 3 were positive and 3 were not significant, and thus 21 were negative and significant. Of 27 coefficients for diapers, 5 were positive and 3 were not significant, leaving 19 significant negative coefficients. As discussed, a negative interaction indicates a relatively high level of consecutive scheduling of competing or own brand promotions that work toward reducing the SSR levels because of purchase acceleration and brand switching effects (e.g., Gupta 1988 has shown that a majority of the sales increase due to promotion comes primarily from brand switching, and to an extent from purchase acceleration). Although positive interaction effects were not expected, they may not be surprising because factors such as awareness created by the previous promotion help increase the sales response to the present promotion.

Overall, out of the possible 108 coefficients for the cracker category in the New York market, 83 (74 negative and 9 positive) parameters were significant. Similarly, of the possible 63 coefficients for the cracker category in the Chicago market, 48 (43 negative and 5 positive) were significant, and in Los Angeles, the number of significant coefficients was 70 (62 negative and 8 positive) out of the possible 90. As such, about 77% of all estimated coefficients were significant; the results for the baking chips (79%) and disposable diapers (80%) were very similar.

Although $R^2$ may not be interpretable in such analysis, adjusted $R^2$s (.37-.90 range) can be reported for all the models tested.[6] Also, multicollinearity was thought to be an issue in estimating the final model (5); however, a close examination revealed that correlations were not severe, ranging from .10 to .27.

Because the model specified has significant interaction effects, it is appropriate to evaluate the overall effect of frequency by including the main effects of frequency as well as its interaction with consecutive scheduling.

## The Overall Effect of Frequency of Price Promotion

We can calculate the overall effect of frequency of price promotions for a brand in a retail chain store. The overall effect is of interest because, as discussed earlier, there is debate over the direction of the effect of frequency of price promotions. We calculated the overall effects $(\alpha_1 + \gamma_1)$, $(\alpha_2 + \gamma_2)$, and $(\alpha_3 + \gamma_3)$ by using the weights of the final model (some listed in Table 4), and the mean consecutive scheduling indexes for the respective brand in the concerned retail chain store (e.g., the mean across all stores and chains are presented in Tables 1, 2, and 3). In other words, we used the weights for the frequency terms (i.e., $\alpha_1$, $\alpha_2$, and $\alpha_3$), weights for the corresponding interaction terms involving CSIs (i.e., $\gamma_1$, $\gamma_2$, and $\gamma_3$) and the CSI indexes for a chain store (i.e., $\mathrm{CSI(P)}_i$, $\mathrm{CSI(F)}_i$, and $\mathrm{CSI(D)}_i$).

Below, we provide three specific examples of computing $\alpha_1 + \gamma_1 \cdot \mathrm{CSI(P)}$, $\alpha_2 + \gamma_2 \cdot \mathrm{CSI(F)}$, and $\alpha_3 + \gamma_3 \cdot \mathrm{CSI(D)}$ within a store when the interaction effects are included. In the cracker category, the differences in the moderating effects of consecutive promotions for Brand 2 in the store belonging to chain $K = 2$ in New York are illustrated for all types of price promotions used in this study:

$$(\alpha_1 + \gamma_1 \cdot \mathrm{CSI(P)}) = 0.024 + (-0.01)(15.40) = -0.130$$
$$(\alpha_2 + \gamma_2 \cdot \mathrm{CSI(F)}) = 0.221 + (-0.00)(6.76) = 0.221$$
$$(\alpha_3 + \gamma_3 \cdot \mathrm{CSI(D)}) = 0.008 + (-0.00)(3.82) = 0.008.$$

In the New York market, the mean consecutive schedule indexes of 15.40, 6.76, and 3.82 for price discounts only, price discounts with feature, and price discounts with display, respectively, were computed for a store in chain $K = 2$. As can be seen from the above example, the signs of $\alpha_1 + \gamma_1 \cdot \mathrm{CSI(P)}$, $\alpha_2 + \gamma_2 \cdot \mathrm{CSI(F)}$, and $\alpha_3 + \gamma_3 \cdot \mathrm{CSI(D)}$ are determined by the joint effect of frequency and the interactions. Thus $\alpha_1 + \gamma_1 \cdot \mathrm{CSI(P)}$ will be positive or negative based on the magnitude and directionality of $\alpha_1$ and $\gamma_1 \cdot \mathrm{CSI(P)}$ in (5). Any overall negative effects for the frequency of price promotions implies that with the increasing frequency of a type of price promotion, a decrease in SSR is achieved.[7] Thus our research indicates that the direction of the effect of frequency of price promoter can be either positive or negative. The actual direction will depend on the extent of consecutive scheduling.

## Evaluating Consistency of Results

To evaluate the model (equation [4]) in terms of its predictive validity and stability of parameters, we used an additional 52 weeks of IRI's INFOSCAN (for the same products and same markets) and corresponding data from the previous 2 years to estimate baseline sales using the PROMOTIONSCAN methodology. Equation (5) was estimated with the new data. With the use of model parameters, the actual SSR (as shown in [4]), was computed for every brand in each retail chain store in every market. Predicted SSR was computed by substituting coefficients estimated from the previous analysis (reported for a sample of retail chains in Table 4) into equation (4) for the corresponding product-market data in the new data set. Predictive validity of the results was evaluated by averaging errors (error = actual SSR – predicted SSR) across brands in a product category, across stores in a retail chain, and across retail chains in a market. In predicting SSR, three criteria were used to judge predictive performance of equation (4) on the holdout data: mean squared deviation (MSD), mean absolute percentage error (MAPE), and the percentage of predictive error being greater than 5% of the actual value for each case (Armstrong 1978). It must be noted that this reanalysis is a very conservative test of the predictive ability and stability of the model parameters because the pattern of effects can change if the intensity and type of retail promotions between competing brands differ significantly from one 52-week period to another in the same retail chains.

The results indicate a high level of predictive performance for the model[8] for each of the nine cases on the three different criteria, as illustrated in Table 5.

Using MSD as the criterion, the highest deviation was 1.14 (that of crackers in the Chicago market), and the lowest deviation was 0.23 (that of crackers in the Los Angeles market), with the average MSD value being 0.62 across all nine cases. We see a similar pattern in the case of MAPE, with values ranging from 0.025 to 0.047 and the average MAPE being 0.039 across the nine cases. Further, as shown in the last column on Table 5, the percentage of prediction errors (> 5%) was a maximum of nine across

**TABLE 5**
**Evaluation of Consistency of SSR Model (4)[a]**

| | *Mean Squared Deviation* | *Mean Absolute Percentage Error* | *Percentage of Predictive Errors > 5%*[b] |
|---|---|---|---|
| Crackers | | | |
| New York | 0.89 | 0.041 | 9 |
| Chicago | 1.14 | 0.044 | 9 |
| Los Angeles | 0.23 | 0.025 | 8 |
| Baking Chips | | | |
| New York | 0.31 | 0.035 | 7 |
| Chicago | 0.30 | 0.034 | 6 |
| Los Angeles | 0.72 | 0.041 | 9 |
| Diapers | | | |
| New York | 0.44 | 0.038 | 9 |
| Chicago | 0.51 | 0.043 | 9 |
| Los Angeles | 0.98 | 0.047 | 12 |

a. The sample sizes of the New York, Chicago, and Los Angeles markets were 540, 600, and 378, respectively.
b. The percentage of times the predicted SSR value is off from the actual SSR value by more than 5% relative to the total number of observations.

the three product categories in the New York market. Similarly, for the Chicago and Los Angeles markets, the percentage of errors vary from 6 to 12 for the three product categories. Thus overall there was a high level of predictive performance for the models, enabling us to draw managerial implications for both retailers and manufacturers.

## STUDY IMPLICATIONS

This research indicates that the short-term sales response of a brand is affected by frequency and consecutive scheduling of price promotions. Also, we see that frequency can have a negative or positive effect on short-term sales response to retail promotion, depending on the existence and extent of consecutive scheduling.

### Managerial Implications

*Retailers' actions affect short-term sales response.* Because retailers cannot be forced by manufacturers to offer retail price promotion support to particular brands, retailers control the frequency and scheduling of price promotions for brands of a product category. As such, this research illustrates that the actions of the retailer affect and modify the short-term sales response of a brand. In other words, there is no fixed short-term sales response for a particular brand, and the sales response varies depending on the actions (frequency and scheduling) of the retailer for that brand, as well as that retailer's actions for competing brands. As our results demonstrate, a retailer can exercise some control over the sales response. However, irrespective of whether a retailer intends to or not, its actions will have some impact on the short-term sales response of a given brand. This issue accentuates the power that the retailer possesses in affecting a promotion's potential in producing increased sales, indicating possible advantages for the retailer when negotiating with manufacturers.

*All retailers are not "equal."* To manufacturers, the above issue implies that all retailers may not be equal in terms of being effective promoters for their brands because the frequency and scheduling of price promotions vary from one retail chain to another, as well as one market to another (as illustrated in Table 1 for Brand 1 of the cracker product category). The extent to which a brand achieves increased sales during a promotion program will depend on the frequency and scheduling decisions (specifically, consecutive scheduling as indicated in this study) of the retailer. Thus the implication is that it may not be optimal for a manufacturer to provide a uniform trade promotion policy for all retail chains in a given market. However, by law, manufacturers must offer the same trade promotion to all retailers in a geographic market. Thus manufacturers may be well served to structure their trade promotion deals in such a way that they appeal to those retailers whose deal response function is most profitable to the manufacturer.

*"Exclusive" promotions not good enough.* At present, the practice among manufacturers is to attempt to gain exclusivity of price promotions for their brand during a promotion period in a retail chain. Our results indicate that promotion activity (of competing or same brand), directly preceding a particular price promotion affects the effectiveness of the given promotion. Given this situation, manufacturers of products that are conducive to purchase acceleration may have to work to achieve not only exclusivity during a brand's promotion period, but also a promotion-free environment in the period before a brand's promotion in order to maximize the effectiveness of a promotion.

*Category management is possible.* This study finds that frequency and scheduling of price promotions of various brands in a category differentially affect the short-term response. Therefore, it is possible for a retailer to control the frequency and scheduling of price promotions of major brands in a category in such a way as to maximize the overall profit for the category in a retail store.

## CONCLUSION

Based on interviews with retail managers, operant conditioning theory, and the phenomena of brand switching and purchase acceleration, it is expected that the frequency of price promotions, the consecutive scheduling of price promotions, and the interaction of Frequency × Consecutive Scheduling will affect the short-term sales response for a brand. The study proposed a nondirectional hypothesis for the effect of frequency, but proposed negative effects for consecutive scheduling and the interaction between consecutive scheduling and frequency. The study analyzed three frequently purchased products in three markets and tested the predictive performance of the model using a different data set on the same products and markets.

The results indicate support for all hypotheses; further, it was seen that the overall effect of frequency could be positive or negative, depending on the extent of consecutive scheduling.

More important, this study illustrates that the short-term sales response for a brand is not fixed, that it is continuously modified by the actions of retailer with respect to promotions. The direct implication to the manufacturer is that all retail chains in a given market may not be equal in terms of being effective promoters, and it may not be optimal for a manufacturer to have a uniform trade promotion policy for all retailers in the city. However, because manufacturers are required by law to offer the same promotion to all retailers in a market, a manufacturer may be better off structuring trade deals that will appeal to those retailers whose deal response function is most profitable to the manufacturer.

### Research Opportunities

Some of the limitations of this study may provide opportunities for future research and may lead to an extension of literature in this area. For example, we studied only consecutive scheduling of price promotions; other schedules (such as alternate weeks, every third week, etc.) should be studied. Further, other measures of consecutive scheduling should be investigated.[9] Also, we used a general case of consecutive scheduling that featured, for example, price discount *only* promotions followed immediately by *any* other price promotion (price discount only, price discount with feature, or price discount with display). An extension of this research should differentiate between consecutive scheduling produced by same type of promotions versus different types of promotions.

Another limitation of this study is that we did not consider magnitude of price discounts; a question of interest is whether magnitude of discount plays a role in the extent to which consecutive scheduling of promotions and frequency affect the short-term sales response to retail price promotions. If household data were also available, then future research could identify the source of variation (such as brand switching, purchase acceleration, and increased consumption) in sales increase due to frequency and scheduling of promotions. This should help retailers evaluate the preferred combination of frequency and scheduling for each product category.

## APPENDIX

The baseline calculation is done in six steps (see Abraham and Lodish 1993):

1. Seasonality adjustment for weekly store data. This adjustment is done once a year at the market level for a product category, using two years (prior to the time period used for model estimation) of data. The same seasonality is used for all stores within the market. The objective is to isolate true seasonal factors of demand from category sales that may be compounded by seasonal promotions.
2. Identification of promotions to isolate weeks that are affected by promotions. Each weekly time series by store for all brands/sizes/flavors in the category is deseasonalized and detrended by dividing the series by category trend and seasonality.
3. Detection of outliers. Using a variable window moving average, outliers are removed. Outliers can be positive (one standard deviation higher than smoothed baseline estimate) or negative (one standard deviation below the smoothed baseline estimate).
4. Calculation of preliminary baselines by smoothing normal periods, reseasonalizing, and retrending. This smoothing is done with a variable window weighted moving average. Updates are made on an ongoing basis with an exponential smoothing process.
5. Adjustments made for out-of-stock situations for slow-moving items. This is when the baseline needs to be adjusted because slow-moving items' sales could fall to zero due to retailer out-of-stock situations as opposed to situations when no consumers buy the product even though it is on the shelf. Step 3 would have treated these observations as outliers even though, in the latter case, they are not.
6. Adjusting the baseline for market-specific factors such as holidays, weather-related factors, seasonal irregularities, and so on.


## ACKNOWLEDGMENTS

The authors' names appear in alphabetical order. The authors thank Information Resources Inc. (IRI; Chicago) for the data, and the editor and reviewers for comments on an earlier version of this manuscript.


## NOTES

1. Although consecutive promotions can occur within a week, the data interval (weekly) precludes the possibility of capturing this effect.

2. The model parameters are brand specific within a chain in a given market.

3. Appropriate pooling tests were also performed to ensure that the store data could be pooled.

4. Details are available from the authors.

5. The *t* values for the coefficients in this table are not reported in order to avoid information clutter. These values can be obtained from the authors upon request.

6. The $R^2$s were computed by taking antilogs of the dependent variable (both predicted and actual) in equation (5).

7. This is possible because actual sales can increase at a decreasing rate with increasing frequency of price promotions.

8. To make sure that the superior predictive performance of the final model was not due to main effects only, another validation model was run using only the coefficients for variables F(P), F(F), and F(D) (which was reestimated without the interaction effects). The predictive performance deteriorated compared to the model with interaction effects, illustrating the significance of the interaction of frequency and consecutive scheduling of price promotions.

9. For example, first we determine the total weeks (say 13) of price promotion for a brand in a given time period (say 52 weeks). If M is the maximum number of consecutive promotions possible (12 in this case) and A is the actual number (say 4) of consecutive promotions, then the ratio A/M = 4/12 can be defined as the consecutive schedule coefficient. Although the results were, in general, similar to the proposed measure in the study, the overall performance of this alternative method was not better in terms of the predictive validity.

## REFERENCES


Abraham, Magid and Leonard Lodish. 1993. "An Implemented System for Improving Promotion Productivity Using Store Scanner Data." *Marketing Science* 12 (3): 248-69.

Armstrong, J. Scott. 1978. *Long Range Forecasting: From Crystal Ball to Computer*. New York: Wiley.

Blattberg, Robert C. and Scott A. Neslin. 1990. *Sales Promotion: Concepts, Methods and Strategies*. Englewood Cliffs, NJ: Prentice-Hall.

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

Curhan, Ronald C. and Robert J. Kopp. 1986. "Factors Influencing Grocery Retailers' Support of Trade Promotions." Report No. 86-104. Cambridge, MA: Marketing Science Institute.

Gatignon, Hubert. 1984. "Competition as a Moderator of the Effect of Advertising on Sales." *Journal of Marketing Research* 21 (November): 387-98.

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

Hardy, Kenneth G. 1986. "Key Success Factors for Manufacturers' Sales Promotions in Package Goods." *Journal of Marketing* 50 (July): 13-23.

Helson, Harry. 1964. *Adaptation-Level Theory*. New York: Harper & Row.

Hsiao, Cheng. 1986. *Analysis of Panel Data*. New York: Cambridge University Press.

Kalwani, Manohar U., Chi-Kin Yim, Heikki J. Rinne, and Yoshi Sugita. 1990. "A Price Expectation Model of Customer Brand Choice." *Journal of Marketing Research* 27 (August): 251-62.

Kamen, Joseph and Robert Toman. 1970. "Psychophysics of Prices." *Journal of Marketing Research* 8 (1): 252-7.

Krishna, Aradhna. 1991. "The Effect of Dealing Patterns on Consumer Perceptions of Deal Frequency and Willingness to Pay." *Journal of Marketing Research* 28 (November): 441-51.

———. 1992. "The Normative Impact of Consumer Price Expectations for Multiple Brands on Consumer Purchase Behavior." *Marketing Science* 11 (Summer): 266-86.

———. 1994a. "The Effect of Deal Knowledge on Consumer Purchase Behavior." *Journal of Marketing Research* 31 (February): 76-91.

———. 1994b. "The Impact of Dealing Patterns on Purchase Behavior." *Marketing Science* 13 (4): 351-73.

Krishna, Aradhna, Imran S. Currim, and Robert W. Shoemaker. 1991. "Consumer Perceptions of Promotional Activity." *Journal of Marketing* 55 (April): 4-16.

Kumar, V. and Robert P. Leone. 1988. "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution." *Journal of Marketing Research* 25 (May): 175-85.

McAlister, L. 1985. "The Impact of Price Promotions on a Brand's Market Share, Sales Pattern, and Profitability." Sloan School of Management Working Paper No. 16-22-85, Massachusetts Institute of Technology.

Naert, Phillipe and Peter Leeflang. 1978. *Building Implementable Marketing Models*. Boston: H. E. Sternfert Kroebe.

Nagle, Thomas T. 1987. *The Strategy and Tactics of Pricing*. Englewood Cliffs, NJ: Prentice-Hall.

Reddy, Srinivas K. and Susan L. Holak. 1991. "The Effects of Market Structure Characteristics on Competitive Reaction Intensity: A Longitudinal Analysis." *Marketing Letters* 2 (3): 293-308.

Skinner, B. F. 1938. *The Behavior of Organisms: An Experimental Analysis*. New York: Appleton-Century-Crofts.

Winer, Russell S. 1986. "A Reference Price Model of Brand Choice for Frequently Purchased Products." *Journal of Consumer Research* 13 (2): 250-6.


## ABOUT THE AUTHORS


**V. Kumar** is associate professor of marketing, CBAA distinguished faculty fellow, and director of marketing research studies at the University of Houston. He has been recognized with numerous teaching and research excellence awards. Dr. Kumar has published numerous articles in many scholarly journals in marketing and forecasting. He has coauthored a text titled *Marketing Research* and is currently working on two other textbooks. He is on the editorial review board of many journals. Dr. Kumar has lectured on marketing-related topics in various universities worldwide. His research interests include developing forecasting models, international marketing strategy and international marketing research issues, models for sales promotions, and new methodologies for product positioning and market segmentation. Dr. Kumar received his doctoral degree from the University of Texas at Austin.

**Arun Pereira** is assistant professor of marketing at Saint Louis University, Missouri. He has published articles about retailing and marketing strategy in scholarly journals such as the *Journal of Retailing*, *International Journal of Research in Marketing*, and *Journal of Business Ethics*. His current research interest focuses on models for sales promotions and marketing strategy. Dr. Pereira received his doctoral degree from the University of Houston.