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To what extent do price promotions have a long-term effect on the components of brand sales, namely, category incidence, brand choice, and purchase quantity? The authors answer this question by using persistence modeling on weekly sales data of a perishable and a storable product derived from a scanner panel. Their analysis reveals, first, that permanent promotion effects are virtually absent for each sales component. Next, the authors develop and apply an impulse response approach to estimate the promotional adjustment period and the total dynamic effects of a price promotion. Specifically, they calculate the long-term equivalent of Gupta's (1988) 14/84/2 breakdown of promotional effects. Because of positive adjustment effects for incidence but negative adjustment effects for choice, the authors find a reversal of the importance of category incidence and brand choice: 66/11/23 for the storable product and 58/39/3 for the perishable product. The authors discuss the implications of the findings and suggest some areas for further research.

The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity

Since the early seventies, price promotions have emerged to account for the main share of the marketing budget in most consumer packaged goods categories (Currim and Schneider 1991), and a substantial body of academic research has established the nature of short-term sales response to temporary price reductions. Although some recent work has examined the long-term effects of price promotions, this area is still "probably the most debated issue in the promotional literature and one for which the jury is still out" (Blattberg, Briesch, and Fox 1995, p. G127).

Any study of long-term effects needs to carefully define and operationalize the long run. In this respect, academic research has proceeded along three research streams, each with different methodologies and findings. First, Mela, Gupta, and Lehmann (1997), Mela, Jedidi, and Bowman (1998), and Jedidi, Mela, and Gupta (1999) examine how promotions change consumers' price and promotional sensitivity over time. The first article considers brand choice; the second, category incidence and purchase quantity; and the third, brand choice and purchase quantity. This stream of research defines "long term" as "the cumulative effect on consumer brand choice, lasting over several years" (Mela, Gupta, and Lehmann 1997, p. 249) and examines this effect with a distributed-lag (Koyck) response model. The key findings are that, as a result of repeated promotional activity in a category, category incidence decreases but purchase quantity increases. Moreover, promotions increase consumer price sensitivity and decrease brand equity over time. Overall, these studies confirm the existence of a negative promotion usage effect on consumer behavior (Blattberg and Neslin 1990).

A second research stream confirms the positive mere purchase effect of promotions. Ailawadi and Neslin (1998) find that promotions induce consumers to buy more and consume faster. They examine both a spline function and a continuous function to model flexible category consumption rates as a function of household inventory. The key finding is that promotion-induced inventory buildup temporarily increases usage rates. Ailawadi, Lehmann, and Neslin (2001) examine market share response to a long-term change in the marketing mix (Procter & Gamble's value pricing strategy). They define deal activity as the percentage of yearly brand sales sold on deal. This variable has strong positive effects on market share in a multiplicative response

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model, and Ailawadi, Lehmann, and Neslin (2001, p. 55) conclude that Procter & Gamble's loss of market share was "attributable to its severe cuts in coupons and deals, and the consequent increase in net price."

Although both research streams model dynamic effects of price promotions, they can capture only transient, not enduring, effects because they assume mean reversion of the dependent variable. First, the Koyck model (Mela, Gupta, and Lehmann 1997) assumes that a fixed fraction $0 < \lambda < 1$ of the effects in one period is retained in the next period. Because $\lim_{n \to \infty} \lambda^n = 0$, this model implies that the dependent variable eventually returns to its historical mean. Second, both flexible functions in Ailawadi and Neslin (1998) imply that consumption rates return to their average levels as the excess inventory is depleted. Finally, the multiplicative response model (Ailawadi, Lehmann, and Neslin 2001) also assumes mean reversion of the sales components. Therefore, these models do not give a complete account of the long-term effects of price promotions on sales.

A third stream of research uses persistence modeling to capture the potential for permanent effects of promotions (Dekimpe, Hanssens, and Silva-Risso 1999). Sales are classified as stationary or evolving. When sales are stationary, they eventually return to their prepromotion mean. In this scenario, promotions can affect sales immediately and over the next several weeks (the adjustment period), but not in a permanent way. In contrast, when sales are evolving, they do not have a fixed mean and therefore could (but need not) be permanently affected by promotions.

Dekimpe, Hanssens, and Silva-Risso (1999) apply persistence modeling to four product categories and use impulse–response functions to estimate permanent versus transitory effects of promotions on sales. A key finding of their research is that permanent effects of promotions are largely absent. This implies that promotions do not structurally change sales over time and that their long-term profitability depends only on the magnitudes of response and cost parameters. However, it is possible that the absence of permanent promotion effects on sales is due to cancellation of permanent effects in the three components of brand sales, that is, category incidence, brand choice, and purchase quantity. For example, the use of promotions can train consumers to buy higher quantities on fewer occasions (Mela, Jedidi, and Bowman 1998). Such a long-term scenario could be attractive to brand managers, because the higher inventory keeps the consumer out of the market for competitive products, but unattractive to retailers, because consumers now need fewer store visits (Bell, Chiang, and Padmanabhan 1999). At present, no study has examined the total over-time impact of price promotions on all three sales components.

In terms of quantification of promotion effects, several studies break down the immediate impact on incidence, choice, and quantity. Gupta (1988) finds a 14/84/2 breakdown in the coffee market, and Bell, Chiang, and Padmanabhan (1999) analyze 13 categories and report an average breakdown of 11/75/14. Does a similar decomposition of promotional effects hold in the long run?

We use persistence modeling to examine whether and to what extent price promotions have a long-term impact on the three components of brand sales. On the basis of a scanner panel, we compute for each store the category incidence (the total number of panelists buying in the product category), brand choice (the share of these consumers buying the brand), and purchase quantity (the average quantity purchased by the brand's consumers). For each component, we test for permanent changes in the time series and examine whether such changes are due to the price shocks of the major brands in the store. Furthermore, for component series that are found to be stationary, we apply an impulse–response approach to estimate the time it takes for the dependent variable to revert to its mean after being shocked by a price promotion. Finally, we quantify the total over-time impact of a price promotion on each sales component and calculate the breakdown for the immediate and the total effects. Therefore, this study is the first to quantify total promotional effects as the sum of immediate, adjustment, and permanent effects on each sales component. This enables us to compare and contrast the relative importance of the three components of promotional effectiveness in the short run and the long run.

The remainder of the article is organized as follows: We define the time windows of promotional effects on the three sales components and review previous studies in this framework. In the next section, we develop hypotheses on the impact of promotions on category incidence, brand choice, and purchase quantity. We then describe our methodology and data and present the findings for a storable product (canned soup) and a perishable product (yogurt). We conclude with the managerial implications and limitations of this work and offer directions for further research.

THE TIME FRAME OF PROMOTIONAL EFFECTS ON THREE SALES COMPONENTS

We classify previous research on promotional effects on two dimensions: (1) the time frame in which the promotional impact on sales is measured, namely, immediate effects, adjustment effects, and permanent effects,[1] and (2) the type of purchase behavior studied, that is, category incidence, brand choice, and purchase quantity.

The *immediate effects* of price promotions are reflected in short-term (contemporaneous) changes in sales. Most previous research falls in this category and reports consistently high promotional effects (Blattberg, Briesch, and Fox 1995; Blattberg and Neslin 1990).

The *adjustment effects* of promotions refer to the transition period between the short-term response and the resulting equilibrium, which can be either mean reversion or a new sales level. These adjustment effects can be positive or negative, and their sign and magnitude greatly affect the overall profitability of the promotion (Blattberg and Neslin 1990; Greenleaf 1995). Dynamic effects are modeled through, among others, purchase loyalty (Guadagni and Little 1983), reference price (e.g., Lattin and Bucklin 1989), inventory (e.g., Gupta 1988), time-varying parameters (e.g., Mela, Gupta, and Lehmann 1997; Papatla and Krishnamurthi 1996), and flexible usage rates (Ailawadi and Neslin

[1]Our terminology is based on the time-series literature and is used throughout this article. Previous authors have introduced alternative terms that fit our framework: Effects are either contemporaneous (immediate) or dynamic (long term), which could be transient (adjustment) or enduring (permanent).

1998). Several studies equate these adjustment effects with long-term effects. Indeed, the implicit assumption underlying distributed lag models (e.g., Mela, Jedidi, and Bowman 1998) is that the impact of marketing effort dies out over time. Although this operationalization allows promotions to have more than a contemporaneous influence on sales, it ignores the more complex, permanent changes found in many sales series (Dekimpe and Hanssens 1995b).

Finally, *permanent effects* of a marketing action require that a proportion of the event's impact is carried forward and sets a new trend. If the sales series is evolving, with no fixed mean, then the permanent effects of marketing efforts can be captured by relating these efforts to the evolution of sales. These permanent effects are the focus of our first research question, as their analysis provides a necessary first step for a complete account of the long-term impact of price promotions on sales.

Recent disaggregate models in the marketing literature (Bucklin, Gupta, and Siddarth 1998; Chiang 1991; Chintagunta 1993) also distinguish the brand-sales components of category incidence, brand choice, and purchase quantity. For retailers, price discounts mainly create store traffic and increase category sales (Putsis and Dhar 1999). Therefore, promotions lose their attraction if the immediate gains in category incidence and quantity are offset by negative effects during the off-promotion weeks. For manufacturers, the over-time impact on brand choice is the most important metric. In the current study, we analyze the dynamic effects of price promotions on time series of all three sales components. Specifically, we compute the total number of panelists buying in the product category (category incidence), the share of these consumers buying a particular brand (brand choice), and the average quantity purchased by the brand's consumers. This breakdown, which is calculated separately for each store in the sample, enables us to compare results from the time-series analysis of the three sales components with the findings from disaggregate analyses that apply this distinction. Table 1 summarizes previous research on promotions along the two dimensions of time frame and type of data.

Three inferences from Table 1 provide the motivation for the current study. First, empirical evidence on permanent effects of price promotions is virtually nonexistent (Dekimpe, Hanssens, and Silva-Risso 1999; Nijs et al. 2001). Second, none of these studies considers the breakdown of sales in category incidence, brand choice, and purchase quantity. Third, all previous persistence modeling has focused on market-level data, whereas managers often need analysis at the account or store level (Bucklin and Gupta 1999). We seek to fill this void by studying the permanent, adjustment, and immediate effects of price promotions on each of the different sales components for each store in our scanner panel data set.

HYPOTHESIS DEVELOPMENT

Consistent with our framework, we first develop hypotheses on the temporal dimension of promotional effectiveness. In particular, we focus on the sign and magnitude of the total promotional impact on the sales components. Table 2 summarizes our hypotheses on the immediate, adjustment, permanent, and total effects of price promotions for storable and perishable products. Our hypotheses on the length of the adjustment period are more tentative, as this topic has not received much attention in the context of price promotions.

Table 1

EMPIRICAL RESEARCH ON THE TEMPORAL EFFECTS OF PRICE PROMOTIONS

	Brand Choice	*Purchase Quantity*	*Category Incidence*
Immediate Effects	Gupta 1988 Chiang 1991 Krishnamurthi, Mazumdar, and Raj 1992 Chintagunta 1993 Bucklin, Gupta, and Siddarth 1998 Bell, Chiang, and Padmanabhan 1999 This study (choice share)	Gupta 1988 Chiang 1991 Krishnamurthi, Mazumdar, and Raj (1992) Chintagunta 1993 Bucklin, Gupta, and Siddarth 1998 Bell, Chiang, and Padmanabhan 1999 This study (average quantity)	Gupta 1988 (timing) Chiang 1991 Chintagunta 1993 Bucklin, Gupta, and Siddarth 1998 Bell, Chiang, and Padmanabhan 1999 This study (category consumers)
Adjustment Effects	Lattin and Bucklin 1989 Greenleaf 1995 Erdem 1996 Papatla and Krishnamurthi 1996 Mela, Gupta, and Lehmann 1997 Ailawadi and Neslin 1998 Foekens, Leeflang, and Wittink 1999 (brand sales) Jedidi, Mela, and Gupta 1999 Van Heerde, Leeflang, and Wittink 2000a (brand sales) Ailawadi, Lehmann, and Neslin 2001 (market share) This study (choice share)	Mela, Jedidi, and Bowman 1998 Ailawadi and Neslin 1998 Ailawadi, Lehmann, and Neslin 2001 (market share) This study (average quantity)	Mela, Jedidi, and Bowman 1998 Jedidi, Mela, and Gupta 1999 This study (category consumers)
Permanent Effects	Dekimpe, Hanssens, and Silva-Risso 1999 (brand sales) Bronnenberg, Mahajan, and Vanhonacker 2000 (market share) This study (choice share)	Dekimpe, Hanssens, and Silva-Risso 1999 (category sales) Nijs et al. 2001 (category sales) This study (average quantity)	This study (category consumers)

Table 2
HYPOTHESES FOR THE PROMOTIONAL EFFECTS ON THE THREE SALES COMPONENTS

Sales Component	*Category Incidence*		*Brand Choice*		*Purchase Quantity*	
Product category	Storable	Perishable	Storable	Perishable	Storable	Perishable
Immediate effects	+	+	+++	+++	++	+
Adjustment effects	+	+	--	--	-	-
Permanent effects	0	0	0	0	0	0
Total effects	++	++	+	+	+	0

Immediate Effects of Price Promotions

Promotions cause a substantial immediate increase in all three sales components (Bell, Chiang, and Padmanabhan 1999; Blattberg, Briesch, and Fox 1995). The economic rationale is clear: Temporary price reductions increase the value of the product to the consumer and require immediate action. The marketing literature distinguishes different consumer behaviors that contribute to the immediate sales boost (Blattberg and Neslin 1990). Category incidence increases because of timing acceleration (purchasing earlier), impulse purchases, and category switching (substituting purchases between categories). Brand choice benefits from consumers switching to the promoted item. Finally, purchase quantity benefits from quantity acceleration (forward buying) and stockpiling behavior. As for the relative magnitude of the promotional effect, Bell, Chiang, and Padmanabhan (1999) report an average elasticity breakdown (incidence/choice/quantity) of 3/75/22 for storable products and 17/75/8 for perishable products. We therefore hypothesize that

H_1: The immediate promotional effects are higher for brand choice than for the other two sales components.

Adjustment Effects of Price Promotions

We distinguish three reasons for adjustment effects: (1) dynamic consumer response, including the postdeal trough, the mere purchase effect, and the promotion usage effect; (2) competitive reaction; and (3) performance feedback.

The postdeal trough logically follows from timing and quantity acceleration. Given their larger stock, consumers will reduce their purchases in subsequent weeks. However, the empirical evidence on postdeal troughs in brand sales is mixed (Blattberg, Briesch, and Fox 1995). On the one hand, Blattberg, Eppen, and Lieberman (1981), Neslin, Henderson, and Quelch (1985), Leone (1987), Jain and Vilcassim (1991), and Van Heerde, Leeflang, and Wittink (2000a) report postdeal troughs. On the other hand, Grover and Srinivasan (1992) and Vilcassim and Chintagunta (1992) find no postpromotion dips. Litvack, Calantone, and Warshaw (1985) consider several categories and do not observe a postpromotion dip for the categories that could experience purchase acceleration. Moriarty (1985) finds significant postpromotion dips for only 3 of 15 cases, by including one-week lagged promotion variables in the sales–response function. As a general rule, the postdeal trough appears small in comparison with the immediate sales increase (Abraham and Lodish 1987).

The mere purchase effect holds that promotion-induced purchases increase future sales (Blattberg and Neslin 1990). Three behavioral theories could account for this effect. First, learning theory holds that promotions offer a risk premium for trial by new consumers, some of whom will like the product and repurchase it in the future (Mela, Gupta, and Lehmann 1997). Second, promotions remind existing consumers to buy the brand and reinforce their tastes for it (Erdem 1996). Both theories imply benefits for both category incidence and brand choice. Third, promotions induce consumers to buy in larger quantities (stockpiling), which can increase their consumption rates (Ailawadi and Neslin 1998; Chandon and Wansink 1997).

The promotion usage effect concentrates on the impact of promotions on consumer perceptions. First, self-perception theory (Bem 1967) implies that consumers are likely to attribute their purchase to an external cause (taking advantage of a promotion) instead of an internal cause (e.g., brand liking). Second, price perception theory holds that consumers form a reference price for the brand based on past prices (Kalyanaram and Winer 1995). This reference serves as an internal standard against which consumers compare current prices (Helson 1964). Promotions lower the reference price, making consumers reluctant to buy the brand at all in nonpromotion periods (Lattin and Bucklin 1989). Finally, object perception theory (Blattberg, Briesch, and Fox 1995) postulates that promotions will damage the brand's quality image.

Given the opposite directions of the mere purchase effect versus the postdeal trough and the promotion usage effect, the net impact of promotions on dynamic consumer response remains an empirical puzzle in marketing literature. Early research reported positive total effects on brand choice and sales (Blattberg and Neslin 1990; Davis, Inman, and McAllister 1992; Guadagni and Little 1983), whereas later studies reported predominantly negative dynamic effects (Jedidi, Mela, and Gupta 1999; Mela, Jedidi, and Bowman 1998).

In addition to dynamic consumer response, competitors may react to the focal brand's promotion (Leeflang and Wittink 1992, 1996). The impact of competitive reaction should differ for brand choice versus incidence. For brand choice, we expect competitive reaction to hurt the focal brand (Bass et al. 1984). In contrast, category incidence should benefit from promotional reaction by competitors in the same category (Putsis and Dhar 1999). If the focal brand's promotion attracts consumers to the category, so should the competitive promotions.

Finally, performance feedback and company decision rules may lead to repetition of marketing actions that were considered successful (Dekimpe and Hanssens 1995a, 1999). Therefore, a successful promotion can increase future promotional activity. Promotional effectiveness may either benefit from this reinforcement or suffer as consumers adjust to a higher level of promotional activity (Assunçao and Meyer 1993; Krishna 1992, 1994).

In summary, the net adjustment effects of price promotions could be positive or negative and will differ for the three sales components. For category incidence, both the mere purchase aspect of dynamic consumer response as well as competitive reaction and performance feedback yield positive effects, whereas the timing acceleration and promotion usage aspect of consumer response yields negative effects. As a net result, we predict positive adjustment effects for category incidence. In contrast, brand choice has been found to suffer from postdeal trough, promotion usage effects, and competitive reactions. Therefore, we predict negative adjustment effects. Finally, average purchase quantity is negatively affected by quantity acceleration but positively affected by timing acceleration. Neither direction has strong empirical support.

H_2: The adjustment effects are (a) positive for category incidence and (b) negative for brand choice.

Permanent Effects of Price Promotions

With the exception of the postdeal trough, all these dynamic effects could be permanent in nature. First, the mere purchase effect may persist if promotion-induced trial results in repeat purchase (Blattberg and Neslin 1990). However, this phenomenon is most likely to occur for new product categories and for new consumers in the geographic area or in the store (Gijsbrechts 1993). Any impact would be small for mature products (Mela, Gupta, and Lehmann 1997). Second, the promotion–usage effect may persist if consumers continue to associate the brand with the negative perception of the promotion. Again, such a permanent phenomenon is unlikely. Moreover, existing models of dynamic choice, including inventory management, predict that sales will eventually return to their prepromotion level (Assunçao and Meyer 1993; Krishna 1992, 1994). Finally, competitive reactions to the promotion typically die out over time, with the rare exception of a discount that escalates into an all-out price war. In summary, permanent sales effects by promotions seem unlikely in mature product categories.

Empirical studies investigating permanent promotional effects are scarce, because most models assume mean-reverting behavior. Dekimpe, Hanssens, and Silva-Risso (1999) report positive permanent effects for one brand's promotions in one of four category sales series. Nijs and colleagues (2001) find evolution in category demand in only 36 of 560 product categories (6.5%) of their Dutch data set. Of product categories, 3% experience a positive permanent impact, and 1% experience a negative permanent impact. In other words, permanent effects of promotions on category sales are the exception rather than the rule. In both studies, however, the absence of permanent effects could be caused by the cancellation of positive effects on one sales component by negative effects on the other. For example, the abovementioned lie-in-wait behavior could persist, resulting in lower incidence but higher purchase quantity levels. Within a mean-reverting model, Mela, Jedidi, and Bowman (1998) find that increased expectations of future promotions reduce the likelihood of category incidence and increase purchase quantity, given incidence. The present study is the first to empirically investigate whether the assumed absence of permanent promotional effects holds for a storable and a perishable product. We expect to find that

H_3: Permanent effects of promotions are absent for all sales components.

Total Effects of Price Promotions

Whereas the time frame of promotional effects may be of some interest to practitioners, their major question is, "What is the total over-time impact of the price promotion I am planning to run?" As discussed previously, both the immediate effects and the adjustment effects are expected to differ for each sales component. Therefore, our hypotheses on the total promotional impact logically follow from H_1–H_3. We expect a positive promotional impact on all three sales components. In other words, negative adjustment effects will not completely cancel out the positive immediate impact (Ailawadi and Neslin 1998; Jedidi, Mela, and Gupta 1999). However, the different signs of the proposed adjustment effects for incidence and choice will greatly affect their relative magnitude in the total effect decomposition. Whereas the immediate benefits for brand choice are largely reduced in the adjustment period (Jedidi, Mela, and Gupta 1999), we expect positive adjustment effects to enhance the category incidence hike. Therefore, the empirical generalization that price promotions have the largest immediate impact on brand choice (Bell, Chiang, and Padmanabhan 1999) will not hold when the total effect horizon is considered. Instead, we expect category incidence effects to dominate the total promotional impact. The relative importance of quantity effects should depend on product storability. For their storable product, Jedidi, Mela, and Gupta (1999) report larger total effects for purchase quantity than for brand choice. We expect the opposite ordering for perishables, which are difficult to stockpile and therefore are less likely to yield increased consumption. We therefore hypothesize the following:

H_4: The total promotional impact is positive for all sales components.

H_5: The total promotional effects are higher for category incidence than for the other two sales components.

H_6: For storable products, the total promotional impact is higher for purchase quantity than for brand choice.

H_7: For perishable products, the total promotional impact is higher for brand choice than for purchase quantity.

Product storability may also influence the magnitude of total effects compared with other categories. Bell, Chiang, and Padmanabhan (1999) find that immediate effects on all sales components are larger for storable products than for perishables. We find no theoretical rationale for this phenomenon to hold in the long run for category incidence and brand choice. In contrast, purchase quantity effects should depend on product storability, as consumers are more flexible in their quantity decisions when it is easy to stockpile the product. Therefore,

H_8: The total promotional impact is larger for storable products than for perishables on purchase quantity only.

The Time Window of Promotional Adjustment

Advertising research has long developed an interest in estimating the time window of advertising carryover effects on sales. Leone (1995) concludes that 90% of the effects of advertising on sales die out within six to nine months. In contrast, the promotional literature has been surprisingly vague about the duration interval of promotional effects. The two exceptions are the studies by Mela, Gupta, and Lehmann (1997) and Mela, Jedidi, and Bowman (1998), who report intervals of, respectively, 33 weeks and 21 weeks and conclude that promotions have a "slightly less enduring effect" than advertising. However, these findings may be specific to the nonfood product under study and to the assumption of exponential decay of promotion effects.

In contrast to advertising, price promotions are tools for generating immediate sales (Blattberg and Neslin 1990). We therefore expect that promotional effects die out soon, that is, within the standard short-term management planning horizon of one quarter. Moreover, the exponential decay assumption in the Koyck model is less appropriate for promotional adjustment effects, which may include both positive and negative coefficients. In our framework, the adjustment period refers to the number of weeks between the short-term response and the long-term equilibrium. In the absence of permanent effects, this period corresponds to the number of weeks with adjustment effects that are significantly different from zero.

The length of the adjustment period may depend on the sales component and on product storability. As for the former, there is no previous literature that can generate a priori predictions. As for the latter, product storability enables rational consumers to sharply adjust their quantity decisions to the promotional pattern in the category (Assunçao and Meyer 1993). For a substantive period after the promotion, these consumers will not return to their previous quantity levels. For perishables, quantity effects are necessarily short-lived because of consumer stockpiling limitations. Therefore, we expect the storable products to show longer quantity adjustment periods than perishable products. In conclusion,

H_9: For each sales component, promotional effects die out within a quarter (13 weeks).

H_{10}: The quantity adjustment period is longer for storable products than for perishables.

METHODOLOGY AND DATA DESCRIPTION

Overview

Three steps are necessary for the assessment of the long-term impact of price promotions on the dependent variables (Bronnenberg, Mahajan, and Vanhonacker 2000; Dekimpe and Hanssens 1995a). First, unit-root tests identify whether there is evolution in the data-generating process of the variables. If evolution is detected, cointegration analysis determines whether a long-term equilibrium exists between the series of the dependent variable and the independent variables of interest. Second, we specify a vector-error correction (VEC) model in case of cointegration and a vector-autoregressive (VAR) model in differences otherwise. Third, impulse–response and multivariate persistence estimates visualize and quantify the long-term impact of price shocks.

If the unit-root tests fail to identify evolution, we conclude that the time series are stationary—they return to their mean (or a deterministic trend) after the effects of a shock have died out. In that case, VAR models are estimated on the levels of the data, and the coefficients of the impulse–response functions can be used to compute the finite total effect of promotions, as well as the length of the promotion–response (adjustment) period.

Data Description

Our data set is constructed from the ACNielsen household scanner data in the Sioux Falls, S. Dak., market for the period July 14, 1986, until September 5, 1988. These data have been made available through the Marketing Science Institute and have been widely used in the marketing literature. On the basis of the previous discussion on product storability, we consider canned soup, a storable product that is not generally bought on impulse, and yogurt, a perishable product that is often bought on impulse (Narasimhan, Neslin, and Sen 1996). The number of consumers in the panel is 2399 for yogurt and 1826 for soup. Total consumption is 690,780 ounces for yogurt and 539,116 ounces for soup. The consumption average is 288 ounces for yogurt and 295 ounces for soup.

To prepare the scanner data for time series analysis, we first compute the number of consumers and the total number of ounces sold per brand and per store. We then select the brands that occupy the major positions in the market (more than 80% for both categories) and the five stores with the highest sales, provided that they belong to different chains. This procedure resulted in four stores, each with three soup brands (two national brands and one private label), and three stores, each with five or six yogurt brands (four national brands and one or two private labels). Table 3 describes the average market shares, prices,[2] and promotional activities. Because the VAR approach requires equally spaced time series, we transform the purchase occasion–based scanner data into weekly ratio-scaled data on the store level. In particular, we compute the weekly number of panelists who made a purchase in the category (category incidence), the fraction of these consumers who bought the brand (brand choice[3]), and the average quantity per purchasing consumer. Although some aggregation bias might result from this procedure (Pesaran and Smith 1995), all consumers are exposed to the same marketing-mix variables, the brands are close substitutes, and the price distribution is not concentrated at an extreme value, which greatly reduces this bias (Allenby and Rossi 1991). Separate analyses for each store provide

[2]We obtained stockkeeping unit market shares from separate store sales information over the full period. These full-period market shares then served as weights to aggregate stockkeeping unit–level prices to brand-level prices.

[3]Because choice share is a limited dependent variable, the normality assumption on its error term may not hold. We therefore perform our analysis using choice = share/(1 – share) as a dependent variable.

Table 3
DATA DESCRIPTION FOR THE SOUP AND YOGURT CATEGORY

Soup	*Brand Name*[a]	*Market Share*[b]	*Price per Ounce*[c]	*Promotion Frequency*[d]	*Promotion Depth*[e]
Store 1					
Brand 1	Campbell's	.69	5.03	6%	21%
Brand 2	Store brand	.19	3.88	14%	29%
Brand 3	Swanson	.01	3.47	9%	12%
Store 2					
Brand 1	Campbell's	.81	4.96	12%	15%
Brand 2	Store brand	.07	3.78	2%	21%
Brand 3	Swanson	.01	3.45	4%	23%
Store 3					
Brand 1	Campbell's	.77	4.53	7%	21%
Brand 2	Store brand	.07	3.45	5%	28%
Brand 3	Swanson	.01	3.06	5%	10%
Store 4[f]					
Brand 1	Campbell's	.81	4.40	10%	3%
Brand 2	Store brand	.04	2.95	5%	4%
Brand 3	Swanson	.01	3.18	1%	1%

Yogurt	*Brand Name*	*Market Share*	*Price per Ounce*	*Promotion Frequency*	*Promotion Depth*
Store 1					
Brand 1	Yoplait	.17	11.19	6%	6%
Brand 2	Weight Watchers	.07	7.96	7%	6%
Brand 3	Danon	.14	8.09	11%	15%
Brand 4	Nordica	.06	7.33	7%	12%
Brand 5	WBB	.09	5.4	15%	24%
Brand 6	Store brand	.31	4.49	6%	7%
Store 2					
Brand 1	Yoplait	.13	9.93	5%	20%
Brand 2	Weight Watchers	.18	7.31	1%	14%
Brand 3	Danon	.16	8.42	2%	19%
Brand 4	Nordica	.14	6.57	19%	21%
Brand 5	Store Brand	.17	5.32	13%	13%
Brand 6	QCH	.12	5.56	5%	16%
Store 3					
Brand 1	Yoplait	.13	9.62	9%	15%
Brand 2	Weight Watchers	.12	7.19	12%	7%
Brand 3	Danon	.11	8.15	5%	25%
Brand 4	Nordica	.12	6.53	21%	14%
Brand 5	Store brand	.12	5.44	17%	33%

[a]National brands are identified in the store file with their full name, whereas private labels such as store brands and generic products are identified with acronyms such as WBB and QCH.
[b]Average market share within the store.
[c]Average price per ounce over all Universal Product Codes and time periods.
[d]Number of weeks the price is at least one standard deviation lower than the expected price from an AR(2) model.
[e]Average discount depth: percentage price difference between promoted and nonpromoted weeks.
[f]Store 4, which hardly offers any promotions, experiences steadily declining sales throughout the store. On the basis of our discussion in the "Empirical Results" section, this store is excluded from the VAR analysis.

variability in the pricing and promotional pattern of the same brand in different retailer settings.

Unit-Root Testing of the Sales Components and Prices

We performed the Augmented Dickey–Fuller test for each series in several versions (for details, see Dekimpe, Hanssens, and Silva-Risso 1999). First, we decide on the number of lags to include in the test by Schwarz's Bayesian information criterion (BIC) and by the maximum lag for which the regression coefficient is significant. Schwarz's BIC is designed to consistently estimate the lag structure as a uniform criterion that minimizes the sum of squared errors while taking model complexity into account. To assess the robustness of this procedure, we also performed the tests using the number of statistically significant lagged terms as the criterion for lag selection. Except for a few series, test conclusions were identical. In comparison with the maximum significant lag criterion, minimization of the BIC has the additional advantage of model parsimony, because fewer lags are included. Second, we account for structural breaks in the data, such as the two new-product entries in the yogurt category. We incorporate these potential breaks in the unit-root test and the VAR model estimation.

Before we proceed with estimating VAR models, we also need to investigate whether a unit root is present in prices. For the yogurt category, prices are mean-stationary with a few exceptions due to two new brand entries. When we account for these interventions by dummy variables, these

Figure 1

SECOND-ORDER VAR FOR A STORE WITH THREE BRANDS

$$\begin{bmatrix} CI_t \\ BC_{1t} \\ PQ_{1t} \\ P_{1t} \\ P_{2t} \\ P_{3t} \end{bmatrix} = \begin{bmatrix} \alpha_{CI} \\ \alpha_{BCI} \\ \alpha_{PQI} \\ \alpha_{p1} \\ \alpha_{p2} \\ \alpha_{p3} \end{bmatrix} + \sum_{i=1}^{2} \begin{bmatrix} \phi^i_{11} & \phi^i_{12} & \phi^i_{13} & \phi^i_{14} & \phi^i_{15} & \phi^i_{16} \\ \phi^i_{21} & \phi^i_{22} & \phi^i_{23} & \phi^i_{24} & \phi^i_{25} & \phi^i_{26} \\ \phi^i_{31} & \phi^i_{32} & \phi^i_{33} & \phi^i_{34} & \phi^i_{35} & \phi^i_{36} \\ \phi^i_{41} & \phi^i_{42} & \phi^i_{43} & \phi^i_{44} & \phi^i_{45} & \phi^i_{46} \\ \phi^i_{51} & \phi^i_{52} & \phi^i_{53} & \phi^i_{54} & \phi^i_{55} & \phi^i_{56} \\ \phi^i_{61} & \phi^i_{62} & \phi^i_{63} & \phi^i_{64} & \phi^i_{65} & \phi^i_{66} \end{bmatrix} \times \begin{bmatrix} CI_{t-i} \\ BC_{1t-i} \\ PQ_{1t-i} \\ P_{1t-i} \\ P_{2t-i} \\ P_{3t-i} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} \\ \gamma_{51} & \gamma_{52} & \gamma_{53} \\ \gamma_{61} & \gamma_{62} & \gamma_{63} \end{bmatrix} \times \begin{bmatrix} DISP_1 \\ DISP_2 \\ DISP_3 \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} \\ \gamma_{51} & \gamma_{52} & \gamma_{53} \\ \gamma_{61} & \gamma_{62} & \gamma_{63} \end{bmatrix} \times \begin{bmatrix} FEAT_1 \\ FEAT_2 \\ FEAT_3 \end{bmatrix} + \begin{bmatrix} \varepsilon_{CI,t} \\ \varepsilon_{BCI,t} \\ \varepsilon_{PQI,t} \\ \varepsilon_{p1,t} \\ \varepsilon_{p2,t} \\ \varepsilon_{p3,t} \end{bmatrix}$$

Notes: CI = category incidence, BC = brand choice for the focal brand (in this case, Brand 1), PQ = average purchase quantity for the focal brand (in this case, Brand 1), P = price for each brand per ounce (weighted average over package sizes), DISP = display dummy variable for each brand, and FEAT = feature dummy variable for each brand.

cases test as stationary as well. Prices in the soup market are trend-stationary; that is, they become stationary after we remove a positive trend that is possibly due to inflation.

Specification of VAR models

The order of the VAR models is based on Schwarz's BIC. For all our series, either a first-order or a second-order VAR was selected. To facilitate comparison across brands and stores, we proceed by estimating a second-order VAR for all series. Such a second-order VAR model for a store with three brands is presented in Figure 1. Stationary variables are included in levels, difference-stationary variables in differences, and trend-stationary variables in detrended levels. When two or more variables are evolving, we also test for cointegration using the Johansen likelihood ratio (trace) test.

An important decision is which variables to include in the VAR estimation and whether to treat them as endogenous or exogenous. The simple base model, as depicted in Figure 1, features the three response variables for the focal brand, the prices of all brands in the market as endogenous variables, and feature and display of all brands as exogenous variables. The treatment of prices as endogenous implies that lagged effects of the performance variables (performance feedback) and competitor prices (competitive reaction) are accounted for. Feature and display are treated as control variables with contemporaneous effects on the response measures. The contemporaneous effects among the endogenous variables are modeled through the residual covariance matrix (Lütkepohl 1993).

Modeling assumptions for tractability include independent errors for each brand and for each sales component. Specifically, the estimation of a VAR model for each brand implies that choice share errors are assumed independent and that category incidence effects are estimated separately for each brand. Even for this relatively simple model, the second-order VAR-model estimates $2 \times (3 + n)^2$ ϕ-coefficients, where n is the number of brands.

A first extension of the base model is the inclusion of feature and display as endogenous variables, because they too can display dynamic effects (Papatla and Krishnamurthi 1996). Although feature and display are not the focus of our research, we validate our results by estimating the extended model and reporting the correlation of estimated promotional effects.

Second, the functional form of the depicted model is linear in incidence, choice, and quantity, similar to previous models in this research stream (Dekimpe, Hanssens, and Silva-Risso 1999). An alternative specification is the multiplicative model, which yields linear equations after logarithms are taken. Compared with the constant elasticity of the log–log model, the linear model yields an elasticity that is increasing in price. The implied decreasing returns to price promotions are intuitive, given our promotional definition. An unexpected, one standard deviation error shock to price will yield increased consumption (i.e., will in all likelihood cross the threshold of being noticed and acted on by some consumers). However, doubling this promotional depth will not result in twice the effect of the lower discount because of limits to increases in all three sales components. Incidence gains are limited by the number of consumers who consider buying into the category. Choice-share gains are limited by hard-core loyals for the other brands. Quantity gains are limited by storability and inventory carrying costs. By means of flexible parametrization methods, Van Heerde, Leeflang, and Wittink (2000b) recently found that most promotions indeed show decreasing returns to the magnitude of the discount. The authors conclude that "test results indicate that the assumption of constant elasticities is untenable" (p. 28) and that "one possible interpretation is that consumers tend to switch at relatively low price discount levels, and that higher price discounts do not result in much further switching" (p. 27). For these reasons, we use a linear specification, and we validate our results by applying the log–log model and examining the correlations between the parameters of the two models.

Impulse–Response Functions

We used the selected VAR models to simulate the effects over time of price shocks of one standard error on the system, using impulse–response functions. This method yields estimates of the incremental effect of the price promotion on the response variable compared with its baseline.[4] The impulse–response function is calculated from an initial shock, which requires the specification of a causal ordering of the contemporaneous shocks (for a detailed discussion, see Dekimpe and Hanssens 1999). We shock brand price first, allowing for contemporaneous effects on competitive prices and the response variable (category incidence, brand

[4]For stationary series, this baseline is the mean value of the full time series, and for evolving series, it is the last observation of the time series.

choice, or purchase quantity).[5] Given that the marketing data are weekly, this ordering is meaningful because firms need time to react to competitive price promotions or demand fluctuations (Leeflang and Wittink 1992). Our simulation only excludes instant price reactions of the focal brand to competitive-price or performance shocks.

Operationalization of the Promotional Effects

In the framework of the impulse–response functions derived from our VAR model, the immediate promotion impact is the effect of a price shock of one standard error on the response variable (for previous applications of this operationalization, see Dekimpe, Hanssens, and Silva-Risso 1999; Srinivasan, Leszczyc, and Bass 2001). Note that this immediate effect is captured by the residual correlation matrix, as contemporaneous price does not directly appear in the regression equation for the response variable. The sign (negative for own-price, positive for cross-price effects) and magnitude of the immediate effect provide a validity check on our findings.

We operationalize the total effects of a price promotion as the sum of all impulse–response weights with a t-statistic greater than one in absolute value (Dekimpe, Hanssens, and Silva-Risso 1999). Because this generous cutoff point translates into wide confidence intervals, we focus on the sign and relative magnitude of total effects. The length of the adjustment period is operationalized as the number of weeks it takes to observe 90% of the significant impulse–response weights. We test the corresponding hypothesis for both product categories by computing the average adjustment period for each sales component, weighted by category sales share for each store.

Finally, the decomposition of promotional effects requires several choices. We need a common scale to compare the promotional impact on the three sales components. To facilitate a comparison with previous literature, we chose to compute elasticities. To that end, we write brand sales as

$$\begin{aligned}\text{Brand sales}_i\ (S) &= \text{number of category consumers (I)}\\ &\times \text{share of consumers for i (C)}\\ &\times \text{average purchase quantity i (Q)}.\end{aligned}$$

Therefore, assuming independence among the three components, we write incremental sales as

$$(1)\quad \frac{\partial S}{\partial P} = \left[\frac{\partial I}{\partial P} \times C \times Q\right] + \left[\frac{\partial C}{\partial P} \times I \times Q\right] + \left[\frac{\partial Q}{\partial P} \times I \times C\right].$$

In this equation, the change in demand on the total number of consumers (incidence) is weighted by choice and quantity, choice changes are weighted by incidence and quantity, and quantity changes by incidence and choice. This procedure parallels the elasticity calculations in household-level models (e.g., Bucklin, Gupta, and Siddarth 1998). The elasticity decomposition becomes

$$\begin{aligned}(2)\quad \eta_S &= \frac{\partial S/S}{\partial P/P} = \left(\left[\frac{\partial I}{\partial P} \times C \times Q\right] + \left[\frac{\partial C}{\partial P} \times I \times Q\right] + \left[\frac{\partial Q}{\partial P} \times I \times C\right]\right)\frac{P}{I \times C \times Q}\\ &= \left[\frac{\partial I}{\partial P} \times \frac{C \times Q \times P}{I \times C \times Q}\right] + \left[\frac{\partial C}{\partial P} \times \frac{I \times Q \times P}{I \times C \times Q}\right] + \left[\frac{\partial Q}{\partial P} \times \frac{I \times C \times P}{I \times C \times Q}\right]\\ &= \left[\frac{\partial I}{\partial P} \times \frac{P}{I}\right] + \left[\frac{\partial C}{\partial P} \times \frac{P}{C}\right] + \left[\frac{\partial Q}{\partial P} \times \frac{P}{Q}\right]\\ &= \eta_{\text{incidence}} + \eta_{\text{choice}} + \eta_{\text{quantity}}.\end{aligned}$$

We apply Equation 2 to calculate the immediate, adjustment, permanent, and total effects. For the adjustment and total effects, the signs of elasticity estimates may differ, which complicates the computation of average elasticities over all brands and stores. Our calculation procedure is the following: For each store, we compute the elasticities per decision variable and per brand. Next, we compute the weighted average across all brands for each decision variable. The weight used is the average choice share of the brand divided by the sum of the average choice shares of all analyzed brands in the store (to ensure that the weights add up to 100%). We repeat this procedure for each decision variable and each store, after which we compute the weighted average across the three stores for each decision variable.[6] Category sales are used as store weights. Finally, we compute the elasticity decomposition by dividing each elasticity by the sum of the absolute values of three elasticities for ease of comparison.

Because of different model assumptions and the possibility of negative effects, our decomposition analysis does not completely correspond to the decomposition procedures of Gupta (1988), Bucklin, Gupta, and Siddarth (1998), or Bell, Chiang, and Padmanabhan (1999). Therefore, we verify that our immediate effect breakdown is similar to the immediate elasticity breakdown obtained in previous research. Moreover, we estimate Bucklin, Gupta, and Siddarth's (1998) household-level model and compare the immediate effects obtained by the two different methodologies on the same data. Finally, we check the robustness of our results by repeating the analysis using logarithms of sales components and prices.

Comparison with Previous Models in the Promotion Literature

Table 4 compares and contrasts our methodology with previous approaches to capture the dynamic effects of price promotions on incidence, choice, and quantity. First, nested logit models have allowed for flexible inventory (e.g., Gupta 1988) and consumption (Ailawadi and Neslin 1998). Second, time-varying parameter models have analyzed the

[5]Note that this simulation is numerically equivalent to the simultaneous-shocking approach used by Dekimpe and Hanssens (1999), provided that the focal variable is shocked first.

[6]We investigated the influence of forecast errors for the adjustment and total effects by also weighting the brand elasticities by the t-statistic of the accumulated impulse–response function. The results are similar: The substantive findings on the decomposition of adjustment and total effects continue to hold.

Table 4

MODEL COMPARISON ON THE DYNAMIC EFFECTS OF PRICE PROMOTIONS

Model	*Mathematical Formulation*	*Definition of Promotion*	*Dynamic Effects of Promotions*	*Time-Varying Components*
Integrated Choice Model Exact specifications vary, but the most typical model combines the nested logit model for incidence and choice and the Poisson model for purchase quantity (Bucklin, Gupta, and Siddarth 1998; Chintagunta 1993)	P_t^h (inc) = $\exp(V_t^h)/[1 + \exp(V_t^h)]$ $V_t^h = c + CV_t^h + INV_t^h + CR_t^h$ $CV_t^h = \ln[\Sigma \exp(U_{jt}^h)]$ P_t^h (choice j|inc) $= \exp(U_{jt}^h/\Sigma U_{jt}^h)$ $U_{jt}^h = u_j + BL_j^h + LBP_{jt}^h + PRICE_{jt} + \text{Feature/Display}_{jt}$ P_t^h (q|inc and choice j) $= (\lambda_{jt}^h)^q/[(\exp(\lambda_{jt}^h) - 1)q!]$ $\lambda_{jt}^h = c_j + PR^h + INV_t^h + BL_j^h + PRICE_{jt} + \text{Feature/Display}_{jt}$	Simulate 1% price decrease; recalculate to obtain price elasticity $PRICE_{jt}$ affects utility U_{jt}^h and thus choice and incidence $PRICE_{jt}$ affects Poisson rate λ_{jt}^h and thus quantity	Inventory (Gupta 1988; Neslin, Henderson, and Quelch 1985) $INV_t^h = INV_{t-1}{}^h + Q_{t-1}{}^h - CR^h$ Last brand purchased (Guadagni and Little 1983) Reference price (Lattin and Bucklin 1989)	Consumption (Ailawadi and Neslin 1998) $CR_t^h = INV_t^h \times \{CR^h/[CR^h + (INV_t^h)^f]\}$ Information set (Erdem 1996; Erdem and Keane 1996)
Time-Varying Parameter Models Price and promotional elasticities vary with time, marketing, and control variables (Jedidi, Mela, and Gupta 1999; Mela, Gupta, and Lehmann 1997; Mela, Jedidi, and Bowman 1998; Papatla and Krishnamurthi 1996)	Similar to the preceding formulation P_t^h (choice j) $= \exp(U_{jt}^h/\Sigma U_{jt}^h)$ $U_{jt}^h = \beta_{j0t} u_j + \beta_{j1t} PRICE_{jt} + \beta_{j2t} PROM_{jt} + \ldots$	PROM = temporary price reduction Promshare = share of promotional purchases LTPROM = long-term exposure to promotions	Past promotional activity 1. $LTPROM_{jq}$ = proportion of PROM weeks in quarter (Mela, Gupta, and Lehmann 1997) 2. $Promshare_t^h = \alpha\, Promshare_{jt-1}^h + (1 - \alpha) PROM_{jt-1}^h$ (Mela, Jedidi, and Bowman 1998; Papatla and Krishnamurthi 1996) 3. $LTPROM_{jt} = PROM_{jt} + \lambda PROM_{jt-1} + \lambda^2 PROM_{jt-2} + \ldots$ (Jedidi, Mela, and Gupta 1999)	Price and promotion elasticities 1) $\beta_{jq} = c_j + \lambda_j \beta_{jq-1} + \gamma_j LTPROM_{qt} + \delta C_{jq}$ (Mela, Gupta, and Lehmann 1997) 2) $\beta_{jkt} = \gamma_{jk0} + \gamma_{jk2} LTPROM_{jt} + \ldots$ (Jedidi, Mela, and Gupta 1999; Mela, Jedidi, and Bowman 1998; Papatla and Krishnamurthi 1996)
VAR Dynamic system Y of sales components and the endogenous prices (Bronnenberg, Mahajan, and Vanhonacker 2000; Dekimpe, Hanssens, and Silva-Risso 1999)	Y = [Sales components, $Price_j$, $Price_c$]′ X = [F_j, F_c, D_j, D_c]′ Exogenous Structural form: $A_0 Y_t = C + \Sigma_{k=1}{}^p A_k Y_{t-k} + BX_t + e_t$ Reduced form (premultiply by A_0^{-1}) $Y_t = C' + \Sigma_{k=1}{}^p \Phi_k Y_{t-k} + \Theta_k X_t + \eta_t$ Final form (divide by lag operator) $Y_t = \Sigma_{k=0}{}^\infty \Psi_k \eta_{t-k} + \Sigma_{k=0}{}^\infty \Psi_k X_{t-k}$	Price shock η_p = Price − E(Price) of one standard deviation E(Price) = expected price from VAR	$\partial Y/\partial \eta_{price} = \Psi_k$ Orthogonalized impulse response by Cholesky decomposition Immediate effect = Ψ_0 Adjustment effect = $\Sigma \Psi_k$ Permanent effect = Ψ_∞	Promotional definition: One standard deviation ε_{price} requires larger dollars off when promotions are predictable and prices are high

Notes: P = probability of category incidence (inc); brand j choice (choice j) and quantity (q), CV = category value, U = utility, INV = inventory, CR = consumption rate, BL = brand loyalty, LBP = last brand purchased, F = feature, D = display, and c = competition.

dynamic effect of promotional activity on consumer price and promotional sensitivity (e.g., Jedidi, Mela, and Gupta 1999; Mela, Gupta, and Lehmann 1997). Finally, VAR models have been applied to marketing problems by Dekimpe, Hanssens, and Silva-Risso (1999) and Bronnenberg, Mahajan, and Vanhonacker (2000). For ease of exposition, we summarize the typical elements of each approach and focus on their differences.

The models differ in mathematical formulation, promotional definition, incorporation of dynamic factors, and time-varying components. As for model formulation, the main differences are that (1) the VAR model treats prices as endogenous—that is, it allows lagged effects of sales components (performance feedback) and competitor prices (competitor reaction) on the brand's current price—and (2) the VAR model requires equally spaced time series in contrast to the unequally spaced purchase occasion data at the household level. We discuss these points in turn.

First, VAR models capture not only direct (immediate and/or lagged) consumer response to promotions but also the performance implications of the induced competitive reaction and company performance feedback. As for the former, a promotional shock may trigger competitive price reactions. As for the latter, the promotion may generate a strong boost in the managerially relevant performance variables, which induces further promotions for the same brand. For this reason, own and competitive prices are endogenous variables: They explain performance and are explained by past prices and performance variables. Our main interest lies in the net result of all these actions and reactions, which can be derived from a VAR model through its associated impulse–response functions.

Second, the VAR approach requires the endogenous performance and marketing variables to be equally spaced time series. Therefore, we transform the purchase occasion–based scanner data into weekly data at the store level. Previous literature has compared advantages and disadvantages of household-level purchase occasion data and weekly store-level data (Allenby and Rossi 1991; Bucklin and Gupta 1999). An important difference is the unit of analysis: purchase occasions and individual probabilities of incidence, choice, and quantity in household-level models versus store-level variables in the VAR model (number of category consumers, the fraction of these consumers who bought the brand, and the average purchase quantity per consumer). For our decomposition approach, note that in the VAR model, the total number of consumers reflects only the occasions when a purchase was made, whereas a household-level approach also models no-purchase (nonincidence). As a result, the incidence and choice measures are related: Choice is observable only when a category purchase is made.[7]

The definition of a price promotion also differs among the three modeling approaches in Table 4. Nested logit models typically consider the price elasticity, whereas the time-varying parameter models examine the elasticity for a temporary price reduction and at long-term promotional activity. Our analysis considers the incremental impact of an unexpected price shock. If consumers indeed incorporate price expectations in their buying behavior, they will respond only to the unanticipated part of a given price reduction (Helson 1964; Kalyanaram and Winer 1995). By definition, all the price shocks in our models are "unexpected," which is not true of the price reductions in a typical household-level model. Therefore, we expect our approach to yield larger elasticity estimates than typical household-level models.

Finally, dynamic effects of promotions are captured by inventory, loyalty, and reference price measures in the nested logit models; by Koyck-type regressions on promotional activity measures in time-varying parameter models; and by impulse–response functions in the VAR approach. Impulse–response functions are the most inclusive in dealing with dynamic effects, because they do not impose a lag structure and allow for competitive reactions and performance feedback. The VAR models also allow past promotional activities to influence the current price and promotional elasticities through their impact on the "shock value" of a current price promotion. Frequent, predictable promotions are incorporated in consumers' expected price levels, so that larger deals would be needed to obtain a price shock of one standard deviation.

[7]We thank an anonymous reviewer for this insight.

EMPIRICAL RESULTS

Following our research design, we start with a discussion of the temporal behavior of the three sales components. Our findings on evolution and time-to-mean reversion describe the temporal boundaries of the promotional effect. Next, we focus on the sign and magnitude of the promotional impact, broken down as immediate effects, adjustment effects, and permanent effects. We compare these effects across sales components and product categories.

Permanent Effects of Promotions on the Sales Components

The unit-root test results in Table 5 show that the time series for all three sales components are stationary for 82% of the brand–store combinations. In other words, the most common competitive scenario in our data is business as usual (Dekimpe and Hanssens 1999). In these cases, no permanent promotional effects are present, and all series revert to their means after the immediate and the adjustment effect.

The few cases with at least one evolving sales component are not of a uniform nature. For the yogurt category, evolution is present only at the brand-choice level for two brands in the first store. Both are small national brands, with average market shares of, respectively, 7% and 6%. In the first case (Brand 2), this evolution is not caused by price changes. Only in the second case (Brand 4) is there evidence of permanent effects of price promotions, with a small persistence of 6.5% of the immediate effect. For clarity, we abstract from this isolated and small permanent effect in the remainder of our analysis.

For the soup category, evolution is present only at the category incidence level for the fourth store. This store experienced a steady decline in the total number of soup consumers, which cannot be explained by price evolution. We expect that external factors may have caused the decline in category incidence, because panelists' visits to and spending in this store showed negative evolution as well. Subsequent cointegration tests demonstrate that soup category incidence is in a long-term equilibrium with these storewide variables. Possible reasons for the storewide decline include new competition from a nearby store or mall or interruptions due to store remodeling. Because it is difficult to measure and interpret promotional effectiveness against this anomalous background, we do not include this store in the subsequent analysis.

In summary, the empirical evidence supports H_3 for all sales components in both product categories. Permanent effects of promotions on category incidence or purchase quantity exist for none of the products in none of the stores in our data. Moreover, only 2 of 29 cases (7%) show evolution in brand choice, and only in 1 case (3%) do we find permanent effects of price promotions. These results are consistent with Nijs and colleagues' (2001) findings: Examining 560 product categories in the Netherlands, they find sales evolution in 6.5% of all cases and permanent effects of price promotions in only 4% (3% positive, 1% negative).

VAR Model Results

For each brand in each store, we estimated the VAR model in Figure 1 on stationary variables, after differencing or detrending as needed.[8] For model comparison purposes, we focus on fit indices and the covariance estimates between each brand's price and its response variables. The expected negative price elasticity implies negative covariance estimates of the brand's price with category incidence and with brand choice. Average purchase quantity may decrease if a promotion attracts mainly light users. Therefore, we investigate only the incidence and choice covariance estimates for sign consistency with expectations (18 estimates for the soup category and 34 for the yogurt category).

For model validation purposes, we compare the fit and the sign of the covariance estimates of the base model with those of the multiplicative model (log–log specification) and the extended endogenous model (with feature and display as endogenous variables). Compared with the multiplicative model, the base linear model always yields lower values for Akaike's information criterion (AIC) and the BIC. Moreover, the number of incorrectly signed error covariance estimates for the log–log specification is 3 of 18 (16.7%) versus none for the linear specification in the soup category. For the incidence and choice components in the yogurt category, the number of incorrect signs is 11 of 34 for the log specification (32.4%) versus 4 of 34 (11.8%) for the linear specification. Compared with the extended endogenous model, the base model yields lower values for the AIC and the BIC (on average, respectively, 30% and 24% lower). The number of incorrectly signed error covariance estimates is similar. In summary, the estimated VAR model outperforms both alternatives in model fit and yields theoretically meaningful relations between price and market response, which allows an analysis of promotional effects by means of the derived impulse–response functions.

Immediate Effects of Price Promotions

Table 6 presents the incidence, choice, and quantity elasticities calculated from the immediate response to an own-price shock. Because promotions are defined as unexpected price decreases, we reverse the sign of the impulse–response estimates to obtain promotional elasticities. This procedure enhances ease of interpretation throughout the article, as positive elasticities indicate beneficial promotional effects on the sales components. All immediate promotional elasticities either have the expected positive sign or do not significantly differ from zero. The average immediate elasticities for category incidence, brand choice, and purchase quantity are 1.78, 2.84, and 1.26 for soup and .88, 4.45, and .81 for yogurt. These estimates are similar to deal discount elasticities in the range [.49, 14.34] reported in previous literature (Blattberg and Neslin 1990, p. 356). The immediate elasticity decomposition is 30/48/22 for soup and 14/73/13 for yogurt. H_1 is supported: Brand choice is the dominant factor in the immediate elasticity breakdown. This empirical finding holds, on average, for each store and each category.

Adjustment Effects of Price Promotions on the Sales Components

Tables 7 and 8 report, respectively, the length of the adjustment period and the cumulative promotional impact on each sales component during this period. The 90% dura-

[8]Detailed model estimates, fit indices, and residual variance–covariance matrices are available from the first author.

Table 5

UNIT-ROOT TEST RESULTS (ABSOLUTE VALUE OF AUGMENTED DICKEY–FULLER TEST)

Soup	*Category Incidence*	*Brand 1 Choice*	*Brand 2 Choice*	*Brand 3 Choice*
Store 1	6.98	7.50	7.22	6.47
Store 2	3.52	8.31	8.20	8.22
Store 3	7.45	8.88	9.07	6.99
Store 4	2.30*	9.44	9.05	11.32

Soup	*Category Sales*	*Brand 1 Quantity*	*Brand 2 Quantity*	*Brand 3 Quantity*
Store 1	7.76	8.92	9.58	5.39
Store 2	5.65	7.18	10.88	10.71
Store 3	11.15	8.03	11.71	8.27
Store 4	2.78*	11.54	9.94	11.25

Yogurt	*Category Incidence*	*Brand 1 Choice*	*Brand 2 Choice*	*Brand 3 Choice*	*Brand 4 Choice*	*Brand 5 Choice*	*Brand 6 Choice*
Store 1	8.69	9.15	.66*	8.81	.08*	7.25	6.94
Store 2	5.63	7.87	8.67	5.63	8.78	8.99	7.86
Store 3	3.37	6.19	5.34	8.41	8.09	N/A	10.86

Yogurt	*Category Sales*	*Brand 1 Quantity*	*Brand 2 Quantity*	*Brand 3 Quantity*	*Brand 4 Quantity*	*Brand 5 Quantity*	*Brand 6 Quantity*
Store 1	7.04	8.88	10.09	7.99	5.19	10.48	7.83
Store 2	8.77	10.11	11.46	8.99	9.04	3.62	7.24
Store 3	4.62	9.53	11.49	10.32	10.07	N/A	10.86

*Failure to reject unit root at the $p < .05$ significance level.

tion interval ranges from 0 to 8 weeks. On average, the adjustment period is approximately 2 weeks for both product categories. For the soup brands, the average adjustment period is 1.92 weeks for incidence, 2.75 weeks for brand choice, and 2.38 weeks for purchase quantity. For yogurt, category incidence takes 2.53 weeks to adjust, whereas brand choice and purchase quantity effects die out in 1.70 and 1.47 weeks, respectively. In summary, our findings support H_9 and H_{10}: The adjustment period is less than a quarter in each case, and the quantity adjustment period is longer for the storable soup category than for the perishable yogurt category.

For the first brand in the first store, Figures 2 and 3 show the dynamic elasticity estimates in the soup and yogurt categories. The irregular shape of the impulse–response functions for promotional effects contrasts sharply with the exponential decay pattern of advertising effects reported in previous research. The postpromotion dip (defined as the occurrence of a significantly negative adjustment effect) is significant for more than half the brands in brand choice (14 of 26) and for a minority of the brands in category incidence (7 of 26) and purchase quantity (8 of 17). The impulse–response functions are able to pick up drastic fluctuations in the dynamic promotional effects.

The cumulative promotional impact during the adjustment period is reflected in the adjustment elasticities in Table 8. As expected, adjustment elasticities reflect both beneficial and harmful promotional effects. Overall, brand choice elasticities are typically negative, whereas category

Table 6

PROMOTIONAL ELASTICITY AND DECOMPOSITION FOR THE IMMEDIATE EFFECTS

	Category Incidence	*Brand Choice*	*Purchase Quantity*
Soup			
Store 1	1.78	3.15	.78
	(31%)	(55%)	(14%)
Store 2	1.56	2.31	1.60
	(28%)	(42%)	(29%)
Store 3	2.02	2.83	1.85
	(30%)	(42%)	(28%)
Average	1.78	2.84	1.26
	(30%)	(48%)	(22%)
Yogurt			
Store 1	.96	5.57	1.41
	(12%)	(70%)	(18%)
Store 2	1.21	4.20	.39
	(21%)	(72%)	(7%)
Store 3	.22	2.27	.03
	(9%)	(90%)	(1%)
Average	.88	4.45	.81
	(14%)	(73%)	(13%)

Table 7

DURATION INTERVAL FOR 90% OF THE TOTAL PROMOTIONAL EFFECTS (IN WEEKS)

		Category Incidence	*Brand Choice*	*Purchase Quantity*
Soup				
Store 1	Brand 1	0	8	3
	Brand 2	1	0	2
	Brand 3	2	2	0
Store 2	Brand 1	5	6	4
	Brand 2	5	2	0
	Brand 3	3	0	0
Store 3	Brand 1	1	2	1
	Brand 2	2	1	0
	Brand 3	0	2	1
Average		1.92	2.75	2.38
Yogurt				
Store 1	Brand 1	7	1	2
	Brand 2	0	2	3
	Brand 3	0	3	1
	Brand 4	0	1	4
	Brand 5	0	0	0
	Brand 6	4	0	0
Store 2	Brand 1	1	7	0
	Brand 2	1	7	5
	Brand 3	8	2	0
	Brand 4	4	1	0
	Brand 5	0	2	0
	Brand 6	0	0	0
Store 3	Brand 1	5	0	6
	Brand 2	4	0	1
	Brand 3	6	1	3
	Brand 4	4	0	0
	Brand 5	3	3	0
Average		2.53	1.70	1.47

Table 8

PROMOTIONAL ELASTICITY AND DECOMPOSITION FOR THE ADJUSTMENT EFFECTS

	Category Incidence	*Brand Choice*	*Purchase Quantity*
Soup			
Store 1	−.23	−1.82	.54
	(−9%)	(−70%)	(21%)
Store 2	8.70	−.28	−.14
	(95%)	(−3%)	(−2%)
Store 3	1.16	−.12	.77
	(56%)	(−6%)	(38%)
Average	2.56	−.98	.41
	(65%)	(−25%)	(10%)
Yogurt			
Store 1	4.51	−.94	−1.20
	(68%)	(−14%)	(−18%)
Store 2	1.21	−2.48	.14
	(31%)	(−65%)	(4%)
Store 3	1.91	−.17	−.14
	(86%)	(−8%)	(−6%)
Average	2.96	−1.24	−.57
	(62%)	(−25%)	(−12%)

Figure 2

IMPULSE ELASTICITY FUNCTIONS FOR SOUP BRAND 1 IN STORE 1

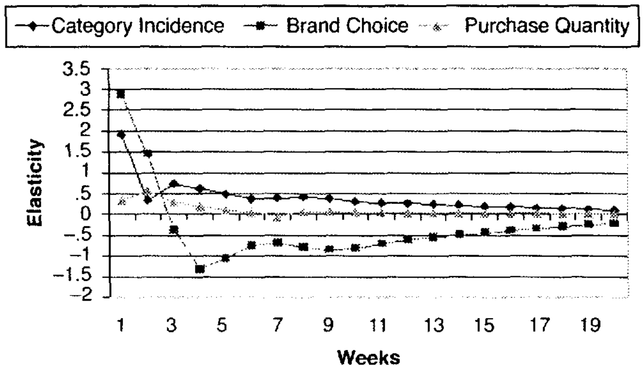
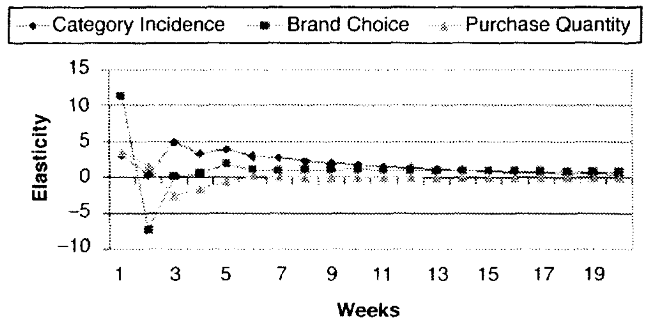


Figure 3

IMPULSE ELASTICITY FUNCTIONS FOR YOGURT BRAND 1 IN STORE 1



incidence effects are typically positive.[9] The average elasticities for category incidence, brand choice, and purchase quantity are 2.56, −.98, and .41 for soup and 2.96, −1.24, and −.57 for yogurt. The relative magnitudes are 65/−25/10 for soup and 58/−31/−11 for yogurt. Thus, H_2 is supported for category incidence and for brand choice. The directional results for purchase quantity are mixed, as the adjustment effects are typically positive for soup brands and negative for yogurt brands.

Total Effects of Price Promotions on the Three Sales Components

Table 9 presents the total promotional elasticity as the sum of immediate and adjustment elasticities. In support of H_4, the total promotional elasticity is positive, on average, for each sales component. With one exception (yogurt quantity in Store 3), this finding holds for each store and each product category. Six of 9 soup brands and 11 of 17 yogurt brands experience positive total elasticities on all sales components. Category incidence effects are almost exclusively positive (8 of 9 soup brands and 15 of 17 yogurt brands). Overall, our results are in line with the category expansion findings in previous literature (Ailawadi and Neslin 1998; Dekimpe, Hanssens, and Silva-Risso 1999).

The average elasticities for category incidence, brand choice, and purchase quantity are 4.92, .83, and 1.67 for soup and 3.83, 2.57, and .24 for yogurt. The relative magnitudes are 66/11/23 for soup and 58/39/3 for yogurt. H_5, H_6, and H_7 are supported: Category incidence dominates the total elasticity breakdown. Furthermore, purchase quantity is more important than brand choice for the storable product, and the opposite holds for the perishable product.

Table 10 breaks down the store-level results into the findings for national brands versus private labels. The main finding is that the reported long-term dominance of category incidence is driven by the national-brand results. Indeed, private labels in both product categories typically obtain higher long-term brand choice elasticities than incidence elasticities. The reason is twofold: Private labels typically obtain lower immediate incidence elasticities than national brands, and private labels typically have positive instead of negative adjustment elasticities for brand choice.

We further investigated the generalizability of our main finding by regressing total elasticities on store, brand type, and product category dummy variables. Only brand type and storability have a significant impact. First, incidence elasticities are significantly lower for private labels than for national brands. This is the result of both the lower immediate and the lower adjustment effects of private labels on category incidence. Second, in support of H_8, the storable product soup obtains higher total quantity elasticities than the perishable product yogurt. The difference between the product categories may be explained by rational consumer

[9]An alternative explanation for positive incidence effects could be loss-leader promotions in other categories, which may attract store switchers who also buy in the target categories. However, the impulse–response functions track the incremental incidence due to a price promotion of a brand in the target category; the effects of price promotions in other categories are reflected in baseline incidence.

behavior, as extra yogurt quantities must be consumed in a short period of time. Studying the same yogurt category, Bucklin, Gupta, and Siddarth (1998) find that the majority of consumers are prone to early buying but not to stockpiling.

Comparison of the Elasticity Breakdown in the VAR Model and a Household-Level Model

Even though equivalent measures for adjustment and total effects do not exist in previous literature, we compare our findings with the immediate elasticities obtained by household-level models. Moreover, we estimate the one-segment version of the household-level model by Bucklin, Gupta, and Siddarth (1998) on the same data set.

For the yogurt category, Bucklin, Gupta, and Siddarth (1998) and Bell, Chiang, and Padmanabhan (1999) report elasticity breakdowns of, respectively, 20/58/22 and 12/78/9.

Table 9
PROMOTIONAL ELASTICITY AND DECOMPOSITION FOR THE TOTAL EFFECTS

	Category Incidence	*Brand Choice*	*Purchase Quantity*
Soup			
Store 1	2.76	.92	1.32
	(55%)	(19%)	(26%)
Store 2	10.25	.02	1.46
	(87%)	(1%)	(12%)
Store 3	3.18	1.56	2.62
	(43%)	(21%)	(36%)
Average	4.92	.83	1.67
	(66%)	(11%)	(23%)
Yogurt			
Store 1	5.47	3.56	.20
	(59%)	(39%)	(2%)
Store 2	2.41	1.32	.53
	(57%)	(31%)	(12%)
Store 3	2.13	2.09	−.11
	(49%)	(48%)	(−3%)
Average	3.83	2.57	.24
	(58%)	(39%)	(3%)

No such findings exist for the soup category, but we can compare this product with coffee, which has similar scores on Narasimhan, Neslin, and Sen's (1996) scales of storability (.62 for soup, .71 for coffee) and impulse buying (−.13 for soup, −.14 for coffee). For coffee, Gupta's (1988) elasticity breakdown is 14/84/2, and Bell, Chiang, and Padmanabhan's (1999) elasticity breakdown is 3/53/45.

We estimated Bucklin, Gupta, and Siddarth's (1998) household-level model on the scanner data that served as the source for our time-series analysis. For both categories, the last 51 weeks of the data were used for model calibration, and the preceding 61 weeks were used for initializing model variables. Households qualified for inclusion in the sample if they made at least one grocery purchase in the first and last six months of the total time period and made at least one product purchase both in initialization and calibration periods. A random sample of 300 panelists in each product category was then drawn from this set of qualified households. The panelists in the yogurt category made 30,180 shopping trips and 2091 choices, and those in the soup category made 32,499 shopping trips and 4567 choices. Parameter estimates from the integrated model appear in the Table 11. These parameter estimates were used to calculate price elasticities for each consumer decision. The elasticities and their breakdowns for the two categories are

Soup: incidence .56 (18%), choice 1.68 (54%), and quantity .86 (28%)
Yogurt: incidence .46 (18%), choice 1.82 (64%), and quantity .56 (20%)

These are comparable to the immediate elasticity breakdowns for the VAR model reported previously:

Soup: incidence 1.78 (30%), choice 2.84 (48%), and quantity 1.26 (22%)
Yogurt: incidence .88 (14%), choice 4.45 (73%), and quantity .81 (13%)

In both categories, we find that the household-level model and the VAR model yield the same dominance for brand choice effects in the short run. Moreover, incidence and quantity obtain about the same percentage breakdown in the yogurt category, but quantity effects are larger in the soup

Table 10
PROMOTIONAL ELASTICITY FOR NATIONAL BRANDS AND PRIVATE LABELS

	Brand Type	*Category Incidence*	*Brand Choice*	*Purchase Quantity*
Soup				
Immediate	National	1.91	2.74	1.2
	Private label	1	3.42	1.63
Adjustment	National	3.33	−1.3	.64
	Private label	−2.01	.84	−.97
Total	National	5.93	.34	1.84
	Private label	−1.01	3.71	.66
Yogurt				
Immediate	National	1.1	4.71	1.22
	Private label	.45	3.96	0
Adjustment	National	4.35	−2.53	−.86
	Private label	.26	.14	0
Total	National	5.45	1.9	.36
	Private label	.71	3.84	0

Table 11
HOUSEHOLD-LEVEL MODEL PARAMETER ESTIMATES

	Soup Category		*Yogurt Category*	
	Estimate	*t-Value*	*Estimate*	*t-Value*
Incidence				
Consumption rate	.05	(19.07)	4.12	(16.11)
Inventory	–.32	(–12.6)	–.094	(–1.76)
Category value	.12	(2.19)	.41	(9.09)
Choice				
Brand loyalty	2.11	(20.93)	1.75	(18.80)
Last brand purchased	.14	(2.77)	1.28	(23.94)
Price	–1.59	(–6.51)	–.42	(–10.62)
Promotion	.73	(4.28)	1.35	(15.06)
Quantity				
Brand loyalty	.17	(3.10)	.12	(2.70)
Inventory	–.17	(–11.65)	–.09	(–1.76)
Price	–.24	(–5.33)	–.09	(–10.6)
Promotion	.25	(2.86)	.12	(3.55)

Notes: Asymptotic t-statistics are in parentheses.

category. However, the aggregate elasticities are higher in absolute value. This may be due to the difference in promotional shock definition in the VAR approach and the 1% price change used in the household-level model. In time-series analysis, a shock of a certain magnitude (i.e., 1%) represents the unanticipated change in price. If consumers react to the unanticipated part of a 1% price change, the real shock value will be less than 1%. Thus, it is intuitive that we obtain higher elasticities than those in the household-level model.[10]

In summary, our aggregate measures of the immediate breakdown yield results that are comparable to the elasticity breakdowns in previous literature. Price promotions have a larger immediate impact on selective demand (brand choice) than on primary demand (category incidence and purchase quantity). Table 12 summarizes our findings on the elasticity breakdown for the immediate, adjustment, permanent, and total effects.[11]

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

This article has established, first, that permanent effects of promotions on aggregate sales components are the exception rather the rule for both product categories under study.

Table 12
SUMMARY OF ELASTICITY DECOMPOSITION

	Category Incidence	*Brand Choice*	*Purchase Quantity*
Immediate Elasticity Breakdown			
Soup	1.78	2.84	1.26
	(30%)	(48%)	(22%)
Yogurt	.88	4.45	.81
	(14%)	(73%)	(13%)
Adjustment Elasticity Breakdown			
Soup	2.56	–.98	.38
	(65%)	(–25%)	(10%)
Yogurt	2.96	–1.24	–.57
	(63%)	(–26%)	(–12%)
Permanent Elasticity	0	0[a]	0
Total Elasticity Breakdown			
Soup	4.92	.83	1.67
	(66%)	(11%)	(23%)
Yogurt	3.83	2.57	.24
	(58%)	(39%)	(3%)

[a]Except for yogurt Brand 4 in Store 1.

Therefore, the reported absence of sales evolution is not due to offsetting permanent effects of promotions on category incidence and purchase quantity. Instead, we find that each sales component generally lacks a permanent promotion effect.

Mature markets are less likely than emerging markets to exhibit permanent effects of marketing actions (Bronnenberg, Mahajan, and Vanhonacker 2000). We expect that for established products, only dramatically shocking the market (breaking with a previous pricing policy, disrupting consumer expectations) can achieve permanent benefits. Further research should analyze the long-term effects of promotions in growth categories to assess whether our hypotheses hold in these markets.

In terms of adjustment effects, we find that promotional effects are short-lived (on average 2 weeks, at most 8 weeks) in both categories. We compare this finding with the advertising decay found by Clarke (1976), which is approxi-

[10]Other reasons may exist for differences between estimates. First, the VAR model calculates elasticity at the mean. Second, the consumer sample and time periods are not exactly the same. In the disaggregate approach, we sample panelists and use the first 60 weeks of data to initialize household variables such as loyalty and inventory.

[11]Our validation procedures test the robustness of our main finding with respect to model specification and weighting choices. The inclusion of feature and display as endogenous variables yields impulse–response functions that are highly correlated with the original findings (94% for soup and 90% for yogurt). The same observation holds for the multiplicative versus the linear model specification (correlation of 79% for soup and 65% for yogurt). The multiplicative specification yields a total elasticity breakdown of 62/28/10 for soup and 67/25/8 for yogurt. Finally, we weigh the brand-level estimates by the t-statistic of the accumulated impulse–response function to arrive at the forecast error-weighted total elasticity decomposition of 52/20/28 for soup and 51/42/7 for yogurt. We conclude that our main empirical finding is not sensitive to these specification and weighting choices.

mately 39 weeks (though based on monthly data; see Mela, Jedidi, and Bowman 1998). The availability of weekly advertising and price data would enable us to make a direct comparison between the effect duration of promotions versus advertising, which is a promising topic for further research.

Finally, our analysis of the total effects shows that the immediate gains on all three sales components are typically not outweighted by negative adjustment effects. Adjustment elasticities are typically positive for category incidence (both categories) and purchase quantity (soup). Negative adjustment effects do occur as a general rule for brand choice but are insufficient to completely offset the immediate promotional impact. The findings for the soup category correspond to Jedidi, Mela, and Gupta's (1999) results of negative long-term effects for choice but positive results for purchase quantity (incidence is not considered). Note that their analysis is based on a storable, nonfood product. For the yogurt category, Ailawadi and Neslin (1998) find significant consumption increases that explain why total quantity effects are positive. The precise reasons for positive incidence effects in our analysis are a promising area for further research, in both household-level and store-level models. In our article, positive incidence adjustment effects typically occur after a few weeks and could be caused by (1) consumer purchase reinforcement and (2) additional promotions in subsequent weeks because of competitive reaction and company performance feedback. First, some of the consumers who made an additional category purchase during the promotion (i.e., impulse buyers, category switchers, and store switchers) may experience taste reinforcement and buy into the category again in subsequent weeks. Second, competitive promotion reaction and own performance feedback in subsequent weeks can also increase incidence. The separation of these effects would add considerable insight to our results.

In contrast to the immediate effects, the breakdown for adjustment effects and total effects make category incidence the dominant factor. The relative magnitude of the total effects of a price shock are 66/11/23 for soup and 58/39/3 for yogurt. A comparison with the immediate breakdown of 30/48/22 for soup and 14/73/13 for yogurt reveals different implications for the three sales components. For purchase quantity, the relative importance of the total impact closely corresponds to that of the immediate impact. In contrast, the importance of category incidence and brand choice components is reversed: Although price promotions have a large immediate impact on brand choice, their total impact on brand choice is relatively low.

Our main finding holds for different stores and categories, but not for private labels. This unanticipated finding provides a promising area for further research. Several plausible explanations deserve future research attention. First, promotions on national brands have superior drawing power toward the category, in both the short (Blattberg, Briesch, and Fox 1995) and the long run. Second, in line with Mela, Gupta, and Lehmann (1997), Mela, Jedidi, and Bowman (1998), and Jedidi, Mela, and Gupta (1999), price promotions may increase consumer price sensitivity. This phenomenon could benefit private labels, which typically have lower base prices than national brands do. The combination of the two factors represents the different benefits of promotions to retailers: Discounts on national brands increase category incidence, and discounts on private labels gain share. Similar to the findings of Putsis and Dhar (1999) and Dekimpe, Hanssens, and Silva-Risso (1999), we observe that, in the long run and assuming profitability, price promotions may benefit the retailer (primary demand) more than the manufacturer (selective demand). Our brand- and store-specific results show considerable variance in effect decomposition. Brand- and store-specific policies may be responsible for these differences, as could be addressed in further research.

In summary, our findings support the notion that brand choices are in equilibrium in mature markets and that price promotions produce only temporary benefits for established brands. Because most consumers have already bought and experienced the brand, the learning effect from mere purchase is limited and easily offset by competitive activity. The opposite results hold for category incidence: Although the immediate effects are smaller than those for brand choice, the short-term gains are reinforced rather than cancelled in the adjustment period. Price promotions can induce noncategory shoppers to make a purchase, and this expansion effect cannot be entirely explained by purchase acceleration. In other words, the incremental brand-specific sales (selective demand) are partly borrowed from sales in off-promotion periods, whereas the immediate boost in category incidence is largely retained for several periods.

The current study has several limitations, which provide promising avenues for further research. First, our data are limited to 26 brand–store combinations in two product categories. A larger set of product categories and brands could quantitatively assess how category and brand characteristics and promotional policies influence the timing, sign, and magnitude of promotional effects. Second, our analysis covers a two-year period in a mature market. Data over longer intervals and/or for emerging markets could reveal more permanent effects than those reported in this study. Third, although competitive price behavior is modeled, we do not distinguish between the different objectives of manufacturer-induced versus retailer-induced promotions (Putsis and Dhar 1999). Finally, the specifics of the store-level aggregation of our data and the VAR methodology invite a replication of our findings with household-level models that allow for complex, dynamic effects and model the nonpurchase option.

Combined with other recent work on long-term promotional effects, our article yields two major managerial implications. First, the general absence of permanent effects reassures practitioners that promotional activity does not structurally damage any of the three sales components. It suffices to monitor sales and profits during and up to two months after the promotion. As long as the immediate and adjustment effects are profitable, playing the promotional game appears better than staying out of it. This implication is confirmed by Ailawadi, Lehmann, and Neslin's (2001) study of the effects of Procter & Gamble's value pricing.

Second, our analysis provides additional support for primary demand—or market expansion—effects of price promotions. The immediate benefits on category incidence and quantity are typically not cancelled by negative adjustment effects. These results emphasize the value of price promotions to the retailer, which is primarily interested in increasing category demand, and could explain why retailers induce manufacturers to promote, even at the expense of their own private labels (Putsis and Dhar 1999). The complex promotions game between retailers and manufacturers offers a promising area for further research.

REFERENCES

Abraham, M. and L. Lodish (1987), "PROMOTER: An Automated Promotion Evaluation System," *Marketing Science*, 6 (2), 101–23.

Ailawadi, Kusum, Don Lehmann, and Scott Neslin (2001), "Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter & Gamble's Value Pricing Strategy," *Journal of Marketing*, 65 (January), 44–61.

——— and Scott Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming It Faster," *Journal of Marketing Research*, 35 (August), 390–98.

Allenby, G.M. and P. Rossi (1991), "There Is No Aggregations Bias: Why Macro Logit Models Work," *Journal of Business and Economic Statistics*, 9, 1–14.

Assunçao, Joao L. and Robert J. Meyer (1993), "The Rational Effect of Price Promotions on Sales and Consumption," *Management Science*, 39 (5), 517–35.

Bass F.M., M.M. Givon, M.V. Kalwani, D. Reibstein, and G.P. Wright (1984), "An Investigation into the Order of the Brand Choice Process," *Marketing Science*, 3, 267–87.

Bell, David, Jeongwen Chiang, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization," *Marketing Science*, 18 (4), 504–26.

Bem, D.J. (1967), "Self-Perception: An Alternative Explanation of Cognitive Dissonance Phenomena," *Psychological Review*, 74, 183–200.

Blattberg, R., R. Briesch, and E. Fox (1995), "How Promotions Work," *Marketing Science*, 14 (3), G122–G132.

———, G. Eppen, and J. Lieberman (1981), "A Theoretical and Empirical Evaluation of Price Deals for Consumer Nondurables," *Journal of Marketing*, 45 (1), 116–129.

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

Bronnenberg, Bart J., Vijay Mahajan, and Wilfried Vanhonacker (2000), "The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution," *Journal of Marketing Research*, 37 (February), 16–31.

Bucklin, Randolph E. and Sunil Gupta (1999), "Commercial Use of UPC Scanner Data: Industry and Academic Perspectives," *Marketing Science*, 18 (3), 247–73.

———, ———, and S. Siddarth (1998), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors," *Journal of Marketing Research*, 35 (May), 189–97.

Chandon, Pierre and Brian Wansink (1997), "When and Why Does Promotional Stockpiling Accelerate Consumption?" Working Paper No. 97-116, School of Commerce, University of Illinois, Champaign-Urbana.

Chiang, Jeonweng (1991), "A Simultaneous Approach to the Whether, What and How Much to Buy Questions," *Marketing Science*, 12 (Spring), 184–209.

Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households," *Marketing Science*, 12, 184–208.

Clarke, D. (1976), "Econometric Measurement of the Duration of Advertising Effects on Sales," *Journal of Marketing Research*, 13 (November), 345–57.

Currim, I. and L. Schneider (1991), "A Taxonomy of Consumer Purchase Strategies in a Promotion Intensive Environment," *Marketing Science*, 10 (Spring), 91–110.

Davis, S., J. Inman, and L. McAllister (1992), "Promotion Has a Negative Effect on Brand Evaluations—Or Does It? Additional Disconfirming Evidence," *Journal of Marketing Research*, 29 (February), 143–48.

Dekimpe, Marnik and Dominique Hanssens (1995a), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

——— and ——— (1995b), "Empirical Generalizations About Market Evolution and Stationarity," *Marketing Science*, 14 (3), G109–G121.

——— and ——— (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 35 (November), 397–412.

———, ———, and J. Silva-Risso (1999), "Long-Run Effects of Price Promotions in Scanner Markets," *Journal of Econometrics*, 89, 269–91.

Erdem, Tulin (1996), "A Dynamic Analysis of Market Structure Based on Panel Data," *Marketing Science*, 15 (4), 359–78.

——— and Michael P. Keane (1996), "Decision Making Under Uncertainty: Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15 (1), 1–20.

Foekens, Eijte W., Peter S.H. Leeflang, and Dick R. Wittink (1999), "Varying Parameter Models to Accomodate Dynamic Promotion Effects," *Journal of Econometrics*, 89, 249–68.

Gijsbrechts, E. (1993), "Prices and Pricing Research in Consumer Marketing: Some Recent Developments," *International Journal of Research in Marketing*, 10, 115–51.

Greenleaf, Eric (1995), "The Impact of Reference Price Effects on the Profitability of Price Promotions," *Marketing Science*, 14, 82–93.

Grover, R. and V. Srinivasan (1992), "Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments," *Journal of Marketing Research*, 29 (February), 72–81.

Guadagni, Peter and John Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (Summer), 203–38.

Gupta, S. (1988), "Impact of Sales Promotions on When, What, and How Much to Buy," *Journal of Marketing Research*, 25 (November), 342–55.

Helson, H. (1964), *Adaptation-Level Theory*. New York: Harper & Row.

Jain, D. and N. Vilcassim (1991), "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach," *Marketing Science*, 10 (1), 1–23.

Jedidi, Kamel, Carl F. Mela, and Sunil Gupta (1999), "Managing Advertising and Promotion for Long-Run Profitability," *Marketing Science*, 18 (1), 1–22.

Kalyanaram, Gurumurthy and Russell S. Winer (1995), "Empirical Generalizations from Reference Price Research," *Marketing Science*, 14 (3), G161–G169.

Krishna, Aradhna (1992), "The Normative Impact of Consumer Price Expectations for Multiple Brands on Consumer Purchase Behavior," *Marketing Science*, 11 (3), 266–86.

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

Krishnamurthi, Lakshman, T. Mazumdar, and S.P. Raj (1992), "Asymmetric Response to Price in Consumer Choice and Purchase Quantity Decisions," *Journal of Consumer Research*, 19, 387–400.

Lal, Rajiv and V. Padmanabhan (1995), "Competitive Response and Equilibria," *Marketing Science*, 14 (3), G101–G108.

Lattin, James and Randolph Bucklin (1989), "Reference Effects of Price and Promotion on Brand Choice Behavior," *Journal of Marketing Research*, 26 (August), 299–310.

Leeflang, P.S.H. and D.R. Wittink (1992), "Diagnosing Competitive Reactions Using (Aggregated) Scanner Data," *International Journal of Research in Marketing*, 9, 39–57.

——— and ——— (1996), "Competitive Reaction Versus Response: Do Managers Overreact?" *International Journal of Research in Marketing*, 13 (2), 103–19.

Leone, Robert P. (1987), "Forecasting the Effect of an Environmental Change on Market Performance: An Intervention Time Series Approach," *International Journal of Forecasting*, 3, 463–78.

——— (1995), "Generalizing What Is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, 14 (2), G141–G151.

Litvack, David S., Roger J. Calantone, and Paul R. Warshaw (1985), "An Examination of Short-Term Retail Grocery Price Effects," *Journal of Retailing*, 61 (Fall), 9–26.

Lütkepohl, Helmut (1993), *Introduction to Multiple Time Series Analysis*, 2d ed. New York: Springer-Verlag.

Mela, Carl F., Sunil Gupta, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (2), 248–61.

———, Kamel Jedidi, and Douglas Bowman (1998), "The Long-Term Impact of Promotions on Consumer Stockpiling Behavior," *Journal of Marketing Research*, 35 (May), 250–62.

Moriarty, Mark M. (1985), "Retail Pomotional Effects on Intra- and Interbrand Store Performance," *Journal of Retailing*, 61 (3), 27–47.

Narasimhan, Chakravarthi, Scott Neslin, and Subrata Sen (1996), "Promotional Elasticities and Category Characteristics," *Journal of Marketing*, 60 (April), 17–30.

Neslin, Scott A., Caroline Henderson, and John Quelch (1985), "Consumer Promotions and the Acceleration of Product Purchases," *Marketing Science*, 4 (2), 147–65.

Nijs, Vincent R., Marnik G. Dekimpe, Jan-Benedict E.M. Steenkamp, and Dominique M. Hanssens (2001), "The Category Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1–22.

Papatla, Purushottam and Lakshman Krishnamurthi (1996), "Measuring the Dynamic Effects of Promotions on Brand Choice," *Journal of Marketing Research*, 33 (1), 20–35.

Pesaran M.H.and R. Smith (1995), "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels," *Journal of Econometrics*, 23, 479–84.

Putsis, William and Ravi Dhar (1999), "Category Expenditure, Promotion, and Competitive Market Interactions: Can Promotions Really Expand the Pie?" working paper, London Business School.

Srinivasan, Shuba, Peter T.L. Popkowski Leszczyc, and Frank M. Bass (2001), "Market Share and Competitive Response: The Impact of Temporary, Evolving, and Structural Changes in Prices," *International Journal of Research in Marketing*, 17 (4), 281–305.

Van Heerde, Harald J., Peter S.H. Leeflang, and Dick R. Wittink (2000a), "The Estimation of Pre- and Postpromotion Dips with Store-Level Scanner Data," *Journal of Marketing Research*, 37 (August), 383–95.

———, ———, and ——— (2000b), "Flexible Decomposition of Sales Promotion Effects Using Store-Level Scanner Data," working paper, Department of Marketing, Tilburg University, [available from first author at heerde@kub.nl].

Vilcassim, N.J. and P.K. Chintagunta (1992), "Investigating Retailer Pricing Strategies from Household Scanner Panel Data," working paper, Department of Economics, University of Chicago.